PERFORMANCE ANALYSIS OF FLEXIBLE MANUFACTURING SYSTEM USING METAHEURISTICS

THESIS

submitted in fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

to

YMCA UNIVERSITY OF SCIENCE & TECHNOLOGY

by

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DECEMBER, 2016

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I, hereby declare that this thesis entitled **PERFORMANCE ANALYSIS OF FLEXIBLE MANUFACTURING SYSTEM USING METAHEURISTICS** by **VINEET JAIN**, being submitted in fulfillment of the requirements for the Degree of Doctor of Philosophy in MECHANICAL ENGINEERING under Faculty of Engineering & Technology of YMCA University of Science & Technology Faridabad, during the academic year 2015-2016, is a bonafide record of my original work carried out under guidance and supervision of **Dr. TILAK RAJ, PROFESSOR, DEPARTMENT OF MECHANICAL ENGINEERING** and has not been presented elsewhere.

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I further declare that to the best of my knowledge, the thesis does not contain any part of any work which has been submitted for the award of any degree either in this university or in any other university.

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ACKNOWLEDGEMENT

I am immensely grateful to my supervisor Dr. Tilak Raj, Professor, Department of Mechanical Engineering, YMCA University of Science and Technology, Faridabad, for they went out of their way to be helpful and provided me a good deal of information and useful insights for this research work.

I am also grateful to Dr. Dinesh Kumar, V.C., YMCA University of Science and Technology, Faridabad, for imparting constant encouragement and support for carrying out this work. The constant guidance and encouragement received from Dr. Sandeep Grover, Dean, Faculty of Engineering and Technology, YMCA University of Science and Technology, Faridabad and Dr. M.L Aggarwal, Chairman of Mechanical Engineering Department, YMCA University of Science and Technology, Faridabad, have been great help in carrying out the present work and their acknowledge with reverential thanks.

I would like to express my thanks to Mr. Ashish Kumar for his constant assistance in availing the research material.

I owe my thanks to Mr. Sachin Jain, Mr. Achin Jain, Mr. Pankaj Jain, Mr. Amarjeet Singh and Mr. Kailash Yadav for giving me immense help regarding industrial resources.

I extend my thanks to Heddam Salim from Algeria, Mohammad Farshchin from Memphis, Ibrahem Maher from Malaysia and Sanoop Kottuvayal Thazha Kuni from India for their guidance.

I would like to acknowledge my gratitude to my revered parents and brother for their blessings to accomplish my task.

In the completion of this research work, I was constantly supported by my wife Ms. Swati Jain. I cannot forgot the hearty support and patience of my children Arsh Jain and Riddhi Jain.

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ABSTRACT

The market competition is becoming more and more complex so the speed of delivery and quality of products have become the main priorities of manufacturing firms. The manufacturing companies need to adopt such type of manufacturing systems which are more flexible in operation and are able to satisfy dynamic market demands. Such needs of the modern industries can be met with the adoption of flexible manufacturing system. Thus the innovation of flexible manufacturing system (FMS) became related to the effort of gaining competitive advantage.

FMS has been developed with the hope that it will be able to tackle new challenges like lower cost, better quality and improved delivery speed. They will be more flexible in their operations and will be able to satisfy different market segments. FMSs are the integrated manufacturing systems which can help the user to achieve the goals of increasing profitability through the increase of productivity and flexibility. Productivity has often been cited as a key factor in a FMS performance. Improving productivity is seen as a key issue for survival and success in the long term of a manufacturing system. To increase the manufacturing flexibility, manufacturing organizations are looking at FMS as a viable alternative to enhance their competitive edge.

A lot of research has been done regarding scheduling and operational issues of FMS. But performance analysis of FMS is still a major issue for researcher. With this aim, an effort has been made in the current research work to analyze the performance of FMS so that it can attract more Indian industries for its useful utilization.

An extensive literature review has been conducted to identify the gaps regarding the performance of FMS. A number of variables of performance, productivity and flexibility have been identified through the previous research done by different researchers. A survey among the Indian manufacturing firms has been conducted to gain insight of analysis of FMS especially for performance, productivity and flexibility of FMS.

Interpretive structural modelling and total interpretive structural modelling techniques have been used to develop hierarchical structures to identify the relationship among the main variables of performance, productivity and flexibility of FMS and to find the driving and the dependence power of the variables. Structural equation modelling is used for confirming the structure which is developed by interpretive structural

modelling and confirming the factors which affect performance, productivity and flexibility of FMS. Graph theory and matrix approach has been used to quantify the factors in term of FMS performance/ productivity/flexibility index.

Ranking of types of flexibility in FMS has been done by combined multiple attribute decision making method, which consists of analytic hierarchy process (AHP), technique for order preference by similarity to ideal situation (TOPSIS), modified TOPSIS, VIKOR and improved preference ranking organization method for enrichment evaluations (PROMETHEE).

Estimation of the makespan of Flexible manufacturing system assembly shop is done by using adaptive neuro-fuzzy inference system (ANFIS). An attempt has also been made to solve tool life management by using the ANFIS to predict the cutting force and surface roughness. Cutting force is optimized by metaheuristics such as genetic algorithm (GA) and teaching learning based optimization (TLBO) to optimize the tool life.

The major contributions of this research are as given below

- The present research provides a comprehensive review of the literature and identifies the variables which affect performance of FMS.
- Out of fifteen variables of performance analysis of FMS, three factors such as quality, productivity and flexibility are identified.
- Out of twenty variables of productivity analysis of FMS, four factors such as people, machine, quality, and flexibility are recognized.
- Out of fifteen variables of flexibility analysis of FMS, four dimensions such as production, product, machine and volume flexibility are identified.
- The driving and dependence power of variables which affect the FMS have been analyzed and models for performance, productivity and flexibility have been prepared.
- Major factors affecting the performance, productivity, and flexibility of FMS have been identified.
- The driving and dependence power of flexibilities have been analyzed by ISM.
- FMS performance index, FMS productivity index, and FMS flexibility index has been proposed by GTMA framework which help any industry to know its own index value to upgrade them.

- Combined multiple attribute decision making methods are used for ranking of flexibility based on fifteen variables. Spearman's rank correlation coefficients observed that the rankings by different methods are consistent.
- NEH algorithm found the makespan and made a model by ANFIS for industry to predict the makespan of FMS assembly shop.
- Optimization of cutting parameters by metaheuristics i.e. G.A and TLBO and discussed the method to optimize parameters.
- ANFIS model is proposed for surface roughness and cutting force prediction.

Keywords: FMS; performance; productivity; flexibility; factors; variables; ISM; EFA; CFA; SEM; GTMA; TISM; fuzzy MICMAC; SPSS; AMOS; MADM, AHP; TOPSIS; Improved PROMETHEE; Fuzzy; Modified TOPSIS; VIKOR; FMS assembly shop; NEH heuristic; makespan estimation; ANFIS; tool life management; cutting force estimation; surface roughness estimation; unmanned production system; metaheuristics; GA, TLBO.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Sr. No.	Description	Abbreviations
1.	Flexible Manufacturing System	FMS
2.	Numerical Controlled	NC
3.	Computer Numerical Control	CNC
4.	Automated Guided Vehicle	AGV
5.	Automatic Storage	AS
6.	Retrieval System	RS
7.	Coordinate Measuring Machine	CMM
8.	Direct Numerical Control	DNC
9.	Material Handling System	MHS
10.	Interpretive Structural Modeling	ISM
11.	Structural Equation Modeling	SEM
12.	Exploratory Factor Analysis	EFA
13.	Confirmatory Factor Analysis	CFA
14.	Graph Theory and Matrix Approach	GTMA
15.	Total Interpretive Structural Modeling	TISM
16.	Multiple Attribute Decision Making	MADM
17.	Multi-Criteria Decision Making	MCDM
18.	Multi-Objective Decision Making	MODM
19.	Simple Additive Weighting	SAW
20.	Weighted Product Method	WPM
21.	Analytic Hierarchy Process	AHP
22.	Technique for Order Preference by Similarity to Ideal Solution	TOPSIS
23.	Compromise Ranking Method	VIKOR
24.	Preference Ranking Organization Method for Enrichment Evaluations	PROMETHEE
25.	Adaptive Neuro-Fuzzy Inference System	ANFIS
26.	Fuzzy Inference System	FIS
27.	Genetic Algorithm	GA
28.	Evolutionary Algorithm	EA
29.	Teaching Learning Based Optimization	TLBO

30.	Statistical Package for Social Sciences	SPSS
31.	Analysis of Moment Structures	AMOS
32.	Nawaz, Enscor and Ham	NEH
33.	Matrix Laboratory	MATLAB
34.	Work in Process	WIP
35.	Structural Self-Interaction Matrix	SSIM
36.	Reachability Matrix	RM
37.	Directed Graph	DIGRAPH
38.	Factor Analysis	FA
39.	Goodness of Fit Index	GFI
40.	Adjusted Goodness of Fit Index	AGFI
41.	Root Mean Square Residual	RMR
42.	Root Mean Square Error of Approximation	RMSEA
43.	Normed-Fit Index	NFI
44.	Non-Normed Fit Index	NNFI
45.	Tucker-Lewis Index	TLI
46.	Relative Fit Index	RFI
47.	Comparative Fit Index	CFI
48.	Incremental Fit Index	IFI
49.	Kaiser-Meyer-Olkin	KMO
50.	Degrees of Freedom	DF
51.	Chi-Square Value	CMIN
52.	Geometric Mean	GM
53.	Consistency Index	CI
54.	Random Index	RI
55.	Consistency Ratio	CR
56.	Neural Networks	NN
57.	Design Of Experiments	DOE
58.	Matrice d'Impacts Croises-Multipication Applique an Classment	MICMAC
59.	Composite Reliability	CR
60.	Average Variance Extracted	AVE
61.	Binary Direct Relationship Matrix	BDRM

62.	Fuzzy Direct Relationship Matrix	FDRM
63.	Fuzzy Set Theory	FST
64.	Flexible Manufacturing System Assembly Shop	FMSAS
65.	Root Mean Squared Error	RMSE
66.	Graphical User Interface	GUI
67.	Membership Functions	MF

CHAPTER I

INTRODUCTION

1.1 INTRODUCTION

A flexible manufacturing system (FMS) is a manufacturing philosophy. It controls material flow effectively through a network of versatile production stations by using an efficient and versatile material handling and storage system. FMS consists innumerable programmable and computerized machine tools connected by an automatic material handling system like robots and automatic guided vehicles (AGVs) and automatic storage and retrieval system (AS/RS) that can process simultaneously medium-sized volumes of the different parts [1].

FMS is capable of producing a variety of parts and handling flexible routing of parts instead of running parts in a straight line through machines [2]. Manufacturing industries adopt the FMS for fulfilling the huge demands of the customized production [3]. It can be observed as the technology that avail a high power for improvement in productivity in the discrete manufacturing systems. FMS is flexible enough to meet the fluctuating market demands. It responds soon to the unexpected changes in the market and introduces a variety of parts. It has been hailed as one of the best solution for the challenges faced by manufacturing industries worldwide [4]. FMS has been known as the absolute method to encourage productivity to fulfill the challenges [5].

David Williamson, a British engineer who was employed by Molins in the middle of 1960s, developed the concept of FMS. Molins applied for a patent for the invention and it was granted in 1965. The concept was called System 24 because it was believed that the group of machine tools comprising the system could operate 24 hours a day. Ingersoll-Rand Company of USA was the first where FMS was installed as a machining system [6, 7].

FMS traits, organizational culture, organizational policy, organizational layout and style and experience of management interact with each other to regulate the inclination of the organization to opt for FMS [8].

FMS comprises high end software and hardware and other equipment such as CNC machine tools, robots, AGVs and coordinate measuring machines (CMMs), etc. FMS has the flexibility to exercise many non-identical part styles at the various workstations simultaneously and the variety of part styles and quantities of production can be managed in response to the flickering demand patterns.

In FMS, computers operate the numerically controlled (NC) machines, robots handle the parts and automated guided vehicles (AGVs) carry the final products to specific destinations. CNC machines are needed for machining of materials. CMMs and machine vision system are needed for inspection work and advance material handling system such as AGVs, robots, conveyors and AS/RS are needed for material movement and storage purposes. Robots, CNC machines and automated material handling systems controlled by dedicated computers which are the main components of FMS [9]. Similarly software used in the FMS environment is very complex [10].

According to Ranky [11] FMS deals with automated material flow using computer-controlled machines, assembly cells, industrial robots, inspection machines and so on, together with computer integrated material-handling and storage systems.

The particular manufacturing situations which are apt for the adoption of FMSs are [12]

- The non-identical high precision parts are machined (typically job shop).
- Direct numerical control (DNC) machines are required in large number.
- Automatic material-handling system (MHS) is applied to move the work pieces into, within and out of the FMS.
- On-line computer control is applied to manage the whole FMS for different parts, production mixes and priorities.

1.2 COMPONENTS OF FMS

Klahorst [13] has defined FMS as a group of machines and parallel equipment which are brought together to execute a group of parts completely. FMS components are shown in Figure 1.1. Basic components of FMS are:

(a) Workstations: Flexible manufacturing systems are being designed with other type of processing equipment likes Machining centers, loading and unloading stations, assembly works stations and inspection stations etc.

The various workstations are:

(i) Machining centers: The workstations used in FMS are predominantly CNC machine tools. It is a common application of FMS. CNC machine tools with appropriate automatic tool changing and tool storage features facilitate quick physical changeover, as necessary. Machining centers can be ordered with automatic pallet changers that can be readily interfaced with the FMS part handling system.

(ii) Loading and unloading stations: It is physical interface between the FMS and the rest of the factory where raw parts enter into the system and completely-processed parts exit the system. Loading and unloading can be performed manually by personnel or it can be automated as part of the material handling system. It should be designed to permit the safe movement of the parts. The station includes a data entry unit and monitor for communication between the operator and computer system, regarding parts to enter into the system and parts to exit the system. In some FMSs, various pallet fixtures to accommodate different pallet sizes may have to be put in place at loading/unloading stations.

(iii) Washing stations: Part is cleaned before it goes to the assembly or inspection station for removal of swarf. Un-removed swarf creates problem during the assembly or inspection process. After being cleaned, the part is carried to other stations by the robots or AGVs.

(iv) Assembly work stations: Flexible automated assembly systems are the assembly operation usually consists of a number of workstations with industrial robots that sequentially assemble components to the base part to create the overall assembly. They can be programmed to perform tasks with variations in sequence and motion pattern to accommodate the different product styles assembled in the system.

(v) Inspection stations: Inspection stations are those stations where various inspection tasks may be carried out. Co-ordinate measuring machines and machine vision are mainly used for inspection purposes.

(b) Automated material-handling system: The various automated material handling systems are used to transport work parts and subassembly parts between the processing stations, sometimes incorporating storage into function.

The various functions of automated material handling and storage system are:

(i) Free movement of work parts between workstations

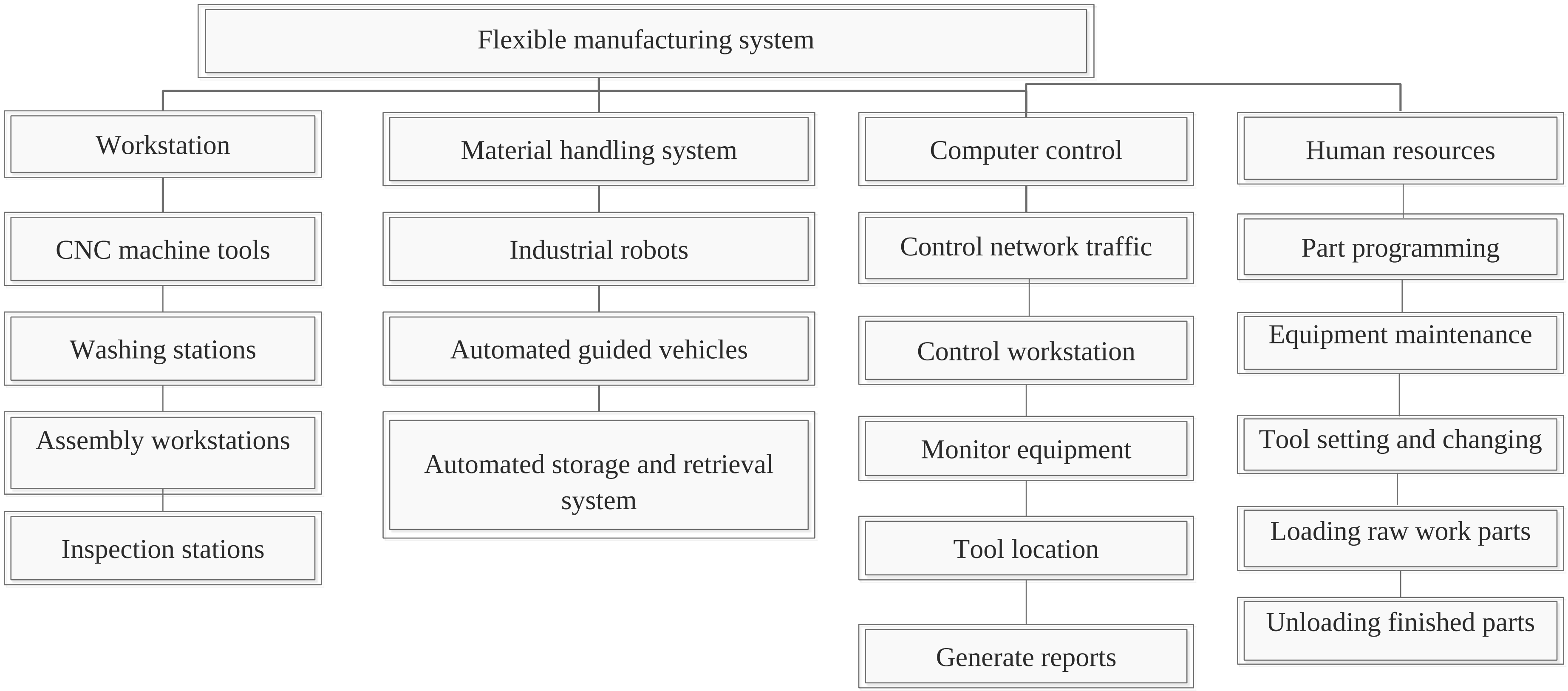

Figure 1.1 Component of FMS

(ii) Handling system should be capable to handle a variety of work part configurations

(iii) Handling system should have temporary storage

(iv) Handling system should be conveniently access for loading and unloading of work parts

(v) Handling system should be controlled by computer system

(c) Computer control system: It is used to control the activities of the processing stations and the automated material handling system in the FMS. The various functions of computer control system are:

(i) To control the work station

(ii) To distribute the control instruction to work station

(iii) To control production

(iv) To control network traffic

(v) To monitor the work handling system

(vi) To control tool especially for tool location and tool life

(vii) To monitor equipment

(viii) To generates reports

(d) Human resources: Humans are also required in the FMS to perform a variety of supporting operations in the system.

The various functions of human resources are:

(i) Loading raw work parts into the system

(ii) Unloading finished parts or assemblies from the system

(iii) Changing and setting tools

(iv) Performing equipment maintenance and repair

(v) Performing NC part programming

(vi) Programming and operating the computer system

1.3 BENEFITS OF FMS

FMS has the main advantage of its high flexibility in manufacturing system to produce new product with in minimum time and effort. The suggested benefits of FMS by Primrose [14], Groover [15] are as follows:

- Increased sales volume, by making products more competitive (e.g. delivery, price, quality, product specification, etc.)
- Speedy production

- Settled fluctuating demands
- Increased machine utilization
- Handling different volumes and variety of parts
- Reduction in floor space needed
- Better control due to automation.
- Elimination of unprofitable orders
- Minimized per unit production cost
- Reduced number of labor
- Reduced work in process inventory
- Curtailed in manufacturing lead time
- Increased system reliability especially for delivery
- Improved ability to match product specification to customer needs
- Improved ability to deliver products to the quality and specification ordered by customers.

1.4 RESEARCH GAPS

During this research work, a lot of research papers related to FMS have been studied and it is found that there are some research gaps in the areas of performance measurement, productivity and flexibility of FMS. The following gaps are identified:

- In the literature related to performance of FMS, not much work has been reported for modelling of FMS performance variables.
- Variables related to FMS productivity need to be modelled.
- Models for factors affecting the flexibility in FMS are not statistically validated.
- In the literature, ranking of flexibility in FMS have not been categorized by different decision making techniques.
- In the literature, model for estimation of makespan of assembly shop is not defined.
- In the literature, model is not available for estimation of cutting forces and surface roughness for unmanned production system regarding tool life.

1.5 RESEARCH OBJECTIVES

Based on the gaps in the existing literature, research objectives have been identified. They are as follows:

1. Performance measurement of FMS.
2. Identification of different variables effecting flexibility and productivity of FMS.
3. Modeling of above variables.
4. Analysis of scheduling problem in FMS.
5. Study of flexibility techniques in FMS.
6. Study of issue of tool life management, especially in case of unmanned shifts, for finding the full production capacity of FMS.
7. Study of different constraints regarding different resources in FMS. These constraints may be limited to Machine tool range to hold different parts and cutting tools, fix range by part handle by robots, fixed path layout by AGV and the rigidity of fixtures.

1.6 METHODOLOGIES USED IN RESEARCH WORK

Following methodologies have been used in analysis and preparation of different models:

(a) Interpretive Structural Modeling (ISM)

A complex system can become a visualized hierarchical structure by interpretive structural modeling (ISM). It is used to analyze and solve complex problems to manage decision-making. The ISM methodology is understood in the sense that the judgments of the groups decide whether the variables are connected or not and how they are concerned if they behave. It is structured since an overall structure is extracted from the complex set of variables on the basis of relationships [16]. It is a modeling technique, in which specific relationships and overall structures are depicted in a digraph model. It provides direction on the complexity of relationships among various elements of a system [17, 18]. It is primarily intended as a group learning process, but individuals can also use it.

(b) Structural Equation Modeling (SEM)

SEM is a technique to represent, to specify, to estimate and assess models of linear relationships among a set of observed variables in terms of a generally smaller number of unobserved variables [19, 20] . SEM resembles path analysis by providing parameter estimates of the direct and indirect links among observed variables [21, 22]. It is possible to accomplish factor analysis in SEM by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). By multivariate data structures, EFA explores the factors of a measurement instrument, whereas CFA verifies the factor structure of a set of observed variables. The SPSS may be employed in the EFA to extract dimension from the variables. Subsequently, CFA may be applied to confirm these dimensions in the factor analysis by AMOS.

(c) Exploratory Factor Analysis (EFA)

EFA, generally used in behavioral and social sciences, is a multivariate statistical technique. Costello and Osborne [23] used the technique and provided researchers with a compilation of 'best practices' in EFA to discuss common practices in studies. The researcher can apply this method frequently without bothering whether the data would fulfill the requirements of the method or not. The influence of sample size, data transformation, factor extraction method, rotation and number of factors on the outcome were investigated.

The primary objectives of an EFA are:

- To find the number of factors.
- To identify the factor loading on the variables.
- To determine the poorly measured dimensions in the study.

(d) Confirmatory Factor Analysis (CFA)

CFA is a theory testing model in contrast to a theory generating method like EFA. In CFA, the researcher begins with a hypothesis prior to the analysis. The model or the hypothesis, specify the variables that are to be correlated with the specific factors. The hypothesis is based on a strong theoretical and/or empirical foundation [24]. The factor structure of a set of observed variables can be verified by CFA which is a statistical technique. It enables the researcher to examine the hypothesis that a relationship exists between the observed variables and their underlying latent construct(s). The researcher uses knowledge of the theory, empirical research, or both, postulates the relationship pattern a priori and then tests the hypothesis statistically [25].

(e) Graph Theory and Matrix Approach (GTMA)

GTMA is a systematic and logical approach that is applied in various disciplines. Digraph or the directed graph models are based on the structure of the system but are flexible enough to analyze changes. The conventional displays as block diagrams, cause and effect diagrams and flowcharts do not present interactions among the factors and unsuitable for further analysis and cannot be processed or expressed in mathematical form [26]. GTMA has an edge over the conventional techniques of representation and quantification. The features mentioned below highlight the uniqueness of the approach over other similar approaches [27]:

- Single numerical index is presented for all the variables.
- GTMA is a systematic methodology to converse qualitative factors into quantitative values and gives an edge to the proposed technique over conventional methods.
- It permits modeling of interdependence of variables under consideration.

(f) Total Interpretive Structural Modeling (TISM)

Origin of TISM is originated from ISM technique. TISM facilitates the development of graphical representations of complex systems. It incorporates the interpretation of each relation i.e. it gives not only direct relation but transitive relation also. The interpretive matrix can be directly applied in case of structural modeling to interpret directed and undirected binary or fuzzy relations. In case of a graphical model, the interpretation of the relation can be shown by the side of the link connecting the pair of elements having the relation. An ISM model can be upgraded as a TISM model, by interpreting both the nodes and links in the structural model, which may have higher applicability in real life situations.

(g) Multiple Attribute Decision Making (MADM)

The most well-known branch of decision making is multiple attribute decision making (MADM). It solves problem of selecting a finite number of alternatives. This method specifies to attribute information to arrive at a choice. MADM methods need comparisons between inter and intra attributes and include appropriate explicit tradeoffs. The decision matrix in MADM methods has four main parts namely (a) alternatives (b) attributes (c) weight or relative importance of each attribute and (d) measures of performance of alternatives with respect to the attributes [28]. MADM is a decision making model which means decision making in the presence of multiple generally conflicting criteria. MCDM is separated into multi objective decision making (MODM) and multi attribute decision making (MADM) based on domain of alternatives [29]. MODM methods comprise decision variable values that are fixed in a continuous or integer domain with either an infinitive or a large number of alternative choices the best of which should satisfy the decision maker's constraints and preference priorities whereas MADM focuses on problems with discrete decision spaces and in these problems the set of decision alternatives is predetermined [30]. There are various MADM methods which are considered in this research work such as:

a) Simple additive weighting (SAW) method

b) Weighted product method (WPM)

c) Analytic hierarchy process (AHP) method

d) Technique for order preference by similarity to ideal solution (TOPSIS) method

e) Modified TOPSIS method

f) Compromise ranking method known as VIKOR

g) Improved preference ranking organization method for enrichment evaluations known as improved PROMETHEE

(h) Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang [31] proposed adaptive neuro-fuzzy inference system (ANFIS). This constructs an input-output mapping i.e. based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. It is an adaptive network, a network of nodes and directional links. This network is associated with a learning rule - for example back propagation or hybrid algorithm. ANFIS can predict data by using sugeno fuzzy inference system (FIS) to relate membership and tune it using either back propagation or hybrid method. The aim of ANFIS is to search a model, which will simulate correctly the inputs to the outputs. In this research, the various input variables are trained and tested by ANFIS method and the performances of models for deduction of surface roughness with unmanned production system are compared and evaluated based on testing performances. Five network layers are used by ANFIS to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction, (iv) decision making and (v) output defuzzification [32].

(i) Genetic Algorithm (GA)

John Holland invented Genetic Algorithm (GA) in the year 1975. According to Holland GA is a heuristic method which is based on 'Survival of the fittest'. It was observed as a useful tool for search and to find approximate solutions to optimization problems. GA is considered the main paradigm of evolutionary computing. A genetic algorithm is a problem solving method. The method uses genetics as its model of problem solving.

GA handles a population of possible solutions. Each solution is represented through a chromosome, which is just an abstract representation. It starts by generating an initial population of chromosomes. GAs are the ways of solving problems by mimicking processes nature uses i.e. Evaluation, Selection, Crossover, Mutation and Stopping criteria.

(j) Teaching Learning Based Optimization (TLBO)

Rao et al. [33] proposed teaching learning based optimization (TLBO) algorithm which is a teaching learning process based on the effect of influence of a teacher on the output of learners in a class. The algorithm mimics teaching-learning ability of teacher and learners in a classroom. In TLBO algorithm, population is the group of learners, different subjects offered to the learners are considered as different design variables and learners' results are analogous to the 'fitness' value of the optimization problem. In the entire population, the best solution is considered as the teacher. The working of TLBO is divided into two parts: 'Teacher phase' and 'Learner phase'.

1.7 ORGANIZATION OF RESEARCH WORK

In order to achieve the objectives framed in section 1.5, it is important to devise a proper methodology involving best practices, methods and usage of necessary software. So, this research work was outlined in 11 chapters. The organization of research work has been depicted in Figure 1.2. A brief description of 11 chapters, which are embodied in this research work, are discussed as below:

Chapter 1: Introduction

This chapter contains the introduction of FMS. Selection of FMS is also discussed. Research gaps are identified from the literature and research objectives are defined based on the research gap. A brief introduction of methodologies to achieve the research objectives as well as organization of thesis have been discussed.

Chapter 2: Literature review

More than 500 research papers have been studied in the areas of performance, productivity, flexibility, makespan estimation and prediction of tool life based on cutting force and surface roughness in FMS. Nearly 400 papers were found relevant to this research work. The variables/factors, which effect performance, productivity, flexibility of FMS, were finally identified. Issues related to the constraints of FMS have been discussed. The different methodologies have been used such as ISM, TISM, SEM, GTMA, MADM, ANFIS, GA and TLBO etc. have been used in this research work.

Chapter 3: Questionnaire survey

This chapter covers the development of questionnaire. A questionnaire has been prepared for performance, productivity, flexibility variables of FMS. Then across the country survey was conducted across the India automobile industries.

Chapter 4: Modeling and analysis of performance variables of FMS

The performance variables of flexible manufacturing system (FMS) by different approaches viz. ISM; SEM; GTMA and a cross-sectional survey within manufacturing firms in the India have been analyzed. ISM has been used to develop a hierarchical structure of performance variables and to find the driving and the dependence power of the variables. EFA and CFA are powerful statistical techniques. By performing EFA, factor structure is placed whereas CFA verified the factor structure of a set of observed variables. CFA is carried by SEM statistical technique. EFA is applied to extract the factors in FMS by the statistical package for social sciences (SPSS) software and confirming these factors by CFA through analysis of moment structures (AMOS) software. SEM using AMOS was used to develop the first order three factor structures. GTMA is a multiple attribute decision making (MADM) methodology used to find intensity/quantification of performance variables in an organization. The FMS performance index has been proposed to quantify the factors which affect FMS.

Chapter 5: Modeling and analysis of productivity variables of FMS

The purpose of this research is to make a model and analysis of the productivity variables of FMS. This study was performed by different approaches viz. ISM; SEM;

GTMA and a cross-sectional survey within manufacturing firms in India. ISM has been used to develop a model of productivity variables and then it has been analyzed. EFA and CFA are powerful statistical techniques. CFA is carried by SEM. EFA is applied to extract the factors in FMS by SPSS software and confirming these factors by CFA through AMOS software. SEM using AMOS was used to develop the first order four factor structures. GTMA is a MADM methodology used to find intensity/quantification of productivity variables in an organization. The FMS productivity index has proposed to quantify the factors which affect FMS.

Chapter 6: Modeling and analysis of flexibility variables of FMS

Fifteen variables were identified from the literature and a model was prepared by TISM and their evaluation was taken by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA was applied to extract the factors in FMS by SPSS software and confirming these factors by CFA through AMOS software. SEM using AMOS was used to perform the first order four factor structures. GTMA is a MADM methodology used to find intensity/quantification of flexibility variables in an organization. The FMS flexibility index has been proposed to intensify the factors which affect FMS.

Chapter 7: Modeling and ranking of types of flexibility in FMS

In this research, modeling was done by ISM and impact of types of flexibility in FMS was decided by combined multiple attribute decision making method, which consists of analytic hierarchy process (AHP), technique for order preference by similarity to ideal situation (TOPSIS), modified TOPSIS, VIKOR and improved preference ranking organization method for enrichment evaluations (PROMETEE). The criteria weights are calculated by using the analytical hierarchy process (AHP). Furthermore, the method uses fuzzy logic to convert the qualitative attributes into the quantitative attributes.

Chapter 8: Makespan estimation of FMS assembly shop

This chapter focuses on to calculate the makespan of flexible manufacturing system assembly shop by using adaptive neuro-fuzzy inference system (ANFIS). On the basis of Nawaz, Enscor and Ham (NEH) heuristic, a model with combined neuro and fuzzy system i.e. ANFIS model is made to predict the makespan of the jobs. This is a case study of automobile company.

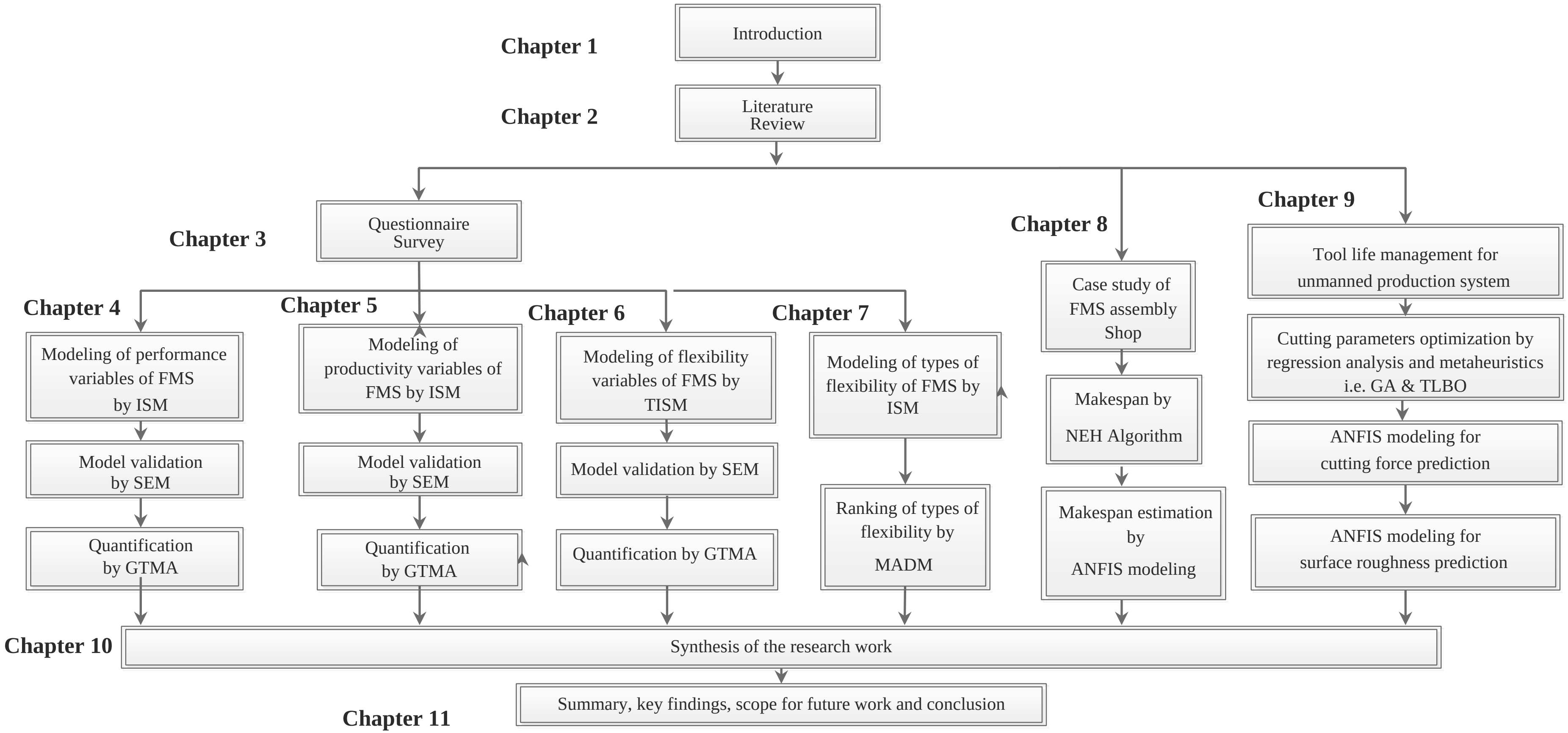

Figure1.2 Organization of the research work

Chapter 9: Study of tool life management especially for unmanned production system

In this chapter, an attempt has been made to solve tool life management by using the ANFIS to predict the cutting force and surface roughness. Cutting force is optimized by different soft computing techniques or metaheuristics such as genetic algorithm (GA) and teaching learning based optimization (TLBO). MATLAB (**mat**rix **lab**oratory) software is used for development of necessary programs and the analysis. In this research, the cutting forces are used as the indicator of the tool life management.

Chapter 10: Synthesis of research work

In this research section, a connection among different methodologies which have been discussed in this research, is shown.

Chapter 11: Summary, key findings, scope for future work and conclusion

In the last chapter of this thesis, the summary of the research, research findings, major implications and limitations of the research with conclusion of the research work have been presented.

1.8 CONCLUSION

It is a common phenomenon among the manufactures to scrutinize the performance of their industry. So, they are interested to acknowledge the factors which are responsible for the magnification of performance, productivity and flexibility of manufacturing system. There are some certain variables which affect the performance, productivity and flexibility of manufacturing system. Therefore the aim of this study is to recognize those factors which affect performance, productivity and flexibility of manufacturing system. Introduction of research work is presented in this chapter. Motivation of the research work, its objectives, methodologies and its organization have been furnished.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

The emerging concept of flexible manufacturing system (FMS) includes a certain degree of flexibility that allows systems to react in case of predicted or unpredicted changes [34]. An FMS is a production system where a discrete number of raw parts are processed and assembled by controlled machines, computers and/or robots [35]. It generally consists of a number of CNC machine tools, robots, material handling system, automated storage and retrieval system and computers or workstations. A typical FMS can fully process the members of one or more part families continuously without human intervention and is flexible enough to suit changing market conditions and product types without buying other equipment.

Manufacturing plants in India are expanding at a very fast rate day by day and demanding major changes in diversity of products, so there is a great demand of FMS in India. The performance of FMS at all stages of production is only measure of survival through the increase in the performance, productivity, flexibility of plants. Model of performance, productivity and flexibility variables which affect FMS evaluated. Evolution of the flexibility is done by different MADM methods. So, these methods have effectively been used for the performance evaluation of FMS.

2.2 IDENTIFICATION OF VARIABLES WHICH AFFECT PERFORMANCE ANALYSIS OF FMS

Indian manufacturing industries are rapidly modernizing by adopting different aspects of advance manufacturing systems. They are putting large potential for increasing the performance, productivity and flexibility of own manufacturing industries through automation. In machine tool industry, FMS provides the ability to handle small batch production of a large variety of parts. Short lead time and reduced work-in-progress are the main benefits to be realized. FMS is versatile mechatronics manufacturing platform which integrate manual production system, handling and processing, robotics, logistics and material flow concept. FMS comprises of individual stations which can be used together or separately depending upon the needs. On the basis of the exhaustive literature review and discussions with the industry experts and the academia, some variables which affect the performance of FMS are identified and discussed as below:

2.2.1 Unit Manufacturing Cost

The cost that is incurred during the production of a product is termed as manufacturing cost. The unit manufacturing cost includes the cost of materials used in the manufacturing of a product and the cost of labor used for the production process.

Ferdows and De Meyer [36] used unit manufacturing cost as a one performance measures of four measures i.e. quality conformance, delivery dependability, speed of new production development and unit manufacturing cost for performance improvement of manufacturing system [37, 38].

2.2.2 Unit Labor Cost

If total labor compensation is divided by output, unit labor cost can be obtained. It is a useful measure of productivity. It establishes the relationship between compensation per hour and real output per hour. It can be used as an indicator of inflationary pressure on producers.

Chen and Adam Jr [39] indicated in their study that labor costs can be reduced up to 94% with FMS installation. Thus, the level of productivity can be affected by changes in unit labor cost which may further affect the total unit cost [40-42].

2.2.3 Manufacturing Lead Time

The manufacturing lead time is the time required to a manufacturing firm to deliver a product to the customer in shortest possible time. This means faster customer deliveries [43]. The manufacturing lead time is the time period between the placement of an order and the shipment of the completed order to the customer. A short manufacturing lead time is a competitive advantage; many customers want the delivery of their products as soon as possible following the placement of the order. Manufacturing lead time is equal to sum of the processing time, setup, moving and waiting time. Generally, it consists of waiting time and throughput time.

A manufacturing company may reduce throughput time by minimizing the time consumed by inspecting, moving and queuing activities. As a result of minimizing such activities, the manufacturing lead time will also reduce and delivery performance will be improved [5, 43, 44].

2.2.4 Effect of Tool Life

In a manufacturing system, the input parameters like speed, feed, depth of cut and cutting forces which influence the accuracy and surface finish govern the tool life. The optimum value of these parameters gives an economical tool life. Generally, productivity of the manufacturing system and dimensional accuracy are influenced by tool life whereas the performance of the manufacturing system is effected by surface finish.

In metal cutting processes tool life is an important consideration. Maximum tool life appears to be the solution for achieving increased productivity and immediate cost-savings. Reducing the number of tool changes allows for minimal disruption to production, which provides better process stabilization, less downtime and consistent delivery of parts out the door and increasing the performance of the manufacturing system [44-46].

2.2.5 Throughput Time

The throughput time is the time to require a manufacturer to make a part or a product. The time required for a manufacturing process covers the entire period from when it first enters manufacturing until it exits manufacturing. It includes the following time intervals:

- *Processing time*. It is the time required for transforming raw materials into finished goods.
- *Inspection time*. It is the time to involve for inspecting raw materials, work-in-process and finished goods, possibly at multiple stages of the production process.
- *Move time*. It is the time required to move items into and out of the manufacturing area, as well as between workstations within the production area.
- *Queue time*. It is the time spent for waiting prior to the processing, inspection and move activities.

Manufacturing efficiency can be improved by minimizing the throughput time which is an important measure of manufacturing performance. A manufacturing company may lessen throughput time by minimizing the time consumed by inspecting, moving and queuing activities. As a result of minimizing such activities, the manufacturing lead time is also reduced and delivery performance is improved [45, 47, 48].

2.2.6 Setup Cost

The cost, involved in making the machine or an equipment ready for producing a product differently characterized, is setup cost. It includes the costs of changing the tools or dies on the equipment, moving materials or components and testing the initial output to be certain if it would meet the specifications. The greater cost of setup is the lost opportunity of manufacturing profitable output while the machine is idle during the setup time. Setup cost is directly proportional to the setup time of machine and therefore increases with enhancement in setup time. The setup time decides the flexibility of the organization. Shorter setup time gives higher flexibility and vice versa. Hence organizations generally prefer to reduce setup time which eventually reduces the setup cost.

Reduction in the setup cost will reflect reduction in the unit cost of the product. Setup cost is viewed as a non-value-added cost that should be minimized. Setup costs play an important role in assembly line production. The cost is fixed and gets amortized over the batch size [40, 49, 50].

2.2.7 Scrap Percentage

Scrap is a left over or residue after a product has been prepared. Low quality raw material or abnormal size of raw material, faulty or wrong product designing, substandard or unsuitable raw material, abnormal machine operation, wrong parts are ordered, when engineering changes aren’t effectively communicated or when designs aren’t properly executed on the manufacturing line etc. are the main causes of scraps. Thus a correct product design helps check scrap. Scrap is secondary, the primary is its impact on an organization which is always the wastage of time and money.

If priority is given to evaluating and improving the manufacturing processes, it becomes much easier to reduce the amount of scrap in the organization and finally the result is the increased performance and productivity in the manufacturing system.

FMS involves the use of special purpose equipment designed to perform one operation with the greatest possible efficiency to reduce scrap. Incorporating inspection into the manufacturing process permits corrections to the process as the product is being made. This result into reduced scrap [15]. But, incorporation of inspection into manufacturing system will affect its capability to manufacture more number of parts. Use of CNC machines and computer control systems have resulted in reduction of scrap [51-53].

2.2.8 Rework Percentage

Reworking is the process to rectify the mistakes occurred during production. It could be as simple as affixing a new label, or as extensive as welding additional material, heat treating and re-machining etc.

Rework costs are caused by many things-when the wrong parts are ordered, when engineering changes aren't effectively communicated or when designs aren't properly executed on the manufacturing line.

Operator training and performance monitoring are essential. If priority is given to evaluating and improving your manufacturing processes, it becomes much easier to reduce the amount of rework in your organization [52, 53].

2.2.9 Setup Time

To produce variety of parts at faster rate it is mandatory to reduce setup time and subsequently manufacturing lead time. Therefore FMS generally employs CNC/NC machines which have automatic tool interchange capabilities that reduce the setup time [40, 49, 51].

2.2.10 Automation

It also reduces the human efforts and introduces some flexibility in the manufacturing system. The high level of automation in an FMS allows a manufacturing system to operate for extended periods of time without human attention. For example, the use of CNC machines with the help of which human efforts can be reduced and flexibility of the production system can be enhanced.

Automation and technological advancements may also help to reduce annual labor costs. However, the initial investment in automation is a significant barrier for many companies [54-57].

2.2.11 Equipment Utilization / Increased Machine Utilization

FMSs achieve a higher average utilization of machines than in a conventional batch production machine shop. Reasons behind this include the following:

a) 24 hr. /day operation

b) Automatic tool changing at machine tools

c) Automatic pallet changing at workstations

d) Queues of parts at stations

e) Dynamic scheduling of production that takes into account irregularities from normal operation.

It should be possible to approach 80–90% asset utilization by implementing FMS technology [15]. Higher machine utilization has been achieved because of reduced set-up times, efficiently handled parts and simultaneously produced several parts [58-60].

2.2.12 Ability of Manufacturing of Variety of Products

Flexible manufacturing system is capable of producing a variety of parts (or productions) with virtually no time lost for changeovers from one part style to the next. There is no lost production time while reprogramming the system and altering the physical set-up (tooling, fixtures and machine setting). Flexibility of any production system is directly linked with the variety of products to be manufactured in that production system. The more is the variety of products to be handled by a particular production system, the more will be its flexibility [61-63].

2.2.13 Capacity to Handle New Product

Flexibility of a particular manufacturing system would be more if it is capable of handling more number of new and unexpected products [64-66]. Primrose [14] has proposed FMS results in introduction of new products. FMS is compared with a functional layout machine shop, the latter will have the ability to produce a much wider range of components, have more capacity to deal with fluctuations in demand and have a greater ability to cope with uncertainty [67].

2.2.14 Use of Automated Material Handling Devices

Material handling systems provide a key integrating function within a manufacturing system. Industrial robots and AGVs are used to pick and place materials from or on to the conveyors, loading and unloading the materials from machines. Use of automated material handling devices affect lead time, work-in-process (WIP) inventory levels and the overall operating efficiency of a facility [60, 68, 69].

2.2.15 Reduced Work in Process Inventory

Because different parts are processed together rather than separately in batches, work-in-process (WIP) is less than in a batch production mode. Inventory reductions of 60–80% are estimated [15]. Reduced WIP may help in improving the routing flexibility [70-73].

2.2.16 Training

A company may have the best manufacturing system components, but if it does not employ and train the best workers it may not produce quality products, which are the only things that can save it from today's stiff competition. Training can be technical, social, ethical or managerial. The whole idea rests on the fact that if workers are improved by the right training that is targeted to their need, their company's productivity and quality will be improved. On the other hand, if they lack proper training say, how to use the company's software, why drug use is bad, why constant lateness or absence from work is bad and such likes, then productivity may be reduced. Workers are the most important component of all the manufacturing systems. They are the ones who will use their initiative and other system components to produce the product to the required specifications and quality. For manufacturing system, the greater the time spent in formal job training, the higher the productivity will be [74]. People are an integral part of the system. If people lack proper training, then the people become part of the productivity problem. Lack of proper training to carry out a job is always a crucial factor [75].

2.2.17 Financial Incentive

Millea and Fuess Jr [76] claimed that money can be used to motivate workers, which in turn, tends to increase productivity. Wages and labor productivity may have a bi-directional relationship. Increasing wage can provide an incentive to improve productivity.

2.2.18 Customer Satisfaction

Bayazit [77] has given a decision that quality affects the flexibility as a factor in FMS. On-line inspection is incorporated into the manufacturing process permits corrections to the process as the product is being made. This brings the overall quality of the product closer to the nominal specification intended by the designer and second concept is process control. A wide range of control schemes intended to operate the individual processes and associated equipment more efficiently. By this product quality is improved and customer satisfaction can be increased [78, 79]. Lubbe [80] proposed that productivity can be increased through becoming more effective by increased customer satisfaction.

2.2.19 Reduction of Rejection

Rejections may be caused due to the incorrect adjustment of a machine tool, malfunctioning equipment and tools, errors in technical specifications, or the workers' low level of skill. Characteristic of production rejects is a discrepancy between the quality of the part or article and current technical requirements (for example, incorrect dimensions or failure to follow a standard formula). Although rejected components can be recycled but it is a waste which adds up to a company's net loss especially in mass produced product layouts where components travel through a series of operations to be a final product.

Reduction in rejection is controlled by the mechanization and automation of production processes and the introduction of advanced forms and methods of technical control. Then product quality will be increased and finally productivity of the manufacturing system [81, 82].

2.2.20 Trained Worker

Lubbe [80] claimed that productivity can be enhanced by using experienced, professional workers. Kilic and Okumus [83] agreed that with higher experience perform better in the job [84-86].

2.2.21 Reduction in Material Flow

Bayazit [77] has found that FMS reduce nonproductive time that exists in the use of automated material handling and storage system. The FMS includes a distributed computer system that is interfaced to the workstations, material handling system and other hardware components. The central computer coordinates the activities of the components to achieve smooth overall operation of the system. Reduction in material flow also aids in the improvement of routing flexibility of the system.

2.2.22 Flexibility in the Design of the Production System

Bayazit [77] had discussed that maximum utilization of equipment for job shop and medium-volume situations can be achieved by using the same equipment for a variety of parts or products. It involves the use of the flexible automation concepts. Prime objectives are to reduce setup time and programming time for the production machine. This normally translates into lower manufacturing lead time and less work-in-process (WIP). The CNC machining heads can be reprogrammed for new jobs very easily. Thus, introducing great amount of flexibility in rigid special purpose machines (SPMs) [87].

2.2.23 Flexible Fixturing

FMS is meant for handling a variety of work part configurations. For prismatic parts, this is usually accomplished by using modular pallet fixtures in the handling system. The fixture is located on the top face of pallet and is designed to accommodate different part configurations by means of common components, quick-change features and other devices that permit a rapid build-up of the fixture for a given part. The base of pallet is designed for the material handling system. For rotational parts, industrial robots are often used to load and unload the turning machines and to move parts between stations [15].

2.2.24 Combination of Operation

Groover [15] has discussed that production occurs as a sequence of operations. Complex parts may require dozens, or even hundreds, of processing steps. The strategy of combined operation involves performing two or more machining operations with one cutting tool.

2.2.25 Use of Reconfigurable Machine Tool

Koren et al. [88] defined reconfigurable manufacturing system (RMS) as a system designed at the outset for rapid changes in structure as well as in hardware and software components in order to quickly adjust production capacity and functionality within a part family in response to sudden changes in market or in regulatory requirements.

2.2.26 Speed of Response

An FMS improves response capability to part design changes, introduction of new parts and changes in the production schedule, machine breakdowns and cutting tool failures [15].

2.2.27 Quality Consciousnesses

Bayazit [77] has suggested that quality affects the flexibility as a factor in FMS. On-line inspection is generally carried out with machine vision or coordinate measuring machine. Improved inspection capabilities have resulted in the improvement of quality.

All variables are listed in Table 2.1 and shown that which variable affect which factor of FMS. Cause and effect diagram of variables affecting performance, productivity and flexibility variables in FMS is shown in Figure 2.1, 2.2 and 2.3 respectively.

Table 2.1 Variables affecting the performance analysis of FMS

Name of Variables	Affecting the factors of FMS		
	Performance	**Productivity**	**Flexibility**
Unit manufacturing cost	Yes	Yes	
Unit labor cost	Yes	Yes	
Manufacturing lead time	Yes	Yes	Yes
Effect of tool life	Yes	Yes	
Throughput time	Yes	Yes	
Set up cost	Yes	Yes	
Scrap percentage	Yes	Yes	Yes
Rework percentage	Yes	Yes	
Setup time	Yes	Yes	Yes
Automation	Yes	Yes	Yes
Equipment utilization	Yes	Yes	Yes
Ability of manufacturing of variety of product	Yes	Yes	Yes
Capacity to handle new product	Yes	Yes	Yes
Use of automated material handling devices	Yes	Yes	Yes
Reduced work in process inventory	Yes	Yes	Yes
Training		Yes	
Financial incentive		Yes	
Customer satisfaction		Yes	
Reduction of rejection		Yes	
Trained worker		Yes	
Reduction in material flow		Yes	Yes
Flexibility in the design of production system			Yes
Flexible fixturing			Yes
Combination of operation			Yes
Use of reconfigurable machine tool			Yes
Speed of response			Yes
Quality consciousness			Yes

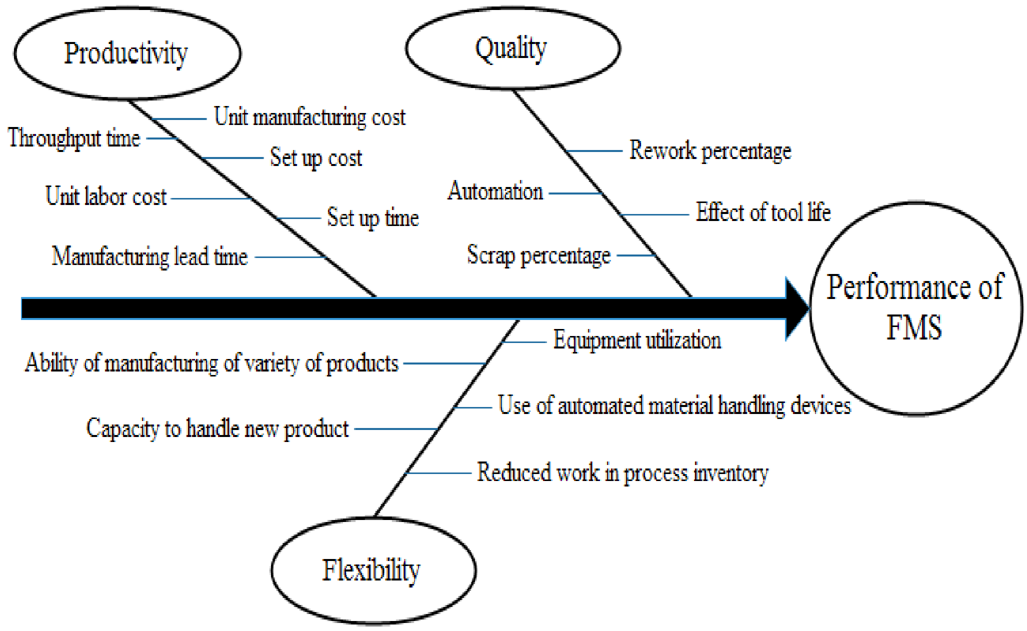

Figure 2.1 Cause and effect diagram of variables affecting performance in FMS

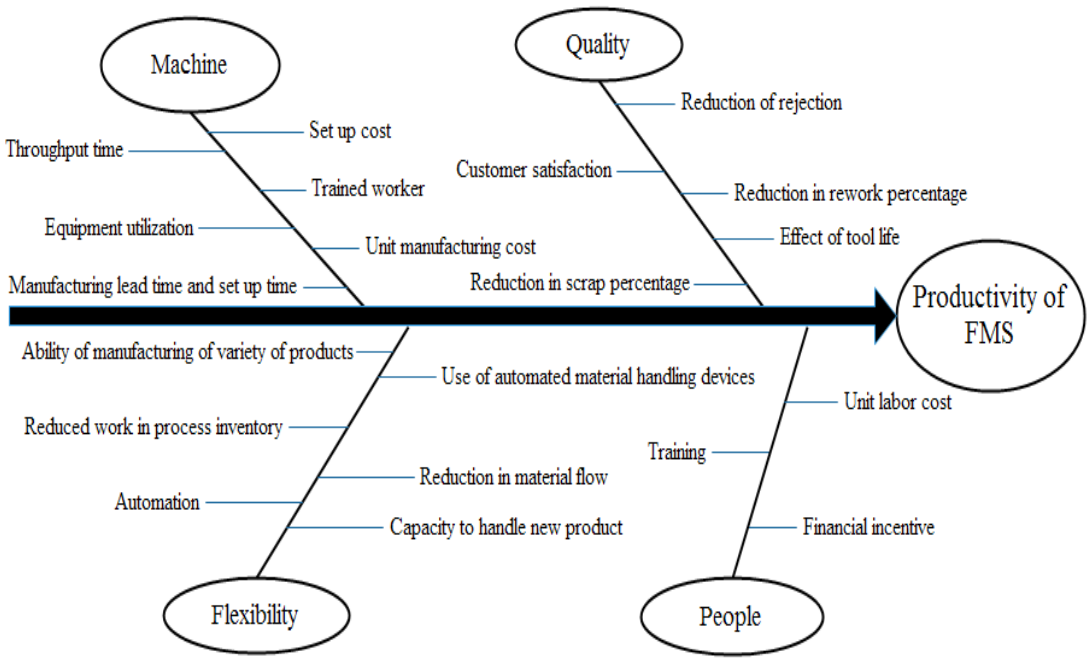

Figure 2.2 Cause and effect diagram of variables affecting productivity in FMS

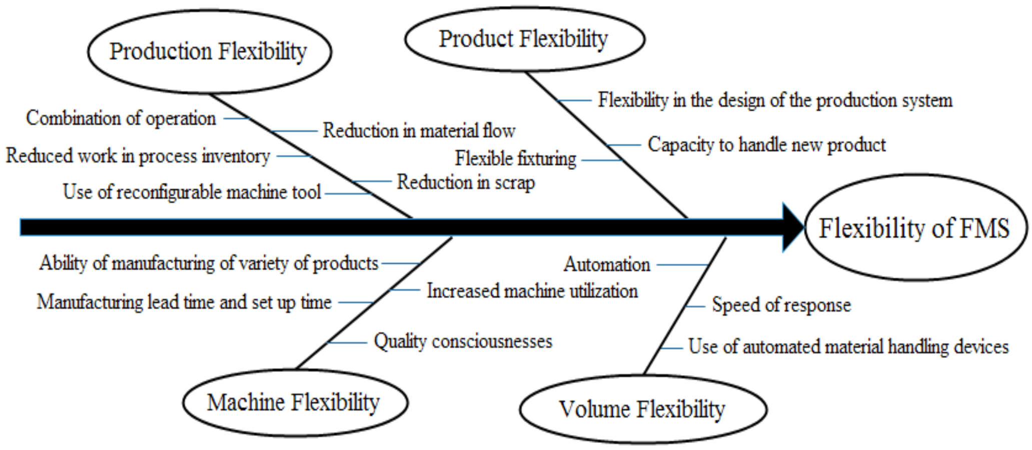

Figure 2.3 Cause and effect diagram of variables affecting flexibility in FMS

2.3 IDENTIFICATION OF FLEXIBILITY IN FMS

Several authors (Groover [15], Sethi and Sethi [89], Stecke et al. [90], Kumar [91], Son and Park [92], Zelenović [93]) carried out an extensive survey of the literature on flexibility in manufacturing and identified varying types of flexibility and at least 50 different terms describing these varying types. These definitions are essentially in agreement with Browne et al. [94]. According to the group of experts fifteen flexibility were taken and these are defined as given below.

(a) Machine Flexibility

It is defined as the capability to adapt a given machine (Workstation) in the system to a wide range of production operations and part styles. The greater the range of operations and part styles, the greater the machine flexibility will be. The machine flexibility can be measured by the number of different operations which can be performed without requiring more effort [95]. It increases higher utilization of machines, shorter lead times especially for new part production, production of complex parts and saving in inventory costs [96].

(b) Routing Flexibility

It has the capacity to produce parts through alternative work station sequences in response to equipment breakdowns, tool failures and other interruptions at individual stations. It has the ability to produce a part using different process routes. In this flexibility a particular part can be delivered to any of the station even any of alternative number. Earlier, first path/route was defined before manufacturing but in FMS parts can be delivered to any station because all are controlled by computer control system.

Material handling system will get signal from computer. It reduces waiting time and increases higher utilization of machines.

(c) Process Flexibility

Process flexibility has the ability to change between productions of different products with minimal delay. It also has the ability to produce a given set of part types although each part possibly using different material, in several ways. Process flexibility increases as the machine setup costs decrease. This flexibility can be measured by the number of parts that can simultaneously be processed without using batches. The motivation of this flexibility is to reduce batch sizes and inventory costs [89, 94].

(d) Product Flexibility

The ability to change over to produce a new (set of) product(s) very economically and quickly. Product flexibility relates to the ease of new-product introduction and product modification. In other words, product flexibility is the ease with which the part mix currently being produced can be changed inexpensively and rapidly. It should be kept in mind that the addition of new parts will invariably involve some setup. This distinguishes product flexibility from process flexibility [89].

Product flexibility can be measured by the time required to switch one part mix to another, not to same part type [97]. This flexibility allows the manufacturing firms to be responsive to the market by enabling it to bring newly designed products quickly to the market [95].

(e) Volume Flexibility

The ability to economically produce parts in high and low total quantities of production, given the fixed investment in the system. A higher level of automation increases this flexibility, partly as a result of both lower machine setup cost and lower variable cost. Volume flexibility has two feature i.e. speed of response and range of variations, the former being useful in the short term and the latter in the long term. This flexibility can be measured by how so ever small the volume is for all part types [63].

(f) Material Handling Flexibility

The ability of the material-handling system to move different parts efficiently throughout the manufacturing system. It covers loading and unloading of parts, transportation from one machine to other and in the end storing them in suitable condition of the manufacturing facility. This flexibility increases the availability of machine, equipment utilization and reduce throughput time [89].

(g) Operation Flexibility

Operation flexibility is the ability to perform more than one operation on a given part type. Part can be produced in different ways, i.e. a number of alternative processes or ways in which a part can be produced within the system. Operation flexibility of a process allows for easier scheduling of parts in real time and increases machine availability and utilization, especially when machines are unreliable [94].

(h) Expansion Flexibility

The ease with which the system can be expanded to increase total production quantities and capability to expand volumes as needed. Capability means to such traits as quality and the technological state. Expansion flexibility helps to reduce implementation time and cost for new products, variations of existing products or added capacity [95].

(i) Production Flexibility

The range or universe of part types that can be produced without the need to purchase new equipment. The range of part types that the FMS can produce. This flexibility is measured by the level of existing technology. Production flexibility allows the firm to compete in a market where new products are frequently demanded. Production flexibility minimizes the implementation time for new products or major modifications of existing products [95].

(j) Programme Flexibility

The ability of a system to operate unattended for additional shifts or the length of time the system can operate unattended. Program flexibility reduces the throughput time by having reduced setup times, improved inspection and gauging and better fixtures and tools. Being able to work untended increases the effective capacity of the production system [98].

(k) Market Flexibility

The ability of a manufacturing system to adapt to changes in the market environment. Market flexibility allows the firm to respond to environments change because of rapid technological innovations, change in customer tastes, short product life cycles, uncertainty in sources of supply etc. [99].

(l) Response Flexibility

It may be the ease with which the FMS responses to market demands i.e. time taken by the system to respond to market demands in terms of time and/or cost, with which changes can be made within the capability envelope, i.e. long-term flexibility.

(m) Product Mix Flexibility

Mix flexibility is the ability to change the relative proportions of different products within an aggregate output level. The total envelope of capability or range of states which the manufacturing system is capable of achieving, i.e. short-term flexibility.

(n) Size Flexibility

The component sizes that can be manufactured without requiring setups that take longer than a specific time period.

(o) Range Flexibility

The total envelope of capability or range of states which the manufacturing system is capable of achieving, i.e. short-term flexibility.

2.4 ISSUES RELATED TO CONSTRAINTS IN FMS

FMS is known as a flexible manufacturing system. The manufacturing organizations want to use FMS to improve the manufacturing capabilities. They want to shift from existing system to advance system i.e. FMS to cope up market condition. But the installation implementation of FMS is not easy. Main problem is integration with the existing system. Initial installation cost of FMS and operational cost will be high if production volume is less. So, it is necessary to have enough volume to justify the use of FMS. According to Jain and Raj [100] flexibility in manufacturing has been identified as one of the key factors to improve the performance of FMS. But, if tooling system is not proper then manufacturing system will not be flexible and performance of FMS will be less. So, tooling system is a constraint in FMS to make a system flexible. Flexibility of a particular manufacturing system would be more if it is capable of handling more number of new and unexpected products. But this machine tool should be versatile to produce different variety of parts otherwise machine tool also be a constraint in FMS. Jain and Raj [101] have explained that productivity is a key factor in a flexible manufacturing system (FMS) and generally, tool life influences productivity of the manufacturing system. If tool life is restricted in some way that effect productivity of manufacturing system so, tool life may be a constraint in FMS. In FMS, material handling systems, industrial robots and AGVs are used to pick and place materials from or on to the conveyors, loading and unloading the materials from machines. Robots are used in manufacturing system to do same jobs but if product shape changes then it may be a constraint. Similarly, AGVs are used for material transportation but its path is defined. If the fixed path of AGV is changed then, it may be a constraint. In manufacturing system, for machining operation or inspection or transportation workpiece should be stationary. For this purpose, a fixture is required and that fixture should be rigid to bear external forces otherwise it also becomes a constraint to FMS. Effective strategies are important for the smooth and economical functioning of any FMS in designing and controlling phases. It is very difficult to cover all problems in detail. From the previous literature, some researchers have taken problems of FMS into planning, designing and controlling [102, 103]. A closed watch is required on each and every problem associated with the successful implementation of an FMS. Machine tools, material handling like AGV, pallet and fixtures and robots etc. are the resources which are jointly controlled by centralized computer system. The few constraints which these resources confront are as given below:

(a) Machine Tool

The Machine tools are used for machining of different components. But they have some means of constraining the workpiece. The relative movement between the workpiece and the cutting tool is restrained by the machine to at least some extent. The maximum desired feed as well as discrete spindle speed are hindrances that are in machine tool.

Some restraints like the machine tool maximum power force, low speed power (or spindle torque) and the component surface roughness have been generalized and represented by an upper feed limit. In the "high" cutting speed region of a machine tool operating range, the machine tool maximum power constraint will come into play and limit both the feed and cutting speed from which a constrained optimum can be selected [104, 105] The machine tool resources is subjected to the following constraints:

1. Tool life constraint: The tool life is generally based on subjective decision and it should not be less than a prescribed value to avoid the frequent tool changes. The minimum desired tool life should be 20 times the machining time of one component although to ensure that at least 20 components are machined. A constraint can be

put on the maximum value of the tool life as well, but often it will be an inactive constraint.

2. Surface roughness constraint: The surface roughness value may be restricted to lie in a zone. Because certain tribological and heat transfer characteristics are dependent on it.
3. Cutting force constraints: Excessive job and tool deflection and breakage of the tool should be avoided. These can be found by physics based or soft computing based models.
4. Machine power constraint: The machine power can be calculated using the following formula:

$$\text{Machine Power} = \frac{\text{main cutting force x cutting speed}}{\text{efficiency of the machine}} \tag{2.1}$$

   It is necessary to limit the machine power to avoid excessive overloading of the spindle motor. If machine power is much lesser than the power of the spindle motor, the machine is underutilized.
5. Geometric constraint: There may be some restrictions based on the geometry of workpiece.
6. Temperature constraints: Dimensional accuracy and tool life especially in dry machining can be maintained by constraining temperature of the workpiece, machine tool and cutting tool.
7. Variable bounds: Cutting speed, feed and depth of cut should be dependent on the type of machine, type of tool and type of material.
8. Flexibility constraints: For a new part, set up time is high because integration of cutting tool, machine tool and material handling device constraints. So, it effect the flexibility of FMS.
9. Cost: CNC machines are the main component of machine tool in FMS. But, it can be controlled only by the computerized system. Moreover the cost of CNC machine is high. So, high cost of CNC machine is a constraint in FMS.
10. Maintenance of machine: Maintenance cost of CNC machines are so high because it required highly skilled technician for maintenance.

The many technological and practical constraints which limit the feasible domain for the selection of optimum cutting conditions should also be accounted in a realistic optimization study.

(b) Tool Management

The basic function of a tool management system is to ensure that the right tools are made available at the right place and at the right time to support the required production schedule. Tool management is defined as a strategy which aims at resolving problems related to various tool activities, including acquisition, storage, database development, selection and allocation, inspection, presetting, delivery, loading, monitoring, replacement, requirement planning and inventory control of tools [106]. In fact, the centralized tool management has introduced the fifth generation of FMS environment, indicating that tool management is one of the more important subsystems in the FMS which influences the whole structure and operation of the system [107].

Tool management is a very complicated task and is often stressed by FMS users and researchers [108, 109]. Despite such complexity, there are successful working FMSs, whose performance has been considerably augmented with efficient tool management [110, 111]. The major constraint in FMS is element of tooling that does not allow manufacturer to realize the full flexibility [112].Tool management is motivated in FMS by two factors i.e. tooling cost and availability of tool [113]. Tooling cost have significance on economic, because tooling accounts for 25-30 per cent of the fixed costs of production in automated machining environment whereas availability of tool in FMS has an impact for flexibility and capability of production system [114]. Several firms have recently developed integrated tool management systems with tremendously encouraging results [111].

The important resource in FMS are tool and need attention for the management. But the constraint in the management of tools are as given below [115]:

1. Tool life: Tool life plays a significant role in manufacturing industry because its effects overall production process. It is an important parameter of tool management because 20% down time attributed to tool failure. Tool life depends on the workpiece material and on cutting conditions. Various methods are used to calculate tool life but due to various combination of factor some time it is difficult to find out the best result. Tools are subject to wear and often need to be reconditioned. Once the tool is worn, it needs replacement or reconditioning, processes which are performed in the tool room.

2. Tool cost: The loading method should take into account the availability of tool copies while assigning the load to the various machines as only few copies of a given tool type are available in the system because of the cost.
3. Tool magazine capacity: Generally, machine tool builders equip their machining centers with large tool magazines to reduce the impact of the capacity constraint which result in high seek time, sometimes greater than the time required to perform an operation because tool magazines have finite capacity. This leads in high spindle idle times between two different operations. This puts constraints on the set of operations that can be assigned to a machine during a given period. Whereas in low capacity magazine, the tools have to be changed manually as per requirement and it increases the nonproductive time. So optimal selection of tool magazine may be another problem in FMS.
4. Tool management in unmanned production: Monitoring in the cutting processes to determine tool life regarding tool breakage, tool wear, and surface roughness (R_a) of the workpiece is a constraint for tool management in unmanned production system.
5. Availability of tool: New cutting tool for new parts may not be readily available and may be problem in reprograming of the system.

(c) Robot

Picking the objects by a robot and placing them in a certain orientation within its workspace require a majority of the applications. In a structured environment this works more or less smoothly as both the picking spot and placing spots are fixed [116]. Industrial Robots should be used not to move from one end position to another but also for loading and unloading machine tools and for simple assembly operations in mass production. They traverse in two, three or occasionally four axes, but the control of intermediate positions between programmed end points is not normally possible.

In a robot operating system interaction with different types of parts is a common problem. These mechanisms model with a single revolute or prismatic joint impose constraints to the motion of the robot. As it is difficult to infer the type of the mechanism (e.g. sliding or rotating) and the corresponding parameters (e.g. radial distance, orientation of rotational axis).The estimated uncertain quantities are [117]:

1. Direction of motion: Robots can pick the object only within its reachable workspace not beyond the workspace. To work in 3D manipulator, minimum 6 degree of freedom is required but at a singular configuration, the manipulator loses one or more degree of freedom.
2. Type of the hinged mechanism: There is a constraint due to joints like as in sliding it can move according to length of slide or in rotating generally it can rotate 0 to 180 degree.
3. Trajectory of robot: Finding a collision-free, optimal assembly path which leads the robot to move parts from initial positions to final assembled position is not easy. Any obstacle in the path of the robot will hamper its movement.
4. Geometrical constraint: Each robot end effector is designed for a particular geometry. It cannot hold the part of other geometry effectively.
5. Capacity of Robot: Robots are used in manufacturing plant to carry material from one station to other stations. So, they are designed for a particular load carrying capacity. They cannot be interchange with robots of different load carrying capacity.
6. Cost: The wages of labor is not as much as the cost of the robot. Therefore the availability of economical labor is a constraint in FMS. Moreover there maintenance is also very expensive.
7. Availability of robot: Generally, robots are not manufactured in India. Those are imported from other countries which hike the cost of robots. Moreover the maintenance is also not readily available.

(d) Automated Material Handling

Material handling systems are integrated with the machining center and the storage and retrieval systems. For prismatic parts material handling is accompanied with modular pallet fixture. In rotational parts industrial robots are used to load/unload the machines and to move parts between stations. The material handling system must be capable of being controlled directly by the computer system to direct it the various workstations load/unload station and storage area.

In FMS, to simplify production line, an unmanned vehicle is used for material handling. Automated guided vehicle (AGV) system is most prominent material handling system in FMS. It consists of multiple automated guided vehicles (AGVs) and is operated by computers. AGVs are unmanned vehicles they carry workpiece among the workstations following fixed guide paths and are controlled either by on-board computers or by a central computer. AGVs are widely used in FMSs as they provide flexibility in routing parts among elements present in the system. These systems are highly complex and costly due to the dynamic environment in which the FMS functions. Hence only careful design and operational planned AGVs are essential for unimpaired performance.

Researchers proposed alternate procedures for estimating the number of AGVs required in manufacturing system. Simulation experiments also conducted to find the number of AGVs, number of pallets, buffer sizes, dispatching rules etc.[118-120] .

The main limitation of the available simulation methods are that they are time-consuming and need large computer memory. Hence, they are limited in their practical usefulness for on-line monitoring of AGVs.

Generally, automated material handling is done by AGV with defined path for movement. There is a fixed path for movement. So, fixed path is a constraint for AGV. There are some constraint as given below [105, 121-123]:

1. Number of AGV: The number of vehicles (AGVs) can be calculated based on a transport profile i.e. the loading and unloading matrix with the number of working shifts, the operating times and the break times. Depending on the planning and operation, additional vehicles should be kept in reserve (repairs and maintenance). Many AGVs create the deadlock situation on the path and increase the price.
2. Path of AGV: A network of guided paths is defined in advance and the guided paths have to pass through all pickup/delivery points. So, AGV’s path cannot be modified with the requirement with immediate effect.
3. Speed of AGV: The vehicles travel at a constant speed on the fixed path layout. The speed does not go up and down on the path according to the requirement because it is not programmed.
4. Movement of AGV: The vehicles just travel forward on the guided path. They do not move backward.
5. Types of product: AGVs are designed to carry only one kind of product at a time. If the specific product is not in production, the AGVs lie idle and cannot be utilized in carrying different designed products.
6. Load carrying capacity: Generally, AGVs are designed according to the load carry capacity therefore it cannot carry more than its capacity.

7. Cost: Although AGV is the main component of material handling system of FMS, its cost of maintenance and operation is high. AGV is also itself costly.
8. Integration of AGV: Integration of AGV with other component of FMS is complicated because AGV move only on a guided path.

(e) Fixture

A fixture locates, holds and supports a workpiece in most of the automated manufacturing, inspection, and assembly operations. Fixtures locate a workpiece in a given orientation for instance cutting tool or measuring device, other components. Such location must be invariant in the sense that the devices must clamp and secure the workpiece in that location for the particular processing operation.

In order to maintain the workpiece stability an operational fixture has to meet several requirements to perform its functions completely. The following constraints are observed as given below [105, 124]:

1. Deterministic location: A locator is usually a fixed component of a fixture that establishes and maintain the position of a part in the fixture so that it is presentable for the machining operation. Due to locating errors in the fixture the workpiece does not set within the machine coordinate frame accurately and uniquely.
2. Total constraint: The external forces should not affect the machining operation so the workpiece should be held tightly by the fixture to prevent its movement.
3. Contained deflection: Due to the elastic/plastic nature of the workpiece, the workpiece deform. Other external forces impacted by the clamping actuation and machining operations also deform the workpiece. So, deformation has to be minimized to achieve the tolerance specifications.
4. Geometric constraint: In the machining operation the cutting tools path should be free without being interfered by the fixture.
5. Flexibility of fixture: Flexibility of fixture is also a constraint in FMS. It is the interface between the FMS and the parts to be machined. As parts differ in size, shape, material and operation, one fixture cannot accommodate for different parts. If it is manual it increases nonproductive time in setting the parts. If it is automated it is costly.

Apart of theses constraints, a fixture design should possess some other necessary characteristics such as quick loading and unloading, minimum number of components, accessibility, design for multiple cutting operations, portability, low cost, etc.

The flexibility of a whole FMS is restricted by the flexibility of any of its components, including fixture systems. The cost of designing and fabricating the fixtures in an FMS can amount to 10- 20% of the total system cost. Traditionally, the function of a fixture is to hold a part in order to keep that part in a desired position and orientation while the part is in manufacturing, assembly, or verification processes [125].

2.5 METHODOLOGIES

To achieve the research objectives, the following methodologies are used in this research work. The methodologies are discussed in detail given below:

2.5.1 Interpretive Structural Modelling (ISM)

Warfield [126] proposed an approach i.e. interpretive structural modelling (ISM) to make a complex system into a visualized hierarchical structure. It is used for analyzing and solving complex problems to manage decision- making. The ISM process transforms unclear, poorly articulated mental models of systems into visible, well-defined models useful for many purposes [17]. It helps in identification of the interrelationships among variables under consideration. The ISM methodology is understood in the sense that the judgments of the groups decide whether the variables are connected or not and how they are concerned if they behave. In this approach an overall structure is extracted from the complex set of variables on the basis of relationships [16]. ISM application has been reviewed from the literature as Azevedo et al. [127] identify and rank performance measures. Govindan et al. [128] discussed about third party reverse logistics provider. Raj et al. [129] have analyzed modelling of flexibility factors. Raj and Attri [26] made a model of TQM barriers. Faisal [130] discussed social responsibility in supply chains. Kannan et al. [131] applied ISM for selection of reverse logistics provider. Raj et al. [10] analyzed the enablers of flexible manufacturing system. Thakkar et al. [132] have evaluated buyer and supplier relationships. Singh et al. [133] discussed critical success factors of advanced manufacturing technologies. Faisal et al. [134] discussed about supply chain risk mitigation. Ravi and Shankar [135] analyzed the productivity improvement of computer hardware supply chain. Ravi and Shankar [135] developed a model for reverse logistics barriers. Jharkharia and Shankar [136] discussed about IT enablement in supply chain enablers. and Mandal and Deshmukh [137] have done vendor selection through ISM model.

The various steps involved in ISM modelling are as follows.

Step 1: Different variables are identified which are related to problems.

Step 2: A contextual relationship is established among variables with respect to whom the pairs of variables would be examined, which is identified in step 1.

Step 3: A structural self-interaction matrix (SSIM) is developed for variables. This indicates the pairwise relationship among the variables of the system under consideration.

Step 4: From SSIM, reachability matrix (RM) is developed and the matrix is checked for transitivity. The transitivity of the contextual relation is a basic assumption made in ISM. It states that if a variable A is related to B and B is related to C, then A is necessarily related to C as shown in Figure 2.4.

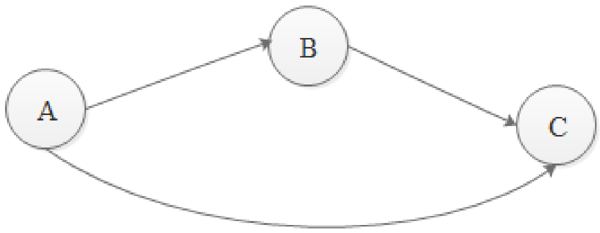

Figure 2.4 Transitive graph

Step 5: The RM is partitioned into different levels.

Step 6: The RM is converted into its conical form, i.e. with most zero (0) elements in the upper diagonal half of the matrix and most unitary (1) elements in the lower half.

Step 7: Based upon the relationship above, a directed graph (digraph) is drawn and transitivity links are removed and then digraph is converted into an ISM model by replacing element nodes with statements.

Step 8: Finally, the ISM model is checked for conceptual inconsistency and necessary modifications are incorporated.

Various steps involved in ISM technique are illustrated in Figure 2.5.

2.5.2 Factor Analysis

Factor analysis (FA) is an old technique that is widely used as a data reduction technique. It is also used for the analysis of data in social and behavioral sciences in general and other applied sciences that deal with large quantities of data (variables)

[138]. Basically, factor analysis is frequently employed in the social sciences where the main interest lies in measuring and relating unobserved constructs, such as emotions, attitudes, beliefs and behavior. The main idea behind the analysis is that the latent variables (referred to also as factors) account for the dependencies among the observed variables (referred to also as items or indicators) in the sense that if the factors are held fixed, the observed variables would be independent. Theoretically, factor analysis can be distinguishable between exploratory and confirmatory analysis, but in practice, the analysis always lies between the two [139].

2.5.3 Structural Equation Modelling (SEM)

Structural equation modelling (SEM) is a technique to represent, to specify, to estimate and to evaluate models of linear relationships among a set of observed variables in terms of a generally smaller number of unobserved variables [19, 20]. Path analysis and confirmatory factor analysis are two special cases of SEM which are regularly used. Structural equation modelling was introduced in the early 1970s; it comprises two divisions, the measurement model and the structural equation model [21]. The measurement model specifies how latent variables or hypothetical constructs depend upon or are indicated by the observed variables. The model describes the measurement properties (reliabilities and validities) of the observed variables. Structural equation modelling resembles path analysis by providing parameter estimates of the direct and indirect links between observed variables [21, 22]. Factor analysis in SEM can be distinguishable between exploratory and confirmatory factor analysis. EFA is commonly used to explore the dimensionality of a measurement instrument by multivariate data structures whereas CFA is a statistical technique used to verify the factor structure of a set of observed variables. Statistical software is an invaluable tool for business decision making and scientific research. Therefore, decision makers and researchers need to be aware of the limitations of individual software packages [140]. The statistical package for social sciences (SPSS) has been used in the EFA to extract dimension from the variables. Subsequently, CFA has been applied to confirm these dimensions in the factor analysis by analysis of moment structures (AMOS). SEM application has been reviewed from the literature as Ramanathan and Muyldermans [141] proposed a methodology for identifying demand based upon promotion using the SEM approach. Su and Yang [142] used this approach for analyzing the impact of ERP on SCM. Lau et al. [143] presented an article related to supply chain integration and

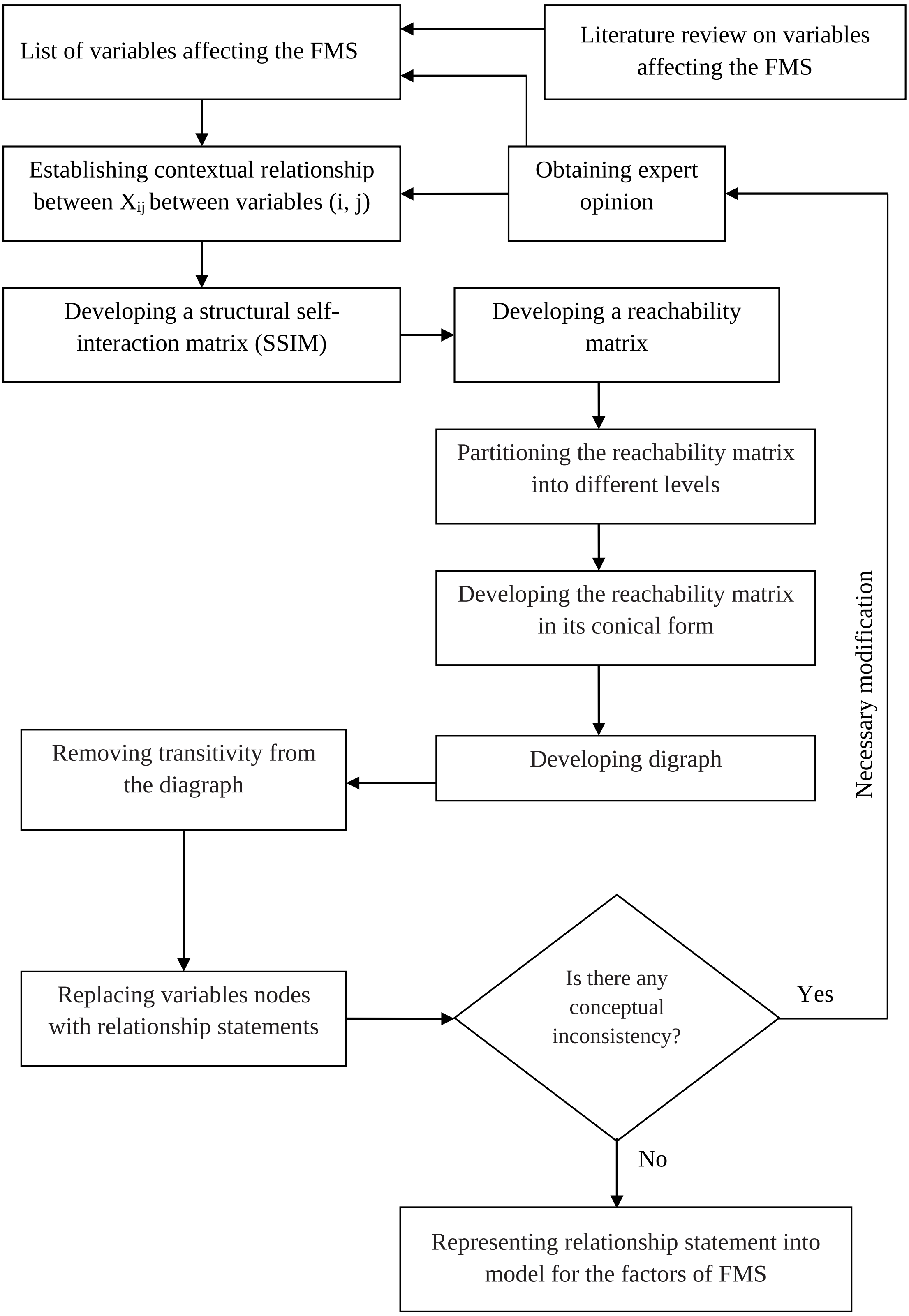

Figure 2.5 Flow diagram for preparing ISM

modular product design. Vázquez-Bustelo et al. [144] studied agility drivers, enablers and results and empirically tested the model. Fitch [145] focused on SEM for risk assessment instruments. Golob [146] proposed an SEM approach for travel behavior research. The SEM analysis proceeds in two steps. First the exploratory factor analysis is used to identify the dimensions of FMS and Next, confirmatory factor analysis to confirm the factor structure of the which identify by the EFA.

2.5.4 Exploratory Factor Analysis (EFA)

Exploratory factor analysis (EFA) is a multivariate statistical technique widely used in social and behavioral sciences. Costello and Osborne [23] discuss common practices in studies using these techniques and provide researchers with a compilation of 'best practices' in EFA. Frequently, the method is blindly applied without checking if the data fulfill the requirements of the method. The influence of sample size, data transformation, factor extraction method, rotation and number of factors on the outcome were investigated.

The primary objectives of an EFA are:

- To find the number of factors/Dimensions
- To identify variables that are poor factor loading
- To identify factors that are poorly measured in the study

2.5.5 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a theory testing model in contrast to a theory generating method like exploratory factor analysis. In confirmatory factor analysis, the researcher begins with a hypothesis prior to the analysis. This model, or hypothesis, specify which variables will be correlated with which factors and which factors are correlated. The hypothesis is based on a strong theoretical and/or empirical foundation [24]. CFA is a statistical technique used to verify the factor structure of a set of observed variables. CFA allows the researcher to test the hypothesis that a relationship between the observed variables and their underlying latent construct(s) exists. The researcher uses knowledge of the theory, empirical research, or both, postulates the relationship pattern a priori and then tests the hypothesis statistically [25].

The use of CFA could be impacted by the following:

- The research hypothesis being tested

- The requirement of sufficient sample size (e.g., 5-20 cases per parameter estimate)
- Measuring instruments
- Multivariate normality
- Parameter identification
- Outliers
- Missing data
- Interpretation of model fit indices [147].

To perform CFA, structural equation modeling (SEM) is one statistical test to determine the significance of the analysis to determine the adequacy of the model fit to the data. SEM has become one of the techniques of choice for researchers across disciplines and increasingly is a 'must' for researchers in the social sciences [148]. A variety of fit indices which can be used as a guideline for prospective structural equation modelers to confirm the model are discussed below:

a) Absolute fit indices:

Absolute fit indices determine how well a-priori model fits the sample data and demonstrate the most superior fit for the proposed model. These measures provide the most fundamental indication of how well the proposed theory fits the data [149]. In this, categories are the Chi-Squared test, goodness-of-fit statistic (GFI), adjusted goodness-of-fit statistic (AGFI), root mean square residual (RMR) and root mean square error of approximation (RMSEA).

b) Model chi-square ($\chi 2$):

The Chi-Square value is the traditional measure for evaluating the overall model fit [150].

c) Goodness-of-fit statistic (GFI):

The GFI calculates the proportion of variance that is accounted for by the estimated population covariance [151]. The goodness-of-fit index (GFI) is based on a ratio of the sum of the squared discrepancies to the observed variance. The GFI ranges from 0 to 1, with values exceeding 0.9 indicating a good fit to the data [152].

d) Adjusted goodness-of-fit statistic (AGFI):

Related to the GFI is the AGFI which adjusts the GFI based upon degrees of freedom, with more saturated models reducing the fit [151]. In addition to this, AGFI tends to increase with sample size. As with the GFI, generally accepted asset value for the AGFI is 0.90 or greater indicate well-fitting models.

e) Root mean square residual (RMR):

The RMR is the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model. Values for the RMR with well-fitting models obtaining values less than .05 [153, 154], however, values as high as 0.08 are deemed acceptable [150].

f) Root mean square error of approximation (RMSEA):

The RMSEA is the second fit statistic [155]. The RMSEA tells us how well the model, with unknown but optimally chosen parameter estimates would fit the population covariance matrix [153]. An RMSEA of between 0.08 and 0.10 provides a mediocre fit and below 0.08 shows a good fit [156].

g) Incremental fit indices:

Incremental fit indices are a group of indices that do not use the chi-square in its raw form but compare the chi square value to a baseline model. For these models, the null hypothesis is that all variables are uncorrelated [149].

h) Normed-fit index (NFI):

The first of these indices to appear in the output is the NFI [157]. This statistic assesses the model by comparing the χ 2 value of the model to the χ 2 of the null model. The null/independence model is the worst- case scenario as it specifies that all measured variables are uncorrelated. Bentler and Bonett [157] recommended values greater than 0.90 indicating a good fit. For example, an NFI of 0.9 means that the model is 90% better fitting than the null model. A major drawback to this index is that it is sensitive to sample size, underestimating fit for samples less than 200 [158, 159] and is thus not recommended to be solely relied on [160]. This problem was rectified by the Non-Normed Fit Index (NNFI).

i) Non-normed fit index (NNFI):

It is also known as the Tucker-Lewis index (TLI) which prefers simpler models. The NNFI adjusts the NFI for the number of degrees of freedom in the model. However, in situations where small samples are used, the value of the NNFI can indicate a poor fit despite other statistics pointing towards a better fit [151, 159, 160]. Higher values of the NNFI indicate a better fitting model and it is common to apply the 0.90 as a cutoff indicating a good fit to the data.

j) Comparative fit index (CFI):

This index was introduced by Bentler [159], based on the non-central chi-square distribution. The CFI also ranges between 0 and 1, with values exceeding 0.90 indicating a good fit to the data. This index is included in all SEM programs and is one of the most popularly reported fit indices due to being one of the measures least affected by sample size [161].

k) Incremental fit Index (IFI):

Bollen [162] defined incremental fit index (IFI) which is given by (chi-square of independence model - chi-square of target model) / (chi-square of independence model - df of target model). IFI values range between 0 and 1, exceeding 0.90 indicating a good fit to the data.

The following steps are followed to perform EFA and CFA:

Step1: Collect and explore data

Relevant variables are chosen from the literature and expert opinion. After this, a survey takes place to collect data regarding these variables. Min. Sample size of at least 5 cases per variable and ideal sample size of at least 20 cases per variable, while total sample size of 200+ preferable. Data set 50 = very poor, 100 = poor, 200 = fair, 300 = good, 500 = very goodand1000+ = excellent.

Step 2: Check the relatively internal consistency

To check relatively internal consistency, reliability test is performed. For this purpose cronbach's alpha is calculated and its value should be greater than 0.7 [163].

Step 3: Check the adequacy of sample size

To check the sample is adequate or not, Kaiser-Meyer-Olkin measure of sampling adequacy test (KMO-test) is performed. Kaiser-Meyer-Olkin (KMO) measure of the sample adequacy is used to validate the use of factor analysis. It is an index used to examine the appropriateness of factor analysis. The value of KMO in between 0.5 and 1.0 indicates the factor analysis is appropriate. Values below 0.5 imply that factor analysis may not be appropriate for the data [164]. Bartlett's test of sphericity is used to examine the hypothesis that the variables are uncorrelated in the population. The significance level gives the result of the test. Very small values (less than 0.05) indicate that there are probably significant relationships among the variables. If the significance value is more than 0.10 then it indicates that the data is not suitable for factor analysis [165].

Step 4: Initial extraction

For initial extraction, communalities are calculated. Communality is the amount of variance a variable share with all the others being considered. Communalities indicate the amount of variance in each variable that is accounted for. Initial communalities are estimates of the variance in each variable accounted for by all components or factors. Extraction communalities are estimates of the variance in each variable accounted for by the factors (or components) in the factor solution. Smaller values indicate the variables which do not fit well with the factor solution and should possibly be dropped from the analysis. Communalities range between 0 and 1. High communalities (> 0.5) mean there is considerable variance explained by the factors extracted. Low commonalities (< 0.5) mean there is considerable variance unexplained by the factors extracted.

Step 5: Choose the variables to retain

Smaller values indicate the variables which do not fit well with the factor solution and should possibly be dropped from the analysis. It may be needed to extract more factors to explain the variance or remove these items from the EFA.

Step 6: Extract initial factors (via principal components analysis)

For extracting initial factors, following techniques are used:

a) Kaiser's criterion, suggested by Guttman and adapted by Kaiser, considers factors with an eigenvalue greater than one as common factors [163].
b) A good factor solution is one that explains the most variance with the fewest factors. Realistically happy with 50-75% of the variance explained.
c) According to Cattell [166] scree test. On a scree plot, because each factor explains less variance than the preceding factors, an imaginary line connecting the markers for successive factors generally runs from top left of the graph to the bottom right. If there is a point below which factors explain relatively little variance and above which they explain substantially more, this usually appears as an "elbow" in the plot. Cattell's guidelines call for retaining factors above the elbow and rejecting those below it.
d) At least 3 items or observed variables per factor with significant factors i.e. > .30.

Step 7: Choose the number of factors to retain

Step 8: Rotate the component matrix with Varimax with Kaiser Normalization.

Step 9 : Decide if changes need to be made (e.g. drop item(s), include item (s) etc.).

Step 10: Identified dimensions and use in the further analysis.

Step 11: Make the path diagram/model according to these dimensions and items.

Step 12: Find the model fit summary

a) χ^2/DF (CMIN/DF)
b) Absolute fit indices: GFI, AGFI, RMR, RMSEA
c) Incremental fit indices: NFI, CFI, TLI, IFI

Step 13: Confirm the factor/dimensions results.

The flow diagram of Exploratory and Confirmatory Factor Analysis are illustrated in Figure 2.6.

2.5.6 Graph Theory and Matrix Approach (GTMA)

GTMA is a systematic and logical approach that is used in various subject fields. The conventional representations like block diagrams, cause and effect diagrams and flowcharts do not depict interactions among factors and are not suitable for further analysis and cannot be processed or expressed in mathematical form. GTMA has an edge over the conventional techniques of representation and quantification.

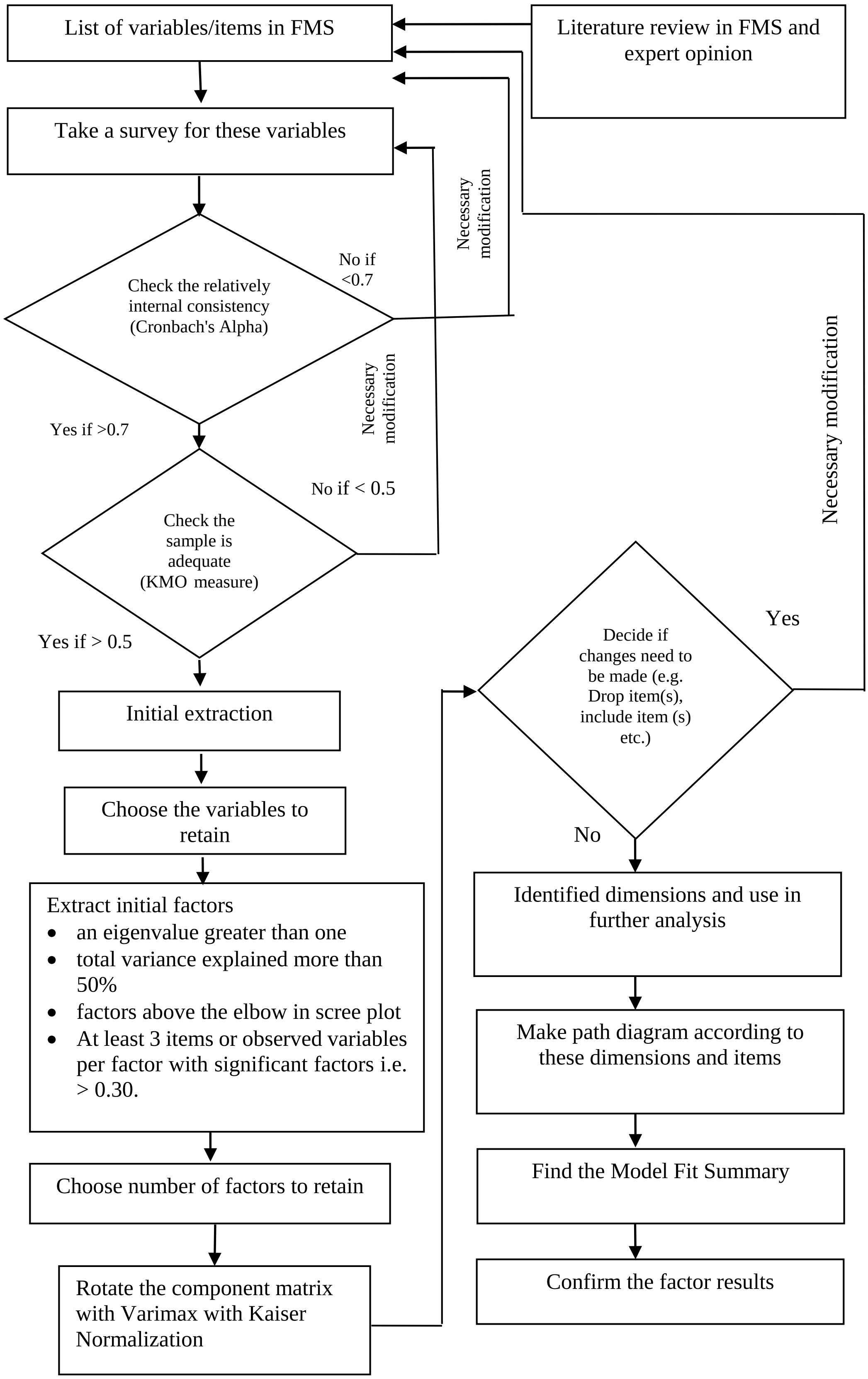

Figure 2.6 Flow diagram of exploratory and confirmatory factor analysis

GTMA application has been reviewed from the literature as Sabharwal and Garg [167] evaluated the economic viability of remanufacturing by using the graph theoretic approach. Malhotra et al. [168] evaluated the barriers affecting reconfigurable manufacturing system. Saha and Grover [169] discussed critical factors of website performance. Raj et al. [27] quantify the barriers of FMS. Dou et al. [170] optimized single-product flow-line. Rao and Padmanabhan [171] selected rapid prototyping process. Garg et al. [172] used for selection of power plants. Rao [173] used for industrial robots selection, identification and comparison. Rao [173] made a material selection model. Grover et al. [174] developed a performance index in TQM environment for human resource. Grover et al. [175] developed a digraph approach for TQM evaluation of an industry. Gandhi and Agrawal [176] used diagraph and matrix approach for FMEA. Hammouche and Webster [177] used GTMA for Layout problem.

This methodology consists of the following elements:

- Digraph representation
- Matrix representation
- Permanent function representation

Which are explained as below:

- Digraph representation :

A digraph is used to represent the performance factors and their interdependences in terms of nodes and edges. Experts, both from industry and academia, have been consulted in identifying and developing the contextual relationship between the elements.

- Matrix representation :

Matrix representation of the FMS performance digraph gives one-to-one representation. This is represented by a binary matrix (f_{ij}), where f_{ij} represents the relative importance between attributes i and j such that,

f_{ij} = 1, if the i-th attribute is more important than the j-th attribute

= 0, otherwise [28].

The FMS's performance matrix, (P) for the FMS digraph is written as:

$$
\begin{array}{c}
 \\
P =
\end{array}
\begin{array}{cc}
\begin{array}{cccccc} F_1 & F_2 & F_3 & - & - & F_M \end{array} & Factor \\
\begin{pmatrix}
F_1 & f_{12} & f_{13} & - & - & f_{1M} \\
f_{21} & F_2 & f_{23} & - & - & f_{2M} \\
f_{31} & f_{32} & F_3 & - & - & f_{3M} \\
- & - & - & - & - & - \\
- & - & - & - & - & - \\
f_{M1} & f_{M2} & f_{M3} & - & - & F_{\mathrm{M}}
\end{pmatrix} &
\begin{array}{c} F_1 \\ F_2 \\ F_3 \\ - \\ - \\ F_M \end{array}
\end{array}
\tag{2.2}
$$

- Permanent function representation:

Permanent is a standard matrix function and is used in combinatorial mathematics [178]. The permanent function is obtained in a similar manner as its determinant. A minus sign appears in the calculation of determinants while in the permanent, i.e. the variable permanent function, positive signs reduce these negative marks.

The FMS's performance intensity function for matrix P* is written as:

$$
Per\ \mathrm{P}^* = \prod_{i=3}^{3} F_i + \sum_i \sum_j \sum_k \left(f_{ij} f_{ji} \right) F_k + \sum_i \sum_j \sum_k \left(f_{ij} f_{jk} f_{ki} + f_{ik} f_{kj} f_{ji} \right) \tag{2.3}
$$

The permanent function of the matrix (i.e. equation 2.3) is a mathematical expression in symbolic form for three factors. These terms are arranged in groupings whose physical significance is explained below:

- The first grouping represents the interactions of the three major elements (i.e., $F_1F_2F_3$).
- The second grouping is absent, as there is no self-loop in the digraph.
- Each term of the third grouping represents a two-element interdependence loop (*i.e.,* $f_{ij} f_{ji}$) and the FMS performance measure of the remaining one unconnected elements.
- Each term of the fourth grouping represents a set of three-element interdependence loops (*i.e.,* $f_{ij} f_{jk} f_{ki}$ or $f_{ik} f_{kj} f_{ji}$).

The following steps to take place to perform GTMA:

1. Firstly, classify the various variables into the primary factors that affect performance in FMS by SPSS.
2. Secondly, a digraph is developed between the elements depending on their interdependencies.

3. Develop a variable digraph considering inheritance and interactions among them. The nodes in the digraph represent variables while edges represent interaction among variables. This is the digraph at each subsystem level.

4. Based on the above mentioned digraphs among the variables, the variables' matrix is developed at the subsystem level with diagonal elements representing inheritances and the off diagonal elements representing interactions among them. The numerical values for inheritance of attributes and their interactions with the help of experts are taken from Table 2.2 and 2.3.

Table 2.2 The inheritance of FMS factor

Sr. No.	Qualitative measure of FMS factor	Assigned value of FMS factor
1	Exceptionally low	1
2	Extremely low	2
3	Very low	3
4	Below average	4
5	Average	5
6	Above average	6
7	High	7
8	Very high	8
9	Extremely high	9
10	Exceptionally high	10

Table 2.3 The values of interdependence of FMS factor

Sr. No.	Qualitative measure of interdependence of FMS factor	Assigned value
1	Very strong	5
2	Strong	4
3	Medium	3
4	Weak	2
5	Very weak	1

5. Determine the value of a permanent function for sub-factor.

6. Repeat steps (3) to (6) for each sub-component.

7. Develop FMS digraph and FMS matrix at system level as explained in steps (2) and (3).
8. At system level, the permanent value of each sub factor (obtained in step (7)) provides inheritance for FMS performance/productivity/flexibility (i.e. diagonal elements). The quantitative value of interactions among factors (i.e. off diagonal elements) is obtained from Table 2.4 through proper interpretation by experts. This will form an FMS performance/productivity/flexibility matrix at the system level.
9. Determine the value of a permanent function of the organization. This is the value of the FMS performance/productivity/flexibility index.

Based on the above-discussed methodology, the intensity of variable affecting performance/productivity/flexibility can be measured.

2.5.7 Total Interpretive Structural Modeling (TISM)

ISM technique has been one of the most popular techniques for identification of the structure within a system, which have become very popular in the last one decade. But ISM does not provide an explanation on interpreting the structural links and ISM model lacks complete transparency [34]. So, to overcome the limitations of ISM methodology, it is extended to total interpretive structural modeling (TISM).

TISM is reviewed by some researcher as Mangla et al. [179] proposed TISM model to evaluate the causality and illustrate factors with interpretation of relations via direct links in the form of interpretive matrix and suggest that factors at the bottom level are crucial for the sustainability focused chain to build its capability on risks and risk issues. Dubey and Ali [180] identified key variables of FMS through systematic literature review and made the relationship among various constructs of FMS and their relationship using ISM and TISM analysis. Sandbhor and Botre [181] implemented TISM methodology for identifying and summarizing the relationships among factors which affect productivity of labor. Srivastava and Sushil [182] identified the variables of adapt in the context of strategy execution and develop a framework to shows the linkages among the identified dimensions/variables. Nasim and Sushil [183] presented a flexible strategy framework for managing the confluence of continuity and change in e-government domain is proposed and is illustrated with the help of a real case project, thus, providing insights for both academia and practitioners. Yadav [184] developed a model of strategic factors related to performance management in the context of Indian

Telecom Service Providers taking dual perspectives in account, i.e. enterprise perspective and subscribers' perspective. Singh and Sushil [185] identified and analyzed the interactions among different enablers of total quality management (TQM) and its outcome variables in service sector specific to the Indian domestic airline industry. TISM based quality framework structural model have been proposed for Indian domestic aviation industry, which is a new effort in the area of TQM implementation in this sector. Sagar et al. [186] explore the connection between various factors that affect customer defection rate in cloud computing through the veil of customer loyalty and put forth a void-in customer loyalty amplification model a void SM. Srivastava and Sushil [187] used TISM to develop a model of strategic performance factors for effective strategy execution. Wasuja and Sagar [188] proposed a cognitive bias amplification model explaining the phenomenon of cognitive bias in specialty pharmaceutical selling specialty drugs. TISM is used to create a hierarchy amongst the factors and interpret the relationships amongst them. Prasad and Suri [189] studied the continuity and change forces in education sector the model has lot of policy implication for planner and implementers in education sector. Nasim [190] attempted toward strategic management of continuity and change forces and understanding relations among these forces by TISM. The central tool of ISM, i.e. reachability matrix and its level partitions is adopted as it is in the process of TISM.

The following steps are followed in TISM methodology [34]:

Step1: Identify and define elements

Identification of different elements (or variables), which are related to problems from the literature published in reputed journals followed by expert opinions from academia and industry.

Step 2: Define contextual relationship

In order to develop the model, it is crucial to state the contextual relationship between the elements. Type of structure that are dealt with such as intent, priority, attribute enhancement, process or mathematical dependence [34]. For example, in case of intent, structure, which is widely used in management, the contextual relationship between different objectives as elements could be 'A should help achieve B' or 'A will help achieve B'.

Step 3: Interpretation of relationship

This is the first step forward over the traditional ISM. Though in ISM, the contextual relationship interprets the nature of the relationship as per the type of structure, but it remains silent on how that relationship really works. Thus, in order to interpret the ISM further and to make it TISM, clarification from the domain experts and stakeholders were asked for the interpretation/logic behind the expressed relationship. Experts not only indicate whether 'elements A will influence/enhance element B' or not, but also will explain 'in what way they will influence/enhance each other?' It is shown in Table 2.4

Table 2.4 Factors, contextual relationship and interpretation

Factor No.	Factor	Contextual relation	Interpretation
	Factors which affect flexibility	Factor A will influence / enhance factor B	How or in what way factor A will influence/enhance factor B

Step 4: Interpretive logic of pairwise comparison

In ISM, the elements are compared to develop self-structural interaction matrix (SSIM), the interpretation of which indicates direction of the relationship only. In order to upgrade it to TISM, it is proposed to make use of the concept of the Interpretive Matrix to fully interpret each paired comparison by answering the interpretive query as mentioned in the previous step, i.e. step III. For paired comparison, the *ith* element is compared individually to all the elements from *(i+1)th* to the *nth* element [191]. For each link the entry could be 'Yes (Y)' or 'No (N)' and if it is 'Yes', then the reason is to be provided. This reveals the interpretive logic of the paired relationships in the form of 'interpretive logic–knowledge base'.

Step 5: Reachability matrix and transitivity check

The paired comparison in the interpretive logic–knowledge base are translated in the form of the reliability matrix by making entry 1 in *i–j* cell, if the corresponding entry in the knowledge base in 'Y', or else it should be entered as 0 for the corresponding entry 'N' in interpretive logic– knowledge base.

This matrix is further checked for the transitivity rule, e.g. if A *Related to B* and B *Related to C* then this implies A *Necessarily Related to see* and updated till full transitivity is established.

Also, for each new transitive link, the interpretive logic– knowledge base is also updated. The 'No' entry is to be changed to 'Yes' and in the interpretation column 'Transitive' is entered. If the transitive relationship can be meaningfully explained, then the logic is written along with the 'Transitive' entry or else left as it is.

A semi structured questionnaire has been personally administered to the domain experts from academia and industry and their responses were further used to develop reachability matrix and for pairwise comparison. To make a clear distinction and decisions for the cutoff for the reachability matrix, if a 60 % response is given affirmative response, i.e. 'Y', the responses is taken as 1; otherwise taken as 0. During the transitivity check, if responses are more than 50%, then the transitivity was taken as significant transitivity otherwise transitive.

Step 6: Level partition on reachability matrix

The level partition is carried out similar to ISM to know the placement of element level-wise and determined the reachability and antecedent sets for all the elements. The intersection of the reachability set and the antecedent set will be the same as the reachability set in the case of the elements in a particular level. The top level elements satisfying the above condition should be removed from the element set and the exercise is to be repeated iteratively till all the levels are determined.

Step 7: Developing digraph

The elements are arranged graphically in levels and the directed links are drawn as per the relationships shown in the reachability matrix. A simpler version of the initial digraph is obtained by eliminating the transitive relationships step-by step by examining their interpretation from the knowledge base. Only those transitive relationships may be retained whose interpretation is crucial.

Step 8: Interaction matrix

The final digraph is translated into a binary interaction matrix form depicting all the interactions by 1 entry. The cells with 1 entry are interpreted by picking the relevant interpretation from the knowledge base in the form of interpretive matrix.

Finally, the digraph is translated into ISM by interpreting the node in box-bullet representation.

Step 9: Total interpretive structural model (TISM)

The connective and interpretive information contained in the interpretive direct interaction matrix and digraph is used to derive the TISM. The nodes in the digraph are replaced by the interpretation of elements placed in boxes. The interpretation in the cells of the interpretive direct interaction matrix is depicted by the side of the respective links in the structural model. This leads to total interpretation of the structural model in terms of the interpretation of its nodes as well as links.

2.5.8 Multiple Attribute Decision Making (MADM) Methodology

The multiple attribute decision making (MADM) refers to an approach that is employed to solve problems involving selected from among a finite number of alternatives. An MADM method is a procedure that specifies how attribute information is to be processed in order to arrive at a choice. MADM application is summarized in Table 2.5.

Table 2.5 MADM applications found in literature

Sr. No.	Name of the authors	Application
1	Chauhan and Vaish [192]	Hard coating material selection
2	Baykasoğlu et al. [193]	For truck selection
3	Fallahpour and Moghassem [194]	Selection for rotor spun knitted fabric
4	İç [195]	Selection of computer-integrated manufacturing technologies
5	Athawale et al. [196]	Industrial robot selection problems
6	Pei and Zheng [197]	A novel approach to multi-attribute decision making
7	Lavasani et al. [198]	Selecting the best barrier for offshore wells
8	Jahan et al. [199]	Technique for materials selection
9	Xu et al. [200]	Linguistic power aggregation operators

10	Kalbar et al. [201]	Selection of an appropriate wastewater treatment technology
11	Daim et al. [202]	Site selection for a data centre
12	Bakhoum and Brown [203]	Ranking of structural materials
13	Sharma and Balan [204]	Supplier selection model
14	San Cristóbal [205]	Selection of a renewable energy project
15	Shemshadi et al. [206]	Supplier selections
16	Kuo and Liang [207]	Evaluate service quality of airports
17	Devi [208]	Robot selection
18	Jahan et al. [209]	Material selection
19	Maniya and Bhatt [210]	Selection of appropriate FMS alternatives
20	Vahdani et al. [211]	Group decision making
21	Afshari et al. [212]	Personnel selection problem
22	Kaya and Kahraman [213]	Renewable energy planning
23	Dağdeviren [214]	Personnel selection in manufacturing systems
24	Sanayei et al. [215]	Supplier selections
25	Zavadskas et al. [216]	Contractor selection for construction works
26	Zeydan and Çolpan [217]	Performance measurement
27	Rao [218]	Improved compromise ranking method
28	Chou et al. [219]	Facility location selection
29	Lixin et al. [220]	Selection of logistics service provider
30	Brauers et al. [221]	Decision-making for road design
31	Önüt et al. [222]	Machine tool selection
32	Tong et al. [223]	Optimization of multi-response processes
33	Liu and Yan [224]	Bidding-evaluation of construction projects
34	Opricovic and Tzeng [225]	Comparison with outranking methods

35	Shyur [226]	Ranking commercial-off-the-shelf products of electronic company
36	Byun and Lee [227]	Selection of a rapid prototyping process
37	Srdjevic et al. [228]	Water management
38	Deng et al. [229]	Inter-company comparison
39	Parkan and Wu [230]	Robot selection

The following MADM methods are used in this research to achieve the objectives of the research:

a) Fuzzy Theory

Rao [28] has consolidated the information on fuzzy MADM. Bellman and Zadeh [231] were the first to relate fuzzy set theory to decision-making problems. Yager and Basson [232] proposed fuzzy sets for decision making. Baas and Kwakernaak [233] proposed a fuzzy MADM method that is widely regarded as the classic work of fuzzy MADM methods. Chen and Hwang [234] proposed an approach to solve more than 10 alternatives and they proposed first converts linguistic terms into fuzzy numbers and then the fuzzy numbers into crisp scores. An 11-point scale is used in the research is shown in the Figure 2.7 and crisp score is shown in Table 2.6.

Table 2.6 Conversion of linguistic terms into fuzzy scores (11-point scale)

Linguistic term	Fuzzy no.	Crisp no.
Exceptionally low	M_1	0.045
Extremely low	M_2	0.135
Very low	M_3	0.255
Low	M_4	0.335
Below average	M_5	0.410
Average	M_6	0.500
Above average	M_7	0.590
High	M_8	0.665
Very high	M_9	0.745
Extremely high	M_{10}	0.865
Exceptionally high	M_{11}	0.955

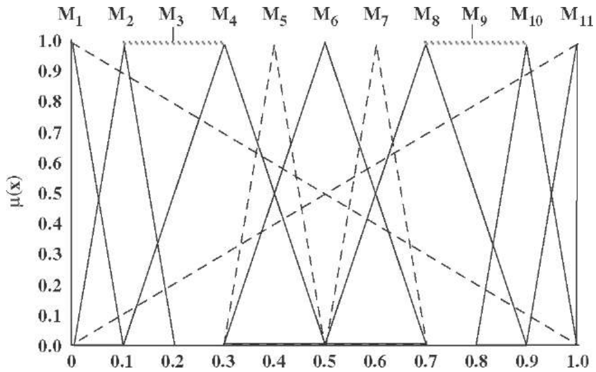

Figure 2.7 Linguistic terms into their corresponding fuzzy

b) Simple Additive Weighting (SAW) Method

Churchman and Ackoff [235] first utilized the SAW method to cope with a portfolio selection problem. The SAW method is probably the best known and widely used method for multiple attribute decision making MADM. The main procedure to find the overall or composite score of the alternative by SAW method is described below [28]:

Step 1: The first step is to determine the objective and to identify the pertinent evaluation attributes.

Step 2: This step represents a matrix based on all the information available on attributes. Each row of this matrix is allocated to one alternative and each column to one attribute. In the case of a subjective attribute (i.e. objective value is not available), a ranked value judgment on a scale is adopted. Chen and Hwang [234] proposed an approach to solve more than 10 alternatives and they proposed first converts linguistic terms into fuzzy numbers and then the fuzzy numbers into crisp scores. An 11-point scale is used in this research is shown in Figure 2.7 and crisp score is shown in Table 2.6.

Step 3: The weights are calculated by using the analytical hierarchy process (AHP).

Step 4: Construct a decision matrix (m × m) that includes m alternatives and m attributes.

Calculate the normalized decision matrix for beneficial attributes:

$$m_{ij} = r_{ij} / r_j^{\max} \quad \text{i=1, ….. m and j= 1,….m} \tag{2.5}$$

Calculate the normalized decision matrix for non-beneficial attributes:

$$m_{ij} = r_j^{\min} / r_{ij} \quad \text{i=1,…..m and j= 1,….m} \tag{2.6}$$

Step 5: Evaluate each alternative, P_i by the following formula:

$$P_i = \sum_{j=1}^{M} w_j \left(m_{ij}\right)_{normal} \tag{2.7}$$

Where $\left(m_{ij}\right)_{normal}$ represents the normalized value of m_{ij} and P_i is the overall or composite score of the alternative A_i. The alternative with the highest value of P_i is considered as the best alternative.

c) Weighted Product Method (WPM)

This method is similar to SAW. The main difference is that, instead of addition in the model, there is multiplication [236]. The overall or composite performance score of an alternative is given by equation 2.8.

$$P_i = \prod_{j=1}^{M} \left[\left(m_{ij}\right)_{normal}\right]^{w_j} \tag{2.8}$$

The normalized values are calculated as explained in SAW method step 4. Each normalized value of an alternative with respect to an attribute, i.e., $\left(m_{ij}\right)_{normal}$ is raised to the power of the relative weight of the corresponding attribute. The alternative with the highest P_i value is considered the best alternative.

d) Analytical Hierarchy Process (AHP) Methodology

Saaty [237] developed AHP, which decomposes a decision-making problem into a system of hierarchies of objectives, attributes (or criteria) and alternatives. The main procedure of AHP using the radical root method (also called the geometric mean method) is as follows:

Step 1: To determine the objective and the evaluation attributes. Then develop a hierarchical structure, objective at the top level, the attributes at the middle level and the alternatives at the last level.

Step 2: To determine the relative importance of different attributes with respect to the goal or objective.

• To construct a pairwise comparison matrix using a scale of relative importance. The judgments are entered using the fundamental scale of the analytic hierarchy process [237]. An attribute compared with itself is always assigned the value 1, so the main diagonal entries of the pairwise comparison matrix are all 1. The numbers 3, 5, 7 and 9 correspond to the verbal judgments 'moderate Importance ', ' strong importance ', ' very strong importance ' and ' absolute importance' (with 2, 4, 6 and 8 for compromise between these values). Assuming M attributes, the pairwise comparison of attribute, i with attribute j yield a square matrix $B_{M \times M}$ where a_{ij}, denotes the comparative importance of attribute, i with respect to attribute j. In the matrix, $b_{ij}=1$ when i = j and $b_{ji} = l / b_{ij}$.

$$B_{MXM} = \begin{array}{c} Attributes \\ B_1 \\ B_2 \\ B_3 \\ - \\ - \\ B_M \end{array} \begin{bmatrix} B_1 & B_2 & B_3 & - & - & B_M \\ 1 & b_{12} & b_{13} & - & - & b_{1M} \\ b_{21} & 1 & b_{23} & - & - & b_{2M} \\ b_{31} & b_{32} & 1 & - & - & b_{3M} \\ - & - & - & - & - & - \\ - & - & - & - & - & - \\ b_{M1} & b_{M2} & b_{M3} & - & - & 1 \end{bmatrix} \tag{2.9}$$

• To find the relative normalized weight (w_j) of each attribute by (i) calculating the geometric mean of the i-th row and (ii) normalizing the geometric means of rows in the comparison matrix. This can be represented as

$$GM_J = \left[\prod_{i=1}^{M} b_{ij} \right]^{\frac{1}{M}} \tag{2.10}$$

and $$w_j = GM_j \,/\, \sum_{j=0}^{M} GM_j \tag{2.11}$$

The geometric mean method of AHP is commonly used to determine the relative normalized weights of the attributes, because of its simplicity, ease, determination of the maximum eigenvalue and reduction in inconsistency of judgments [238].

• To calculate matrices A3 and A4 such that A3 = A1 * A2 and A4 = A3 / A2, where A2 = $[w_1, w2,\ldots ,w_j]^T$.

• To determine the maximum eigenvalue λ_{max} that is the average of the matrix A4 Calculates the consistency index (CI) = (λ_{max} - M) / (M -1). The smaller the value of CI, the smaller is the deviation from the consistency.

• To obtain the random index (RI) for the number of attributes used in decision making [239].

To calculate the consistency ratio (CR) = CI/RI. Usually, a CR of 0.1 or less is considered as acceptable and it reflects an informed judgment attribute to the knowledge of the analyst regarding the problem under study.

Step 3: To express the attribute values (may be qualitative or quantitative). It then normalized the values of attributes.

Step 4: To obtain the overall or composite performance scores for the alternatives by multiplying the relative normalized weight (w_j) of each attribute (obtained in step 2) with its corresponding normalized weight value for each alternative (obtained in step 3) and summing over the attributes for each alternative.

e) Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) Methodology

The TOPSIS method was developed by Hwang and Yoon [240]. This method is based on the concept that the chosen alternative should have the shortest Euclidean distance from the ideal solution and the farthest from the negative ideal solution. The main procedure of the TOPSIS method for the selection of the best alternative from among those available is described below:

Step 1: To determine the objective and to identify the pertinent evaluation attributes and develop a hierarchical structure.

Step 2: To represent a matrix based on all the information available on attributes. Such a matrix is called a decision matrix. Each row of this matrix is allocated to one alternative and each column to one attribute. Therefore, an element d_{ij} of the decision table 'D' gives the value of the j-th attribute in original real values, that is, non-normalized form and units, for the, i-th alternative.

If the number of alternatives is M and the number of attributes in N, then the decision matrix is an M x N matrix can be represented as:

$$D_{MXM} = \begin{array}{c} Attributes \\ D_1 \\ D_2 \\ D_3 \\ - \\ - \\ D_M \end{array} \begin{bmatrix} D_1 & D_2 & D_3 & - & - & D_N \\ d_{11} & d_{12} & d_{13} & - & - & d_{1N} \\ d_{21} & d_{22} & d_{23} & - & - & d_{2N} \\ d_{31} & d_{32} & d_{33} & - & - & d_{3N} \\ - & - & - & - & - & - \\ - & - & - & - & - & - \\ d_{M1} & d_{M2} & d_{M3} & - & - & d_{MN} \end{bmatrix} \quad (2.12)$$

In the case of a qualitative attribute (i.e. quantitative value is not available); a ranked value judgment on a scale is adopted by using fuzzy set theory. Once a qualitative attribute is represented on a scale then the normalized values of the attribute assigned for different alternatives are calculated in the same manner as that for quantitative attributes.

Step 3: To obtain the normalized decision matrix, R_{ij}. This can be represented as

$$R_{ij} = d_{ij} / \left[\sum_{j=1}^{M} d_{ij}^2 \right]^{1/2} \tag{2.13}$$

Step 4: To decide on the relative importance (i.e., weights) of different attributes with respect to the objective. It is same as step 2 in AHP Methodology. A set of weights w_j (for j= 1, 2, ..., M) such that $\sum w_j = 1$ may be decided upon.

Step 5: To obtain the weighted normalized matrix V_{ij}. This is done by the multiplication of each element of the column of the matrix, R_{ij} with its associated weight w_j .Hence, the elements of the weighted normalized matrix V_{ij} are expressed as:

$$V_{ij} = w_j R_{ij} \tag{2.14}$$

Step 6: To obtain the ideal (best) and negative ideal (worst) solutions in this step. The ideal (best) and negative ideal (worst) solutions can be expressed as:

$$V^+ = \left\{ \left(\sum_{i}^{max} V_{ij} / j \in J \right), \left(\sum_{i}^{min} V_{ij} / j \in J^{'} \right) / i = 1, 2, .., N \right\} \tag{2.15}$$

$$= \left\{ V_1^+, V_2^+, V_3^+, \ldots\ldots.., V_M{}^+ \right\}$$

$$V^- = \left\{ \left(\sum_{i}^{max} V_{ij} / j \in J \right), \left(\sum_{i}^{min} V_{ij} / j \in J^{'} \right) / i = 1, 2, .., N \right\} \tag{2.16}$$

$$= \left\{ V_1^-, V_2^-, V_3^-, \ldots\ldots.., V_M{}^- \right\}$$

Where J= (j=1, 2,….., M) /j is associated with beneficial attributes and

J’= (j=1, 2,....., M) /j is associated with non-beneficial attributes.

V_j^+ indicates the ideal (best) value of the considered attribute among the values of the attribute for different alternatives. In the case of beneficial attributes (i.e., those of which higher values are desirable for the given application), V_j^+ indicates the higher value of the attribute. In the case of non-beneficial attributes (i.e., those of which lower values are desired for the given application). V_j^+ indicates the lower value of the attribute.

V_j^- indicates the negative ideal (worst) value of the considered attribute among the values of the attribute for different alternatives. In the case of beneficial attributes (i.e., those of which higher values are desirable for the given application), V_j^- indicates the lower value of the attribute. In the case of non-beneficial attributes (i.e., those of which lower values are desired for the given application), V_j^- indicates the higher value of the attribute.

Step 7: To obtain the separation measure. The separation of each alternative from the ideal one is given by the Euclidean distance in the following equations.

$$S_i^+ = \left\{ \sum_{J=1}^{M} \left(V_{ij} - V_j^+ \right)^2 \right\}^{0.5}, \qquad (2.17)$$

Where i=1, 2,… N

$$S_i^- = \left\{ \sum_{J=1}^{M} \left(V_{ij} - V_j^- \right)^2 \right\}^{0.5}, \qquad (2.18)$$

Where i=1, 2,… N

Step 8: To find the relative closeness of a particular alternative to the ideal solution, P_i, can be expressed in this step as follows.

$$P_i = \frac{S_i^-}{\left(S_i^+ + S_i^- \right)} \qquad (2.19)$$

Step 9: To arrange alternative in the descending order according to the value of P_i indicating the most preferred and least preferred feasible solutions. P_i may also be called the overall or composite performance score of alternative A_i.

f) Modified TOPSIS Method

The technique for order preference by similarity to ideal situation (TOPSIS) method was developed by Hwang and Yoon. This method is based on the concept that the chosen alternative should have the shortest Euclidean distance from the ideal solution and the farthest from the negative ideal solution. In the TOPSIS method, the normalized decision matrix R_{ij} is weighted by multiplying each column of the matrix by its associated attribute weights. The overall performance of an alternative is then determined by Its Euclidean distance to V_j^+ and V_j^- . However, this distance is interrelated with the attribute weights and should be incorporated in the distance measurement. This is because all alternatives are compared with V_j^+ and V_j^-, rather than directly among themselves. Deng et al. [229] have used modified TOPSIS in which they have presented the weighted Euclidean distances, rather than creating a weighted decision matrix. In this process, the positive ideal solutions (R^+) and the negative ideal solutions (R^-), which are not dependent on the weighted decision matrix.

The main procedure of the modified TOPSIS method for the selection of the best flexibility from among those available is described below [28].

Step 1: To determine the objective, alternatives and to identify the pertinent evaluation attributes.

Step 2: To represent a matrix based on all the information available on attributes. Each row of this matrix is allocated to one alternative and each column to one attribute. In the case of a subjective attribute (i.e., objective value is not available), a ranked value judgement on a scale is adopted. An 11-point scale is used in this research for crisp score as shown in Table 2.6.

Step 3: To obtain the positive ideal solution (best) and negative ideal solution (worst). The ideal (best) and negative ideal (worst) solutions can be expressed as:

$$R^+ = \left\{ \left(\sum_i^{\max} R_{ij} \mid j \in J \right), \left(\sum_i^{\min} R_{ij} \mid j \in J^{'} \right) / i = 1, 2, ...N \right\} \tag{2.20}$$

$$= \left\{ R_1^+, R_2^+, R_3^+, ..., R_M^+ \right\}$$

$$R^- = \left\{ \left(\sum_i^{\max} R_{ij} \mid j \in J \right), \left(\sum_i^{\min} R_{ij} \mid j \in J^{'} \right) / i = 1, 2, ...N \right\} \tag{2.21}$$

$$= \left\{ R_1^-, R_2^-, R_3^-, ..., R_M^- \right\}$$

Where J= (j=1, 2,….., M) / j is associated with beneficial attributes and

J’= (j=1, 2,....., M) / j is associated with non-beneficial attributes.

Step 4: To find the weights of attributes as analytic hierarchy process (AHP) method [237]. It is same as step 2 in AHP Methodology.

Step 5: To calculate the weighted Euclidean distances as:

$$D_i^+ = \left\{ \sum_{j=1}^{M} W_j \left(R_{ij} - R_j^+ \right)^2 \right\}^{0.5} \tag{2.22}$$

Where i=1, 2,…, N

$$D_i^- = \left\{ \sum_{j=1}^{M} W_j \left(R_{ij} - R_j^- \right)^2 \right\}^{0.5} \tag{2.23}$$

Where i=1, 2,…, N

Step 6: To find the relative closeness of a particular alternative to the ideal solution, $P_{i\text{-mod}}$, can be expressed as follows:

$$P_{i-\text{mod}} = D_i^- / \left(D_i^+ + D_i^- \right) \tag{2.24}$$

Step 7: To arrange alternative in the descending order according to the value of $P_{i\text{-mod}}$ indicating the most preferred and least preferred feasible solutions. $P_{i\text{-mod}}$ may also be called the overall or composite performance score of alternative A_i. A Flow diagram for Modified TOPSIS is shown in Figure 2.8.

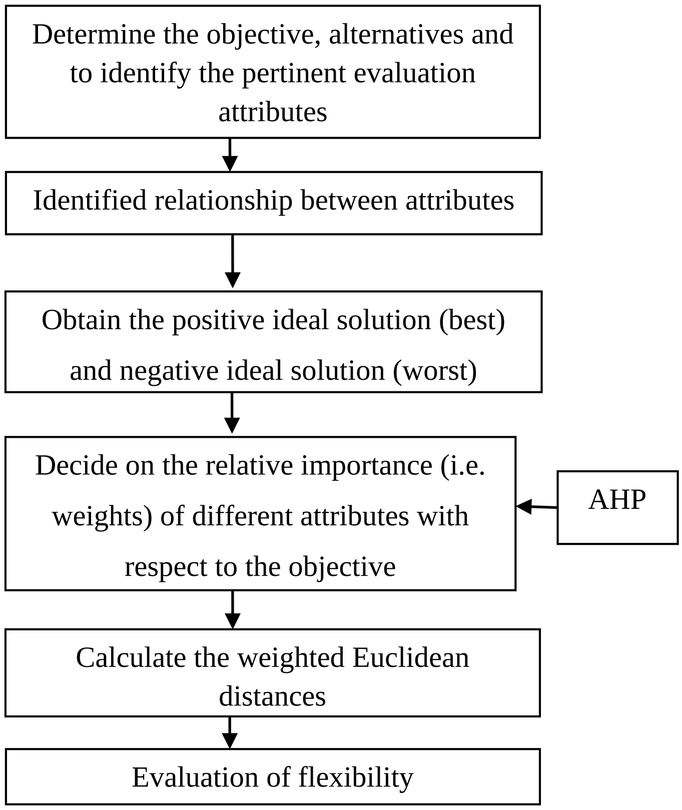

Figure 2.8 Flow diagram for modified TOPSIS

g) Improved PROMETHEE Methodology

The preference ranking organization method for enrichment evaluations (PROMETHEE) method was introduced by Mareschal et al. [241] and belongs to the category of outranking methods.

It may be added here that the original PROMETHEE method can effectively deal mainly with quantitative criteria. However, there exists some difficulty in the case of qualitative criteria. In the case of a qualitative criterion (i.e. Quantitative value is not available); a ranked value judgment on a fuzzy conversion scale is adopted in this research. By using fuzzy set theory, the value of the criteria can be first decided as linguistic terms, converted into corresponding fuzzy numbers and then converted to the crisp scores. The improved PROMETHEE methodology for ranking of flexibility is described below:

Step 1: To determine the objective, to identify the pertinent evaluation attributes and then shortlist the alternatives. After short listing the alternatives, prepare a decision table, including the measures or values of all criteria for the shortlisted alternatives.

Step 2: To find the weights of attributes by using the analytic hierarchy process (AHP) method [237]. It is same as step 2 in AHP Methodology.

Step 3: After calculating the weights of the criteria using the AHP method, the next step is to have the information on the decision maker preference function, which he/she uses when comparing the contribution of the alternatives in terms of each separate criterion.

The preference function (P_i) translates the difference between the evaluations obtained by two alternatives (a1 and a2) in terms of a particular criterion, into a preference degree ranging from 0 to 1. Let $P_{i,a1a2}$ be the preference function associated with the criterion c_i.

$$P_{i,\,a1a2} = G_i\,[c_i\,(a1) - c_i\,(a2)] \tag{2.25}$$

$$0 \leq P_{i,a1a2} \leq 1 \tag{2.26}$$

where G_i is a non-decreasing function of the observed deviation (d) between two alternatives a1 and a2 over the criterion c_i.

Step 4: To specify a preference function P_i and weight w_i for each criterion c_i (i = 1, 2 , M) of the problem. The multiple criteria preference index Π_{a1a2} is then defined as the weighted average of the preference functions P_i.

$$\prod_{a1a2} = \sum_{i=1}^{M} w_i P_{i,a1a2} \tag{2.27}$$

Π_{a1a2} represents the intensity of preference of the decision maker of alternative a1 over alternative a2, when considering simultaneously all the criteria. Its value ranges from 0 to 1[242].

For PROMETHEE outranking relations, the leaving flow, entering flow and the net flow for an alternative *a* belonging to a set of alternatives *A* are defined by the following equations:

$$\varphi^{+}(a) = \sum_{x \varepsilon A} \Pi_{xa} \tag{2.28}$$

$$\varphi^{-}(a) = \sum_{x \varepsilon A} \Pi_{ax} \tag{2.29}$$

$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a) \tag{2.30}$$

$\varphi^{+}(a)$ is called the leaving flow, $\varphi^{-}(a)$ is called the entering flow and $\varphi(a)$ is called the net flow. $\varphi^{+}(a)$ is the measure of the outranking character of a (i.e. dominance of alternative an overall other alternatives) and $\varphi^{-}(a)$ gives the outranked character of *a* (i.e. degree to which alternative *a* is dominated by all other alternatives). The net flow, $\varphi(a)$ represents a value function, whereby a higher value reflects a higher attractiveness of alternative *a*. The net flow values are used to indicate the outranking relationship between the alternatives.

The proposed decision making framework using PROMETHEE method provides a complete ranking of the alternatives from the best to the worst one using the net flows.

h) VIKOR Methodology

The compromise solution was introduced in MCDM by Po-Lung Yu in 1972 and it was extended by Milan Zeleny. Opricovic had developed the basic ideas of VIKOR in his Ph.D. dissertation in 1979and an application was published in 1980. Opricovic use VIseKriterijumska Optimizacija I Kompromisno Resenje (abbreviated as VIKOR), which means: multicriteria optimization and compromise solution. VIKOR is a helpful tool in MADM, particularly in a situation where the decision maker is not able, or does not know how to express preference at the beginning of system design. The obtained compromise solution could be accepted by the decision makers because it provides a maximum 'group utility' (represented by $E_{i\text{-}min}$) of the 'majority' and a minimum of individual regret (represented by Fi-min) of the 'opponent' [243]. The compromise solutions could be the basis for negotiations, involving the decision maker's preference by attribute weights. The compromise solution is a feasible solution that is the closest to the ideal solution and a compromise means an agreement made by mutual concession [28]. The main procedure of the combined fuzzy, AHP and VIKOR method is described below:

Step 1: To determine the objective and to identify the pertinent evaluation attributes.

Step 2: To convert qualitative attribute to their corresponding fuzzy number. A ranked value judgment on a fuzzy conversion scale is adopted in this research i.e. qualitative into quantitative because quantitative value is not available. By using fuzzy set theory, the value of the criteria can be first decided as linguistic terms, converted into corresponding fuzzy numbers and then converted to the crisp scores [244]. An 11-point scale is used in the research is shown in the Figure 2.7 and crisp score is shown in Table 2.6.

Step 3: To find the weights of attributes by using the analytic hierarchy process (AHP) method [237]. It is same as step 2 in AHP Methodology.

Step 4: To determine the best, i.e., $(m_{ij})_{max}$ and the worst, i.e., $(m_{ij})_{min}$, values of all attributes.

Step 5: To calculate the values of E_i and F_i:

$$E_i = \sum_{j=1}^{M} w_j \left[\left(m_{ij}\right)_{\max} - \left(m_{ij}\right) \right] / \left[\left(m_{ij}\right)_{\max} - \left(m_{ij}\right)_{\min} \right] \tag{2.31}$$

$$F_i = Max^m of \left\{ w_j \left[\left(m_{ij} \right)_{\max} - \left(m_{ij} \right) \right] / \left[\left(m_{ij} \right)_{\max} - \left(m_{ij} \right)_{\min} \right] \mid j = 1, 2, ..., M \right\} \quad (2.32)$$

Step 6: To calculate the values of P_i:

$$P_i = v\left(\left(E_i - E_{i-\min} \right) / \left(E_{i-\max} - E_{i-\min} \right) \right) + (1 - v)\left(\left(F_i - F_{i-\min} \right) / \left(F_{i-\max} - F_{i-\min} \right) \right) \quad (2.33)$$

where E_{i-max} is the maximum value of E_i and E_{i-min} the minimum value of E_i. F_{i-max} is the maximum value of F_i and F_{i-min} is the minimum value of F_i. v is introduced as the weight of the strategy of 'the majority of attributes' or v is the weight of the decision making strategy of maximum group utility. Normally, the value of v is taken as 0.5. However, v can take any value from 0 to 1.

Step 7: To arrange the alternatives in the ascending order, according to the values of P_i. Similarly, arrange the alternatives according to the values of E_i and F_i separately. Thus, three ranking lists can be obtained. The compromise ranking list for a given v is obtained by ranking with P_i measures. The best alternative, ranked by P_i, is the one with the minimum value of P_i.

Step 8: For given attribute weights, propose a compromise solution, alternative ($A^{(1)}$), which is the best ranked by the measure P_{i-min}, if the following two conditions are satisfied [245]:

Condition 1: 'Acceptable advantage':

$$P(A^{(2)}) - P(A^{(l)}) \geq DQ \quad (2.34)$$

Where $A^{(2)}$ is the second-best alternative in the ranking list by P; DQ = 1/ (M-1). M is the number of alternatives.

Condition 2: 'Acceptable stability in decision making' alternative:

A set of compromise solutions is proposed to as follows, if one of the conditions is not satisfied.

- Alternatives $A^{(1)}$ and $A^{(2)}$ if only condition 2 is not satisfied
- Alternatives $A^{(1)}$, $A^{(2)}$, ….. , $A^{(M)}$ if condition 1 is not satisfied; $A^{(M)}$ is determined by the relation $P(A^{(M)}) - P(A^{(l)}) < DQ$ for maximum M.

The alternative $A^{(1)}$ should also be the best ranked by E or/and F.

These steps of VIKOR method are illustrated in the flow diagram (Figure 2.9)

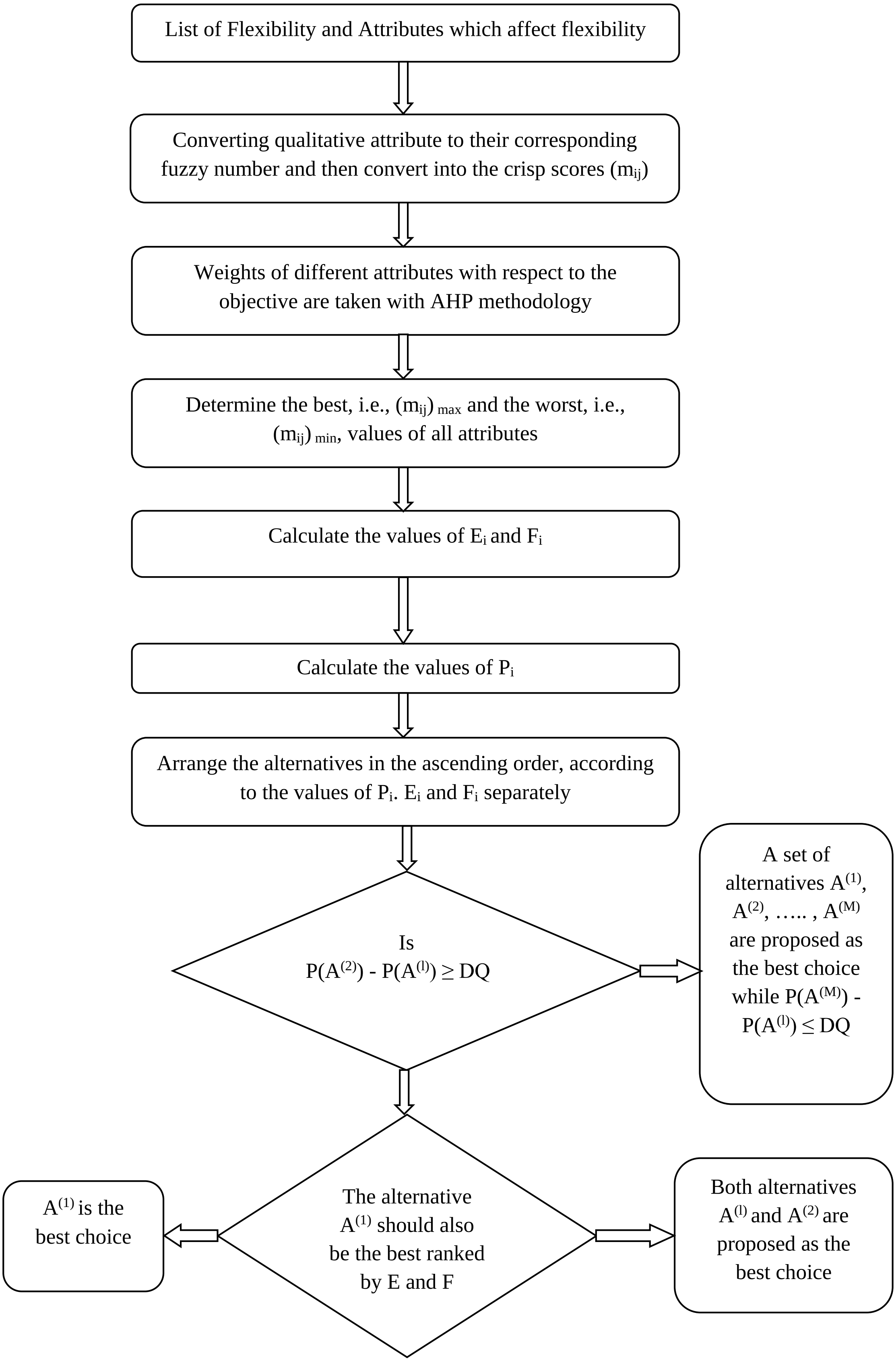

Figure 2.9 Flowchart of VIKOR method for evaluation of flexibility in FMS

2.5.9 Adaptive Neuro-Fuzzy Inference System (ANFIS) Methodology

Jang [31] proposed adaptive neuro-fuzzy inference system (ANFIS) to construct an input-output mapping based on both human knowledge (in the form of fuzzy if-then rules) and stipulated input-output data pairs. It is an adaptive network, a network of nodes and directional links. This network is associated with a learning rule - for example back propagation or hybrid algorithm. ANFIS can predict data using sugeno fuzzy inference system (FIS) to relate membership and tune it using either back propagation or hybrid method. The goal of ANFIS is to find a model, which will simulate correctly the inputs to the outputs. They are evaluated on the base of testing performances. Here, ANFIS work has been reviewed from the literature as Lo [246] described the ANFIS model to detect the tool state. Chien and Tsai [247] applied network model for developing tool wear prediction models. Choudhury and Bartarya [248] focused on the Neural Networks (NN) and Design of Experiments (DOE) and the results showed that NN come ahead of the DOE in nearness of the predictions to the experimental values of flank wear as the average errors in the flank wear in case of NN are less than that obtained using DOE. Sokołowski [249] discussed selected aspects of fuzzy logic system implementation in machine tool and cutting process monitoring. Ojha and Dixit [250] used neural networks to predict the tool life. The comparison between neural networks and multiple regression shows the superiority of the former. Pal and Chakraborty [251] used back propagation neural network model to predicted Ra by taking main cutting force, feed force, cutting speed, feed and depth of cut as input parameters. They found that the model with cutting forces as additional input give better results. Zhang et al. [252] developed an in-process surface roughness adaptive control system in turning operations. Iqbal et al. [253] developed an approach based on the least-squares regression for estimating tool wear in machining. Iqbal et al. [254] developed a fuzzy expert system for parameter optimization that includes prediction of tool life and surface finish in hard milling process. Kumanan et al. [255] proposed two different hybrid intelligent techniques for the prediction of surface roughness (R_a) in end milling. Ho et al. [256] used an ANFIS with the hybrid taguchi-genetic learning algorithm to predict the work piece R_a for the end milling process. Samanta [257] presented a model for surface roughness in end milling using adaptive neuro-fuzzy inference system and genetic algorithms. Dong and Wang [258] proposed a model for predicting R_a for end milling process with ANFIS and leave-one-out cross-validation approach. Svalina et al. [259] used an ANFIS approach for machined surface roughness prediction. Pousinho et al. [260] proposed a approach for electricity prices forecasting in a competitive market. Roy [261] designed an intelligence technique-based expert system using adaptive neuro-fuzzy inference system (ANFIS) for predicting tool wear in milling operation.

ANFIS model has five network layers which are used to perform the following fuzzy inference steps: (i) input fuzzification, (ii) fuzzy set database construction, (iii) fuzzy rule base construction, (iv) decision making and (v) output defuzzification [32].

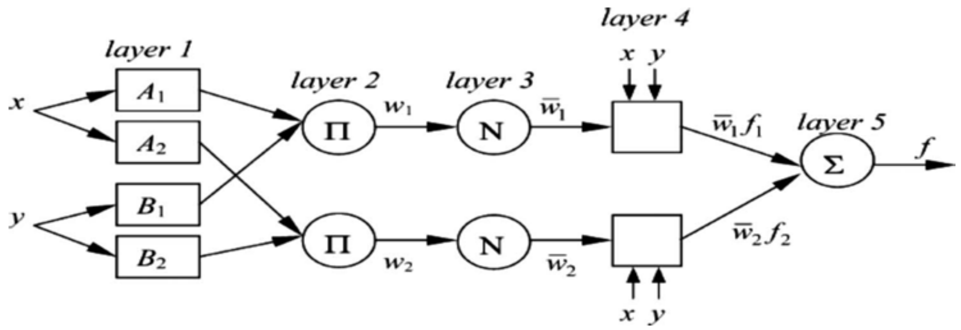

Figure 2.10 Schematic diagram of ANFIS [262]

Precisely the model consists five layers of adaptive network with two inputs (x and y), two linguistic values and output f. Basically, inference system is constructed by five layers (Figure 2.10) and each ANFIS layer consists of several nodes described by the node function. The present layers' inputs are derived from the nodes in the previous layers. The rule base of ANFIS contains fuzzy IF – THEN rules of the sugeno type. For a first-order sugeno fuzzy inference system, the two rules may be stated as:

Rule 1: IF x is A_1 AND y is B_1, THEN f is $f_1(x,y)$

Rule 2: IF x is A_2 AND y is B_2, THEN f is $f_2(x,y)$,

where x and y are the inputs of ANFIS, A_i and B_i are the fuzzy sets and $f_i\,(x,y)$ is a first order polynomial and represents the outputs of the first order sugeno fuzzy inference system. The structure of ANFIS is shown in Figure 2.10 and the node function in each layer is described below. Svalina et al. [259] have suggested to represent the parameter sets that are adjustable in these nodes are presented by adaptive nodes, denoted by squares, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system.

Layer 1: This layer contains adaptive nodes with node functions like i explained as below:

$Q_{1,i} = \mu_{A_i}(x)$ for i=1, 2 (2.35)

$Q_{2,i} = \mu_{B_{i-2}}(y)$ for i=3, 4 (2.36)

where x and y are the input to node i, A_i and B_i are the linguistic labels such as small or large, μ (x) and μ (y) are the membership functions. Many sorts of the membership functions which are there can be used. However, a gaussian membership function has been chosen to represent the linguistic terms because the relationship between the processing time and makespan is not linear, so this function assured a smooth transition between 0 and 1. It can be written as follows:

First parameter membership functions

$$\mu A_i(x) = \exp\left[-0.5\left(\frac{(x - a_{i1})}{b_{i1}}\right)^2\right] \tag{2.37}$$

Second parameter membership functions

$$\mu \mathrm{B}_i(y) = \exp\left[-0.5\left(\frac{(y - a_{i2})}{b_{i2}}\right)^2\right] \tag{2.38}$$

Where $a_{i,1}$, $a_{i,2}$, $b_{i,1}$ and $b_{i,2}$ are the parameter set. The bell-shaped functions vary while the values of this parameter are changing.

Layer 2: In this layer every node is a fixed node, which is marked by a circle and the node function has to be multiplied by input signals so that it can serve as output for every node. The nodes of this layer are called rule nodes. Each node computes the firing strength of the associated rule i.e.w_1.

$Q_{2,i} = w_1 = \mu A_i(x) \times \mu \mathrm{B}_i(y)$ (2.39)

Layer 3: Every node in this layer is also a fixed node, marked by a circle and labeled N to show the normalization of the firing levels.

$Q_{3,i} = \overline{w_i} = \dfrac{w_i}{\sum w_i}$ for i=1, 2 (2.40)

Layer 4: Every node i in this layer is an adaptive node with a node function and marked by a square:

$$Q_{4,i} = \overline{w_i} \times f_i \text{ for } i=1, 2 \tag{2.41}$$

Here f_1 and f_2 are the fuzzy IF-THEN rules as follows:

Rule 1: IF x is A_1 AND y is B_1, THEN f_1 is $=p_1x+q_1y+r_1$

Rule 2: IF x is A_2 AND y is B_2, THEN f_2 is$= p_2x+q_2y+r_2$,

Where $\overline{w_i}$ is normalized firing strength from layer 3 and $[p_i, q_i, r_i]$ is the parameter set of this node and marked as the consequent parameters.

Layer 5: One fixed node of this layer is marked by a circle. The node has to compute the overall output as the summation of all incoming signals:

$$Q_{5,i} = f_{out} = \sum \overline{w_i} \times f_i = \text{overall output.} \tag{2.42}$$

The first layer and the fourth layer are the two adaptive layers with square nodes in this ANFIS architecture. In the first layer, there are two modifiable parameters known as premise parameters $[a_i, b_i]$ which relates to the input membership functions. In the fourth layer, there are also three modifiable parameters known as consequent parameters $[p_i, q_i, r_i]$ pertaining to the first-order polynomial.

In this research, the various input variables are trained and tested by ANFIS method and the performances of models for deduction of surface roughness with unmanned production system are compared and evaluated based on testing performances. Flow diagram of ANFIS shown in Figure 2.11.

Implementation of ANFIS:

Step 1: To define the architecture of ANFIS model

Step 2: To give input training data into the ANFIS model

Step 3: To set the input and output parameters and membership function.

Step 4: To define the ANFIS structure for membership function.

Step 5: To trained the ANFIS model

Step 6: To give input testing data into the ANFIS model

Step 7: To test the ANFIS model

Step 8: To find the test output of the ANFIS model

Step 9: To plot regression analysis between output and actual

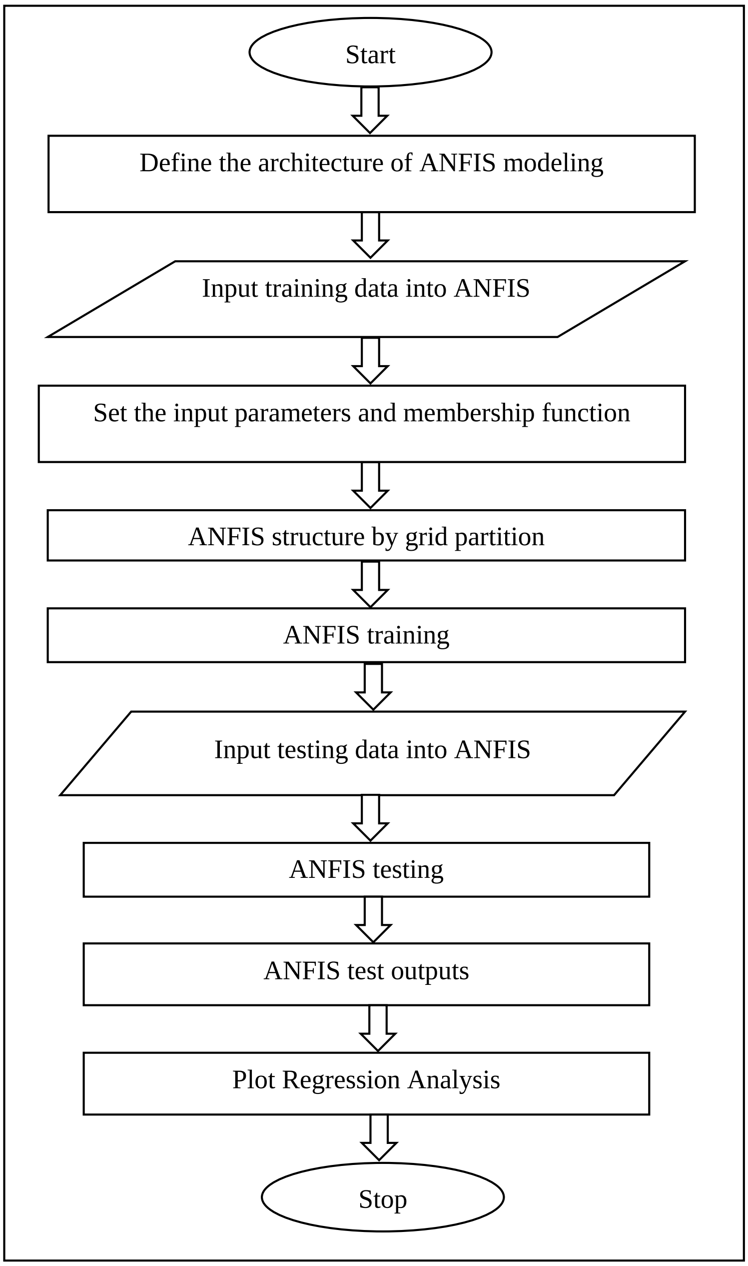

Figure 2.11 Flow diagram of ANFIS model

2.5.10 NEH Algorithm

Nawaz et al. [263] proposed a Nawaz, Enscor and Ham (NEH) algorithm to construct a jobs sequence in an iterative manner.

NEH heuristic has been reviewed from the literature as Taillard [264] compared the NEH heuristic with taboo search algorithm and found that NEH results are good. Zheng and Wang [265] found that NEH heuristic is an effective heuristic for flow shop scheduling. Kalczynski and Kamburowski [266] used NEH heuristic for minimizing the makespan in permutation flow shops. Kalczynski and Kamburowski [267] used NEH heuristic to minimize makespan in permutation flow shops. Dong et al. [268] also used NEH heuristic to minimize makespan in the permutation flow shops. Yagmahan and Yenisey [269] used NEH heuristic with ant colony optimization for multi-objective flow shop scheduling problem. Shafaei et al. [262] used NEH heuristic with an adaptive neuro fuzzy inference system for estimating the makespan.

An overview of the NEH algorithm can be stated as follows.

Step l. To calculate total process times for each job i

$$T_i = \sum_{j=1}^{j=m} t_{i,j} \tag{2.43}$$

where $t_{i,j}$ is the process time of job i on machine j.

Step 2. To arrange the jobs according to descending order of T_i.

Step 3. The two jobs are picked from the first and second position of the list of step 2 and the best sequence is found for these two jobs by calculating makespan for the two possible sequences. The relative positions of these two jobs should remain same with respect to each other in the remaining steps of the algorithm. Set i = 3.

Step 4. Next the job is picked in the i^{th} position of the list generated in Step 2 and the best sequence is found by placing it at all possible i positions in the partial sequence found in the previous step without changing the relative positions to each other of the already assigned jobs. The number of enumerations at this step equals i.

Step 5. If n = i, then STOP, otherwise set i = i+1 and go to Step 4.

2.5.11 Genetic algorithm (GA)

GA is one of the most applicable soft computing or metaheuristics technique applied in research work. It is conceptually a genetic representation of solution for a well-defined problem. This approach is a class of general purpose search methods adjoining elements of directed and stochastic search which can make an appropriate balance between exploration and exploitation of search space. In this approach accumulated information is utilized by the selection mechanism and new region of search space are explored through genetic operators. It is like other approach start with creation of initial population with different type of solution and classified with respect to their fitness. Each individual is a potential solution and it is further evaluated by their fitness value. Flow chart of genetic algorithm shown in Figure 2.12. The summary the GA work of the researchers by using different ways is discussed as below.

Onwubolu and Kumalo [270] had done the optimization of multipass turning operations with genetic algorithms. Suresh et al. [271] used genetic algorithmic approach for optimization of surface roughness prediction model. Wang et al. [272] defined optimal selection of cutting conditions and cutting tools in multipass turning operations by using genetic algorithms. Cus and Balic [273] optimized the cutting processes by GA approach. Reddy and Rao [274] selected optimum tool geometry and cutting conditions for a surface roughness prediction model by using genetic algorithms for end milling. Sardinas et al. [275] used genetic algorithm for multi-objective optimization of cutting parameters in turning processes. Singh and Venkateswara Rao [276] optimized the tool geometry and cutting parameters for hard turning by GA. Kilickap et al. [277] optimized the drilling parameters on surface roughness in drilling of AISI 1045 using response surface methodology and genetic algorithm. Bhushan et al. [278] used GA approach for optimization of surface roughness parameters in machining of Al alloy SiC particle composite. Ahilan et al. [279] developed the neural network models for prediction of machining parameters in CNC turning process and optimized by GA. Kant and Sangwan [280] predicted and optimization of machining parameters for minimizing power consumption and surface roughness in machining by RSM. Sangwan et al. [281] optimized the machining parameters to minimize surface roughness using integrated ANN-GA approach.

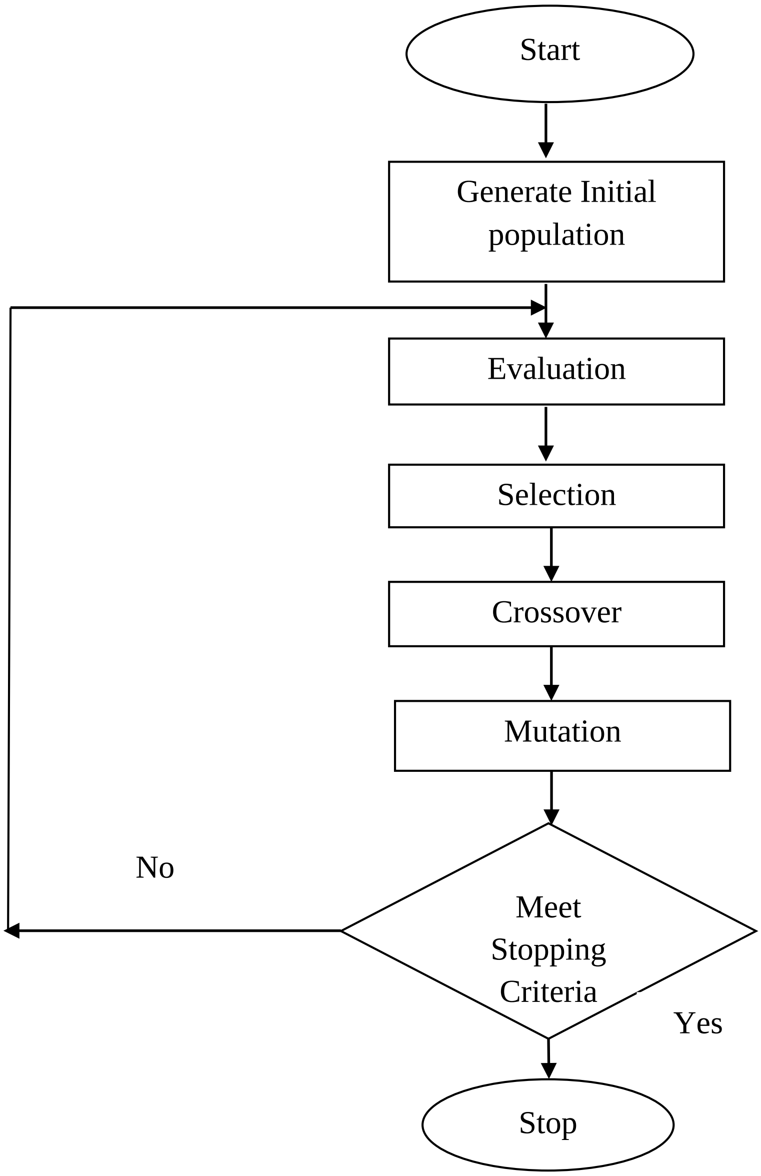

Figure 2.12 Flow chart of Genetic Algorithm

GA is a search algorithm act on the principle of the natural selection and the natural genetics selection. There are lot of selection methods. The reproduction, crossover and mutation are the three basic operation of GA. In classical genetic algorithm, the cross over operator acts as the principal operator and the achievement of a genetic backbone operator. Genetic operator executes a random search and cannot promise to yield improved off springs. There are many empirical studies on a comparison between cross over and mutation. It is well known fact that mutation can sometime play very significant role than crossover. Crossover is basically blending of chromosomes from the parents and produce new chromosomes for the offspring. Randomly two strings selected and then decided whether to crossover using a parameter called crossover probability. The efficiency of the genetic algorithm is entirely governed by population size, number of generations, crossover rate and mutation rate [282-284]. It is governed by the principle of Darwin's theory.

Genetic algorithms works with a set of individuals, representing possible solutions of the task. The selection principle is applied by using a criterion, giving an evaluation for the individual with respect to the desired solution. The best-suited individuals create the next generation. It optimizes with both continuous and discrete variables efficiently. It doesn't require any derivative information. It searches from a wide sampling of the cost surface simultaneously. It handles a large no. of variables at a time. It optimizes variables with extremely complex cost surfaces. It provides a list of optimum variables, not just a single solution. Genetic algorithm has following steps

1. Generate initial population - in most of the algorithms the first generation is randomly generated, by selecting the genes of the chromosomes among the allowed alphabet for the gene. Because of the easier computational procedure it is accepted that all populations have the same number (N) of individuals.

2. Evaluation of function - calculate the values of the function that we want to minimize or maximizes. The fitness is evaluated based on the chromosomes.

3. Check for termination of the algorithm – check the condition for termination of algorithm. As in the most optimization algorithms, it is possible to stop the genetic optimization by:

• Value of the function: the value of the function of the best individual is within defined range around a set value.

• Maximal number of iterations: this is the most widely used stopping criteria. It guarantees that the algorithms will give some results within some time, whenever it has reached the extreme or not.

• Stall generation: if within initially set number of iterations (generations) there is no improvement of the value of the fitness function of the best individual the algorithms stops.

4. Selection – between all individuals in the current population are chose those, who will continue and by means of crossover and mutation will produce offspring population. At this stage elitism could be used – the best n individuals are directly transferred to the next generation. The elitism guarantees, that the value of the optimization function cannot get worst (once the extreme is reached it would be kept).

5. Crossover – the individuals chosen by selection recombine with each other and new individuals will be created. The aim is to get offspring individuals that inherit the best possible combination of the characteristics (genes) of their parents.
6. Mutation – by means of random change of some of the genes, it is guaranteed that even if none of the individuals contain the necessary gene value.
7. New generation – the elite individuals chosen from the selection are combined with those who passed the crossover and mutation and form the next generation. It works smoothly with both numerical and experimental data.
Implementation steps of the GA are summarized below:

Step 1: Initialize the population and that population is known as chromosomes.

Step 2: A loop is formed to generate new population. The following steps are repeated until population is completed.

a) Evaluation

b) Selection

c) Crossover

d) Accepting

Step 3: Repeat the step 2 till the termination criterion is met.

2.5.12 Teaching-Learning Based Optimization (TLBO) Methodology

Teaching-learning based optimization (TLBO) algorithm is proposed by Rao et al. [33] which is a teaching-learning process based on the effect of influence of a teacher on the output of learners in a class. The algorithm copies teaching-learning ability of teacher and learners in a classroom. In TLBO algorithm, population is the group of learners, different design variables are different subjects offered to the learners and analogous to the 'fitness' value of the optimization problem are learners' results. In the entire population, the best solution is considered as the teacher. The summary the TLBO work of the researchers by using different ways is discussed as below.

Rao and Kalyankar [285] identified TLBO for the process parameter optimization in this work are electrochemical machining process and electrochemical discharge machining process. Niknam et al. [286] proposed a new multi-objective optimization algorithm based on modified teaching–learning-based optimization algorithm in order to solve the optimal location of automatic voltage regulators in distribution systems at presence of distributed generators. Rao and Kalyankar [287] proposed TLBO for large scale non-linear optimization problems for finding the global solutions. Rao and Kalyankar [287] used TLBO as a parameter optimization of machining processes. Singh et al. [288] discussed the application of TLBO algorithm for optimal coordination of DOCR relays in a looped power system. Rao and Kalyankar [289] used a modified teaching-learning-based optimization algorithm for multi-objective optimization of heat exchangers. Rao and Kalyankar [290] optimized parameter of modern machining processes by using teaching–learning-based optimization algorithm. Pawar and Rao [291] optimized parameter of multi-pass turning process by using teaching–learning-based optimization algorithm. Pawar and Rao [291] also used teaching–learning-based optimization algorithm for parameter optimization of machining processes. Baykasoğlu et al. [292] have tested the performance of TLBO algorithm on combinatorial problems like as flow shop and job shop scheduling cases. Rao and More [293] used TLBO algorithm for optimal design of the heat pipe. Camp and Farshchin [294] used TLBO method for engineering optimization problems for design of space trusses. Lin et al. [295] have used TLBO algorithm for scheduling in turning processes for minimizing makespan and carbon footprint. Rao et al. [296] optimized the thermal performance of a smooth flat-plate solar air heater by using teaching–learning-based optimization algorithm. Rao and Waghmare [297] optimized the design of robot grippers by using teaching-learning-based optimization algorithm. Dede and Ayvaz [298] concluded that the TLBO algorithm can be effective for combined size and shape optimization of the structures.

The working of TLBO is divided into two parts: ‘Teacher phase’ and ‘Learner phase’. Working of both the phases is explained below [290].

Teacher Phase:

Teacher phase is the first part of the algorithm. There learners learn through the teacher. Here a teacher tries to increase the mean result of the classroom from any value M_1 to his or her level (i.e., T_A). But practically, it is not possible, that a teacher can move the mean of the classroom M_1 to any other value M_2 which is better than M_1 depending on his or her capability. Consider M_j to be the mean and T_i to be the teacher at any iteration i. Now T_i will do the efforts to improve existing mean M_j

to get the new mean will be designated as M_{new} and the difference between the existing mean and new mean is given by

$$Difference\_\mathrm{Mean}_i = r_i \left(M_{new} - T_f M_j \right) \tag{2.44}$$

where T_f is the teaching factor, which decides the value of mean to be changed and r_i is the random number in the range [0, 1]. Value of T_f can be either 1 or 2, which is a heuristic step and it is decided randomly with equal probability as

$$T_f = round\left[1 + rand\left(0,1\right)\left\{2-1\right\} \right] \tag{2.45}$$

During the algorithm the teaching factor is generated randomly in the range of 1–2. 1 corresponds to no increase in the knowledge level and 2 correspond to complete transfer of knowledge. The values between 1 and 2 show the amount of transfer level of knowledge.

The learners' capabilities are responsible for the transfer level of knowledge. Although an attempt is made by considering the values of T_f in between 1 and 2 in the present work but no improvement has been observed in the results. Hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria.

Based on this Difference Mean, the existing solution is updated according to the following expression:

$$X_{new,i} = X_{old,i} + Differenc\_\mathrm{Mean}_{\mathrm{i}} \tag{2.46}$$

Learner Phase:

In the second part of the algorithm, learners increase their knowledge by interacting among themselves.

A learner learns new things from the other learner who has more knowledge than him or her. Mathematically, the learning phenomenon of this phase is expressed below.

At any iteration i, considering two different learners X_i and X_j, where $i \neq j$,

$$X_{new,\mathrm{i}} = X_{old,i} + r_i \left(X_i - X_j \right) if\ f\left(X_i\right) < f\left(X_j\right) \tag{2.47}$$

$$X_{new,i} = X_{old,i} + r_i \left(X_j - X_i \right) if\, f\left(X_j \right) < f\left(X_i \right) \quad (2.48)$$

Accepted X_{new} if it gives better function value. Flow chart of TLBO algorithm shown in Figure 2.13.Implementation steps of the TLBO are summarized as given below [33].

Steps in the TLBO

The optimization methodology based on TLBO consists of following steps:

Step 1: To initialize the population (i.e. *n*=number of learners') and design variables of the optimization problem (i.e. number of subjects offered to the learner) with the termination criteria (i.e., number of generation) and evaluate them.

Step 2: In teacher phase, first step is to calculate mean of each decision variables (z_1, z_2...) of the optimization problem and find out mean row vector (i.e. M = [z_1, z_2...]). The new mean (M_{new}) is the best solution (i.e. min (F_1, F_2...) of the iteration and will act as a teacher.

Step 3: To evaluate the difference between the current mean result and best mean result according to equation (2.44) by utilizing the teaching factor (T_f).

Step 4: To update the learners' knowledge with the help of teacher's knowledge according to equation (2.46).

Step 5: To update the learners' knowledge by utilizing the knowledge of some other learner according to equations (2.47) and (2.48). In learner phase, choose any two learners (data sets) and calculate its function values. Based on their function values the new data set (X_{new}) is calculated.

Accepted X_{new} if it gives better function value otherwise not.

Step 6: Repeat the procedure from step 2 to 5 till the termination criterion is met.

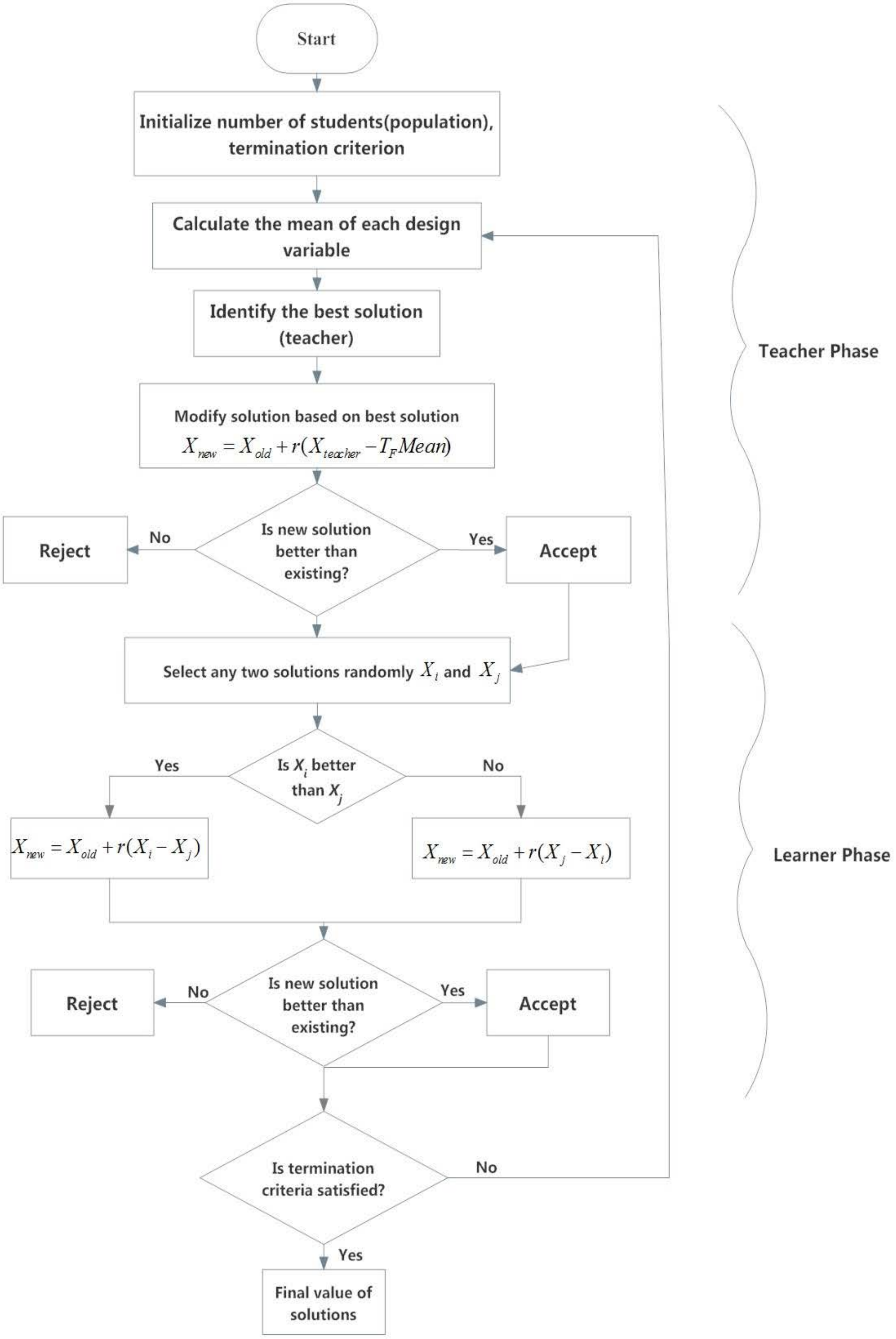

Figure 2.13 Flow diagram of TLBO [294]

2.6 CONCLUSION

The manufacturers are aspired to become more competitive, so they adopt FMS. This system is integrated with automated material handling systems, robots, numerically controlled machine tools and automated inspection stations.

FMS offer high capital utilization, reduced labor costs, reduce work-in-process inventories and shorter lead times etc. Major benefits of this systems that it is flexible and more responsive to changes in production requirements and its effect that productivity increased.

Manufacturing systems should be truly flexible, being able to react dynamically to the changing demands placed upon them and full ability to create a capability to design and implement such systems quickly.

It is also found from the cause effect diagram that performance of FMS is affected by three factors i.e. productivity, flexibility and quality. Productivity of FMS is affected by four factors i.e. machine, quality, flexibility and people. Flexibility of FMS is affected by main four factors i.e. production flexibility, product flexibility, machine flexibility and volume flexibility.

It is further noticed that fifteen variables affect performance of FMS, twenty variables affect productivity of FMS and fifteen variables affect flexibility of FMS. Fifteen flexibility are considered for the FMS.

In this research, some issues of constraints especially in FMS are discussed. These issues are related to machine tool, tool management, material handling i.e. AGV, robot and fixtures. Constraints may be limited to machine tool range to hold different parts and cutting tools, fix range of handling the parts by robots, fixed path layout by AGV and the rigidity of fixtures. By paying proper attention on these constraints, a manufacturing system will be flexible and productivity and performance of manufacturing system will be increased. If the manufacturing firms to adopt and implement the FMSs then study of tool management and material handling system is mandatory.

The different methodologies are discussed in detail to achieve research objectives.

CHAPTER III

QUESTIONNAIRE SURVEY

3.1 INTRODUCTION

To examine the suitability and to identify some critical issues of FMSs in the context of Indian industries, a questionnaire based survey was conducted. The findings and approach of the questionnaire based survey are presented in this chapter. The key observations from this survey have been reported and discussed in this chapter.

3.2 QUESTIONNAIRE DEVELOPMENT

The questionnaire-based survey was designed keeping in view the available literature and conferring with the domain experts from academia and industries. The survey was conducted on FMSs performance, productivity and flexibility affecting variables. As the respondents are not so enthusiastic to such surveys and showed reluctance to spare time for such activity, the questionnaire was designed with care so that responses can be given with minimum effort and time. The questionnaire was developed on a seven point Likert scale. The questionnaire was divided into two sections. First section dealt with the company profile while the second section dealt with variables which affect the performance, productivity and flexibility of FMS.

3.3 QUESTIONNAIRE ADMINISTRATION

The different aspects of the questionnaire administration have been discussed in the following sections:

3.3.1 Target Industries for Questionnaire Administration

The questionnaire was administrated Indian manufacturing industries. Mainly automotive industries were focused. The companies selected for the survey in this sector included automobile original equipment manufacturers (OEMs), tier one (direct suppliers to OEMs) and tier two (key suppliers to tier one suppliers, without supplying a product directly to OEM companies) manufacturing industries.

3.3.2 Questionnaire Administration

The questionnaire was administrated to Indian manufacturing industries. In total 480 questionnaires were sent to companies for the response. The questionnaire used a seven point Likert scale, ranging from 1 representing strong disagreement, 2 representing disagreement, 3 representing slight disagreement, 4 representing neither disagreement nor agreement, 5 representing slight agreement, 6 representing agreement, 7 representing strong agreement. 7 representing strong agreement. A neutral response, 'neither disagreement nor agreement', was adopted to reduce uninformed response, since it was assured that respondents need not feel compelled to answer every questionnaire item.

3.4 QUESTIONNAIRE SURVEY RESPONSE AND RESPONDENTS PROFILE

Total 480 questionnaires were sent to different industries but 340 questionnaires were received. Out of the 340 responses, 319 questionnaires were usable, resulting in a 66.46 % response rate, which is sufficient for a survey of this type [299].

Table 3.1 Data of the responding companies

Sr. No.	Description of data	Range	Number of firms
1	Number of employees	Less than 100	05
		101-500	25
		501-1000	60
		1001-3000	25
		More than 3000	10
2	Turnover (US$ million)	Less than 10	10
		10-20	45
		20-100	40
		100-200	20
		More than 200	10

3.5 OBSERVATION FROM THE SURVEY

It is highly crucial to understand the effect of the FMSs in Indian industrial environment in terms of performance, productivity and flexibility measurement. For this purpose, the questionnaire based survey of the Indian industries has been conducted to assess the variables which affect the performance, productivity and flexibility of FMSs in Indian scenario. The various important variables were emphasized in this survey, which affect FMSs. The survey results have been presented in the following sections:

3.5.1 Related to Performance Variables of FMS

Automobile manufacturing industries want to focus on the performance of the company. So, they are interested in knowing on which variables they should focus to improve the performance of the firms. Some performance variables were discussed with them and found that automation (mean score 6.05), use of automated material handling devices (mean score 6.02) and effect of tool life (mean score 6.00) are the dominant variables which affect the performance of FMS. Other variables mean score is shown in Figure 3.1 and Table 3.2.

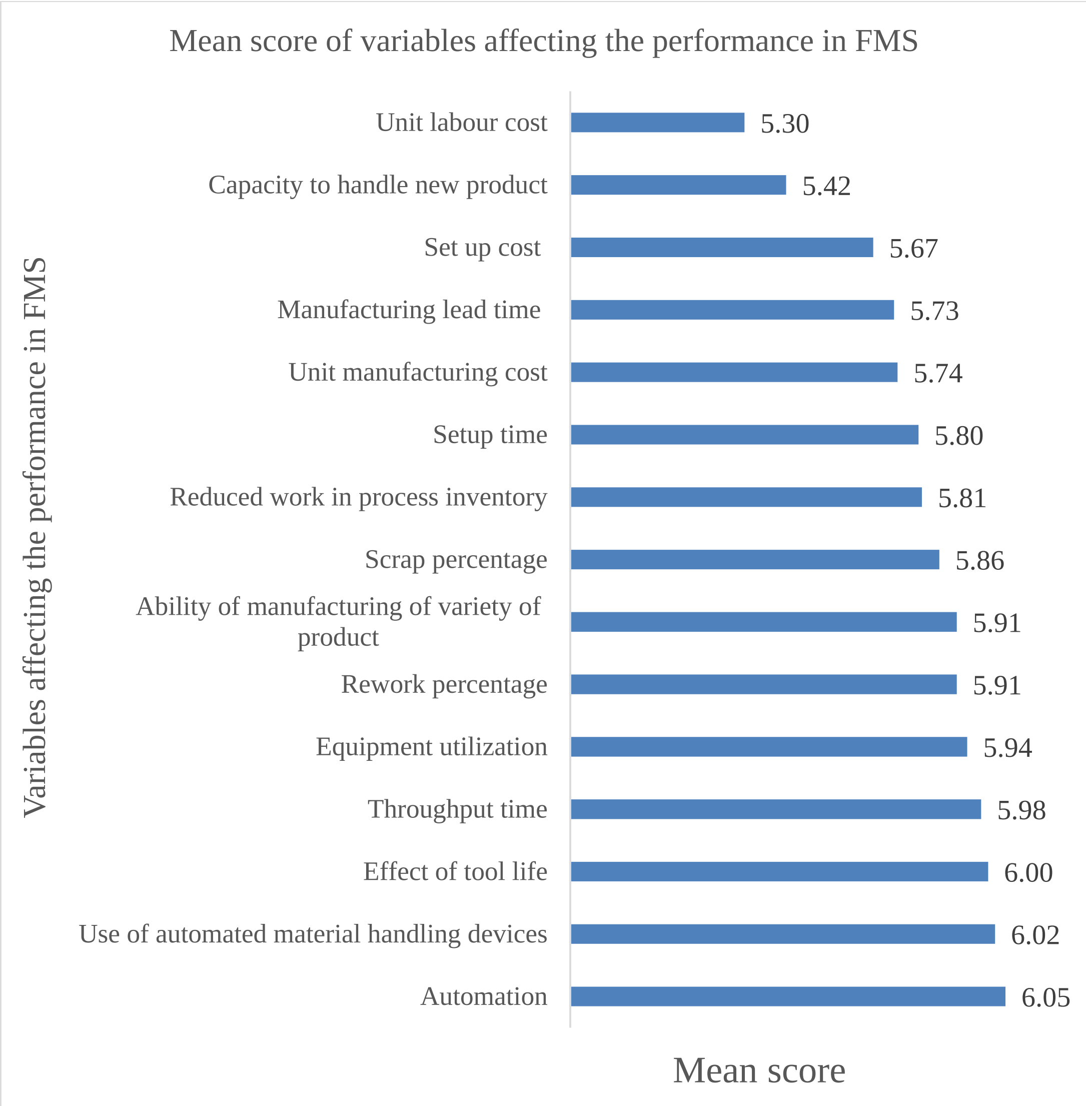

Figure 3.1 Variables affecting the performance in FMS

Table 3.2 Rank and mean score of variables affecting the performance in FMS

Sr. No.	Variables	Mean Score	Rank
1	Automation	6.05	1
2	Use of automated material handling devices	6.02	2
3	Effect of tool life	6.00	3
4	Throughput time	5.98	4
5	Equipment utilization	5.94	5
6	Rework percentage	5.91	6
7	Ability of manufacturing of variety of product	5.91	6
8	Scrap percentage	5.86	8
9	Reduced work in process inventory	5.81	9
10	Setup time	5.80	10
11	Unit manufacturing cost	5.74	11
12	Manufacturing lead time	5.73	12
13	Set up cost	5.67	13
14	Capacity to handle new product	5.42	14
15	Unit labor cost	5.30	15

3.5.2 Related to productivity variables of FMS

Every manufacturing industry wants to increase its productivity. So, industries are interested to focus on such variables which improve the productivity of the firms. Some productivity variables were discussed with them and found that use of automated material handling devices (mean score 5.84), financial incentive (mean score 5.82), effect of tool life (mean score 5.81) and automation (mean score 5.81) are the dominant variables which affect the productivity of FMS. Other variables mean score is shown in Figure 3.2 and Table 3.3.

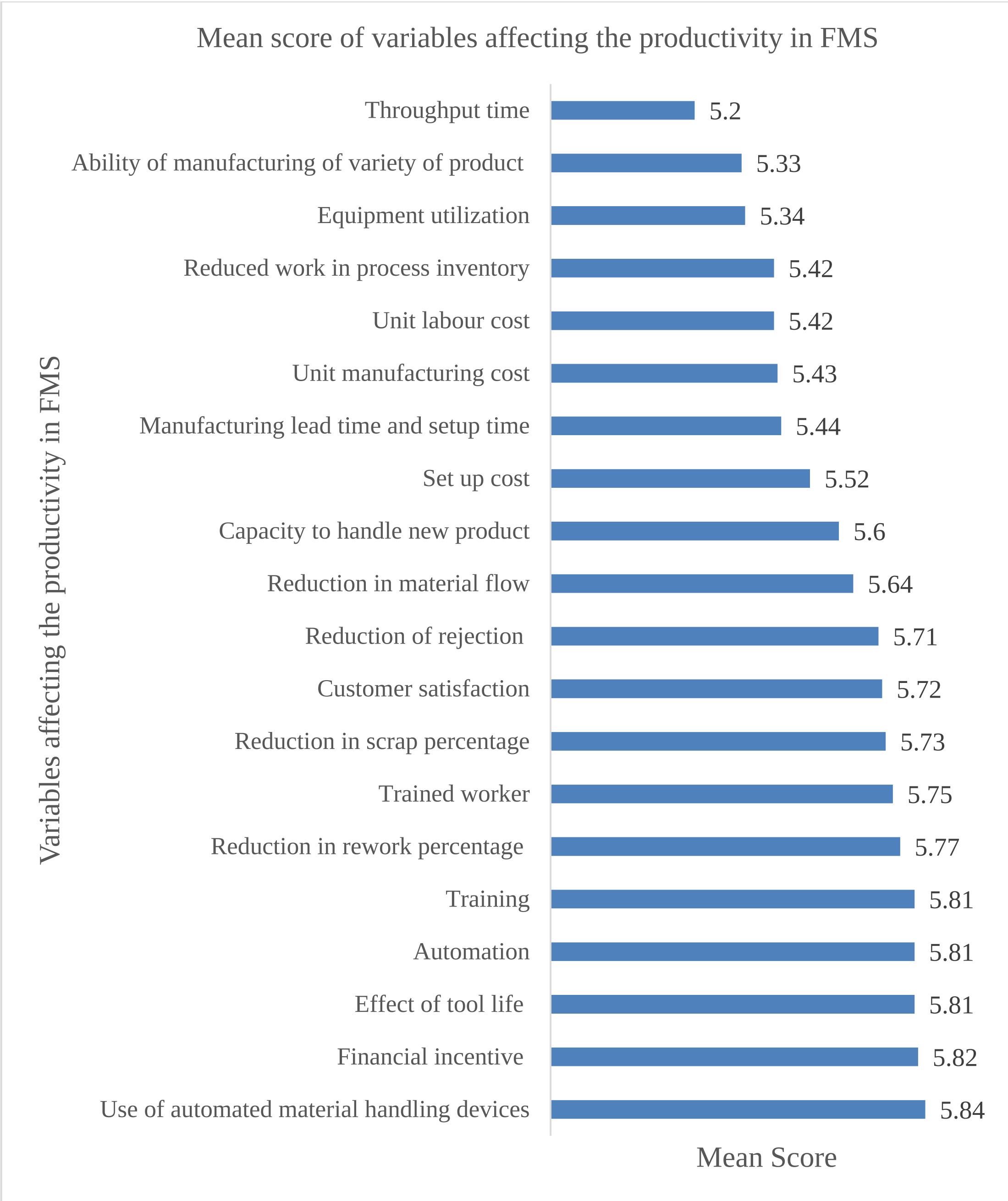

Figure 3.2 Variables affecting the productivity in FMS

Table 3.3 Rank and mean score of variables affecting the productivity in FMS

Sr. No.	Variables	Mean Score	Rank
1	Use of automated material handling devices	5.84	1
2	Financial incentive	5.82	2
3	Effect of tool life	5.81	3
4	Automation	5.81	3
5	Training	5.81	3
6	Reduction in rework percentage	5.77	6
7	Trained worker	5.75	7
8	Reduction in scrap percentage	5.73	8
9	Customer satisfaction	5.72	9
10	Reduction of rejection	5.71	10
11	Reduction in material flow	5.64	11
12	Capacity to handle new product	5.6	12
13	Set up cost	5.52	13
14	Manufacturing lead time and setup time	5.44	14
15	Unit manufacturing cost	5.43	15
16	Unit labor cost	5.42	16
17	Reduced work in process inventory	5.42	16
18	Equipment utilization	5.34	18
19	Ability of manufacturing of variety of product	5.33	19
20	Throughput time	5.2	20

3.5.3 Related to Flexibility Variables of FMS

Flexibility is one of the main requirement to enhance the competitiveness of organizations. Flexibility in the manufacturing system enables to cope with the sudden demands of market. So, some flexibility variables were discussed with them and found that flexible fixturing (mean score 5.84), automation (mean score 5.82), use of automated material handling devices (mean score 5.81) and use of reconfigurable machine tool (mean score 5.81) are the dominant variables which affect the flexibility of FMS. Other variables mean score is shown in Figure 3.3 and Table 3.4.

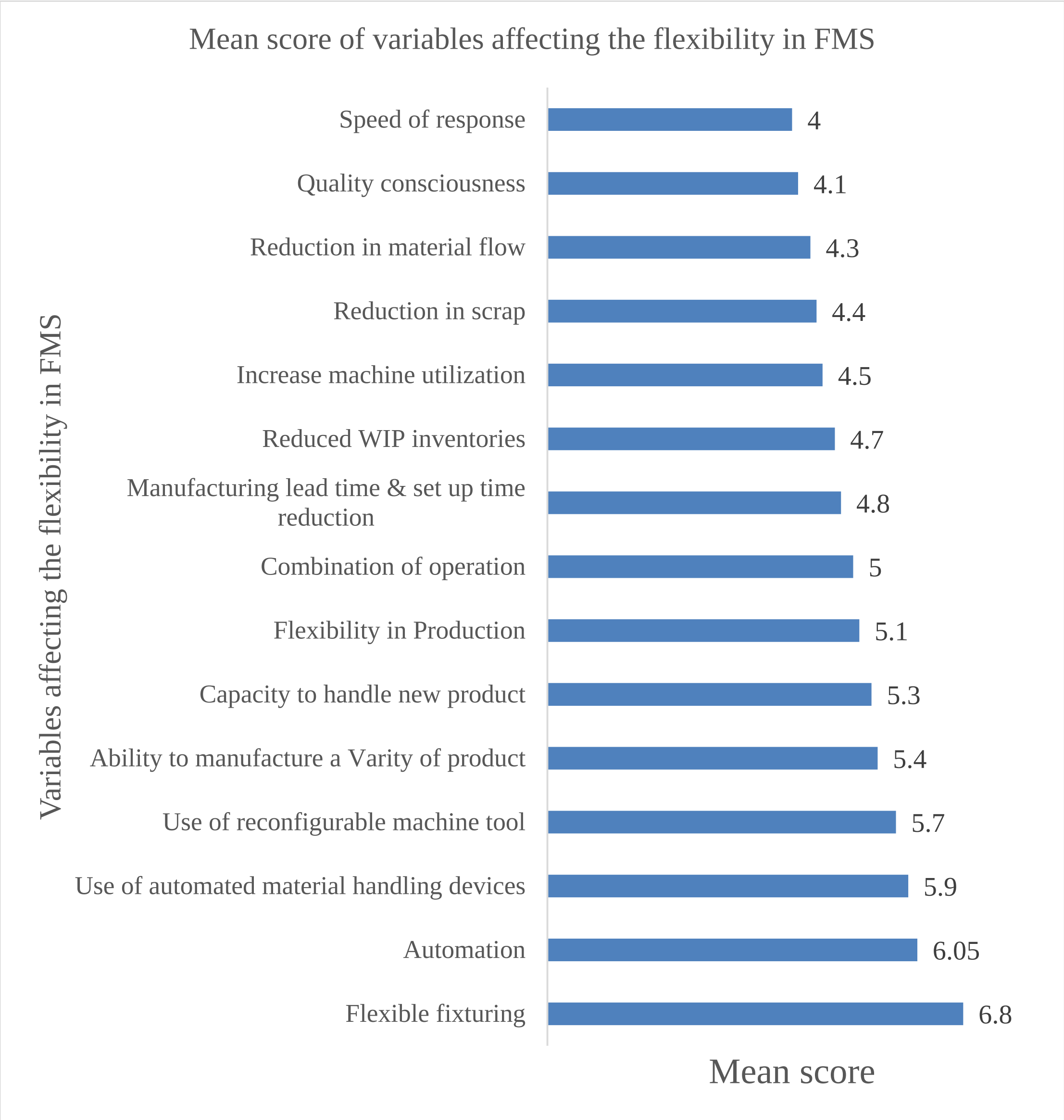

Figure 3.3 Variables affecting the flexibility in FMS

Table 3.4 Rank and mean score of variables affecting the flexibility in FMS

Sr. No.	Variables	Mean Score	Rank
1	Flexible fixturing	6.8	1
2	Automation	6.05	2
3	Use of automated material handling devices	5.9	3
4	Use of reconfigurable machine tool	5.7	4
5	Ability to manufacture a variety of product	5.4	5
6	Capacity to handle new product	5.3	6
7	Flexibility in production	5.1	7
8	Combination of operation	5	8
9	Manufacturing lead time and set up time reduction	4.8	9
10	Reduced WIP inventories	4.7	10
11	Increase machine utilization	4.5	11
12	Reduction in scrap	4.4	12
13	Reduction in material flow	4.3	13
14	Quality consciousness	4.1	14
15	Speed of response	4	15

3.6 CONCLUSION

The objective of this questionnaire based survey was to know about the mindset of the Indian and Japanese person's. In survey, questionnaire was filled by Indian and Japanese persons. Variables affecting the performance, productivity and flexibility of the FMS are included in the questionnaire. The findings of this survey found the inclination of Indian industries towards FMS.

After being surveyed the first three ranking variables which affect performance are automation, use of automated material handling devices and effect of tool life. The first three ranking variables which affect productivity are use of automated material handling devices, financial incentive, effect of tool life, automation and training. The first three ranking variables which affect flexibility are flexible fixturing, automation and use of automated material handling devices.

So, the variables like automation, use of automated material handling devices and effect of tool life are the common variables which affect performance, productivity and flexibility in FMS.

The variables like flexible fixturing, use of automated material handling devices and automation are the main variables in FMS.

CHAPTER IV

MODELING AND ANALYSIS OF PERFORMANCE VARIABLES OF FMS

4.1 INTRODUCTION

High expectations of present day customers have become very critical for the manufacturing industries. They need to give prominence to improve the performance of FMS to meet the challenges of today's volatile market [129]. FMSs have been developed with the hope that they will be able to tackle new challenges like cost, quality, improved delivery speed and more flexibility in their operations and to satisfy different market segments.

An FMS consists of innumerable programmable and computerized machine tools connected by an automatic material handling system like robots and automatic guided vehicles (AGVs) and automatic storage and retrieval system (AS/RS) that can process simultaneously medium-sized volumes of the different parts [1]. In these systems, machines and material handling systems are controlled by a central computer system [199]. The basic objective of the flexible manufacturing concept is to achieve the efficiency and utilization levels of mass production, while retaining the flexibility of manually operated job shops. The individual machines are quite versatile and capable of performing with many different types of operations [300]. Flexibility in manufacturing has been identified as one of the key factors to improve the performance of FMS. A significant challenge for many manufacturers is to achieve flexibility in addition to achieving productivity and quality [301]. FMS is crucial for modern manufacturing to enhance productivity involved with high product proliferation [302]. Productivity is a key factor in a FMS performance and to improve profitability and the wage earning capacity of employees. Li et al. [303] discussed that a high level of quality leads to high level of performance. FMSs promise to provide quality and economies of

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From this chapter the following paper has been published.

V. Jain and T. Raj, "Modeling and analysis of FMS performance variables by ISM, SEM and GTMA approach," *International Journal of Production Economics,* vol. 171, pp. 84-96, 2016.

scope - the ability to achieve productivity and flexibility simultaneously and also to achieve economies of scope by reducing the time and cost of product variety [301]. Manufacturing firms are under constant and intense pressure to improve their operations continuously and efficiently by enhancing quality, productivity and flexibility. So, performance of manufacturing system can be increased by increasing the quality, productivity and flexibility of a manufacturing organization.

The main objectives of this chapter are as follows:

- To identify the variables which affect the performance of FMS from the literature
- To establish relationship among these variables by using ISM
- To identify the factors/dimensions which affect the performance of FMS by exploratory factor analysis through SPSS
- To confirm the factor structure of the same using confirmatory factor analysis with AMOS
- Evaluation of intensity of performance variables of FMS by GTMA.

On the basis of the exhaustive literature review and discussions with the industry experts and the academia, 15 variables were identified. These variables are given below with their references.

1. Unit manufacturing cost [36-38]
2. Unit labor cost [40-42]
3. Manufacturing lead time [5, 304, 305]
4. Effect of tool life [44-46]
5. Throughput time [45, 47, 48]
6. Set up cost [40, 49, 50]
7. Scrap percentage [51-53]
8. Rework percentage [52, 53]
9. Setup time [40, 49, 51]
10. Automation [54-57]
11. Equipment utilization [58-60]
12. Ability of manufacturing of variety of product [61-63]
13. Capacity to handle new product [64-66]
14. Use of automated material handling devices [60, 68, 69]

15. Reduced work in process inventory [70-73]

After identification of variables affecting performance of FMS, an ISM model is prepared which is discussed in the following sections:

4.2 ISM MODEL FOR PERFORMANCE VARIABLES OF FMS

In this section, the development of the model using ISM is described below.

4.2.1 Development of Structural Self-Interaction Matrix (SSIM)

ISM methodology suggests the role of experts (both from industry and academia) opinions in developing the contextual relationship between the variables. The following four symbols have been used to denote the direction of the relationship between two variables (i and j):

V is used for the relation from variable i to j (i.e. if variable i reach to variable j)

A is used for the relation from variable j to i (i.e. if variable j reach to variable i)

X is used for both direction relations (i.e. if variable i and j reach to each other)

O is used for no relation between two variables (i.e. if variable i and j are unrelated). Based on the contextual relationship, the SSIM is developed and it is presented in Table 4.1.

4.2.2 Reachability Matrix (RM)

The reachability matrix (RM) is obtained from SSIM. The RM indicates the relationship between variables in the binary form. The various relationships between variables depicted by symbols V, A, X and O used earlier in SSIM are replaced by binary digits of 0 and 1 is called initial reachability matrix. The following rules are used to substitute V, A, X and O of SSIM to get RM:

- if the cell (i, j) is assigned with symbol V in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry becomes 0 in the initial RM
- if the cell (i, j) is assigned with symbol A in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry becomes 1 in the initial RM
- if the cell (i, j) is assigned with symbol X in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry also becomes 1 in the initial RM
- if the cell (i, j) is assigned with symbol O in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry also becomes 0 in the initial RM.

Table 4.1 Structural self-interactive matrix

Variables	15	14	13	12	11	10	9	8	7	6	5	4	3	2
1	A	A	O	O	A	O	A	A	A	A	A	A	A	A
2	A	A	O	O	O	O	O	A	A	O	A	A	A	
3	X	A	O	O	A	A	A	A	A	O	X	A		
4	O	O	V	V	V	A	O	V	V	O	V			
5	A	A	V	V	V	A	A	A	A	O				
6	O	O	O	O	O	O	O	O	O					
7	O	A	O	O	V	A	O	A						
8	V	O	V	V	V	A	V							
9	V	A	V	V	V	A								
10	V	V	V	V	V									
11	V	A	O	O										
12	O	A	V											
13	A	A												
14	O													

Following these rules, the initial reachability matrix is shown in Table 4.2. The final RM is obtained by incorporating the transitivity. Final RM is shown in Table 4.3 wherein transitivity is marked as 1*.

4.2.3 Level Partitioning the RM

Once the reachability matrix has been created, it must be processed to extract the digraph (structural model). Warfield [126] has presented a series of partitions which are induced by the reachability matrix on the set and subset of different elements. From these partitions, one can identify many properties of the structural model [306]. Based on the suggestions of Warfield [126] and Farris and Sage [306], the reachability set and antecedent set for each variable are found from the final reachability matrix. The reachability set consists of the variable (i) itself and the other variable which are reachable from that particular variable (i). For every column which contains 1 in the row of considered variable (i), the variable that column represents is included in the reachability set. Similarly, the antecedent set consists of the variable (i) itself and the other variables

Table 4.2 Initial reachability matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1
4	1	1	1	1	1	0	1	1	0	0	1	1	1	0	0
5	1	1	1	0	1	0	0	0	0	0	1	1	1	0	0
6	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
7	1	1	1	0	1	0	1	0	0	0	1	0	0	0	0
8	1	1	1	0	1	0	1	1	1	0	1	1	1	0	1
9	1	0	1	0	1	0	0	0	1	0	1	1	1	0	1
10	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1
11	1	0	1	0	0	0	0	0	0	0	1	0	0	0	1
12	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
14	1	1	1	0	1	0	1	0	1	0	1	1	1	1	0
15	1	1	1	0	1	0	0	0	0	0	0	0	1	0	1

which may reach the variable (i). For every row which contains 1 in the column of considered variable (i), the variable that row represents is included in the antecedent set. After finding the reachability set and antecedent set for each variable, the intersection for these sets is derived for all the variables and levels of different variables are determined.

The top level variables are those variables which will not reach the other variables above their own level in the hierarchy. For this reason, the reachability set for a top level variable (i) will consist of that variable (i) itself and all other variables within the same level which this variable (i) may reach, i.e. components of a strongly connected subset. Similarly, the antecedent set for a top level variable (i) will consist of that variable (i) itself and all other variables which may reach it from lower levels and any variable of a strongly connected subset involving variable (i) in the top level. As a result, the intersection of the reachability set and the antecedent set will be the same as the reachability set [306]. Once the top level variable is identified, it is removed from consideration and other top level variables of the remaining sub graph are found. This procedure is continued till all levels of the structure are identified. These identified levels help in the development of digraph and the final model. Top level variable is positioned at the top of digraph and so on.

Table 4.3 Final reachability matrix

Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	1	0	1	0	0	0	0	0	1*	1*	1*	0	1
4	1	1	1	1	1	0	1	1	1*	0	1	1	1	0	1*
5	1	1	1	0	1	0	0	0	0	0	1	1	1	0	1*
6	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0
7	1	1	1	0	1	0	1	0	0	0	1	0	1*	0	1*
8	1	1	1	0	1	0	1	1	1	0	1	1	1	0	1
9	1	1*	1	0	1	0	0	0	1	0	1	1	1	0	1
10	1*	1*	1	1	1	0	1	1	1	1	1	1	1	1	1
11	1	1*	1	0	1*	0	0	0	0	0	1	0	1*	0	1
12	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
14	1	1	1	0	1	0	1	0	1	0	1	1	1	1	1*
15	1	1	1	0	1	0	0	0	0	0	1*	1*	1	0	1

* entries are included to incorporate transitivity.

In the present case, the 15 variables, along with their reachability set, antecedent set, intersection set and levels are presented in Tables 4.4 to 4.10. Level identification process of these variables are completed in seven iterations as shown in Tables 4.4 to 4.10.

4.2.4 Development of the Conical Matrix

A conical matrix is developed by clubbing together factors in the same level, across rows and columns of the final RM as shown in Table 4.11.

Table 4.4 Iteration 1

No.	Reachability set	Antecedent set	Intersection set	Level
1	1	1,2,3,4,5,6,7,8,9,10,11, 14,15	1	I
2	1,2	2,3,4,5,7,8,9,10,11,14, 15	2	
3	1,2,3,5,11,12,13,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
4	1,2,3,4,5,7,8,9,11,12,13, 15	4,10	4	
5	1,2,3,5,11,12,13,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
6	1,6	6	6	
7	1,2,3,5,7,11,13,15	4,7,8,10,14	7	
8	1,2,3,5,7,8,9,11,12,13,15	4,8,10	8	
9	1,2,3,5,9,11,12,13,15	4,8,9,10,14	9	
10	1,2,3,4,5,7,8,9,10,11,12, 13,14, 15	10	10	
11	1,2,3,5,11,13,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
12	12,13	3,4,5,8,9,10,12,14,15	12	
13	13	3,4,5,7,8,9,10,11,12, 13,14, 15	13	I
14	1,2,3,5,7,9,11,12,13,14,15	10,14	14	
15	1,2,3,5,11,12,13,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	

Table 4.5 Iteration 2

No.	Reachability set	Antecedent set	Intersection set	Level
2	2	2,3,4,5,7,8,9,10,11,14,15	2	II
3	2,3,5,11,12,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
4	2,3,4,5,7,8,9,11,12,15	4,10	4	
5	2,3,5,11,12,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
6	6	6	6	II
7	2,3,5,7,11,15	4,7,8,10,14	7	
8	2,3,5,7,8,9,11,12,15	4,8,10	8	
9	2,3,5,9,11,12,15	4,8,9,10,14	9	
10	2,3,4,5,7,8,9,10,11,12,14,15	10	10	
11	2,3,5,11,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	
12	12	3,4,5,8,9,10,12,14,15	12	II
14	2,3,5,7,9,11,12,14,15	10,14	14	
15	2,3,5,11,12,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	

Table 4.6 Iteration 3

No.	Reachability set	Antecedent set	Intersection set	Level
3	3,5,11,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	III
4	3,4,5,7,8,9,11,15	4,10	4	
5	3,5,11,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	III
7	3,5,7,11,15	4,7,8,10,14	7	
8	3,5,7,8,9,11,15	4,8,10	8	
9	3,5,9,11,15	4,8,9,10,14	9	
10	3,4,5,7,8,9,10,11,14,15	10	10	
11	3,5,11,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	III
14	3,5,7,9,11,14,15	10,14	14	
15	3,5,11,15	3,4,5,7,8,9,10,11,14,15	3,5,11,15	III

Table 4.7 Iteration 4

No.	Reachability set	Antecedent set	Intersection set	Level
4	4,7,8,9	4,10	4	
7	7	4,7,8,10,14	7	IV
8	7,8,9	4,8,10	8	
9	9	4,8,9,10,14	9	IV
10	4,7,8,9,10,14	10	10	
14	7,9,14	10,14	14	

Table 4.8 Iteration 5

No.	Reachability set	Antecedent set	Intersection set	Level
4	4,8	4,10	4	
8	8	4,8,10	8	V
10	4,8,10,14	10	10	
14	14	10,14	14	V

Table 4.9 Iteration 6

No.	Reachability set	Antecedent set	Intersection set	Level
4	4	4,10	4	VI
10	4,10	10	10	

Table 4.10 Iteration 7

Variable No.	Reachability set	Antecedent set	Intersection set	Level
10	10	10	10	VII

4.2.5 Development of ISM Model

Based on the conical matrix, an initial digraph, including transitivity links is obtained. This is generated by nodes and lines of the edges. After removing the indirect links, a final digraph is developed. Next, the digraph is converted into an ISM model by replacing nodes of the elements with statements as shown in Figure 4.1.

4.2.6 Check for Conceptual Inconsistency

Conceptual inconsistency is checked by identifying and removing the intransitivity in the model.

Table 4.11 Conical matrix

Variables	1	13	2	6	12	3	5	11	15	9	7	8	14	4	10	Drive Power
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
2	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2
6	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	2
12	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	2
3	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	8
5	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	8
11	1	1	1	0	0	1	1	1	1	0	0	0	0	0	0	7
15	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	8
9	1	1	1	0	1	1	1	1	1	1	0	0	0	0	0	9
7	1	1	1	0	0	1	1	1	1	0	1	0	0	0	0	8
8	1	1	1	0	1	1	1	1	1	1	1	1	0	0	0	11
14	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0	11
4	1	1	1	0	1	1	1	1	1	1	1	1	0	1	0	12
10	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	14
Dependence Power	13	12	11	1	9	10	10	10	10	5	5	3	2	2	1	

4.2.7 MICMAC Analysis

Matrice d'Impacts croises-multipication applique an classment (cross-impact matrix multiplication applied to classification) is abbreviated as MICMAC. The main purpose of MICMAC analysis is to analyze the drive power and dependence power of variables. The variables are separated into four clusters [307].

The first cluster consists of 'autonomous variables' which have weak drive power and weak dependence. They are relatively disconnected from the system, with which they have few links, which may be very strong. The second cluster consists of 'dependent variables' which have weak drive power but strong dependence power. The third cluster includes 'linkage variables' which have strong drive power as well as strong dependence. They are also unstable. Any action on them will have an effect on others and also a feedback effect on themselves. Fourth cluster has the 'independent variables' having strong drive power but weak dependence power. It is generally observed that a variable with a very strong drive power called the 'key variable' falls into the category of independent variables. The drive power and dependence power of variables is shown in Table 4.11. Thereafter, the drive power and dependence power diagram is depicted as shown in Figure 4.2. As an example, it is observed from Table 4.11 that variable 10 has a drive power of 14 and dependence power of 1, hence in Figure 4.2, it is positioned in a space which corresponds to drive power of 14 and dependence of 1, i.e. in the fourth cluster. Now, its position in the fourth cluster shows that it is an independent variable. Likewise, all the components are positioned in places corresponding to their driving power and dependence.

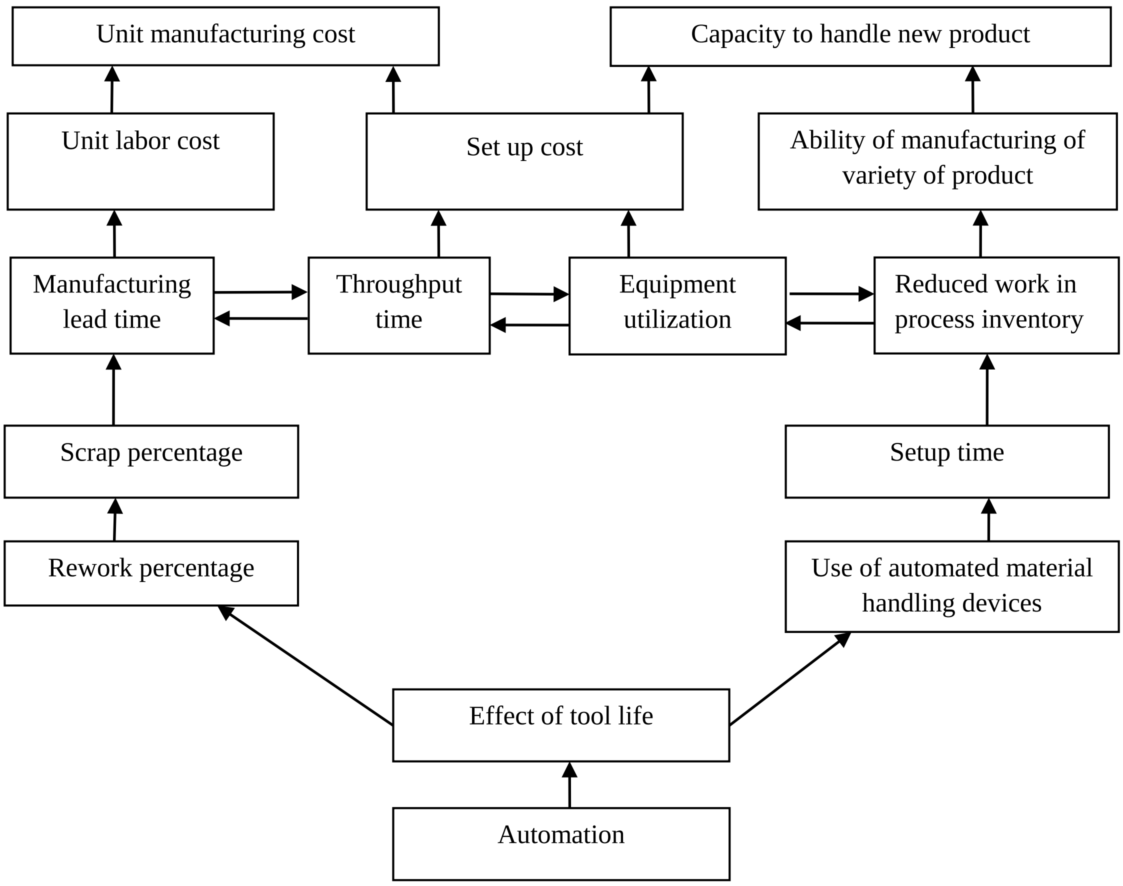

Figure 4.1 ISM model showing the levels of FMS performance variables

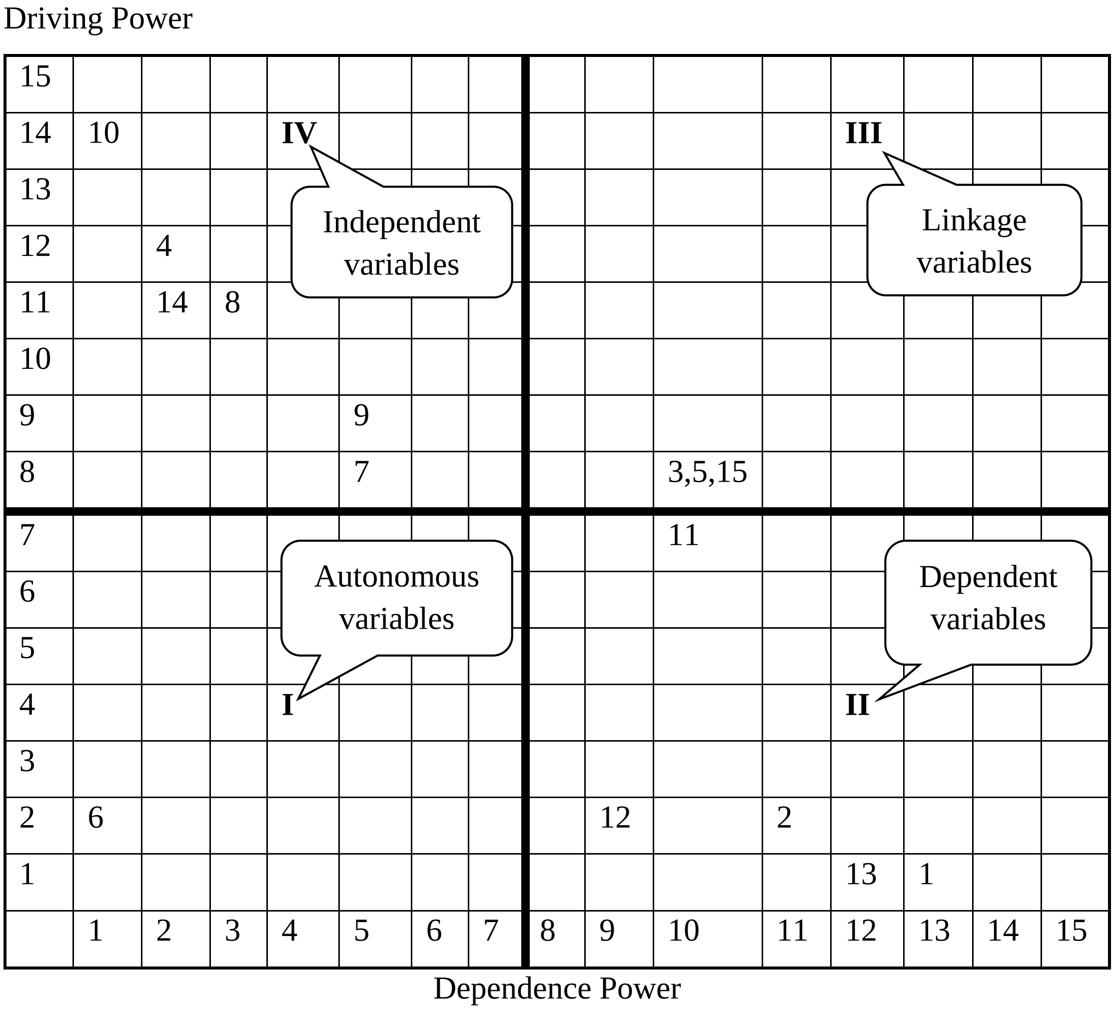

Figure 4.2 Clusters of performance variables in FMS

4.3 MODEL ANALYSES BY SEM

Data analysis proceeds in two steps. First the EFA is used to identify the underlying dimensions of performance variables in FMS. Next, CFA to confirm the factor structure of the performance dimensions in FMS.

4.3.1 Exploratory Factor Analysis (EFA)

In the first stage an EFA was performed on sample size (i.e. n = 290) using the 15-variables related to the performance variables in FMS. An EFA was performed on the 15 items of the performance variables in FMS using the principal component analysis with varimax rotation [163]. The criteria used for factor extraction is the eigenvalue should be greater than one; variance should be 50-75% explained; retaining the factors above the elbow in scree test as shown in Figure 4.3; and at least three items per factor with significant factor loading i.e. > 0.30. The results of the EFA are shown in Table 4.12. Three factors were extracted that have eigenvalue greater than one, accounting for 69.225 percent of the total variance explained and above the elbow of scree plot. From Table 4.12, all 15 items loaded properly on the factors so, all items were taken. Also, based on the cronbach's alpha criteria, all items were taken. Factor loadings greater than 0.50 were retained for further analysis. Reliability of the factors was estimated using the cronbach's alpha. A cronbach's alpha value of greater than or equal to 0.7 is considered acceptable for the factor to be reliable [308]. All the factors had a satisfactory value of cronbach's alpha. Hence the factors are reliable.

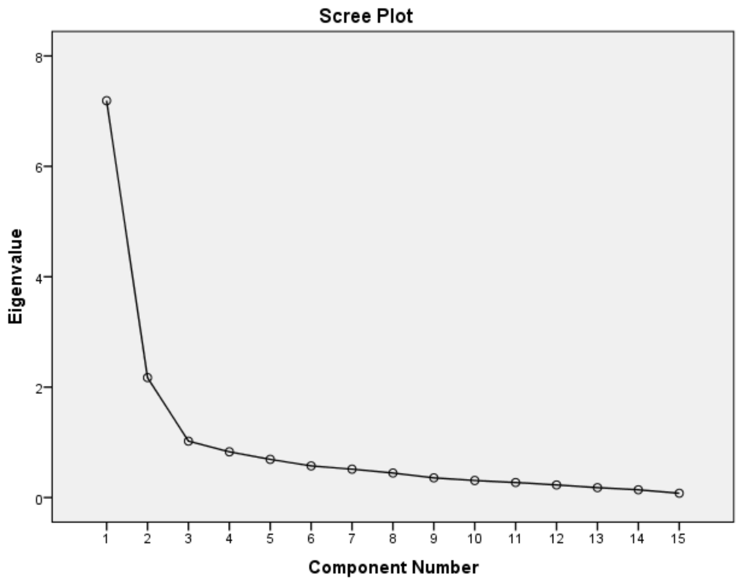

Figure 4.3 Scree Plot

4.3.2 Confirmatory Factor Analysis (CFA)

After identifying three clear factors through EFA, the next phase is to confirm the factor structure on same sample size. SEM using AMOS was used to perform the CFA. CFA revealed that the measurement items loaded in accordance with the pattern revealed in the EFA.

- **Model fit**

The measurement model indicated an acceptable model fit of the data

CMIN (χ2) =185. 888, df = 81, p =.000; CMIN/DF (χ 2/ DF) = 2.295 (< 5); CFI =0.964; TLI = 0.953; IFI = 0.964; NFI = 0.938; RFI=0. 920; GFI=0. 913; and RMSEA = 0.07 [309].

In addition, all the indicators loaded significantly on the latent constructs. The values of the fit indices indicate a reasonable fit of the measurement model with data [310].

Table 4.12 Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization with Reliability Statistics (EFA result)

Sr. No.	Dimensions	Variables/Items	Factor loading	Cronbach's alpha
1	Quality	Effect of tool life	.889	.932
		Scrap percentage	.873	
		Rework percentage	.840	
		Automation	.897	
2	Productivity	Unit manufacturing cost	.803	.858
		Unit labor cost	.795	
		Manufacturing lead time	.684	
		Throughput time	.675	
		Set up cost	.635	
		Setup time	.524	
3	Flexibility	Equipment utilization	.706	.875
		Ability to manufacture a variety of product	.725	
		Capacity to handle new product	.749	
		Use of automated material handling devices	.799	
		Reduced work in process inventory	.787	

In short the measurement model conforms to the three factor structure of the performance evaluation of FMS. Path diagram of CFA is shown in Figure 4.4.

- **Reliability of the performance variables of FMS**

The cronbach's alpha for the performance variables of FMS was 0.919 which is acceptable and shows that the variables are reliable. Further evidence of the reliability of the scale is provided in Table 4.13, which shows the composite reliability (CR) and average variance extracted (AVE) scores of the different factors obtained [308, 311]. CR of all the latent variables is greater than the acceptable limit of 0.70 [312]. The AVE for all the factors is greater than 0.5, which is acceptable [311]. This shows the internal consistency of the variables used in the study.

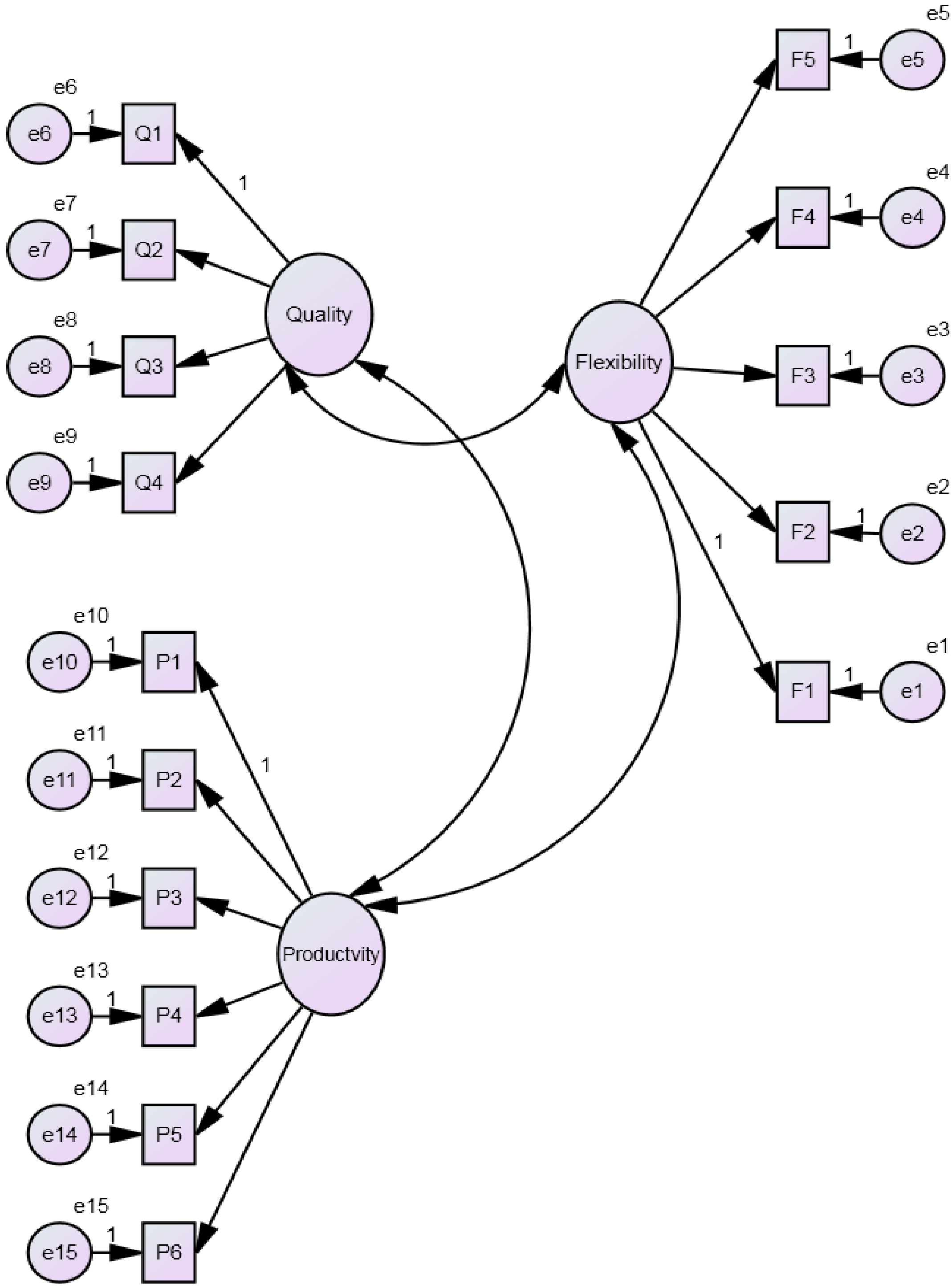

Figure 4.4 Path diagram of SEM

Table 4.13 Confirmatory factor analysis results

Sr. No.	Dimensions	Variables/Items	Standardized estimate	p-value (* significant at p < 0.001)	AVE	CR
1	Quality	Automation	0.911	*	0.78	0.94
		Scrap percentage	0.888	*		
		Effect of tool life	0.902	*		
		Rework percentage	0.836	*		
2	Productivity	Unit labor cost	0.945	*	0.55	0.88
		Unit manufacturing cost	0.964	*		
		Manufacturing lead time	0.639	*		
		Setup time	0.693	*		
		Throughput time	0.539	*		
		Set up cost	0.566	*		
3	Flexibility	Equipment utilization	0.751	*	0.61	0.89
		Ability to manufacture a variety of product	0.773	*		
		Capacity to handle new product	0.71	*		
		Use of automated material handling devices	0.87	*		
		Reduced work in process inventory	0.803	*		

- **Construct validity**

Construct validity is the extent to which a set of measured variables actually reflects the latent construct they are designed to measure [308]. Construct validity was established in this study by establishing the face validity, convergent validity and discriminant validity. Face validity was established by adopting the measurement items used in the study of the existing literature and adapting the same to the present research context.

Convergent validity was assessed by examining the factor loadings and average variance extracted of the constructs as suggested by [311]. All the indicators had significant loadings onto the respective latent constructs ($p < 0.001$) with values varying between 0.539 and 0.964 (Table 4.13). In addition, AVE for each construct is greater than or equal to 0.50 which further supports the convergent validity of the constructs. Fornell and Larcker [311] stated that discriminant validity can be measured by comparing the AVE with the corresponding inter-construct squared correlation estimates. From Table 4.14 it can be inferred that the AVE values of all the factors i.e. quality, productivity and flexibility are greater than the squared inter-construct correlations which supports the discriminant validity of the constructs. The AVE values of all the performance factors are greater than the squared inter-construct correlations, which supports the discriminant validity of the constructs. Therefore, the measurement model reflects good construct validity and desirable psychometric properties. So, three factors which affect the performance of FMS variables are shown in Figure 4.5.

Table 4.14 Discriminant validity

	Quality	**Productivity**	**Flexibility**
Quality	0.78		
Productivity	0.247	0.55	
Flexibility	0.224	0.521	0.61

Note: Diagonal elements in the correlation matrix of constructs are the AVE values and off diagonal are the squared inter construct correlations; for discriminant validity to be present the diagonal elements should be greater than the off diagonal.

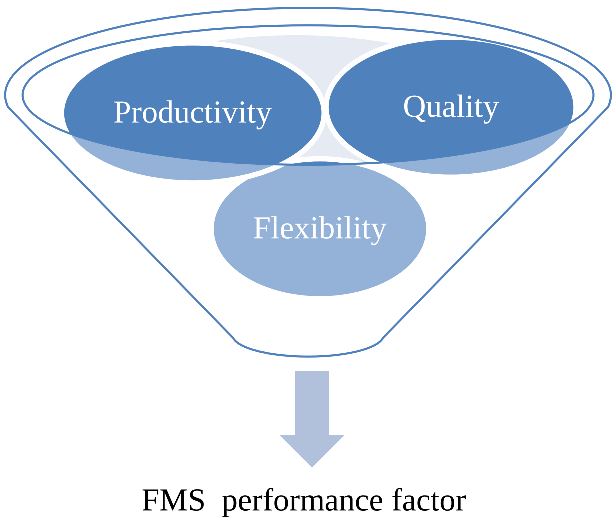

Figure 4.5 FMS performance factor

On the basis of these fifteen variable, three factors are extracted i.e. quality, productivity and flexibility [92, 313].

1. Quality factors include the effect of tool life, scrap percentage, rework percentage and automation variables. In a manufacturing system, the tool life is governed mainly by the input parameters like speed, feed, depth of cut and cutting forces which influences the accuracy and finish of the machined surface. Generally, tool life influences productivity of the manufacturing system and dimensional accuracy. While surface finish directly affect the performance of the manufacturing system. Scrap percentage is automatically reduced when surface finish will be accurate and simultaneously rework percentage will also be reduced. Automation reduces the human efforts and introduces some flexibility in the manufacturing system. The high level of automation in an FMS allows it to operate for extended periods of time without human attention. So, finally improve the quality of a system.

2. Productivity factors include the variables like unit manufacturing cost, unit labour cost, manufacturing lead time, throughput time, set up cost and setup time. Productivity indicates the efficiency of converting inputs (resources) to outputs. Unit manufacturing cost will be lower than profit of the manufacturing organization will be higher. Increases in labor productivity indicate that a manufacturing organization's workforce is becoming more efficient. The ability of a manufacturing firm to deliver a product to the customer in shortest possible time where time is referred to manufacturing lead time. It is closely correlated with reduced WIP. Because different parts are processed together rather than separately in batches, WIP is less than in a batch production mode. This means faster customer deliveries. Reduction in set-up time and subsequently in manufacturing lead time enables the production system to produce variety of parts at faster rate. FMS generally employs CNC/NC machines which have automatic tool interchange capabilities that reduce the set-up time.

3. Flexibility factors include the equipment utilization, ability to manufacture a variety of product, capacity to handle new product, use of automated material handling devices and reduced work in process inventory. FMSs achieve a higher average utilization than machine in a conventional batch production machine shop. It should be possible to approach 80–90% asset utilization by implementing FMS technology. Higher machine utilization has been achieved because of reduced set-up times, efficiently handled parts

and simultaneously produced several parts. With higher utilization of machine and flexible automated system, capable of producing a variety of parts (or productions) with virtually no time lost for changeovers from one part style to the next. There is no lost production time while reprogramming the system and altering the physical set-up (tooling, fixtures and machine setting). Flexibility of a particular manufacturing system would be more if it is capable of handling more number of new and unexpected products.

Material handling systems provide a key integrating function within a manufacturing system. Industrial robots and AGVs are used to pick and place materials from or on to the conveyors, loading and unloading the materials from machines. Use of automated material handling devices affect lead time, WIP, inventory levels and the overall operating efficiency of a facility [314-316].

4.4 EVALUATION OF INTENSITY OF VARIABLES AFFECTING PERFORMANCE

Analysis of variable is done by graph theory matrix approach as given below:

1. After identifying three clear factors through EFA (principal components analysis) and confirming this model by CFA, a digraph is developed for these three factors, as shown in Figure 4.6.

2. The digraphs for each category of factors (Figures 4.7–4.9) are developed considering the variables that affect the particular category of factors. The nodes in the digraph represent the variables and their mutual interaction is described by different edges.

3. The inheritance of variables and their interdependencies is discussed with the experts as per Tables 2.2 and 2.3 and the FMS performance' matrix for each category is written as:

$$P_1^* = \begin{array}{c} \begin{matrix} F_{11} & F_{12} & F_{13} & F_{14} \end{matrix} \\ \begin{pmatrix} 9 & 4 & 4 & 4 \\ 0 & 8 & 0 & 0 \\ 0 & 4 & 9 & 5 \\ 0 & 3 & 0 & 8 \end{pmatrix} \end{array} \begin{array}{c} \text{variable} \\ F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \end{array}$$

$$
\begin{array}{c}
\begin{array}{cccccc} F_{21} & F_{22} & F_{23} & F_{24} & F_{25} & F_{26} \end{array} \quad \text{variable} \\
P_2^* = \begin{pmatrix} 8 & 4 & 0 & 0 & 0 & 0 \\ 0 & 9 & 0 & 3 & 4 & 3 \\ 0 & 4 & 8 & 4 & 4 & 0 \\ 0 & 4 & 4 & 8 & 4 & 0 \\ 0 & 4 & 3 & 4 & 9 & 0 \\ 0 & 4 & 0 & 0 & 0 & 8 \end{pmatrix} \begin{array}{c} F_{21} \\ F_{22} \\ F_{23} \\ F_{24} \\ F_{25} \\ F_{26} \end{array}
\end{array}
$$

$$
\begin{array}{c}
\begin{array}{ccccc} F_{31} & F_{32} & F_{33} & F_{34} & F_{35} \end{array} \quad \text{variable} \\
P_3^* = \begin{pmatrix} 8 & 3 & 3 & 0 & 4 \\ 0 & 8 & 3 & 0 & 3 \\ 0 & 4 & 8 & 0 & 0 \\ 4 & 4 & 2 & 9 & 4 \\ 0 & 0 & 0 & 0 & 8 \end{pmatrix} \begin{array}{c} F_{31} \\ F_{32} \\ F_{33} \\ F_{34} \\ F_{35} \end{array}
\end{array}
$$

4. In the present work, the value of the permanent function for each category is calculated by a computer program which is developed in C++ language. The value of permanent function for each category is as follows:

Per P_1^* = 5184, Per P_2^* = 1015808, Per P_3^* = 43776

The FMS performance' matrix at the system level is prepared as per equation 2.3. In this matrix, the values of the diagonal elements are selected from the sub-system level:

F_1 = Per P_1^* = 5184; F_2 = Per P_2^* = 1015808; F_3 = Per P_3^* = 43776

$$
\begin{array}{c}
\begin{array}{ccc} F_1 & F_2 & F_3 \end{array} \quad \text{Factor} \\
P^* = \begin{pmatrix} 5184 & 5 & 4 \\ 3 & 1015808 & 3 \\ 3 & 5 & 43776 \end{pmatrix} \begin{array}{c} F_1 \\ F_2 \\ F_3 \end{array}
\end{array}
$$

5. Value of permanent function of the system is evaluated. The value of Per P* at the system level of above matrix is 2.3×10^{14}, which indicates the FMS performance index for the variables considered. It is suggested to find hypothetical best and hypothetical worst value of the FMS performance index. The FMS performance index is at its best when the inheritance of all its factors is at its best. Since, inheritance of factors has been evaluated considering variables and applying graph theoretic approach at the subsystem level, it is evident that the FMS performance index is at its best when the inheritance of variables is at its best. At the subsystem level, maximum value of per P_1^* is obtained

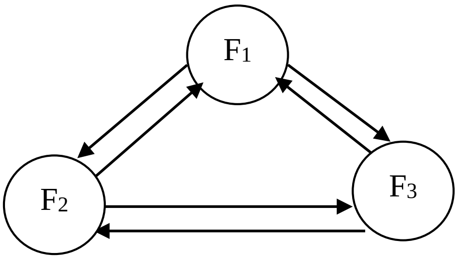

Figure 4.6. Digraph for factors

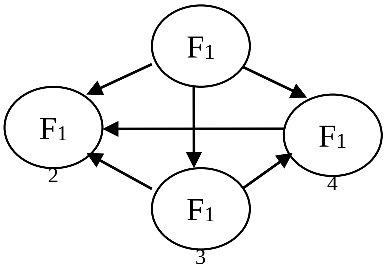

Figure 4.7 Digraph for quality

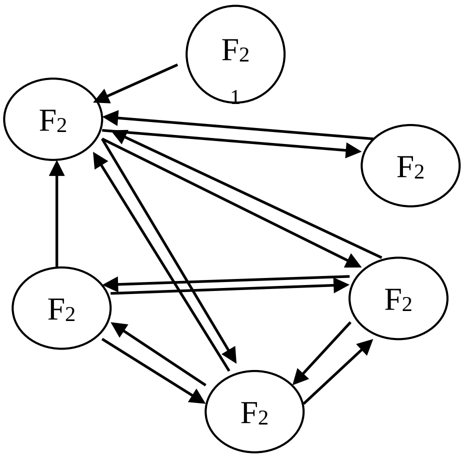

Figure 4.8 Digraph for productivity

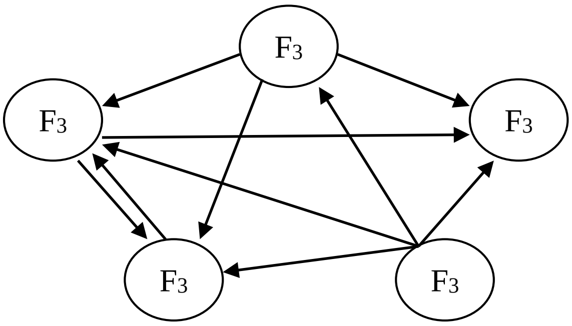

Figure 4.9 Digraph for flexibility

when inheritance of all the sub-factors are maximized, i.e., value taken from Table 2.2 is 10. Therefore, FMS performance' matrix for this category is rewritten as:

$$
\begin{array}{cc}
 & \begin{array}{ccccc} F_{11} & F_{12} & F_{13} & F_{14} & \text{variable} \end{array} \\
P_1^* = & \begin{pmatrix} 10 & 4 & 4 & 4 \\ 0 & 10 & 0 & 0 \\ 0 & 4 & 10 & 5 \\ 0 & 3 & 0 & 10 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \end{array}
\end{array}
$$

The maximum value of per P_1^* for the first category is 10000.

Similarly, the FMS performance index is at its worst when the inheritance of all its factors and variables is at its worst. This is the case when inheritance of the entire variables is minimum, i.e. value taken from Table 2.3 is 1. Thus, FMS performance matrix for this category is rewritten as:

$$
\begin{array}{cc}
 & \begin{array}{ccccc} F_{11} & F_{12} & F_{13} & F_{14} & \text{variable} \end{array} \\
P_1^* = & \begin{pmatrix} 1 & 4 & 4 & 4 \\ 0 & 1 & 0 & 0 \\ 0 & 4 & 1 & 5 \\ 0 & 3 & 0 & 1 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \end{array}
\end{array}
$$

The minimum value of per P_1^* for the first category is 1. Similarly, maximum and minimum values for each subsystem are evaluated and different values of permanent of subsystem matrices are summarized in Table 4.15. The maximum value of the FMS performance index at system level is measured by considering maximum values of all subsystems and minimum value of the FMS performance index at system level is measured by considering minimum values of all subsystems. The value of per P indicates the value of the FMS performance index. Thus, the maximum and minimum value of FMS performance index indicates the scope within which it can change. Experts can use this range to decide a threshold value for performance in FMS.

Table 4.15 The maximum and minimum values of the permanent function

Permanent function at the Subsystem/system level	*Maximum value*	*Minimum value*	*Current value*
Per P_1^*	10000	1	5184
Per P_2^*	2344640	3461	1015808
Per P_3^*	112000	13	43776
Per P^*	2×10^{15}	86840	2.3×10^{14}

4.5 RESULT AND DISCUSSION

This research has provided an insight into the modelling and analysis of performance variables of the flexible manufacturing system (FMS). Productivity, quality and flexibility are critical measures of manufacturing performance. Productivity indicates the efficiency of converting inputs (resources) to outputs. Quality refers to the degree of excellence in making products. Flexibility measures the adaptability to various changes in manufacturing environments [92]. The ISM model developed in this research provides the managers with an opportunity to understand the driving and the dependence power of the variables. The managerial implications as emerging from this study are as follows.

The driving and dependence power (Figure 4.2) indicates that there is one autonomous performance variable i.e. set up cost (6) in FMS. Autonomous variables are weak drivers and weak dependents and do not have much influence on the system. The autonomous variable in this study indicates that the considered variables do not have much influence on the performance in FMS and management should pay attention to all the other variables. Dependent variables are unit manufacturing cost (1), unit labor cost (2), equipment utilization (11), ability of manufacturing of a variety of product (12) and capacity to handle new product (13). These variables are weak drivers and depend strongly on one another. The management should therefore accord high priority in tackling these variables. Besides tackling these variables, management should also understand the dependence of these variables on other levels in the ISM. Linkage variables are manufacturing lead time (3), throughput time (5) and reduced work in process inventory (15). These variables have strong drive power as well as strong dependence power. So, they are unstable. Independent variables are the effect of tool life (4), rework percentage (8), setup time (9), scrap percentage (7), automation (10) and use of automated material handling devices (14). Independent variables have strong driving power and less dependent power. Hence, these are strong drivers and may be treated as the root causes of all the variables. These variables may be treated as the 'key variables ' in FMS.

Three factors were extracted that have eigenvalue greater than one, accounting for 69.225 percent of the total variance explained and above the elbow of scree plot. All 15 items loaded properly on the factors so, all items were taken. Also, based on the cronbach's alpha criteria, all items were taken. Factor loadings greater than 0.50 were retained for further analysis. Reliability of the factors was estimated using the cronbach's alpha. From EFA, using SPSS, three factors were extracted in analysis; quality, productivity and flexibility. Structural equation modelling (SEM) using AMOS was used to perform the first order three factor structure. The measurement model indicated an acceptable model fit of the data (CMIN ($\chi 2$) =185.888, df = 81, p =.000; CMIN/DF (χ 2/ DF) = 2.295 (< 5); CFI =0.964; TLI = 0.953; IFI = 0.964; NFI = 0.938; RFI=0.920; GFI=0.913; and RMSEA = 0.07). The cronbach's alpha for the performance variables of FMS was 0.919 which is acceptable and shows that the variables are reliable. Composite reliability (CR) of all the latent variables is greater than the acceptable limit of 0.70. The average-variance extracted for all the factors is greater than 0.5, which is acceptable. AVE values of all the factors i.e. quality, productivity and flexibility are greater than the squared inter-construct correlations which supports the discriminant validity of the constructs. Further, there is also a need to quantify the performance variables so that the management can understand the contribution of various performance variables of FMS and whether their efforts to increase the performance of FMS. This dynamic behavior of various performance variables of FMS can be quantified with the help of graph theory and matrix approach. Thus an index that would quantify the performance variables of FMS would be developed by extending the graph theory in the domain of performance variables of FMS.

4.6 CONCLUSION

As a conclusion of this research study, an attempt has been made to identify the performance variables of FMS environment and as given below:

1. A logical procedure based on methodology as ISM, SEM and GTMA together is suggested which helps to focus on performance of flexible manufacturing system.
2. There are three factors like quality, productivity and flexibility which affect performance of FMS.
3. The SEM analysis confirm the relationships between variables. Direct as well as indirect relationship between variables can be specified and estimated.
4. The proposed FMS performance index evaluates and ranks the performance variables with their factors.

CHAPTER V

MODELING AND ANALYSIS OF PRODUCTIVITY VARIABLES OF FMS

5.1 INTRODUCTION

Productivity is one of the most common measures of an organization's competitiveness. It has often been cited as a key factor in industrial performance and actions to increase it are said to improve profitability and the wage earning capacity of employees [317]. The concept of productivity is generally defined as the relation between output and input. Productivity is the ratio of output to input for a specific production situation. Rising productivity implies either more output is produced with the same amount of inputs, or that fewer inputs are required to produce the same level of output [318]. Improving productivity is seen as a key issue for survival and success in the long term of a manufacturing system. To enhance productivity, the organization may either consider reducing inputs while keeping outputs constant, or increasing output while keeping inputs constant [83]. Productivity is considered as one of the basic variables governing economic production activities [319]. At the same time, productivity is also seen as one of the most vital factors affecting a manufacturing company's competitiveness.

According to Tangen [319], the organization can either consider one of the followings to increase productivity levels:

- Increase output and input, but the increase in input is proportionally less than the increase in output
- Increase output while keeping the input constant
- Increase output while reducing input
- Keep output constant while decreasing input
- Decrease output and input, but the decrease in input is proportionally more than the decrease in output.

From this chapter the following paper has been published.

V. Jain and T. Raj, "Modelling and analysis of FMS productivity variables by ISM, SEM and GTMA approach," *Frontiers of Mechanical Engineering*, vol. 9, pp. 218-232, 2014.

There are a number of variables that can be used to represent productivity. FMSs have been developed with the hope that they will be able to tackle new challenges like cost, quality, improve delivery speed and productivity and to operate to be more flexible in their operations and to satisfy different market segments. An FMS can be defined as general-purpose manufacturing machines, coupled with material-handling systems and have the capabilities to perform different types of operations. In these systems, machines and material handling systems are controlled by a central computer system [320]. Flexibility in manufacturing has been identified as one of the key factors to improve the performance of FMS. A significant challenge for many manufacturers is to achieve flexibility in addition to achieving productivity and quality [301]. FMS is crucial for modern manufacturing to enhance productivity involved with high product proliferation [302]. A high level of quality leads to high level of performance [303]. FMS promise to provide quality and economies of scope - the ability to achieve productivity and flexibility simultaneously and also to achieve economies of scope by reducing the time and cost of product variety [301]. Therefore, manufacturing firms are under constant and intense pressure to improve their operations continuously and efficiently by enhancing productivity to increase performance of the system.

The main objectives of this chapter are as follows:

- To identify the variables which affect the productivity of FMS from the literature
- To establish relationship among these variables by using ISM
- To identify the factors/dimensions which affect the productivity of FMS by exploratory factor analysis through SPSS
- To confirm the factor structure (first order four factors) of the same using confirmatory factor analysis with AMOS
- Evaluation of intensity of productivity variables of FMS by GTMA.

On the basis of the exhaustive literature review and discussions with the industry experts and the academia, twenty variables have been identified which are as mentioned below:

1. Training [74, 75]
2. Financial incentive [76]
3. Unit labor cost [40, 41]
4. Effect of tool life [44, 45]

5. Customer satisfaction [78, 79]
6. Reduction in scrap percentage [52, 53]
7. Reduction in rework percentage [52, 53]
8. Reduction of rejection [81, 82]
9. Equipment utilization [58, 59]
10. Trained worker[84-86]
11. Manufacturing lead time and setup time [304, 305]
12. Unit manufacturing cost [37, 38]
13. Throughput time [45, 48]
14. Set up cost [40, 49]
15. Automation [55, 56]
16. Use of automated material handling devices [68, 69]
17. Reduction in material flow [321, 322]
18. Reduced work in process inventory [71, 73]
19. Capacity to handle new product[64, 65]
20. Ability of manufacturing of variety of product [61, 62]

After identification of variables affecting productivity of FMS, an ISM model is prepared which is discussed in the following sections:

5.2 ISM MODEL FOR PRODUCTIVITY VARIABLES OF FMS

In this section, the development of the model using ISM is described below.

5.2.1 Development of Structural Self-Interaction Matrix (SSIM)

ISM methodology suggests the role of expert (both from industry and academia) opinions in developing the contextual relationship between the variables. The following four symbols have been used to denote the direction of the relationship between two variables (i and j):

V is used for the relation from variable i to j (i.e. if variable i reach to variable j)

A is used for the relation from variable j to i (i.e. if variable j reach to variable i)

X is used for both direction relations (i.e. if variable i and j reach to each other)

O is used for no relation between two variables (i.e. if variable i and j are unrelated).

Based on the contextual relationship, the SSIM is developed and it is presented in Table 5.1.

5.2.2 Reachability Matrix (RM)

The RM is obtained from SSIM. The RM indicates the relationship between variables in the binary form. The various relationships between variables depicted by symbols V, A, X and O used earlier in SSIM are replaced by binary digits of 0 and 1 is called initial reachability matrix. The following rules are used to substitute V, A, X and O of SSIM to get RM:

- if the cell (i, j) is assigned with symbol V in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry becomes 0 in the initial RM
- if the cell (i, j) is assigned with symbol A in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry becomes 1 in the initial RM
- if the cell (i, j) is assigned with symbol X in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry also becomes 1 in the initial RM
- if the cell (i, j) is assigned with symbol O in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry also becomes 0 in the initial RM.

Following these rules, the initial reachability matrix is shown in Table 5.2. The final RM is obtained by incorporating the transitivity. Final RM is shown in Table 5.3 wherein transitivity is marked as 1*.

5.2.3 Level Partitioning the RM

From the final reachability matrix, the reachability and the antecedent set for each variable can be found [17, 126]. The matrix is partitioned by assessing the reachability and antecedent set for each variable. This procedure is completed in seven iterations, summarized in Table 5.4.

5.2.4 Development of the Conical Matrix

A conical matrix is developed by clubbing together variables in the same level, across rows and columns of the final RM as shown in Table 5.5.

5.2.5 Development of ISM Model

Based on the conical matrix, an initial digraph, including transitivity links is obtained. This is generated by nodes and lines of the edges. After removing the indirect links, a final digraph is developed. Next, the digraph is converted into an ISM model by replacing nodes of the elements with statements as shown in Figure 5.1.

5.2.6 Check for Conceptual Inconsistency

Conceptual inconsistency is checked by identifying and removing the intransitivity in the model.

5.2.7 MICMAC Analysis

Matrice d'Impacts croises-multipication applique an classment (cross-impact matrix multiplication applied to classification) is abbreviated as MICMAC. The main purpose of MICMAC analysis is to analyze the drive power and dependence power of variables. The variables are separated into four clusters [307]. The first cluster consists of 'autonomous variables' which have weak drive power and weak dependence. They are relatively disconnected from the system, with which they have few links, which may be very strong. The second cluster consists of 'dependent variables' which have weak drive power but strong dependence power. The third cluster includes 'linkage variables' which have strong drive power as well as strong dependence. They are also unstable. Any action on them will have an effect on others and also a feedback effect on themselves. Fourth cluster has the 'independent variables' having strong drive power but weak dependence power. It is generally observed that a factor with a very strong drive power called the 'key variable' falls into the category of independent variables. The drive power and dependence power of variables is shown in Table 5.5. Thereafter, the drive power and dependence power diagram is depicted as shown in Figure 5.2. As an example, it is observed from Table 5.5 that variable 1 has a drive power of 19 and dependence power of 1, hence in Figure 5.2, it is positioned in a space which corresponds to drive power of 19 and dependence of 1, i.e. in the fourth cluster. Now, its position in the fourth cluster shows that it is an independent variable. Likewise, all the components are positioned in places corresponding to their driving power and dependence.

Table 5.1 Structural self-interactive matrix

Variables	**20**	**19**	**18**	**17**	**16**	**15**	**14**	**13**	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
1	V	V	O	O	O	V	O	V	V	V	V	V	V	V	V	V	V	V	O
2	O	O	O	O	O	O	O	O	O	O	O	V	O	O	O	O	O	O	V
3	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O	
4	V	V	V	V	O	O	O	V	V	V	A	V	V	V	V	V			
5	O	O	O	O	O	O	O	O	O	O	O	O	O	O	O				
6	A	A	V	V	O	A	O	V	V	O	A	A	A	A					
7	O	O	V	V	O	A	O	V	V	O	A	A	A						
8	O	O	V	V	O	A	O	V	V	V	A	O							
9	A	A	A	A	A	A	V	O	V	A	A								
10	V	V	V	V	O	V	O	V	V	V									
11	V	V	V	V	A	A	O	V	V										
12	O	O	O	O	O	A	A	O											
13	O	O	A	A	A	A	O												
14	O	O	O	O	O	O													
15	V	V	V	V	X														
16	V	V	V	V															
17	A	A	A																
18	A	A																	
19	X																		

Table 5.2 Initial reachability matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	1	1
2	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	1	1	1	1	1	0	1	1	1	0	0	0	1	1	1	1
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	1	0	0
7	0	0	0	0	0	1	1	1	1	0	1	1	1	0	0	0	1	1	0	0
8	0	0	0	0	0	1	1	1	0	0	1	1	1	0	0	0	1	1	0	0
9	0	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	0	0	0
10	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1
11	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	1	1	1	1
12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0
15	0	0	0	0	0	1	1	1	0	0	1	1	1	0	1	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	1	1	1	1	1
17	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
18	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0
19	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1
20	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1

Table 5.3 Final reachability matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1	0	1	1	1	1	1	1	1	1	1	1	1	1*	1	1*	1*	1*	1	1
2	0	1	1	0	0	0	0	0	0	1	0	0	1*	0	1*	0	1*	1*	1*	1*
3	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	1	1	1	1	1	0	1	1	1	1*	0	0	1	1	1	1
5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	1	0	0
7	0	0	0	0	0	1	1	1	1	0	1	1	1	1*	0	0	1	1	1*	1*
8	0	0	0	0	0	1	1	1	0	0	1	1	1	0	0	0	1	1	1*	1*
9	0	0	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	0	0	0
10	0	0	0	1	0	1	1	1	1	1	1	1	1	0	1	1*	1	1	1	1
11	0	0	0	0	0	0	0	0	1	0	1	1	1	0	0	0	1	1	1	1
12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0
15	0	0	0	0	0	1	1	1	0	0	1	1	1	0	1	1	1	1	1	1
16	0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	1	1	1	1	1
17	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
18	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1	0	0
19	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1
20	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	1	1	1

* entries are included to incorporate transitivity.

Table 5.4 Iterations (Level of Variable)

No.	Variables Name	Reachability set	Antecedent set	Intersection set	Level
3	Unit labor cost	3	1,2,3	3	I
5	Customer satisfaction	5	1,4,5	5	I
12	Unit manufacturing cost	12	1,4,6,7,8,9,10,11,12,14,15	12	I
13	Throughput time	13	1,2,4,6,7,8,10,11,13,15,16,17,18	13	I
14	Set up cost	9,14	1,4,7,9,14	9,14	II
17	Reduction in material flow	17	1,2,4,6,7,8,10,11,15,16,17,18,19,20	17	III
18	Reduced work in process inventory	18	1,2,4,6,7,8,10,11,15,16,18,19,20	18	IV
6	Reduction in scrap percentage	6	1,4,6,7,8,10,15,19,20	6	V
19	Capacity to handle new product	19,20	1,2,4,7,8,10,11,15,16,19,20	19,20	VI
20	Ability to manufacture a variety of product	19,20	1,2,4,7,8,10,11,15,16,19,20	1920	VI
11	Manufacturing lead time and setup time	11	1,4,7,8,10,11,15,16	11	VII
7	Reduction in rework percentage	7,8	1,4,7,8,10,11,15	7,8	VIII
8	Reduction of rejection	7,8	1,4,7,8,10,11,15	7,8	VIII
16	Use of automated material handling devices	15,16	1,10,15,16	15,16	VIII
4	Effect of tool life	4	1,4,10	4	IX
10	Trained worker	10	1,10	10	X
1	Training	1	1	1	XI
2	Financial incentive	2	2	2	XI

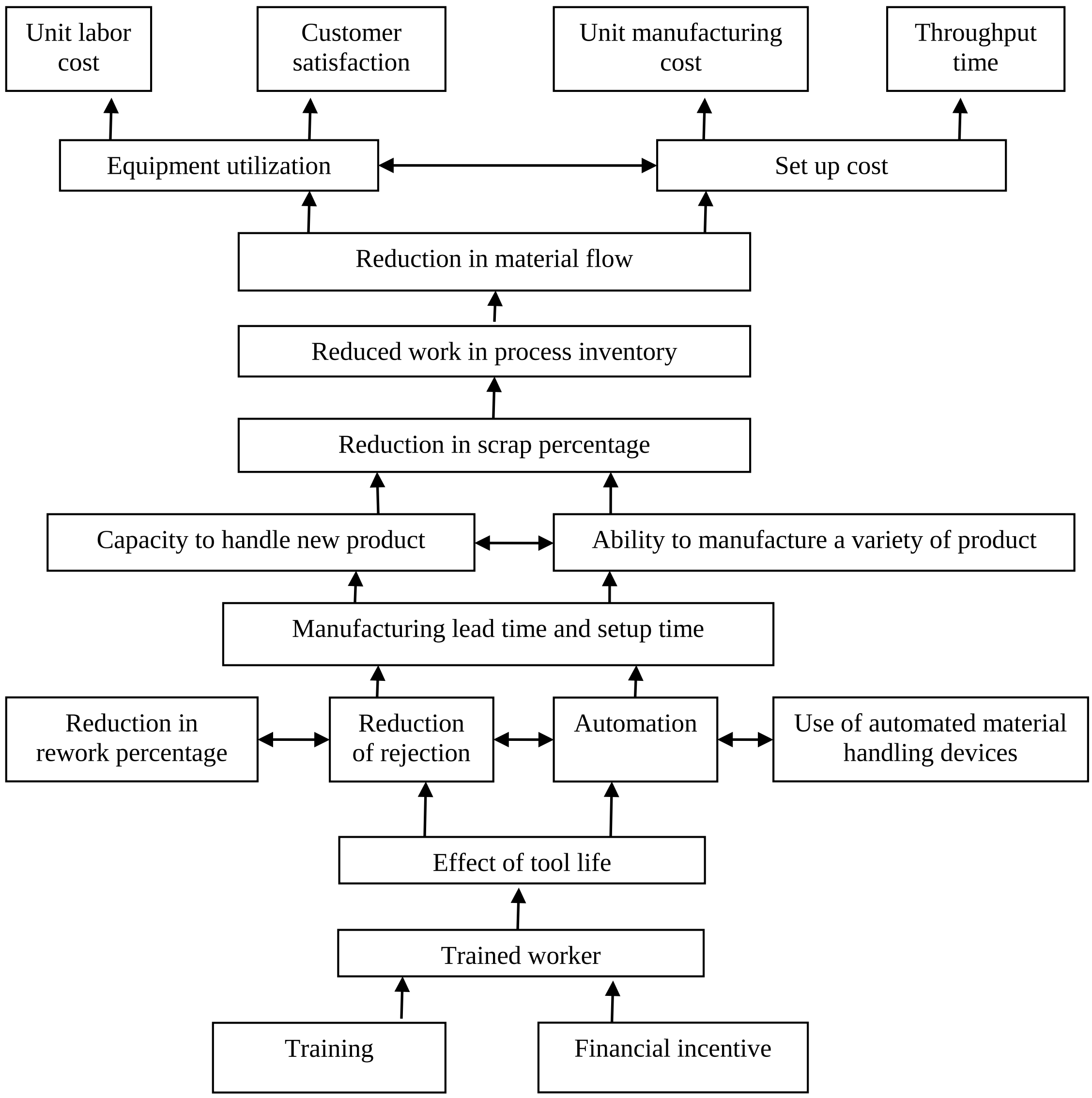

Figure 5.1 ISM model showing the levels of FMS productivity variables

Table 5.5 Conical matrix

Variables	3	5	12	13	9	14	17	18	6	19	20	11	7	8	15	16	4	10	1	2	Drive Power
3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
5	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
12	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
13	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
9	0	0	1	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	4
14	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3
17	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
18	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4
6	0	0	1	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	5
19	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	6
20	0	0	0	0	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	6
11	0	0	1	1	1	0	1	1	0	1	1	1	0	0	0	0	0	0	0	0	8
7	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	12
8	0	0	1	1	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	10
15	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	12
16	0	0	0	1	1	0	1	1	0	1	1	1	0	0	1	1	0	0	0	0	9
4	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	0	0	14
10	0	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	15
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	19
2	1	0	0	1	0	0	1	1	0	1	1	0	0	0	1	0	0	1	0	1	9
Dependence Power	3	3	11	13	12	5	14	13	10	11	11	8	6	6	5	4	3	3	1	1	

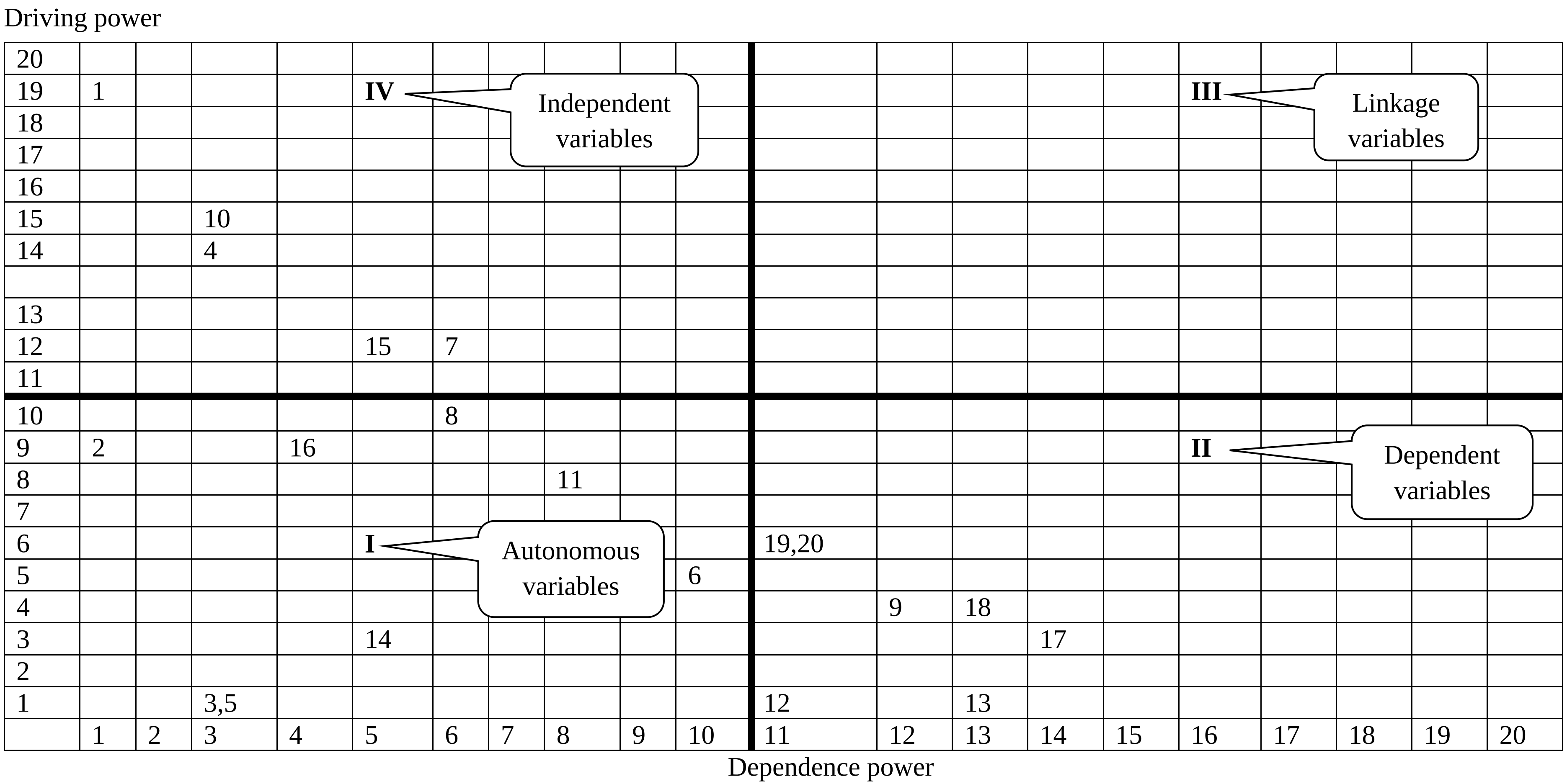

Figure 5.2 Clusters of variables affecting the productivity in FMS

5.3 MODEL ANALYSES BY SEM

Data analysis proceeds in two steps. First the EFA is used to identify the underlying dimensions of productivity variables in FMS. Next, CFA to confirm the factor structure of the productivity dimensions in FMS.

5.3.1 Exploratory Factor Analysis (EFA)

In the first stage an EFA was performed on sample size (i.e. n = 319) using the 20-variables related to the productivity variables in FMS. An EFA was performed on the 20 items of the productivity variables in FMS using the principal component analysis with varimax rotation [163]. The criteria used for factor extraction is the eigenvalue should be greater than one and at least three items per factor with significant factor loading i.e. > 0.30. The results of the EFA are shown in Table 5.6.

Four factors were extracted that have eigenvalue greater than and significant factor loading i.e. > 0.30 with three items per factor. From Table 5.6, All 20 items loaded properly on the factors, so, all items were taken. Also, based on the cronbach's alpha criteria, all items were taken. Factor loadings greater than 0.50 were retained for further analysis. Reliability of the factors was estimated using the cronbach's alpha. A cronbach's alpha value of greater than or equal to 0.7 is considered acceptable for the factor to be reliable [308]. All the factors had a satisfactory value of cronbach's alpha. Hence the factors are reliable.

5.3.2 Confirmatory Factor Analysis (CFA)

After identifying four clear factors through EFA, the next phase is to confirm the factor structure on same sample size. SEM using AMOS was used to perform the CFA. CFA revealed that the measurement items loaded in accordance with the pattern revealed in the EFA.

- **Model fit**

The measurement model indicated an acceptable model fit of the data CMIN ($\chi 2$) =397. 350, df = 159, p =.000; CMIN/DF (χ 2/ DF) = 2.499 (< 5); CFI =0. 964; TLI = 0.957; IFI = 0.964; NFI = 0.941; RFI=0.930; GFI= 0.890; RMR= 0.05 and RMSEA = 0.069 [309]. In addition, all the indicators loaded significantly on the latent constructs. The values of the fit indices indicate a reasonable fit of the measurement model with data [310]. In short the measurement model conforms to the four factor structure of the productivity evaluation of FMS. Path diagram of CFA is shown in Figure 5.3.

Table 5.6 Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization with Reliability Statistics (EFA result)

Sr. No.	Dimensions	Variables/Items	Factor loading	Cronbach's alpha
1	People	Training Financial incentive Unit labor cost	.849 .854 .851	.909
2	Quality	Effect of tool life Customer satisfaction Reduction in scrap percentage Reduction in rework percentage Reduction of rejection	.856 .808 .821 .842 .789	.953
3	Machine	Equipment utilization Trained worker Manufacturing lead time and setup time Unit manufacturing cost Throughput time Set up cost	.803 .851 .834 .780 .754 .640	.942
4	Flexibility	Automation Use of automated material handling devices Reduction in material flow Reduced work in process inventory Capacity to handle new product Ability to manufacture a variety of product	.848 .845 .830 .839 .764 .818	.937

- **Reliability of the productivity variables of FMS**

The cronbach's alpha for the productivity variables of FMS was 0.954 which is acceptable and shows that the variables are reliable. Further evidence of the reliability of the scale is provided in Table 5.7, which shows the composite reliability (CR) and average variance extracted (AVE) scores of the different factors obtained [308, 311]. CR of all the latent variables is greater than the acceptable limit of 0.70 [312]. The AVE for all the factors is greater than 0.5, which is acceptable [311]. This shows the internal consistency of the variables used in the study.

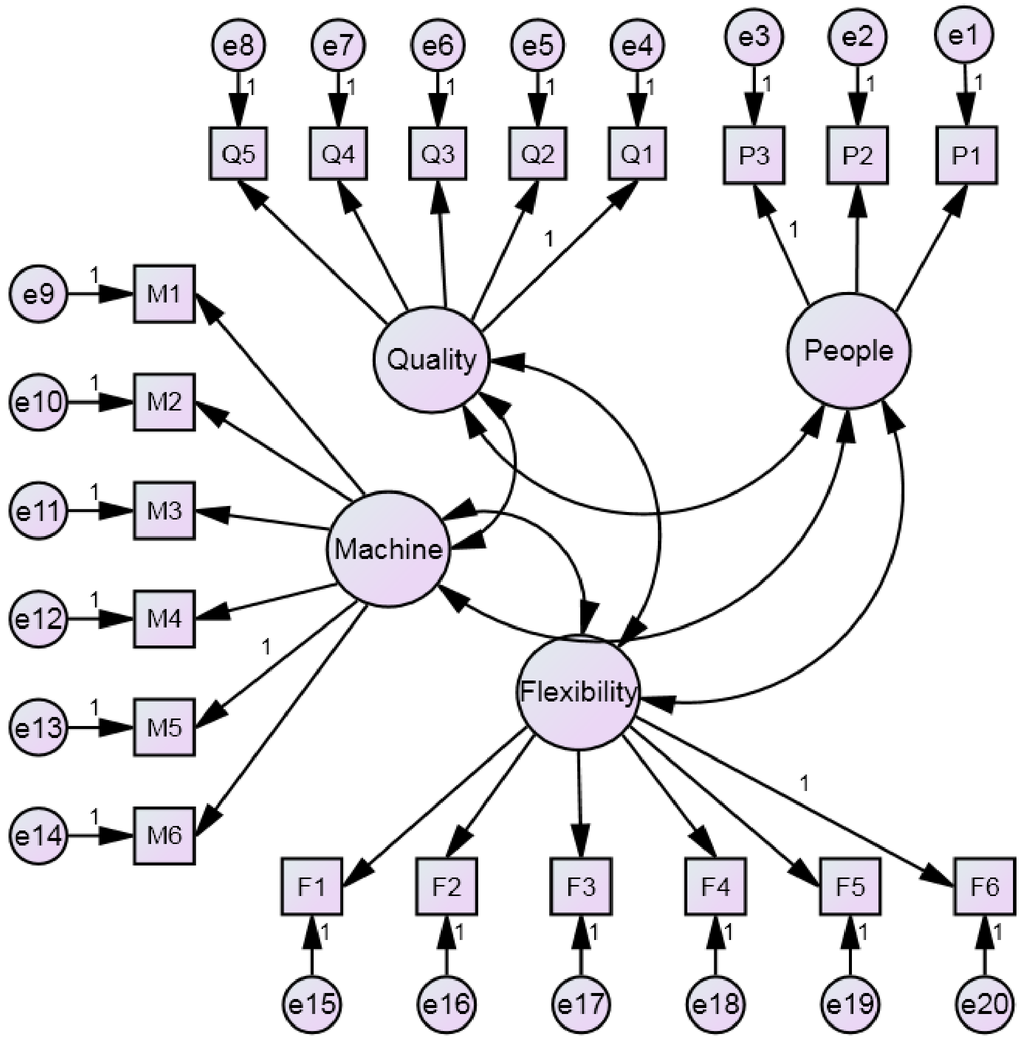

Figure 5.3 Path diagram of SEM

- **Construct validity**

Construct validity is the extent to which a set of measured variables actually reflects the latent construct they are designed to measure [308]. Construct validity was established in this study by establishing the face validity, convergent validity and discriminant validity. Face validity was established by adopting the measurement items used in the study of the existing literature and adapting the same to the present research context.

Convergent validity was assessed by examining the factor loadings and average variance extracted of the constructs as suggested by [311]. All the indicators had significant loadings onto the respective latent constructs ($p < 0.001$) with values varying between 0.725 and 0.948 (Table 5.7). In addition, AVE for each construct is greater than or equal to 0.50, which further supports the convergent validity of the constructs. Fornell and Larcker [311] states that discriminant validity can be measured by comparing the AVE with the corresponding inter-construct squared correlation estimates. From Table 5.8 it can be inferred that the AVE values of all the factors i.e. people, quality, machine and flexibility are greater than the squared inter-construct correlations which supports the discriminant validity of the constructs. The AVE values of all the productivity factors are greater than the squared inter-construct correlations, which supports the discriminant validity of the constructs. Therefore, the measurement model reflects good construct validity and desirable psychometric properties.

Table 5.8 Discriminant Validity

	People	**Quality**	**Machine**	**Flexibility**
People	0.78			
Quality	0.270	0.80		
Machine	0.325	0.454	0.72	
Flexibility	0.225	0.270	0.297	0.73

Note: Diagonal elements in the correlation matrix of constructs are the AVE values and off diagonal are the squared inter construct correlations; for discriminant validity to be present the diagonal elements should be greater than the off diagonal.

5.4 EVALUATION OF INTENSITY OF VARIABLES AFFECTING PRODUCTIVITY

Analysis of variable is done by graph theory matrix approach as given below:

1. After identifying four clear factors through EFA (principal components analysis) and confirming this model by CFA, A digraph is developed for these four factors, as shown in Figure 5.4.
2. The digraphs for each category of factors are developed considering the variables that affect the particular category of factors. The nodes in the digraph represent the variables and their mutual interaction is described by different edges.

Table 5.7 Confirmatory Factor Analysis Results

Sr. No.	Dimensions	Variables/Items	Standardized estimate	p-value (* significant at p < 0.001)	AVE	CR
1	People	Training	0.894	*	0.78	0.91
		Financial incentive	0.945	*		
		Unit labor cost	0.803	*		
2	Quality	Effect of tool life	0.939	*	0.80	0.95
		Customer satisfaction	0.883	*		
		Reduction in scrap percentage	0.916	*		
		Reduction in rework percentage	0.886	*		
		Reduction of rejection	0.841	*		
3	Machine	Equipment utilization	0.881	*	0.72	0.94
		Trained worker	0.948	*		
		Manufacturing lead time and setup time	0.911	*		
		Unit manufacturing cost	0.885	*		
		Throughput time	0.727	*		
		Set up cost	0.723	*		
4	Flexibility	Automation	0.907	*	0.73	0.94
		Use of automated material handling devices	0.906	*		
		Reduction in material flow	0.880	*		
		Reduced work in process inventory	0.865	*		
		Capacity to handle new product	0.827	*		
		Ability to manufacture a variety of product	0.725	*		

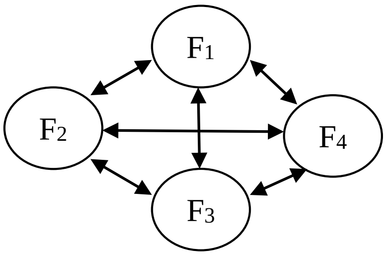

Figure 5.4 Digraph for Factors

3. The inheritance of variables and their interdependencies discuss with the experts as per Tables 2.2 and 2.3 and the FMS productivity' matrix for each category is written as:

$$\begin{array}{cc} & \begin{array}{ccc} F_{11} & F_{12} & F_{13} \end{array} \quad \text{variable} \\ P_1^* = & \begin{pmatrix} 8 & 3 & 3 \\ 4 & 9 & 3 \\ 3 & 3 & 8 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \end{array} \end{array}$$

$$\begin{array}{cc} & \begin{array}{ccccc} F_{21} & F_{22} & F_{23} & F_{24} & F_{25} \end{array} \quad \text{variable} \\ P_2^* = & \begin{pmatrix} 9 & 4 & 4 & 4 & 4 \\ 0 & 8 & 0 & 0 & 3 \\ 3 & 2 & 8 & 2 & 2 \\ 4 & 4 & 3 & 9 & 4 \\ 2 & 2 & 4 & 4 & 8 \end{pmatrix} \begin{array}{c} F_{21} \\ F_{22} \\ F_{23} \\ F_{24} \\ F_{25} \end{array} \end{array}$$

$$\begin{array}{cc} & \begin{array}{cccccc} F_{31} & F_{32} & F_{33} & F_{34} & F_{35} & F_{36} \end{array} \quad \text{variable} \\ P_3^* = & \begin{pmatrix} 9 & 0 & 0 & 3 & 3 & 0 \\ 4 & 9 & 4 & 4 & 4 & 0 \\ 4 & 0 & 8 & 3 & 4 & 0 \\ 0 & 0 & 0 & 9 & 0 & 3 \\ 4 & 0 & 4 & 4 & 8 & 0 \\ 0 & 0 & 0 & 3 & 0 & 8 \end{pmatrix} \begin{array}{c} F_{31} \\ F_{32} \\ F_{33} \\ F_{34} \\ F_{35} \\ F_{36} \end{array} \end{array}$$

$$\begin{array}{cc} & \begin{array}{cccccc} F_{41} & F_{42} & F_{43} & F_{44} & F_{45} & F_{46} \end{array} \quad \text{variable} \\ P_4^* = & \begin{pmatrix} 9 & 3 & 3 & 3 & 3 & 3 \\ 3 & 9 & 4 & 4 & 1 & 1 \\ 0 & 0 & 8 & 3 & 0 & 0 \\ 0 & 1 & 4 & 9 & 2 & 0 \\ 0 & 0 & 0 & 0 & 8 & 4 \\ 0 & 0 & 0 & 3 & 3 & 8 \end{pmatrix} \begin{array}{c} F_{41} \\ F_{42} \\ F_{43} \\ F_{44} \\ F_{45} \\ F_{46} \end{array} \end{array}$$

4. In the present work, the value of the permanent function for each category is calculated by a computer program which is developed in C^{++} language. The value of permanent function for each category is as follows:

$$\text{Per } P_1^* = 888, \text{ Per } P_2^* = 128676, \text{ Per } P_3^* = 629856, \text{ Per } P_4^* = 634644$$

The FMS productivity' matrix at the system level is prepared as per equation (2.3). In this matrix, the values of the diagonal elements are selected from the sub-system level:

F_1 = Per P_1^* = 888; F_2 = Per P_2^* = 128676; F_3 = Per P_3^* = 629856; F_4 = Per P_4^* = 634644

$$\begin{array}{cc} & \begin{array}{cccc} F_1 & F_2 & F_3 & F_4 \end{array} \quad \text{variable} \\ P^* = & \begin{pmatrix} 888 & 4 & 4 & 4 \\ 3 & 128676 & 4 & 4 \\ 1 & 3 & 629856 & 4 \\ 1 & 4 & 4 & 634644 \end{pmatrix} \begin{array}{c} F_1 \\ F_2 \\ F_3 \\ F_4 \end{array} \end{array}$$

5. Value of permanent function of the system is evaluated. The value of Per P* at the system level of above matrix is 45.67×10^{18}, which indicates the FMS productivity index for the variables considered. It is suggested to find hypothetical best and hypothetical worst value of the FMS productivity index. The FMS productivity index is at its best when the inheritance of all its factors is at its best. Since, inheritance of factors has been evaluated considering variables and applying graph theoretic approach at the subsystem level, it is evident that the FMS productivity index is at its best when the inheritance of variables is at its best. At the subsystem level, maximum value of per P_1^* is obtained when inheritance of all the sub-factors are maximized, i.e., value taken from Table 2.2 is 10. Therefore, FMS productivity' matrix for this category is rewritten as:

$$\begin{array}{cc} & \begin{array}{ccc} F_{11} & F_{12} & F_{13} \end{array} \quad \text{variable} \\ P_1^* = & \begin{pmatrix} 10 & 3 & 3 \\ 4 & 10 & 3 \\ 3 & 3 & 10 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \end{array} \end{array}$$

The maximum value of per P_1^* for the first category is 1363.

Similarly, the FMS productivity index is at its worst when the inheritance of all its factors and variables is at its worst. This is the case when inheritance of the entire variables is minimum, i.e. value taken from Table 2.2 is 1. Thus, FMS productivity matrix for this category is rewritten as:

$$\begin{array}{cc} & \begin{array}{ccc} F_{11} & F_{12} & F_{13} \end{array} & \text{variable} \\ P_1^* = & \begin{pmatrix} 1 & 3 & 3 \\ 4 & 1 & 3 \\ 3 & 3 & 1 \end{pmatrix} & \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \end{array} \end{array}$$

The minimum value of per P_1^* for the first category is 94. Similarly, maximum and minimum values for each subsystem are evaluated and different values of permanent of subsystem matrices are summarized in Table 5.9. The maximum value of the FMS productivity index at system level is measured by considering maximum values of all subsystems and minimum value of the FMS productivity index at system level is measured by considering minimum values of all subsystems. The value of per P indicates the value of the FMS productivity index. Thus, the maximum and minimum value of FMS productivity index indicates the scope within which it can change. Experts can use this range to decide a threshold value for productivity in FMS.

Table 5.9 The maximum and minimum values of the permanent function

Permanent function at the Subsystem/system level	***Maximum value***	***Minimum value***	***Current value***
Per P_1^*	1363	94	888
Per P_2^*	232864	6001	128676
Per P_3^*	1447520	770	629856
Per P_4^*	1472780	2756	634644
Per P^*	676.64×10^{18}	11.97×10^{11}	45.67×10^{18}

5.5 RESULT AND DISCUSSION

This chapter has provided an insight into the modelling and analysis of productivity variables of the flexible manufacturing system (FMS). The ISM model developed in this research provides the managers with an opportunity to understand the driving and the dependence power of the variables. Training is the highest driving power and unit labor cost, customer satisfaction, unit manufacturing cost and throughput time are the low driving power. ISM model is showing all levels of variables. Four factors were extracted that have eigenvalue greater than and significant factor loading i.e. > 0.30 with three items per factor. All twenty variables loaded properly on the factors, so, all items were taken. Also, based on the cronbach's alpha criteria, all items were taken. Factor loadings greater than 0.50 was retained for further analysis. Reliability of the factors was estimated using the cronbach's alpha. From EFA, using SPSS, four factors were extracted in analysis i.e. people, quality, machine and flexibility. Structural equation modelling (SEM) using AMOS was used to perform the first order four factor structure. The measurement model indicated an acceptable model fit of the data CMIN (χ2) =397. 350, df = 159, p =.000; CMIN/DF (χ 2/ DF) = 2.499 (< 5); CFI =0.964; TLI = 0.957; IFI = 0.964; NFI = 0.941; RFI=0.930; GFI= 0.890; RMR= 0.05 and RMSEA = 0.069 .The cronbach's alpha for the productivity variables of FMS was 0.954 which is acceptable and shows that the variables are reliable. Composite reliability (CR) of all the latent variables is greater than the acceptable limit of 0.70. The average-variance extracted for all the factors is greater than 0.5, which is acceptable. AVE values of all the factors i.e. people, quality, machine and flexibility are greater than the squared inter-construct correlations which supports the discriminant validity of the constructs. Further, there is also a need to quantify the productivity variables so that the management can understand the contribution of various productivity variables of FMS and whether their efforts to increase the productivity of FMS. This dynamic behavior of various productivity variables of FMS can be quantified with the help of graph theory and matrix approach. Thus an index that would quantify the productivity variables of FMS would be developed by extending the graph theory in the domain of productivity variables of FMS.

5.6 CONCLUSION

In this chapter, an attempt has been made to identify the major variables of productivity in FMS environment. Manufacturing companies can take quick decisions regarding the productivity variables of FMS. The result of this study shows that all the considered variables are very important for FMS productivity.

1. A logical procedure based on an ISM, SEM and GTMA together is suggested which helps to focus on productivity of flexible manufacturing system among a large number of available variables.
2. There are four factors like people, quality, machine and flexibility which affect productivity of FMS.
3. The SEM analysis provides flexibility in determining the relationships between variables. Direct as well as indirect relationship between variables can be specified and estimated.
4. The proposed flexible manufacturing system productivity index evaluates and ranks the productivity variables. This leads to the selections of a suitable productivity variables of flexible manufacturing system for any application.

CHAPTER VI

MODELING AND ANALYSIS OF FLEXIBILITY VARIABLES OF FMS

6.1 INTRODUCTION

The emerging concept of flexible manufacturing system (FMS) includes a certain degree of flexibility that allows systems to react in case of predicted or unpredicted changes [34]. This was introduced in response to the need for greater responsiveness to changes in products, production technologies and markets. Flexibility in manufacturing can be defined as the ability to change or react with little penalty in time, effort, cost or performance [323]. To enhance productivity involved with high product proliferation in modern manufacturing, FMS are essential [302]. Scheduling and manufacturing flexibility are among the manufacturing strategies considered by researcher to improve the FMS performance. Shafiq et al. [324] explained that the benefit will escalate when the flexibility of the system increased. Chowdary [325] unified a framework that flexibility is the one of the main factors for evaluation and selection of manufacturing systems. FMS is meant for enhancing the flexibility in a production system, it is a very difficult task to achieve real-life flexibility. There are certain factors in the achievement of this flexibility. These factors consist mutual relationship [129].

From this chapter the following papers have been published.

V. Jain and T. Raj, "Modeling and analysis of FMS flexibility factors by TISM and fuzzy MICMAC," *International Journal of System Assurance Engineering and Management*, vol. 6, pp. 350-371, 2015.

V. Jain and T. Raj, "Evaluating the Variables Affecting Flexibility in FMS by Exploratory and Confirmatory Factor Analysis," *Global Journal of Flexible Systems Management*, vol. 14, pp. 181-193, 2013.

V. Jain and T. Raj, "Evaluating the intensity of variables affecting flexibility in FMS by graph theory and matrix approach," *International Journal of Industrial and Systems Engineering*, vol. 19, pp. 137-154, 2015.

In this chapter, an effort has been made to accomplish the above task of analysis of these factors through the use of total interpretive structural modelling (TISM) approach which shows the interrelationships of the variables, their driving power and dependencies are analyzed by fuzzy MICMAC. In accordance with the TISM methodology, the opinions of experts were sought to develop the relationship matrix, which is later used in the development of TISM model.

The main objectives of this chapter are as follows:

- To identify the variables which affect the flexibility of FMS from the literature
- To establish relationship among these variables by using total interpretive structural modeling (TISM)
- To find out driving and the dependence power of variables, using fuzzy MICMAC analysis
- To identify the factors/dimensions which affect the flexibility of FMS by exploratory factor analysis through SPSS
- To confirm the factor structure of the same using confirmatory factor analysis with AMOS
- Evaluation of intensity of flexibility variables of FMS by graph theory matrix approach (GTMA)

On the basis of the exhaustive literature review and discussions with the industry experts and the academia, fifteen variables have been identified which are as mentioned below.

1. Ability to manufacture a variety of products [326]
2. Capacity to handle new products [327]
3. Flexibility in production [328]
4. Flexible fixturing [125]
5. Combination of operation [3]
6. Automation [329]
7. Use of automated material handling devices [330]
8. Increase machine utilization [331]
9. Use of the reconfigurable machine tool [10]
10. Manufacturing lead time and set up-time reduction [36]

11. Speed of response [332]
12. Reduced WIP inventories [333]
13. Reduction in material flow [334]
14. Quality consciousness [335]
15. Reduction in scrap [14]

After identification of variables affecting flexibility of FMS, a TISM model is prepared which is discussed in the following sections:

6.2 MODELING OF FMS FLEXIBILITY VARIABLES BY TISM

In this section, the development of the model using TISM is described below.

1. On the basis of the literature review and discussions with the industry experts and the academia, 15 variables were identified.
2. Contextual relationship is made between different elements of intent structure. Contextual relation and interpretation of the relationship is taken as per Table 2.4.
3. Interpretive logic–knowledge base pairwise comparison is shown in Table 6.1.
4. The paired comparison in the interpretive logic–knowledge base are translated in the form of an initial reachability matrix (Table 6.2) and this matrix has further been checked for the transitivity rule and shown in Table 6.3 as reachability matrix.
5. The level partition is carried out and iterations are shown in Table 6.4.
6. The variables are arranged graphically in levels and the directed links are drawn as per the relationships shown in the reachability matrix. Only those significant transitive relationships may be retained whose interpretation is crucial and shown in Figure 6.1
7. The final digraph is translated into a binary interaction matrix and interpretive matrix is shown in Table 6.5 and 6.6 respectively.

   The digraph may be translated into ISM by interpreting the node in box-bullet representation.
8. The connective and interpretive information contained in the interpretive direct interaction matrix and digraph is used to derive the TISM. TISM is shown in Figure 6.2.

Table 6.1 Interpretive logic - knowledge base

Sr. No.	Variable No.	Paired comparison of variables	Y/N	In what way a variable will influence/enhance other variable? Give reason in brief
F1 Ability to manufacture a variety of product				
1	F1-F2	Ability to manufacture a variety of product will influence/enhance Capacity to handle new product	Y	Develop new product
	F2-F1	Capacity to handle new product will influence/enhance Ability to manufacture a variety of product	N	
	F1-F3	Ability to manufacture a variety of product will influence/enhance Flexibility in the design of production system	N	
	F3-F1	Flexibility in the design of production system will influence/enhance Ability to manufacture a variety of product	N	
	F1-F4	Ability to manufacture a variety of product will influence/enhance Flexible fixturing	N	
	F4-F1	Flexible fixturing will influence/enhance Ability to manufacture a variety of product	Y	Handling of variety of products
	F1-F5	Ability to manufacture a variety of product will influence/enhance Combination of operation	N	
	F5-F1	Combination of operation will influence/enhance Ability to manufacture a variety of product	N	
	F1-F6	Ability to manufacture a variety of product will influence/enhance Automation	N	

	F6-F1	Automation will influence/enhance Ability to manufacture a variety of product	Y	Reduce human effort to product complicated parts
	F1-F7	Ability to manufacture a variety of product will influence/enhance Use of automated material handling devices	N	
	F7-F1	Use of automated material handling devices will influence/enhance Ability to manufacture a variety of product	N	
	F1-F8	Ability to manufacture a variety of product will influence/enhance Increase machine utilization	N	
	F8-F1	Increase machine utilization will influence/enhance Ability to manufacture a variety of product	N	
	F1-F9	Ability to manufacture a variety of product will influence/enhance Use of reconfigurable machine tool	N	
	F9-F1	Use of reconfigurable machine tool will influence/enhance Ability to manufacture a variety of product	Y	Rapid change in structure to cope up with a variety of products
	F1-F10	Ability to manufacture a variety of product will influence/enhance Manufacturing lead time and setup time reduction	N	
	F10-F1	Manufacturing lead time and setup time reduction will influence/enhance Ability to manufacture a variety of product	N	
	F1-F11	Ability to manufacture a variety of product will influence/enhance Speed of response	N	
	F11-F1	Speed of response will influence/enhance Ability to manufacture a variety of product	N	
	F1-F12	Ability to manufacture a variety of product will influence/enhance Reduced WIP inventories	N	

	F12-F1	Reduced WIP inventories will influence/enhance Ability to manufacture a variety of product	N	
	F1-F13	Ability to manufacture a variety of product will influence/enhance Reduction in material flow	N	
	F13-F1	Reduction in material flow will influence/enhance Ability to manufacture a variety of product	N	
	F1-F14	Ability to manufacture a variety of product will influence/enhance Quality consciousness	N	
	F14-F1	Quality consciousness will influence/enhance Ability to manufacture a variety of product	N	
	F1-F15	Ability to manufacture a variety of product will influence/enhance Reduction in scrap	N	
	F15-F1	Reduction in scrap will influence/enhance Ability to manufacture a variety of product	N	
F2 Capacity to handle new product				
	F2-F3	Capacity to handle new product will influence/enhance Flexibility in the design of Production system	N	
	F3-F2	Flexibility in the design of Production system will influence/enhance Capacity to handle new product	Y	The same equipment can be used for new products
	F2-F4	Capacity to handle new product will influence/enhance Flexible fixturing	N	
	F4-F2	Flexible fixturing will influence/enhance Capacity to handle new product	Y	Handling of new products
	F2-F5	Capacity to handle new product will influence/enhance Combination of operation	N	
	F5-F2	Combination of operation will influence/enhance Capacity to handle new product	N	
	F2-F6	Capacity to handle new product will influence/enhance Automation	N	
	F6-F2	Automation will influence/enhance Capacity to handle new product	Y	Reduce high human skill to product new parts

	F2-F7	Capacity to handle new product will influence/enhance Use of automated material handling devices	N	
	F7-F2	Use of automated material handling devices will influence/enhance Capacity to handle new product	N	
	F2-F8	Capacity to handle new product will influence/enhance Increase machine utilization	N	
	F8-F2	Increase machine utilization will influence/enhance Capacity to handle new product	N	
	F2-F9	Capacity to handle new product will influence/enhance Use of reconfigurable machine tool	N	
	F9-F2	Use of reconfigurable machine tool will influence/enhance Capacity to handle new product	Y	Rapid change in structure to cope up with new parts
	F2-F10	Capacity to handle new product will influence/enhance Manufacturing lead time and setup time reduction	N	
	F10-F2	Manufacturing lead time and setup time reduction will influence/enhance Capacity to handle new product	N	
	F2-F11	Capacity to handle new product will influence/enhance Speed of response	N	
	F11-F2	Speed of response will influence/enhance Capacity to handle new product	N	
	F2-F12	Capacity to handle new product will influence/enhance Reduced WIP inventories	N	
	F12-F2	Reduced WIP inventories will influence/enhance Capacity to handle new product	N	
	F2-F13	Capacity to handle new product will influence/enhance Reduction in material flow	N	
	F13-F2	Reduction in material flow will influence/enhance Capacity to handle new product	N	
	F2-F14	Capacity to handle new product will influence/enhance Quality consciousness	N	
	F14-F2	Quality consciousness will influence/enhance Capacity to handle new product	N	
	F2-F15	Capacity to handle new product will influence/enhance Reduction in scrap	N	

	F15-F2	Reduction in scrap will influence/enhance Capacity to handle new product	N	
F3 Flexibility in the design of production system				
	F3-F4	Flexibility in the design of Production system will influence/enhance Flexible fixturing	N	
	F4-F3	Flexible fixturing will influence/enhance Flexibility in the design of production system	Y	Handling a variety of work part configurations
	F3-F5	Flexibility in the design of production system will influence/enhance Combination of operation	N	
	F5-F3	Combination of operation will influence/enhance Flexibility in the design of production system	N	
	F3-F6	Flexibility in the design of production system will influence/enhance Automation	N	
	F6-F3	Automation will influence/enhance Flexibility in the design of production system	Y	System can operate for extended period of time without human attention
	F3-F7	Flexibility in the design of production system will influence/enhance Use of automated material handling devices	N	
	F7-F3	Use of automated material handling devices will influence/enhance Flexibility in the design of production system	N	
	F3-F8	Flexibility in the design of production system will influence/enhance Increase machine utilization	Y	Similar process can be done on same machine
	F8-F3	Increase machine utilization will influence/enhance Flexibility in the design of production system	N	
	F3-F9	Flexibility in the design of production system will influence/enhance Use of reconfigurable machine tool	N	

	F9-F3	Use of reconfigurable machine tool will influence/enhance Flexibility in the design of production system	Y	Can response for sudden change
	F3-F10	Flexibility in the design of production system will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F3	Manufacturing lead time and set up time reduction will influence/enhance Flexibility in the design of production system	N	
	F3-F11	Flexibility in the design of production system will influence/enhance Speed of response	N	
	F11-F3	Speed of response will influence/enhance Flexibility in the design of production system	N	
	F3-F12	Flexibility in the design of production system will influence/enhance Reduced WIP inventories	N	
	F12-F3	Reduced WIP inventories will influence/enhance Flexibility in the design of production system	N	
	F3-F13	Flexibility in the design of production system will influence/enhance Reduction in material flow	N	
	F13-F3	Reduction in material flow will influence/enhance Flexibility in the design of production system	N	
	F3-F14	Flexibility in the design of production system will influence/enhance Quality consciousness	N	
	F14-F3	Quality consciousness will influence/enhance Flexibility in the design of production system	N	
	F3-F15	Flexibility in the design of production system will influence/enhance Reduction in scrap	N	
	F15-F3	Reduction in scrap will influence/enhance Flexibility in the design of production system	N	
F4 Flexible fixturing				

	F4-F5	Flexible fixturing will influence/enhance Combination of operation	N	
	F5-F4	Combination of operation will influence/enhance Flexible fixturing	N	
	F4-F6	Flexible fixturing will influence/enhance Automation	N	
	F6-F4	Automation will influence/enhance Flexible fixturing	N	
	F4-F7	Flexible fixturing will influence/enhance Use of automated material handling devices	N	
	F7-F4	Use of automated material handling devices will influence/enhance Flexible fixturing	N	
	F4-F8	Flexible fixturing will influence/enhance Increase machine utilization	Y	Can be hold different parts
	F8-F4	Increase machine utilization will influence/enhance Flexible fixturing	N	
	F4-F9	Flexible fixturing will influence/enhance Use of reconfigurable machine tool	N	
	F9-F4	Use of reconfigurable machine tool will influence/enhance Flexible fixturing	N	
	F4-F10	Flexible fixturing will influence/enhance Manufacturing lead time and set up time reduction	Y	Accommodate different parts and Quick response
	F10-F4	Manufacturing lead time and set up time reduction will influence/enhance Flexible fixturing	N	
	F4-F11	Flexible fixturing will influence/enhance Speed of response	Y	Improve production schedule
	F11-F4	Speed of response will influence/enhance Flexible fixturing	N	
	F4-F12	Flexible fixturing will influence/enhance Reduced WIP inventories	Y	Can hold more parts
	F12-F4	Reduced WIP inventories will influence/enhance Flexible fixturing	N	
	F4-F13	Flexible fixturing will influence/enhance Reduction in material flow	N	
	F13-F4	Reduction in material flow will influence/enhance Flexible fixturing	N	
	F4-F14	Flexible fixturing will influence/enhance Quality consciousness	N	
	F14-F4	Quality consciousness will influence/enhance Flexible fixturing	N	
	F4-F15	Flexible fixturing will influence/enhance Reduction in scrap	N	

	F15-F4	Reduction in scrap will influence/enhance Flexible fixturing	N	
F5 Combination of operation				
	F5-F6	Combination of operation will influence/enhance Automation	N	
	F6-F5	Automation will influence/enhance Combination of operation	Y	Combined tool
	F5-F7	Combination of operation will influence/enhance Use of automated material handling devices	N	
	F7-F5	Use of automated material handling devices will influence/enhance Combination of operation	N	
	F5-F8	Combination of operation will influence/enhance Increase machine utilization	Y	Set up time reduced
	F8-F5	Increase machine utilization will influence/enhance Combination of operation	N	
	F5-F9	Combination of operation will influence/enhance Use of reconfigurable machine tool	N	
	F9-F5	Use of reconfigurable machine tool will influence/enhance Combination of operation	Y	Transitivity
	F5-F10	Combination of operation will influence/enhance Manufacturing lead time and set up time reduction	Y	Perform two or more operation with single cutting tool
	F10-F5	Manufacturing lead time and set up time reduction will influence/enhance Combination of operation	N	
	F5-F11	Combination of operation will influence/enhance Speed of response	Y	Reduce lead time
	F11-F5	Speed of response will influence/enhance Combination of operation	N	
	F5-F12	Combination of operation will influence/enhance Reduced WIP inventories	Y	Perform two or more operation on single machine
	F12-F5	Reduced WIP inventories will influence/enhance Combination of operation	N	
	F5-F13	Combination of operation will influence/enhance Reduction in material flow	Y	Reduced WIP

	F13-F5	Reduction in material flow will influence/enhance Combination of operation	N	
	F5-F14	Combination of operation will influence/enhance Quality consciousness	N	
	F14-F5	Quality consciousness will influence/enhance Combination of operation	N	
	F5-F15	Combination of operation will influence/enhance Reduction in scrap	N	
	F15-F5	Reduction in scrap will influence/enhance Combination of operation	N	
F6 Automation				
	F6-F7	Automation will influence/enhance Use of automated material handling devices	Y	For unloading and loading the parts
	F7-F6	Use of automated material handling devices will influence/enhance Automation	N	
	F6-F8	Automation will influence/enhance Increase machine utilization	Y	Proper feeding of parts
	F8-F6	Increase machine utilization will influence/enhance Automation	N	
	F6-F9	Automation will influence/enhance Use of reconfigurable machine tool	N	
	F9-F6	Use of reconfigurable machine tool will influence/enhance Automation	Y	Rapid change in structure
	F6-F10	Automation will influence/enhance Manufacturing lead time and set up time reduction	Y	Fast processing of parts
	F10-F6	Manufacturing lead time and set up time reduction will influence/enhance Automation	N	
	F6-F11	Automation will influence/enhance Speed of response	Y	Reduce human effort
	F11-F6	Speed of response will influence/enhance Automation	N	
	F6-F12	Automation will influence/enhance Reduced WIP inventories	Y	Combination of operation
	F12-F6	Reduced WIP inventories will influence/enhance Automation	N	
	F6-F13	Automation will influence/enhance Reduction in material flow	Y	Different operation on a single machine
	F13-F6	Reduction in material flow will influence/enhance Automation	N	

	F6-F14	Automation will influence/enhance Quality consciousness	Y	Use CNC machine and computer based technology
	F14-F6	Quality consciousness will influence/enhance Automation	N	
	F6-F15	Automation will influence/enhance Reduction in scrap	Y	Precise operation
	F15-F6	Reduction in scrap will influence/enhance Automation	N	
F7 Use of automated material handling devices				
	F7-F8	Use of automated material handling devices will influence/enhance Increase machine utilization	N	
	F8-F7	Increase machine utilization will influence/enhance Use of automated material handling devices	N	
	F7-F9	Use of automated material handling devices will influence/enhance Use of reconfigurable machine tool	N	
	F9-F7	Use of reconfigurable machine tool will influence/enhance Use of automated material handling devices	Y	Transitivity
	F7-F10	Use of automated material handling devices will influence/enhance Manufacturing lead time and set up time reduction	Y	Fast movement of material
	F10-F7	Manufacturing lead time and set up time reduction will influence/enhance Use of automated material handling devices	N	
	F7-F11	Use of automated material handling devices will influence/enhance Speed of response	Y	Fast movement of material
	F11-F7	Speed of response will influence/enhance Use of automated material handling devices	N	
	F7-F12	Use of automated material handling devices will influence/enhance Reduced WIP inventories	Y	Transitivity

	F12-F7	Reduced WIP inventories will influence/enhance Use of automated material handling devices	N	
	F7-F13	Use of automated material handling devices will influence/enhance Reduction in material flow	N	
	F13-F7	Reduction in material flow will influence/enhance Use of automated material handling devices	N	
	F7-F14	Use of automated material handling devices will influence/enhance Quality consciousness	N	
	F14-F7	Quality consciousness will influence/enhance Use of automated material handling devices	N	
	F7-F15	Use of automated material handling devices will influence/enhance Reduction in scrap	N	
	F15-F7	Reduction in scrap will influence/enhance Use of automated material handling devices	N	
F8 Increase machine utilization				
	F8-F9	Increase machine utilization will influence/enhance Use of reconfigurable machine tool	N	
	F9-F8	**Use of reconfigurable machine tool will influence/enhance Increase machine utilization**	**Y**	**Modified according to requirement**
	F8-F10	Increase machine utilization will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F8	Manufacturing lead time and set up time reduction will influence/enhance Increase machine utilization	N	
	F8-F11	Increase machine utilization will influence/enhance Speed of response	N	
	F11-F8	Speed of response will influence/enhance Increase machine utilization	N	
	F8-F12	Increase machine utilization will influence/enhance Reduced WIP inventories	N	

	F12-F8	Reduced WIP inventories will influence/enhance Increase machine utilization	N	
	F8-F13	Increase machine utilization will influence/enhance Reduction in material flow	N	
	F13-F8	Reduction in material flow will influence/enhance Increase machine utilization	N	
	F8-F14	Increase machine utilization will influence/enhance Quality consciousness	N	
	F14-F8	Quality consciousness will influence/enhance Increase machine utilization	N	
	F8-F15	Increase machine utilization will influence/enhance Reduction in scrap	N	
	F15-F8	Reduction in scrap will influence/enhance Increase machine utilization	N	
F9 Use of reconfigurable machine tool				
	F9-F10	Use of reconfigurable machine tool will influence/enhance Manufacturing lead time and set up time reduction	Y	Transitivity
	F10-F9	Manufacturing lead time and set up time reduction will influence/enhance Use of reconfigurable machine tool	N	
	F9-F11	Use of reconfigurable machine tool will influence/enhance Speed of response	Y	Response to sudden changes in market
	F11-F9	Speed of response will influence/enhance Use of reconfigurable machine tool	N	
	F9-F12	**Use of reconfigurable machine tool will influence/enhance Reduced WIP inventories**	**Y**	**Operations can be done with slight modification**
	F12-F9	Reduced WIP inventories will influence/enhance Use of reconfigurable machine tool	N	
	F9-F13	**Use of reconfigurable machine tool will influence/enhance Reduction in material flow**	**Y**	**Less movement of WIP**
	F13-F9	Reduction in material flow will influence/enhance Use of reconfigurable machine tool	N	
	F9-F14	Use of reconfigurable machine tool will influence/enhance Quality consciousness	Y	Transitivity
	F14-F9	Quality consciousness will influence/enhance Use of reconfigurable machine tool	N	

	F9-F15	Use of reconfigurable machine tool will influence/enhance Reduction in scrap	Y	Transitivity
	F15-F9	Reduction in scrap will influence/enhance Use of reconfigurable machine tool	N	
F10 Manufacturing lead time and set up time reduction				
	F10-F11	Manufacturing lead time and set up time reduction will influence/enhance Speed of response	N	
	F11-F10	Speed of response will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F12	Manufacturing lead time and set up time reduction will influence/enhance Reduced WIP inventories	Y	CNC/NC machines which have automatic tool interchange capabilities
	F12-F10	Reduced WIP inventories will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F13	Manufacturing lead time and set up time reduction will influence/enhance Reduction in material flow	N	
	F13-F10	Reduction in material flow will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F14	Manufacturing lead time and set up time reduction will influence/enhance Quality consciousness	N	
	F14-F10	Quality consciousness will influence/enhance Manufacturing lead time and set up time reduction	N	
	F10-F15	Manufacturing lead time and set up time reduction will influence/enhance Reduction in scrap	N	

	F15-F10	Reduction in scrap will influence/enhance Manufacturing lead time and set up time reduction	Y	Minimum Rework
F11 Speed of response				
	F11-F12	Speed of response will influence/enhance Reduced WIP inventories	N	
	F12-F11	Reduced WIP inventories will influence/enhance Speed of response	N	
	F11-F13	Speed of response will influence/enhance Reduction in material flow	N	
	F13-F11	Reduction in material flow will influence/enhance Speed of response	N	
	F11-F14	Speed of response will influence/enhance Quality consciousness	N	
	F14-F11	Quality consciousness will influence/enhance Speed of response	N	
	F11-F15	Speed of response will influence/enhance Reduction in scrap	N	
	F15-F11	Reduction in scrap will influence/enhance Speed of response	Y	Minimum rework
F12 Reduced WIP inventories				
	F12-F13	Reduced WIP inventories will influence/enhance Reduction in material flow	N	
	F13-F12	Reduction in material flow will influence/enhance Reduced WIP inventories	Y	Improved Routing flexibility
	F12-F14	Reduced WIP inventories will influence/enhance Quality consciousness	N	
	F14-F12	Quality consciousness will influence/enhance Reduced WIP inventories	N	
	F12-F15	Reduced WIP inventories will influence/enhance Reduction in scrap	N	
	F15-F12	**Reduction in scrap will influence/enhance Reduced WIP inventories**	**Y**	**Minimum scrap so minimum rework**
F13 Reduction in material flow				
	F13-F14	Reduction in material flow will influence/enhance Quality consciousness	N	
	F14-F13	Quality consciousness will influence/enhance Reduction in material flow	N	
	F13-F15	Reduction in material flow will influence/enhance Reduction in scrap	N	

	F15-F13	Reduction in scrap will influence/enhance Reduction in material flow	Y	Reduced WIP due to less rework
F14 Quality consciousness				
	F14-F15	Quality consciousness will influence/enhance Reduction in scrap	N	
	F15-F14	Reduction in scrap will influence/enhance Quality consciousness	N	

Bold shows significant transitivity

Table 6.2 Initial reachability matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0
F4	1	1	1	1	0	0	0	1	0	1	1	1	0	0	0
F5	0	0	0	0	1	0	0	1	0	1	1	1	1	0	0
F6	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1
F7	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0
F8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F9	1	1	1	0	0	1	0	0	1	0	1	0	0	0	0
F10	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
F11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
F14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
F15	0	0	0	0	0	0	0	0	0	1	1	0	1	0	1

Table 6.3 Reachability matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0
F4	1	1	1	1	0	0	0	1	0	1	1	1	0	0	0
F5	0	0	0	0	1	0	0	1	0	1	1	1	1	0	0
F6	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1
F7	0	0	0	0	0	0	1	0	0	1	1	1*	0	0	0
F8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
F9	1	1	1	0	1*	1	1*	1*	1	1*	1	1*	1*	1*	1*
F10	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0
F11	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
F14	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
F15	0	0	0	0	0	0	0	0	0	1	1	1*	1	0	1

*Transitivity

Table 6.4 Iterations

Variables	Reachability set	Antecedent set	Intersection set	Level
2	2	1,2,3,4,6,9	2	L-1
8	8	3,4,5,6,8,9	8	L-1
11	11	4,5,6,7,9,11,15	11	L-1
12	12	4,5,6,7,9,10,12,13,15	12	L-1
14	14	6,9,14	14	L-1
1	1	1,4,6,9	1	L-2
3	3	3,4,6,9	3	L-2
10	10	4,5,6,7,9,10,15	10	L-2
13	13	5,6,9,13,15	13	L-2
4	4	4	4	L-3
5	5	5,6,9	5	L-3
7	7	6,7,9	7	L-3
15	15	6,9,15	15	L-3
6	6	6,9	6	L-4
9	9	9	9	L-5

Table 6.5 Interaction matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	-	**1**	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	-	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	**1**	-	0	0	0	0	**1**	0	0	0	0	0	0	0
F4	**1**	0	**1**	-	0	0	0	0	0	**1**	**1**	0	0	0	0
F5	0	0	0	0	-	0	0	**1**	0	**1**	**1**	0	**1**	0	0
F6	**1**	0	**1**	0	**1**	-	**1**	0	0	0	0	0	0	**1**	**1**
F7	0	0	0	0	0	0	-	0	0	**1**	**1**	0	0	0	0
F8	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0
F9	**1**	0	**1**	0	0	**1**	0	*1*	-	0	**1**	*1*	*1*	0	0
F10	0	0	0	0	0	0	0	0	0	-	0	**1**	0	0	0
F11	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	**1**	-	0	0
F14	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0
F15	0	0	0	0	0	0	0	0	0	**1**	**1**	*1*	**1**	0	-

Bold direct link

Italic Significant transitive link

Table 6.6 Interpretive matrix

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	-	Develop new product	-	-	-	-	-	-	-	-	-	-	-	-	-
F2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
F3	-	Same equipment can be used for new products	-	-	-	-	-	Similar process can be done on same machine	-	-	-	-	-	-	-
F4	Handling of variety of products	-	Handling a variety of work part configurations	-	-	-	-	-	-	Accommodate different parts and Quick response	Improve production schedule	-	-	-	-
F5	-	-	-	-	-	-	-	Set up time reduced	-	Perform two or more operation with single cutting tool	Reduce lead time	-	Reduced WIP	-	-

F6	Reduce human effort to product complicated parts	-	System can operate for extended period of time without human attention	-	Combined tool	-	For unloading and loading the parts	-	-	-	-	-	-	Use CNC machine and computer based technology	Precise operation
F7	-	-	-	-	-	-	-	-	-	Internal movement of material	Fast movement of material	-	-	-	-
F8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
F9	Rapid change in structure to cope up with variety of products	-	Can response for sudden change	-	-	Rapid change in structure	-	Modified according to requirement	-	-	Response to sudden changes in market	Operations can be done with slight modification	Less movement of WIP	-	-
F10	-	-	-	-	-	-	-	-	-	-	-	CNC/NC machines which have automatic tool interchange capabilities	-	-	-
F11	-	Develop new	-	-	-	-	-	-	-	-	-	-	-	-	-

		product													
F12	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
F13	-	Same equipment can be used for new products	-	-	-	-	-	Similar process can be done on same machine	-	-	-	-	-	-	-
F14	Handling of variety of products	-	Handling a variety of work part configurations	-	-	-	-	-	-	Accommodate different parts and Quick response	Improve production schedule	-	-	-	-

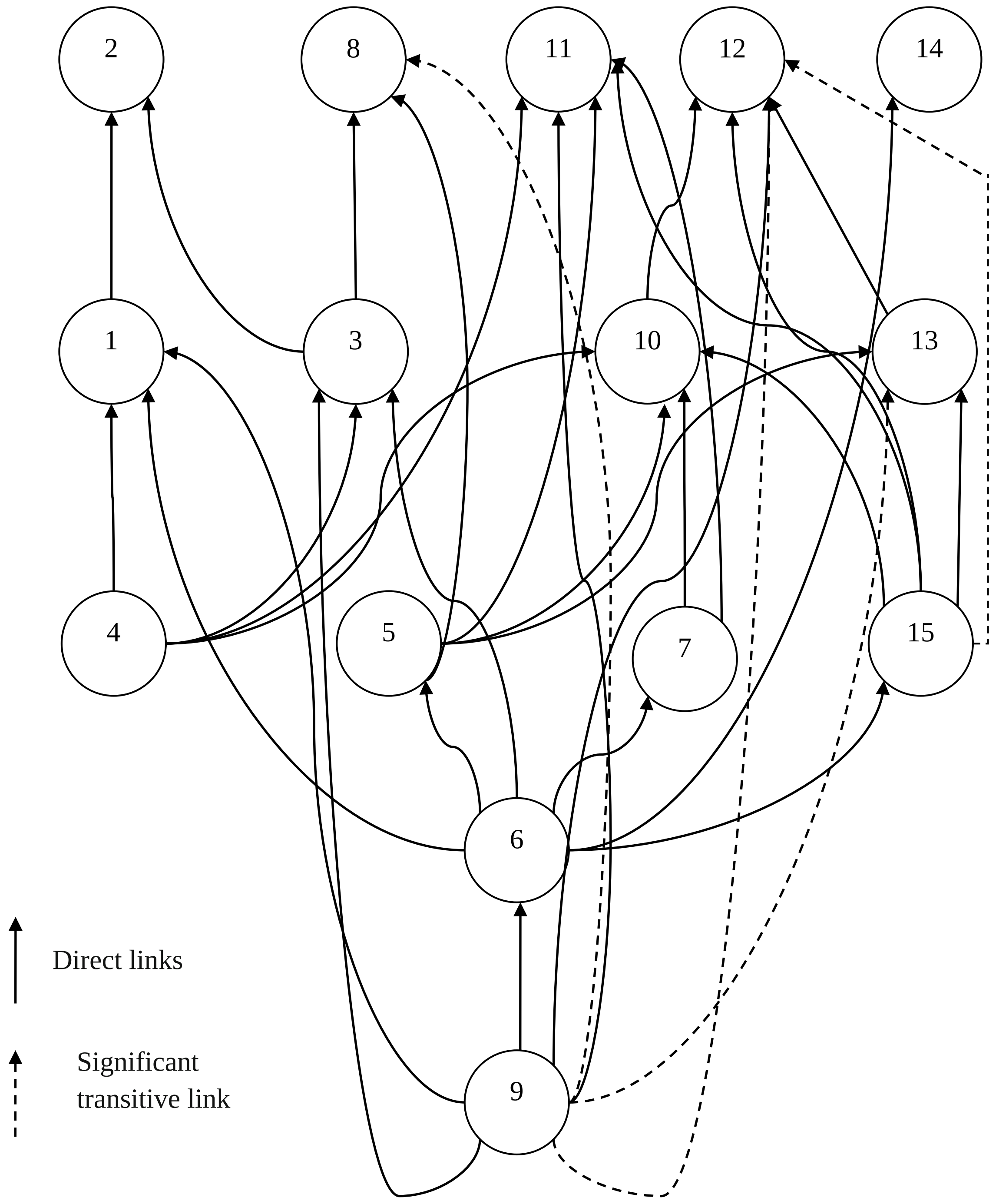

Figure 6.1 Diagraph with significant transitive links

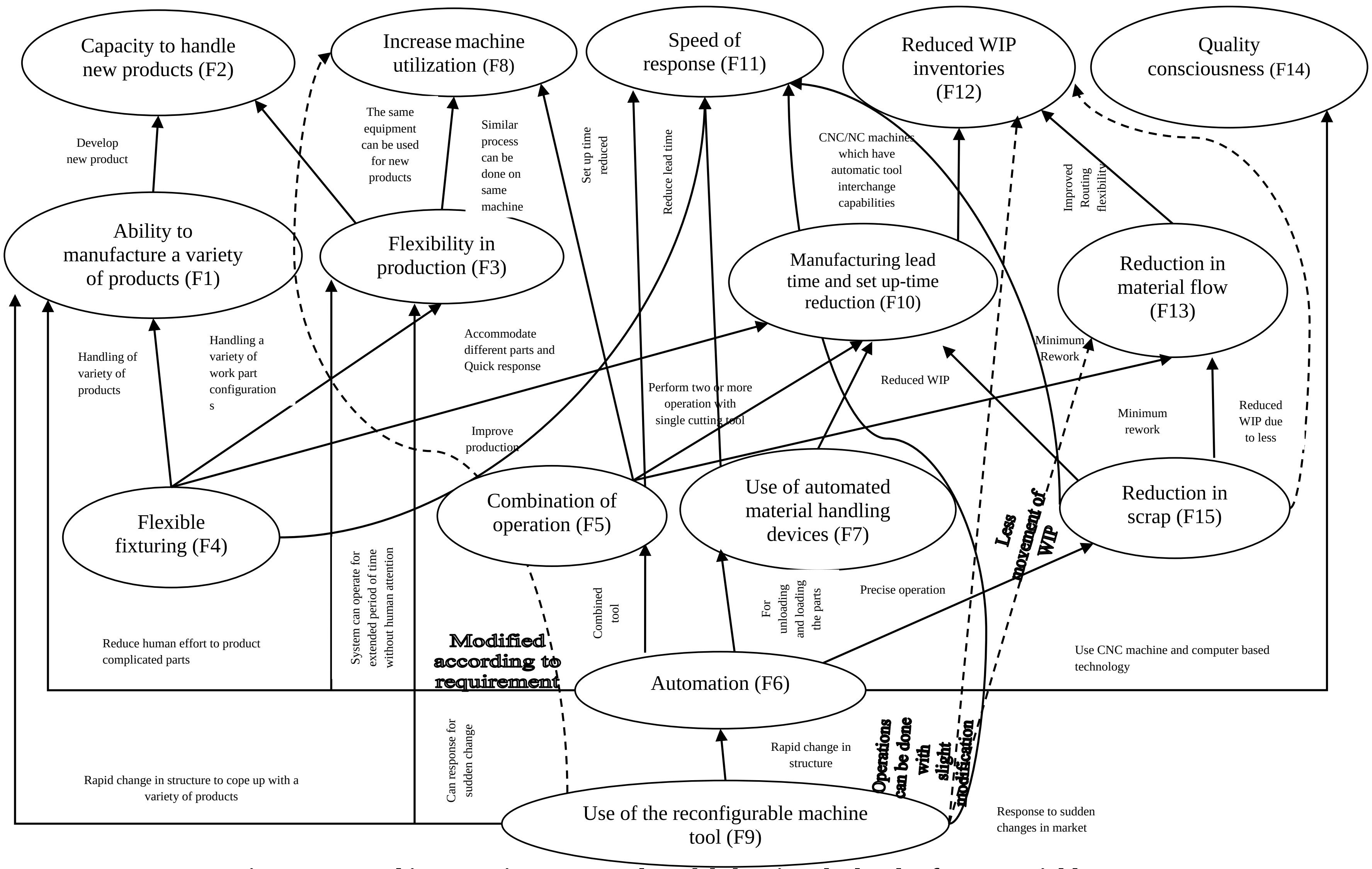

Figure 6.2 Total interpretive structural model showing the levels of FMS variables

6.3 ANALYSIS OF FMS FLEXIBILITY VARIABLES BY TISM FUZZY MICMAC

For developing the TISM model, the relation between two variables is denoted by 0 and 1. If there is no relationship between two variables then it is denoted by 0 and if there is a relationship between two variables then it is denoted by 1. From Table 6.2, the relationship between F1 and F2 having equal importance and denoted by the binary number 1. However, the relationship between these variables cannot be always equal. Some relations may be strong, some may be especially strong and some relations may be better. To overcome this drawback of TISM model, the fuzzy TISM is used for the MICMAC analysis. Fuzzy MICMAC analysis is reviewed from the literature as Dubey and Ali [180] used fuzzy MICMAC in the analyzed relationship among various constructs of FMS and their relationship using ISM and TISM analysis. Gorane and Kant [336] used ISM and fuzzy MICMAC approach for modeling of supply chain management enablers. Gorane and Kant [336] established the relationships among supply chain management enablers by using ISM and find out driving and the dependence power of enablers, using fuzzy MICMAC. Debata et al. [337] evaluated medical tourism enablers with ISM and fuzzy MICMAC. Khan and Haleem [338] developed an integrated model of smart organization enablers by using ISM methodology and fuzzy MICMAC. Khurana et al. [339] have done modeling of information sharing enablers for building trust in the Indian manufacturing industry by an integrated ISM and fuzzy MICMAC approach. Qureshi et al. [340] provided an integrated model using ISM and fuzzy MICMAC to identify and classify various key criteria required for the selection of 3PL service providers. Arya and Abbasi [341] identified and classified the key variables and their role in environmental impact assessment. The TISM Fuzzy MICMAC analysis is carried out as per following procedure.

6.3.1 Binary Direct Relationship Matrix

A binary direct relationship matrix *(*BDRM) is obtained by examining the direct relationship among the variables in the TISM as given in Table 6.2. From Table 6.2, the transitivity is ignored and the diagonal entries are converted to zero. (The BDRM so derived, is shown in Table 6.7).

6.3.2 Development of Fuzzy Direct Relationship Matrix (FDRM)

The conventional MICMAC analysis considers only binary type of relationship; however, this research uses fuzzy set theory (FST) to increase the sensitivity of MICMAC analysis. In fuzzy MICMAC, an additional input of possibility of interaction between the variables is introduced.

Table 6.7 Binary direct relationship matrix

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**	**F14**	**F15**
F1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
F4	1	1	1	0	0	0	0	1	0	1	1	1	0	0	0
F5	0	0	0	0	0	0	0	1	0	1	1	1	1	0	0
F6	1	1	1	0	1	0	1	1	0	1	1	1	1	1	1
F7	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
F8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F9	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0
F10	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
F11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F13	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
F14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F15	0	0	0	0	0	0	0	0	0	1	1	0	1	0	0

The possibility of interaction can be defined by qualitative consideration on 0-1 scale and is given in Table 6.8.

Table 6.8 Possibility of numerical value of the reachability

Possibility of reachability	**No**	**Very low**	**Low**	**Medium**	**High**	**Very high**	**Complete**
Value	0	0.1	0.3	0.5	0.7	0.9	1

Again the opinion of same academician and industry expert as mentioned in Section 3 are considered to rate the relationship between the two variables (Table 6.8). The values of the relationship between two variables are then superimposed on the BDRM to obtain a fuzzy direct relationship matrix (FDRM). The FDRM is given in Table 6.9.

6.3.3 Fuzzy MICMAC Stabilized Matrix

The FDRM is taken as the base to start the process. The matrix is multiplied repeatedly until the hierarchies of the driver power and dependence stabilize. The multiplication process follows the principle of fuzzy matrix multiplication [336, 342].

Fuzzy matrix multiplication is basically a generalization of Boolean matrix multiplication. According to FST, when two fuzzy matrices are multiplied the product matrix is also a fuzzy matrix.

Multiplication follows the given rule: $C = A; B = \max k\ [\min a_{ik}; b_{kj}]$

Where $A = [a_{ik}]$ and $B = [b_{kj}]$

A stabilized matrix is shown in Table 6.10. The driving power of the variables in fuzzy MICMAC is derived by summing the entries of possibilities of interactions in the rows and the dependence of the variables is determined by summing the entries of possibilities of interactions in the columns. The driver power dependence power diagram is shown in Figure 6.3.

Table 6.9 Fuzzy direct relationship matrix

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**	**F14**	**F15**
F1	0	0.5	0	0	0	0	0	0	0	0	0.1	0	0	0	0
F2	0	0	0	0	0	0	0	0	0	0	0.3	0	0	0	0
F3	0.1	0.7	0	0	0.1	0	0	0.5	0.1	0.1	0.1	0	0	0	0.1
F4	0.9	0.7	0.5	0	0.1	0.1	0	0.7	0	0.5	0.7	0.7	0.1	0	0.1
F5	0	0	0	0	0	0	0	0.7	0	0.7	0.7	0.7	0.7	0	0
F6	0.9	0.7	0.5	0.1	0.7	0	0.9	0.7	0.1	0.7	0.7	0.5	0.5	0.5	0.7
F7	0	0	0.1	0	0	0.1	0	0	0	0.7	0.7	0	0	0.1	0
F8	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0	0
F9	0.7	0.7	0.9	0.1	0	0.5	0	0.3	0	0	0.5	0.1	0.3	0	0
F10	0	0	0	0	0	0	0	0	0	0	0.3	0.3	0	0	0
F11	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F12	0	0	0	0	0	0	0	0	0	0.3	0.1	0	0.1	0	0
F13	0	0	0	0	0	0	0	0	0	0.1	0.1	0.3	0	0	0
F14	0	0	0	0	0	0	0	0	0	0	0.1	0	0	0	0
F15	0	0	0	0	0	0	0	0	0	0.5	0.7	0.3	0.7	0.1	0

Table 6.10 Fuzzy MICMAC stabilized matrix

	F1	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**	**F10**	**F11**	**F12**	**F13**	**F14**	**F15**	**SUM**
F1	0.1	0.1	0	0	0	0	0	0	0	0	0.1	0	0	0	0	0.3
F2	0.1	0.1	0	0	0	0	0	0	0	0	0.1	0	0	0	0	0.3
F3	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	1.5
F4	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.3	0.3	0.1	0.1	0.1	2.1
F5	0.1	0.1	0	0	0	0	0	0	0	0.3	0.3	0.3	0.1	0	0	1.2
F6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.3	0.3	0.1	0.1	0.1	2.1
F7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.3	0.1	0.1	0.1	1.9
F8	0.1	0.1	0	0	0	0	0	0	0	0.1	0.1	0.1	0.1	0	0	0.6
F9	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.3	0.3	0.3	0.1	0.1	0.1	2.1
F10	0.1	0.1	0	0	0	0	0	0	0	0.3	0.1	0.1	0.1	0	0	0.8
F11	0.1	0.1	0	0	0	0	0	0	0	0	0.1	0	0	0	0	0.3
F12	0.1	0.1	0	0	0	0	0	0	0	0.1	0.3	0.3	0.1	0	0	1
F13	0.1	0.1	0	0	0	0	0	0	0	0.3	0.1	0.1	0.1	0	0	0.8
F14	0.1	0.1	0	0	0	0	0	0	0	0	0.1	0	0	0	0	0.3
F15	0.1	0.1	0	0	0	0	0	0	0	0.3	0.3	0.3	0.1	0	0	1.2
SUM	1.5	1.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	2.5	2.9	2.5	1.1	0.5	0.5	

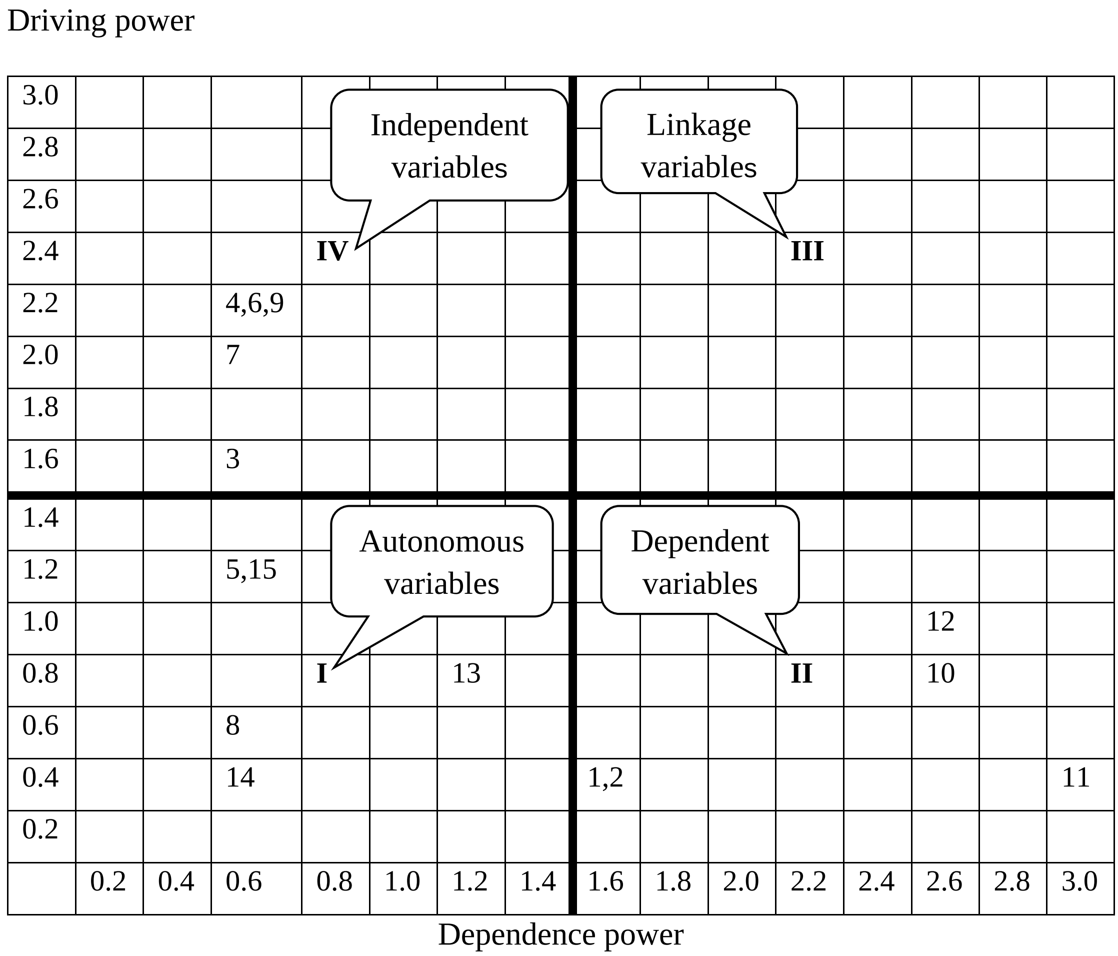

Figure 6.3 Clusters of variables affecting the flexibility in FMS

6.4 EVALUATION OF VARIABLES BY EFA AND CFA

The analysis proceeds in two steps. EFA is performed by SPSS software and CFA is performed by AMOS software.

Analysis of variable takes place as given below:

i. 15 variables which affect flexibility of FMS are identified through literature and expert opinion. After this, a survey takes place to get data. Sample size 300 is collected from surveys. Data set 300 is good to carry on the analysis.

ii. Reliability test is to perform to check relatively internal consistency of variables through to measure cronbach's Alpha. The value of cronbach's Alpha is 0.807 good, i.e. more than 0.7. Table 6.11 shows the reliability statistics (cronbach's alpha value).

iii. KMO and Bartlett’s test is performed and the result of the test is shown in Table 6.12. From the Table 6.12, it is observed that the KMO value is 0.847and the significance value is 0.000. Therefore, the data are appropriate to proceed with factor analysis.

iv. Table 6.13 shows the result of communalities. From the Table 6.13, it is to be noted most of the variables have their communalities above 0.5. Only variable 6 and variable 10 have 0.486 and 0.438 respectively.

v. According to communalities result, fifteen variables or items are taken.

vi. Four components are extracted which have an eigenvalue greater than one and explain the total variance 54.705 which is acceptable i.e. shown in Table 6.14. According to scree plot, four components extracted with three items or observed variables per factor, which has a significant loading more than 0.30. Scree plot is shown in Figure 6.4.

vii. Four components have taken from extract initial factors as shown in Table 6.15.

viii. Rotation of the component matrix with Varimax with Kaiser Normalization is shown in Table 6.16.

Table 6.11 Cronbach's Alpha

Case Processing Summary			
		N	**%**
Cases	Valid	300	100.0
	Excluded[a]	0	.0
	Total	300	100.0
a. List wise deletion based on all variables in the procedure.			

Reliability Statistics		
Cronbach's Alpha	**Cronbach's Alpha Based on Standardized Items**	**N of Items**
0.807	0.808	15

Table 6.12 KMO and Bartlett's test

Test		Values
Kaiser-Meyer-Olkin Measure of sampling adequacy		0.847
	Approx. Chi-Square	1014.114
Bartlett's Test of sphericity	df	105
	Sig.	0.000

Table 6.13 Communalities

Variables	Initial	Extraction
var1	1.000	0.674
var2	1.000	0.563
var3	1.000	0.585
var4	1.000	0.552
var5	1.000	0.547
var6	1.000	0.486
var7	1.000	0.507
var8	1.000	0.511
var9	1.000	0.586
var10	1.000	0.438
var11	1.000	0.527
var12	1.000	0.576
var13	1.000	0.606
var14	1.000	0.520
var15	1.000	0.526

ix. Finally, four components taken after Rotation of the component matrix with Varimax with Kaiser Normalization. No change is taking place.

x. Based on the exploratory factor analysis results, the variables were classified into four suitably named dimensions. The dimensions and the corresponding variables are shown in Table. 6.17.

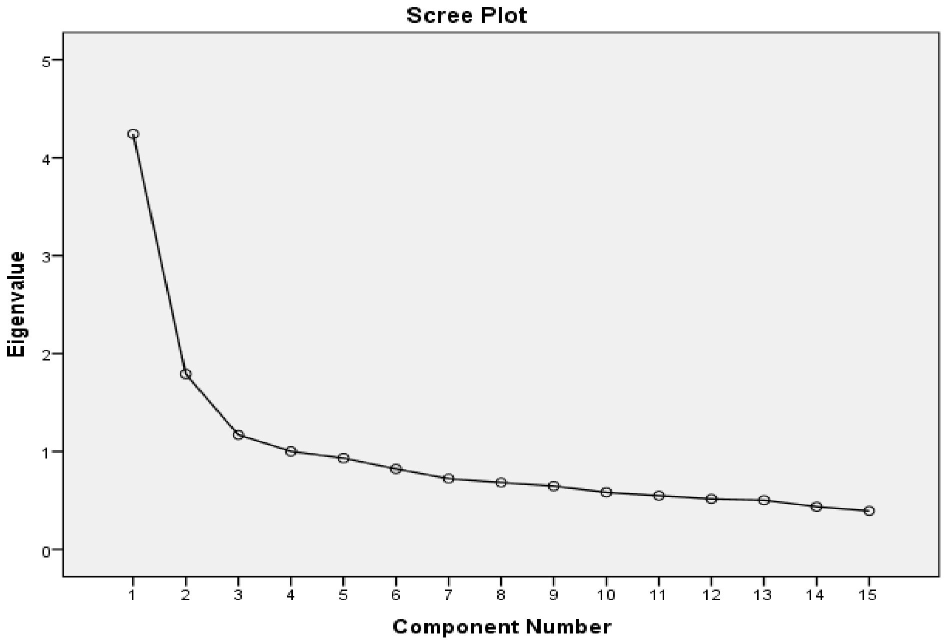

Figure 6.4. Scree plot

Table 6.14 Total variance explained

No.	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	**% of Variance**	**Cumulati-ve %**	**Total**	**% of Variance**	**Cumulati-ve %**	**Total**	**% of Variance**	**Cumulative %**
1	4.243	28.283	28.283	4.243	28.283	28.283	2.558	17.056	17.056
2	1.791	11.943	40.227	1.791	11.943	40.227	2.147	14.314	31.370
3	1.170	7.800	48.026	1.170	7.800	48.026	1.812	12.081	43.450
4	1.002	6.678	54.705	1.002	6.678	**54.705**	1.688	11.254	54.705
5	.933	6.220	60.925						
6	.823	5.485	66.410						
7	.723	4.822	71.231						
8	.683	4.553	75.785						
9	.647	4.314	80.098						
10	.584	3.893	83.991						
11	.550	3.666	87.657						
12	.517	3.444	91.102						
13	.503	3.356	94.457						
14	.437	2.914	97.371						
15	.394	2.629	100.000						

Extraction Method: Principal Component Analysis.

Table 6.15 Component matrix

Component matrix[a]				
	Component			
	1	2	3	4
var1	.206	.586	.326	.427
var2	.493	.495	.225	.158
var3	.597	.381	.067	-.283
var4	.626	.129	-.315	-.212
var5	.663	.241	.095	-.199
var6	.554	.238	.211	.280
var7	.627	.013	-.337	.019
var8	.392	.220	-.554	-.042
var9	.342	.004	.381	-.569
var10	.454	.111	-.386	.268
var11	.641	-.205	.168	-.214
var12	.591	-.439	-.164	.087
var13	.592	-.461	.137	.154
var14	.479	-.494	.174	.127
var15	.504	-.418	.193	.246
Extraction Method: Principal Component Analysis.				
a. 4 components extracted.				

Table 6.16 Rotated component matrix

	Component			
	1	**2**	**3**	**4**
var1	-.104	-.027	.813	-.046
var2	.030	.197	.680	.249
var3	.012	.362	.350	.575
var4	.149	.631	.075	.356
var5	.182	.346	.341	.527
var6	.284	.185	.594	.134
var7	.296	.622	.111	.145
var8	-.057	.711	.032	.042
var9	.116	-.108	-.003	.749
var10	.184	.583	.217	-.135
var11	.502	.179	.068	.488
var12	.656	.366	-.086	.069
var13	.757	.119	.062	.120
var14	.714	.019	.001	.100
var15	.712	.033	.128	.034
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.				
a. Rotation converged in 5 iterations.				

Table 6.17 Factors/Dimensions in flexible manufacturing system

Sr. No.	Dimensions	Variables
1	Production flexibility (PD F)	Combination of operation Reduced WIP inventories Reduction in material flow Use of reconfigurable machine tool Reduction in scrap
2	Machine flexibility (M F)	Increase machine utilization Ability to manufacture a variety of product Manufacturing lead time and setup time reduction Quality consciousness
3	Product flexibility (P F)	Capacity to handle new product Flexible fixturing Flexibility in the design of production system
4	Volume flexibility (V F)	Automation Use of automated material handling devices Speed of response

The analysis revealed the following dimensions:

a) Production flexibility: The range or universe of part types that can be produced without the need to purchase new equipment. The range of part types that the FMS can produce. This flexibility is measured by the level of existing technology.

b) Machine flexibility: It is defined as the capability to adapt a given machine (Workstation) in the system to a wide range of production operations and part styles. The greater the range of operations and part styles, the greater the machine flexibility.

c) Product flexibility: The ability to change over to produce a new (set of) product(s) very economically and quickly. Product flexibility relates to the ease of new-product introduction and product modification.

d) Volume flexibility: The ability to economically produce parts in high and low total quantities of production, given the fixed investment in the system. A higher level of automation increases this flexibility, partly as a result of both lower machine setup costs and lower variable costs.

xi. After identifying four clear factors through EFA (principal components analysis), the next stage is to confirm the factor structure. Structural equation modeling (SEM) using AMOS was used to perform the first-order confirmatory factor analysis on the proposed measurement model in Figure 6.5. The model consists of the first-order four-factor structure, (production flexibility, machine flexibility, product flexibility and volume flexibility) with the measurement variables loading in accordance with the pattern revealed in the exploratory factor analysis on a sample.

xii. The model indicated an acceptable model fit of the data

CMIN (χ2) = 154.638, DF =84,

p=. 000 < 0.05;

CMIN/DF (χ 2/ DF) =1. 841 < 2;

GFI = 0.937 > 0.9;

AGFI=0. 909> 0.9;

RMR = 0. 03 < 0.05;

RMSEA = 0.053< 0.08

NFI = 0.902 > 0.9;

CFI = 0.924> 0.9;

TLI = 0.905> 0.9; and

IFI = 0.926> 0.9.

xiii. SEM model conforms to the first-order four-factor structure (production flexibility, machine flexibility, product flexibility and volume flexibility) of the flexible manufacturing system.

6.5 VALUATION OF INTENSITY OF VARIABLES AFFECTING FLEXIBILITY

The analysis proceeds after EFA analysis. With the help of SPSS software factors extracted from the variables and graph theory matrix approach is performed to evaluating the intensity of variables affecting flexibility in FMS. Analysis of variable takes place as given below

i. After identifying four clear factors through EFA (principal components analysis), A digraph is developed for these four factors as shown in Figure 6.6 and the SSIM developed as given in Table 2.2.

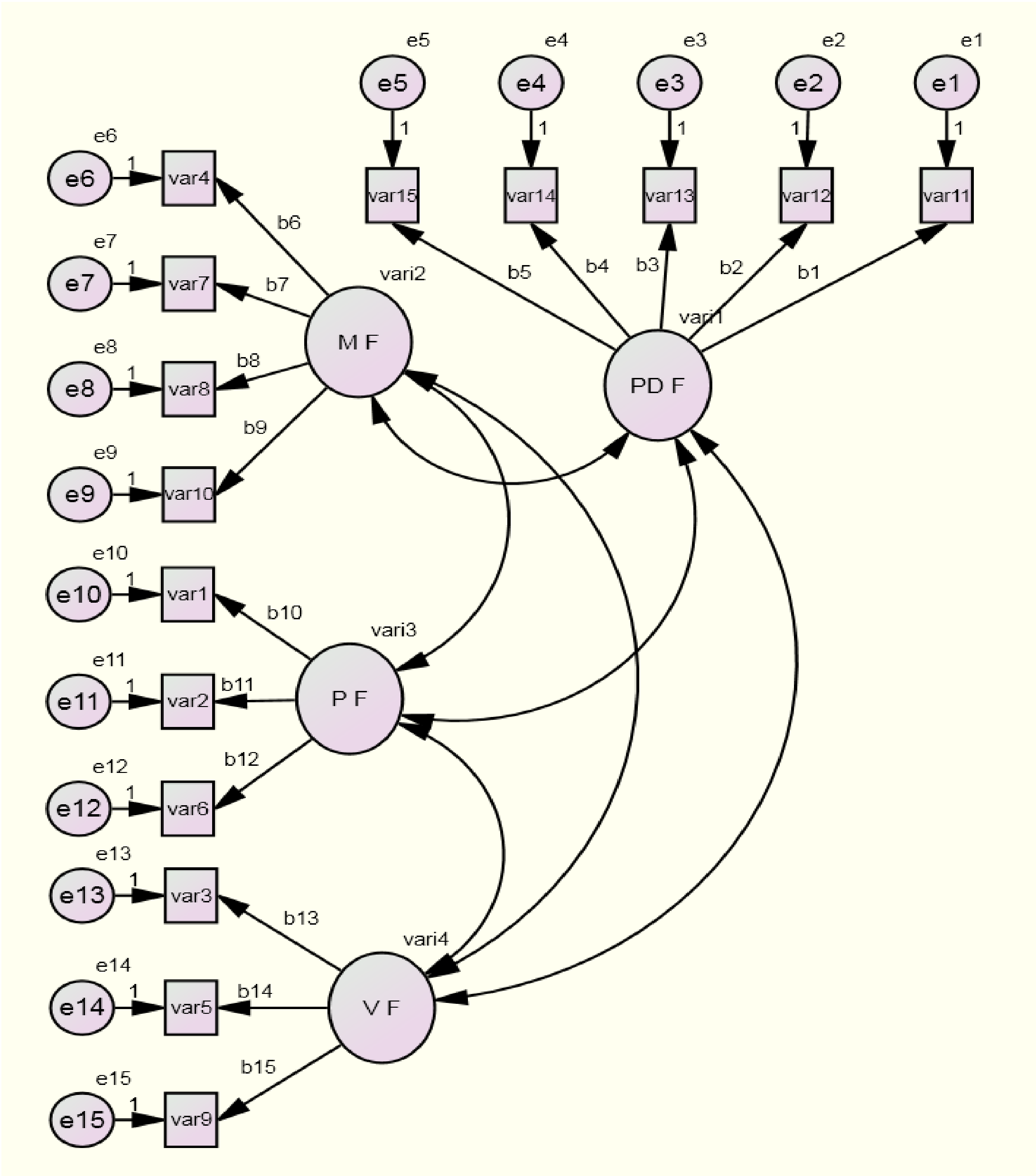

Figure 6.5. Path diagram of SEM for CFA

ii. The digraphs for each category of factors are developed considering the variables that affect the particular category of factors. The nodes in the digraph represent the variables and their mutual interaction is depicted by different edges.

iii. The inheritance of variables and their interdependencies discuss with the experts as per Tables 2.2 and 2.3 and the FMS flexibility' matrix for each category is written as:

$$\begin{array}{c} \\ F_1^* = \\ \\ \end{array} \begin{array}{cccccc} F_{11} & F_{12} & F_{13} & F_{14} & F_{15} & \text{variable} \end{array}$$

$$F_1^* = \begin{pmatrix} 8 & 3 & 4 & 3 & 4 \\ 0 & 7 & 3 & 0 & 0 \\ 0 & 0 & 8 & 0 & 0 \\ 4 & 3 & 3 & 9 & 3 \\ 0 & 3 & 4 & 0 & 8 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \\ F_{15} \end{array} \tag{6.1}$$

$$\begin{array}{ccccc} F_{21} & F_{22} & F_{23} & F_{24} & \text{variable} \end{array}$$

$$F_2^* = \begin{pmatrix} 9 & 0 & 3 & 0 \\ 4 & 7 & 0 & 0 \\ 5 & 3 & 9 & 0 \\ 0 & 2 & 3 & 6 \end{pmatrix} \begin{array}{c} F_{21} \\ F_{22} \\ F_{23} \\ F_{24} \end{array} \tag{6.2}$$

$$\begin{array}{cccc} F_{31} & F_{32} & F_{33} & \text{variable} \end{array}$$

$$F_3^* = \begin{pmatrix} 8 & 0 & 0 \\ 4 & 9 & 2 \\ 4 & 3 & 7 \end{pmatrix} \begin{array}{c} F_{31} \\ F_{32} \\ F_{33} \end{array} \tag{6.3}$$

iv. In the present work, the value of the permanent function for each category is calculated by a computer program which is developed in C^{++} language. The value of permanent function for each category is as follows:

Per F_1^* = 37632, Per F_2^* = 4248, Per F_3^* = 552, Per F_4^* = 808

v. The FMS flexibility' matrix at the system level is developed as per equation 2.3. In this matrix, the values of the diagonal elements are taken from the sub-system level:

F_1 = Per F_1^* = 37632; F_2 = Per F_2^* = 4248; F_3 = Per F_3^* = 552; F_4 = Per F_4^* = 808

$$\begin{array}{ccccc} F_1 & F_2 & F_3 & F_4 & \text{variable} \end{array}$$

$$F^* = \begin{pmatrix} 37632 & 4 & 4 & 5 \\ 4 & 4248 & 3 & 5 \\ 4 & 3 & 552 & 4 \\ 3 & 3 & 3 & 808 \end{pmatrix} \begin{array}{c} F_1 \\ F_2 \\ F_3 \\ F_4 \end{array}$$

vi. Value of permanent function of the system is evaluated. The value of Per F* at the system level of above matrix is 7.13×10^{13}, which indicates the FMS flexibility index for the variables considered. It is suggested to find hypothetical best and hypothetical worst value of the FMS flexibility index. The FMS flexibility index is at its best when the inheritance of all its factors is at its best. Since, inheritance of factors has been evaluated considering variables and applying graph theoretic approach at the subsystem level, it is evident that the FMS flexibility index is at its best when the inheritance of variables is at its best. At the subsystem level, maximum value of per F_1^* is obtained when inheritance of all the sub-factors are maximized, i.e., value taken from Table 2.2 is 10. Thus, FMS flexibility' matrix for this category is rewritten as :

$$
\begin{array}{cc}
 & \begin{array}{ccccc} F_{11} & F_{12} & F_{13} & F_{14} & F_{15} \end{array} \quad \text{variable} \\
F_1^* = & \begin{pmatrix} 10 & 3 & 4 & 3 & 4 \\ 0 & 10 & 3 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 \\ 4 & 3 & 3 & 10 & 3 \\ 0 & 3 & 4 & 0 & 10 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \\ F_{15} \end{array}
\end{array}
$$

The maximum value of per F_1^* for the first category is 112000.

Similarly, the FMS flexibility index is at its worst when the inheritance of all its factors and variables is at its worst. This is the case when inheritance of the entire variables is minimum, i.e. value taken from Table 2.2 is 1. Thus, FMS flexibility matrix for this category is rewritten as:

$$
\begin{array}{cc}
 & \begin{array}{ccccc} F_{11} & F_{12} & F_{13} & F_{14} & F_{15} \end{array} \quad \text{variable} \\
F_1^* = & \begin{pmatrix} 1 & 3 & 4 & 3 & 4 \\ 0 & 1 & 3 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 4 & 3 & 3 & 1 & 3 \\ 0 & 3 & 4 & 0 & 1 \end{pmatrix} \begin{array}{c} F_{11} \\ F_{12} \\ F_{13} \\ F_{14} \\ F_{15} \end{array}
\end{array}
$$

The minimum value of per F_1^* for the first category is 13.

Similarly, maximum and minimum values for each subsystem are evaluated and different values of permanent of subsystem matrices are summarized in Table 6.18. The maximum value of the FMS flexibility index at system level is evaluated by considering maximum values of all subsystems and minimum value of the FMS flexibility index at system level is evaluated by considering minimum values of all subsystems. The value of per F indicates the value of the FMS flexibility index. Thus, the maximum and minimum value of FMS flexibility index indicates the range within which it can vary. Experts can use this range to decide a threshold value for flexibility in FMS.

Table 6.18 The maximum and minimum values of the permanent function

Permanent function at the Subsystem/system level	***Maximum value***	***Minimum value***	***Current value***
Per F_1^*	112000	13	37632
Per F_2^*	11860	52	4248
Per F_3^*	1060	7	552
Per F_4^*	1444	121	808
Per F^*	20.33×10^{13}	736698	7.13×10^{13}

6.6 RESULT AND DISCUSSION

The main objective of this chapter is to create a model of flexibility factors to assist in enhancing the flexibility of the manufacturing system. In this chapter TISM-based model has been developed to analyze the interactions among different FMS variables. The managers can get an insight of these variables and understand their relative importance and interdependence. The driver power dependence matrix gives some valuable insights about the relative importance and interdependence among the FMS variables. The results of the TISM are in five levels discuss below as:

Capacity to handle new products (2), increase machine utilization (8), speed of response (11), reduced WIP inventories (12) and quality consciousness (14) are at first level. Ability to manufacture a variety of products (1), flexibility in production (3), manufacturing lead time and set up-time reduction (10) and reduction in material flow (13) are at second level. Flexible fixturing (4), combination of operation (5), use of automated material handling devices (7), and reduction in scrap (15) are at third level. Automation (6) at fourth level and use of the reconfigurable machine tool (7) at fifth level.

The second objective of this chapter is to analyze the driving and the dependence power of the flexibility variables that influence the FMS in an organization through TISM fuzzy MICMAC analysis. Through fuzzy MICMAC analysis the variables are classified into four clusters (Figure 6.3). The first cluster consists of the autonomous variables which have weak driver power and weak dependence. These variables are relatively disconnected from the system, with which they have only a few links, which may be strong. A second cluster consists of the dependent variables that have weak driving power but strong dependence. Third cluster has the linkage variables that have strong driving power and also strong dependence. These variables are unstable and any action of these variables will have an effect on others and also a feedback on themselves. The fourth cluster includes the independent variables having strong driving power but weak dependence. The analysis of fuzzy MICMAC is as follows.

The driver power dependence Figure 6.3 indicates that there are five autonomous variables i.e. combination of operation (variable 5), increase machine utilization (variable 8), reduction in material flow (variable 13); quality consciousness (variable 14); reduction in scrap (variable 15) affecting the flexibility of FMS. Autonomous variables are weak drivers and weak dependents and do not have much influence on the system. Dependent variables have ability to manufacture a variety of products (variable 1), capacity to handle new product (variable 2), manufacturing lead time and set up-time reduction (variable 10), speed of response (variable 11) and reduced WIP inventories (variable 12). These variables are weak drivers, but strongly depend on one another. The management should therefore accord high priority in tackling these variables. The driving-dependence power diagram (Figure 6.3) indicates that there are no linkage variables. They have strong driving power as well as high dependencies. These variables can create a positive environment regarding the flexibility affecting in FMS. It is further observed from figure 6.3 that variables flexibility in production (variable 3); flexible fixturing (variable 4); automation (variable 6); use of automated material handling devices (variable 7); and use of reconfigurable machine tool (variable 9) are independent variables, i.e. they have strong driving power and less dependent on other variables. Therefore, these are strong drivers and may be treated as the root causes of all the variables. These variables may be treated as the 'key variables' for affecting the flexibility in FMS.

Four components are extracted, which have an eigenvalue greater than one and explain the total variance 54.705 and according to scree plot, which has a significant loading more than 0.30. As seen from the data analysis, four factors are extracted in analysis; production flexibility, machine flexibility, product flexibility and volume flexibility.

The SEM results of the analysis were examined to determine the degree of fit of the model. There is not a clear single measure for testing model fit, thus several measures should be considered together to reach a conclusion.

Analysis of the model resulted in a chi-square CMIN ($\chi 2$) = 154.638, DF =84, p= 0. 000, CMIN/DF (χ 2/ DF) =1. 841 < 2 which indicates that the data fit the model. Other indicators also confirmed the good fit. Goodness-of-Fit index (GFI) of 0.937 indicates that the model fits very well because a GFI of 1.0 indicates a perfect fit. The root mean square error of approximation (RMSEA) value of 0.05 is below the acceptable limit of 0.08 and implies a good model fit. The adjusted goodness-of-fit index (AGFI) value is 0.909 and is close to its recommended value of 0.9. Root mean square residual (RMR) value is 0. 03 i.e. below the acceptable limit of 0.05. Normed-fit index (NFI) is 0.902; Comparative Fit Index (CFI) is 0.924; Non-normed Fit Index (NNFI, also known as the Tucker-Lewis Index or TLI) is 0.905; and Incremental fit Index (IFI) is 0.926. The values of NFI, CFI, TLI and the IFI are indicating good model fits because these values are above the recommended value of 0.9. Structural equation modeling (SEM) using AMOS was used to perform the first-order four-factor structure (production flexibility, machine flexibility, product flexibility and volume flexibility) with the measurement variables loading. Overall, the fit indices indicate that the model produces the covariance matrix as well. Using all these criteria uniformly shows the overall adequacy of factor solutions. The proposed work has very high industrial relevance in its application like extraction of factors and then confirmation of these factors. Hence, with the knowledge of the intensity of various variables, some precautions and good decisions may be taken by the managers to handle these variables which affect flexibility of FMS. In advance, industries can know the strength of various variables which affect flexibility of FMS and steps can be taken to increase the flexibility. As flexibility increases performance of the FMS increases.

The results of the analysis have been examined to determine the intensity of variables affecting flexibility in FMS by graph theory and matrix approach (GTMA). GTMA methodology helps in the calculation of intensity of different variables. Hence, with the knowledge of the intensity of various variables, some precautions and good decisions may be taken by the managers to handle these variables which affect flexibility of FMS. It was observed in the present work that production flexibility has the maximum intensity. The future direction of this research is improving the system as the current value of flexibility index of this work is 7.13×10^{13} which is below than the maximum value of 20.33×10^{13}. This value in itself speaks of the scope of improvement in the variables to increase the flexibility in FMS. Table 6.18 shows the results of system or sub-system levels.

6.7 CONCLUSIONS

In this chapter, an attempt has been made to identify the major variables of flexibility in FMS environment. Manufacturing companies can take quick decisions regarding the flexibility variables of FMS. The result of this study shows that all the considered variables are very important for FMS flexibility.

1. A logical procedure based on the TISM, SEM and GTMA together is suggested which helps to focus on flexibility of flexible manufacturing system among a large number of available variables.
2. There are four factors like production flexibility, machine flexibility, product flexibility and volume flexibility which affect mainly flexibility of FMS.
3. The SEM analysis provides flexibility in determining the relationships between variables. Direct as well as indirect relationship between variables can be specified and estimated.
4. The proposed flexible manufacturing system flexibility index evaluates and ranks the flexibility variables. This leads to the selections of a suitable flexibility variables of flexible manufacturing system for any application.

CHAPTER VII

MODELING AND RANKING OF TYPES OF FLEXIBILITY IN FMS

7.1 INTRODUCTION

FMS consists innumerable programmable and computerized machine tools connected by an automatic material handling system like robots and automatic guided vehicles (AGVs) and automatic storage and retrieval system (AS/RS) that can process simultaneously medium-sized volumes of the different parts [1]. FMS is capable of producing a variety of part types and handling flexible routing of parts instead of running parts in a straight line through machines [2]. FMS characterizes organizational culture, organizational strategy, organizational size and structure and management experience and style interact to determine the tendency of the organization to adopt FMS [8]. FMS are crucial for modern manufacturing to enhance productivity involved with high product proliferation [302].

The word 'flexibility' comes from the Latin word meaning 'bendable'. Stockton and Bateman [343] have suggested flexibility is the ability of a manufacturing system to:

- Change between existing part types
- Change the operation routes of components

From this chapter the following papers have been published.

V. Jain and T. Raj, "A hybrid approach using ISM and modified TOPSIS for the evaluation of flexibility in FMS," *International Journal of Industrial and Systems Engineering,* vol. 19, pp. 389–406, 2015.

V. Jain and T. Raj, "Evaluation of flexibility in FMS by VIKOR methodology," *International Journal of Industrial and Systems Engineering,* vol. 18, pp. 483-498, 2014.

V. Jain and T. Raj, "Ranking of Flexibility in Flexible Manufacturing System by Using a Combined Multiple Attribute Decision Making Method," *Global Journal of Flexible Systems Management,* vol. 14, pp. 125-141, 2013.

- Change the operations required to process a component
- Change production volumes, i.e. either expansion or contraction
- Add new part types
- Add new processes to the system.

The flexibility of a manufacturing system can be defined as the ability of the system to respond to changes either in the environment or in the system itself [344]. Flexibility in manufacturing is defined as the ability to change or react with little penalty in time, effort, cost or performance [323]. Flexibility is one of the critical dimensions of enhancing the competitiveness of organizations. Flexibility is one of the most sought-after properties in modern manufacturing systems [345]. According to Chen and Chung [346] flexibility refers to the ability of the manufacturing system to respond quickly to changes in part demand and part mix. Das [49] has defined it as the ability of a system or facility to adjust to changes in its internal or external environment. Several researchers have classified flexibility under different categories. Park and Son [347] and Son and Park [348] have identified four types of flexibility—process, product, demand and equipment flexibility. Browne et al. [94] have proposed eight types of flexibilities including machine flexibility, routing and expansion, etc., Azzone and Bertele [349] have suggested six types of flexibility: process, product, production, routing, expansion and volume flexibility. Sethi and Sethi [89] have identified eleven types of flexibility: product, process, program, production, volume, routing, expansion, operation, machine, material handling and market flexibility.

From literature fifteen flexibilities and fifteen variables which affect the flexibility in a flexible manufacturing system have been identified. The ranking of these flexibilities is analyzed by combined multiple attribute decision making methods, i.e. AHP, TOPSIS, Modified TOPSIS Improved PROMETHEE and VIKOR.

The proposed methods easily handle qualitative criteria involved in the decision-making process. Multi-objective techniques seem to be an appropriate tool for ranking or selecting one or more alternatives from a set of the available options based on the multiple objectives.

The purpose of the ranking of flexibility is to accord a proper attention of researchers and production managers to focus the flexibility in FMS. Olhager [66] has proved that flexibility is usually considered to be the best step towards manufacturing excellence. The impact of flexibility and its contributing means on increasing profitability of the manufacturing system.

The main objectives of this chapter are as follows:

- To identify different types of flexibility and variables affecting these flexibilities in FMS.
- To establish relationship among these flexibilities by using ISM
- To find the ranking of different types of flexibility based on variables by using combined multiple attribute decision making methods, i.e. AHP, TOPSIS, Modified TOPSIS Improved PROMETHEE and VIKOR.

On the basis of the exhaustive literature review and discussions with the industry experts and the academia, 15 flexibilities and 15 variables were identified and discussed in chapter 2 in detailed. These flexibilities and variables are given below:

The fifteen flexibilities are as given below:

1. Machine flexibility
2. Routing flexibility
3. Process flexibility
4. Product flexibility
5. Volume flexibility
6. Material handling flexibility
7. Operation flexibility
8. Expansion flexibility
9. Production flexibility
10. Programme flexibility
11. Market flexibility
12. Response flexibility
13. Product mix flexibility
14. Size flexibility
15. Range flexibility

The fifteen variables are as given below:

1. Ability to manufacture a variety of products
2. Capacity to handle new products
3. Flexibility in production
4. Flexible fixturing
5. Combination of operation
6. Automation
7. Use of automated material handling devices
8. Increase machine utilization
9. Use of the reconfigurable machine tool
10. Manufacturing lead time and set up-time reduction
11. Speed of response
12. Reduced WIP inventories
13. Reduction in material flow
14. Quality consciousness
15. Reduction in scrap

After identification of different types of flexibilities of FMS, an ISM model is prepared which is discussed in the following sections:

7.2 ISM MODEL FOR FLEXIBILITIES OF FMS

In this section, the development of the model using ISM is described below.

7.2.1 Development of Structural Self-Interaction Matrix (SSIM)

ISM methodology suggests the use of expert opinions in developing the contextual relationship between the variables. Experts, both from industry and academia, have been consulted in identifying and developing the contextual relationship between the flexibilities.

The following four symbols have been used to denote the direction of the relationship between two flexibilities (i and j):

V is used for the relation from flexibility i to j (i.e. if flexibility i influence or reach to flexibility j)

A is used for the relation from flexibility j to i (i.e. if flexibility j reach to flexibility i)

X is used for both direction relations (i.e. if flexibility i and j reach to each other)

O is used for no relation between two flexibilities (i.e. if flexibility i and j are unrelated). Based on the contextual relationship, the SSIM is developed and it is presented in Table 7.1. As symbol V is assigned to a cell (1, 7) because flexibility 1 influences to flexibility 7.

Table 7.1 Structural self-interactive matrix

Variables	**15**	**14**	**13**	**12**	**11**	**10**	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**
1	A	V	O	A	V	O	A	O	V	A	V	A	A	V
2	O	O	O	O	O	O	A	V	V	A	V	A	O	
3	V	X	X	V	V	O	A	O	A	A	V	A		
4	X	V	V	V	V	O	A	V	V	O	V			
5	V	V	O	A	V	O	A	X	A	A				
6	V	O	O	O	O	O	A	V	O					
7	V	V	V	A	O	O	A	O						
8	V	X	A	O	V	O	A							
9	V	V	V	V	V	O								
10	O	O	O	O	O									
11	A	A	A	X										
12	V	O	O											
13	V	A												
14	A													

7.2.2 Development of the Reachability Matrix (RM)

The RM is obtained from SSIM. The RM indicates the relationship between flexibilities in the binary form. The various relationships between flexibilities depicted by symbols V, A, X and O used earlier in SSIM are replaced by binary digits of 0 and 1. The following rules are used to substitute V, A, X and O of SSIM to get RM:

- if the cell (i, j) is assigned with symbol V in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry becomes 0 in the initial RM
- if the cell (i, j) is assigned with symbol A in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry becomes 1 in the initial RM

- if the cell (i, j) is assigned with symbol X in the SSIM, then; this cell (i, j) entry becomes 1 and the cell (j, i) entry also becomes 1 in the initial RM
- if the cell (i, j) is assigned with symbol O in the SSIM, then; this cell (i, j) entry becomes 0 and the cell (j, i) entry also becomes 0 in the initial RM.

The RM thus derived is known as initial RM (Table 7.2). The final RM is obtained by incorporating the transitivity. Final RM is shown in Table 7.3 wherein transitivity is marked as 1*.

Table 7.2 Initial reachability matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	0	0	1	0	1	0	0	0	1	0	0	1	0
2	0	1	0	0	1	0	1	1	0	0	0	0	0	0	0
3	1	0	1	0	1	0	0	0	0	0	1	1	1	1	1
4	1	1	1	1	1	0	1	1	0	0	1	1	1	1	1
5	0	0	0	0	1	0	0	1	0	0	1	0	0	1	1
6	1	1	1	0	1	1	0	1	0	0	0	0	0	0	1
7	0	0	1	0	1	0	1	0	0	0	0	0	1	1	1
8	0	0	0	0	1	0	0	1	0	0	1	0	0	1	1
9	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
12	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1
13	0	0	1	0	0	0	0	1	0	0	1	0	1	0	1
14	0	0	1	0	0	0	0	1	0	0	1	0	1	1	0
15	1	0	0	1	0	0	0	0	0	0	1	0	0	1	1

Table 7.3 Final reachability matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	1	0	0	1	0	1	1*	0	0	1	1*	1*	1	1*
2	0	1	0	0	1	0	1	1	0	0	1*	0	1*	1*	1*
3	1	0	1	0	1	0	0	1*	0	0	1	1	1	1	1
4	1	1	1	1	1	0	1	1	0	0	1	1	1	1	1
5	0	0	0	0	1	0	0	1	0	0	1	1*	0	1	1
6	1	1	1	0	1	1	0	1	0	0	1*	0	0	1*	1
7	0	0	1	0	1	0	1	0	0	0	0	0	1	1	1
8	0	0	0	0	1	0	0	1	0	0	1	1*	0	1	1
9	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
10	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	1	1	0	0	1*
12	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1
13	0	0	1	0	0	0	0	1	0	0	1	0	1	0	1
14	0	0	1	0	0	0	0	1	0	0	1	0	1	1	0
15	1	0	0	1	0	0	0	0	0	0	1	0	0	1	1

* entries are included to incorporate transitivity.

7.2.3 Partitioning the RM

From the final reachability matrix, the reachability and the antecedent set for each flexibility can be found (Warfield, 1974). The matrix is partitioned by assessing the reachability and antecedent set for each flexibility. This process is completed in eight iterations, summarized in Table 7.4, as follows:

In Table 7.4, variable 10 (programme flexibility), 11 (market flexibility), 12 (response flexibility), 15 (range flexibility) are put at the level 1. These variables will be positioned at the top of ISM in the digraph. Variable 5 (volume flexibility), 8 (expansion flexibility), 14 (size flexibility) are at the level II. Variable 3 (process flexibility) and 13 (product mix flexibility) are at the level III. Variable 7 (operation flexibility) is at the level IV. Variable 2 (routing flexibility) is at the level V. Variable1 (machine flexibility) is at the level VI. Variable 4 (product flexibility) and 6 (material handling flexibility) are at the level VII. Variable 9 (production flexibility) is at the level VIII.

Table 7.4 Iterations

No.	Flexibility	Reachability set	Antecedent set	Intersection set	Level
10	Programme flexibility	10	10	10	I
11	Market flexibility	11,12,15	1,2,3,4,5,6,8,9,11,12, 13,14,15	11,12,15	I
8	Expansion flexibility	5,8,14	1,2,3,4,5,6,8,9,13,14	5,8,14	II
13	Product mix flexibility	3, 13	1, 2,3,4,7,9,13	3, 13	III
7	Operation flexibility	7	1, 2,4,7,9	7	IV
2	Routing flexibility	2	1, 2,4,6,9,	2	V
1	Machine flexibility	1	1,4,6,9	1	VI
4	Product flexibility	4	4, 9	4	VII
6	Material handling flexibility	6	6, 9	6	VII
9	Production flexibility	9	9	9	VIII

7.2.4 Development of the Conical Matrix

A conical matrix is developed by clubbing together flexibilities in the same level, across rows and columns of the final RM, as shown in Table 7.5. The drive power of a flexibility is derived by summing up the number of ones in the rows and its dependence power by summing up the number of ones in the columns.

7.2.5 Development of ISM Model

Based on the conical matrix, an initial digraph, including transitivity links is obtained. This is generated by nodes and lines of the edges. After removing the indirect links, a final digraph is developed (Figure 7.1). Next, the digraph is converted into an ISM model by replacing nodes of the elements with statements as shown in Figure 7.2.

Table 7.5 Conical matrix

Variables	**10**	**11**	**12**	**15**	**5**	**8**	**14**	**3**	**13**	**7**	**2**	**1**	**4**	**6**	**9**	**Drive Power**
10	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**
11	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	**3**
12	0	1	1	1	1	0	0	0	0	1	0	1	0	0	0	**6**
15	0	1	0	1	0	0	1	0	0	0	0	1	1	0	0	**5**
5	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	**6**
8	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	**6**
14	0	1	0	0	0	1	1	1	1	0	0	0	0	0	0	**5**
3	0	1	1	1	1	1	1	1	1	0	0	1	0	0	0	**9**
13	0	1	0	1	0	1	0	1	1	0	0	0	0	0	0	**5**
7	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	**6**
2	0	1	0	1	1	1	1	0	1	1	1	0	0	0	0	**8**
1	0	1	1	1	1	1	1	0	1	1	1	1	0	0	0	**10**
4	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	**12**
6	0	1	0	1	1	1	1	1	0	0	1	1	0	1	0	**9**
9	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	**14**
Dependence Power	**1**	**13**	**8**	**13**	**10**	**10**	**11**	**7**	**8**	**6**	**5**	**7**	**3**	**2**	**1**	

7.2.6 MICMAC Analysis

Matrice d'Impacts croises-multipication applique an classment (cross-impact matrix multiplication applied to classification) is abbreviated as MICMAC. The main purpose of MICMAC analysis is to analyses the drive power and dependence power of flexibilities. The flexibilities are separated into four clusters [307]. The first cluster consists of 'autonomous flexibilities' which have weak drive power and weak dependence. They are relatively disconnected from the system, with which they have few links, which may be very strong. The second cluster consists of 'dependent

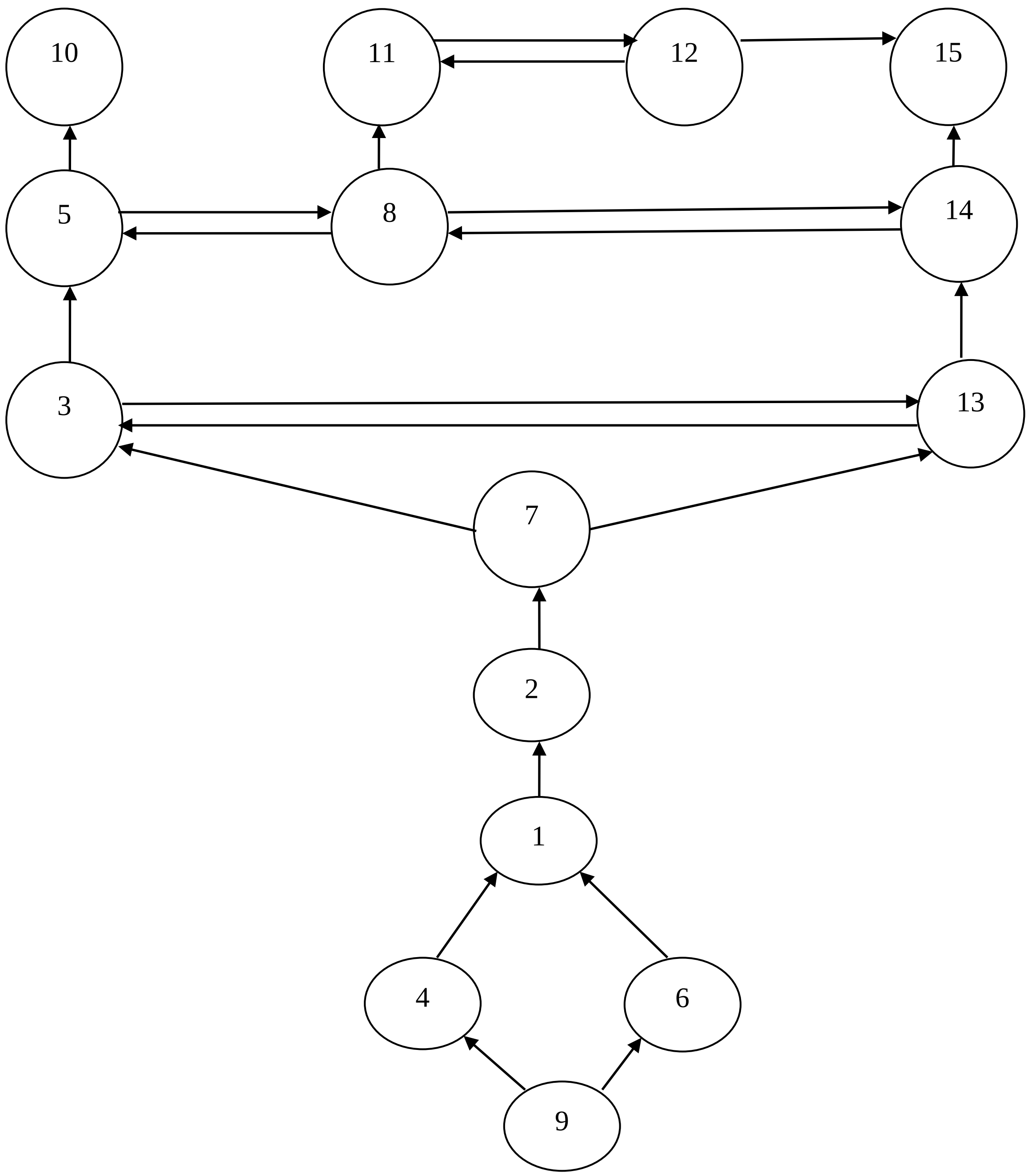

Figure 7.1 Diagraph showing the levels of FMS flexibilities

flexibilities' which have weak drive power but strong dependence power. The third cluster includes 'linkage flexibilities' which have strong drive power as well as strong dependence. They are also unstable. Any action on them will have an effect on others and also a feedback effect on themselves. Fourth cluster has the 'independent flexibilities' having strong drive power but weak dependence power. It is generally observed that a flexibility with a very strong drive power called the 'key flexibility' falls into the category of independent flexibilities. The drive power and dependence power

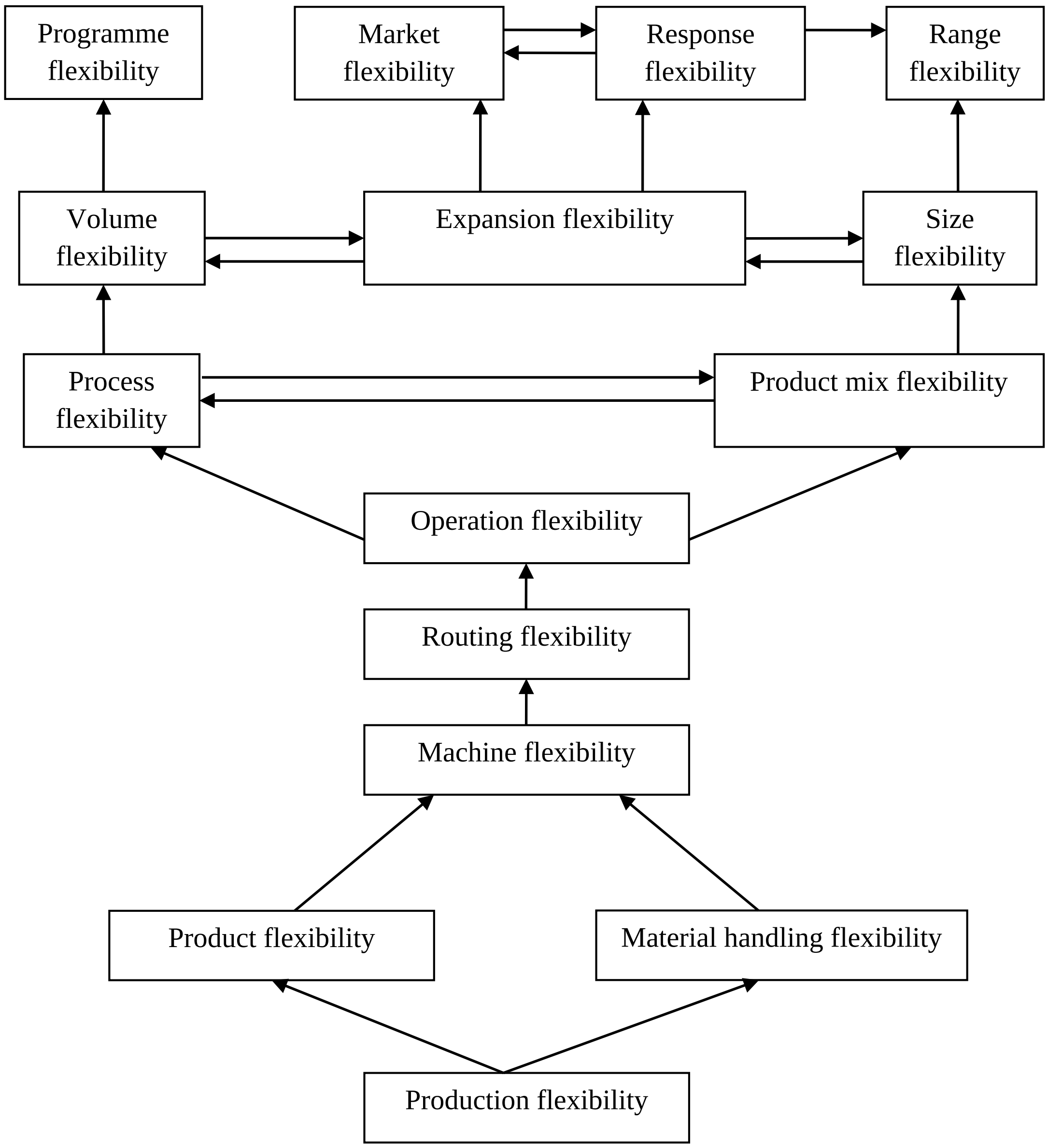

Figure 7.2 ISM model showing the levels of FMS flexibilities.

of flexibility is shown in Table 7.5. Thereafter, the drive power and dependence power diagram is depicted as shown in Figure 7.3. As an example, it is observed from Table 7.5 that flexibility 9 has a drive power of 14 and dependence power of 1, hence in Figure 7.3, it is positioned in a space which corresponds to drive power of 14 and dependence of 1, i.e. in the fourth cluster. Now, its position in the fourth cluster shows that it is an independent flexibility. Likewise, all the components are positioned in places corresponding to their driving power and dependence.

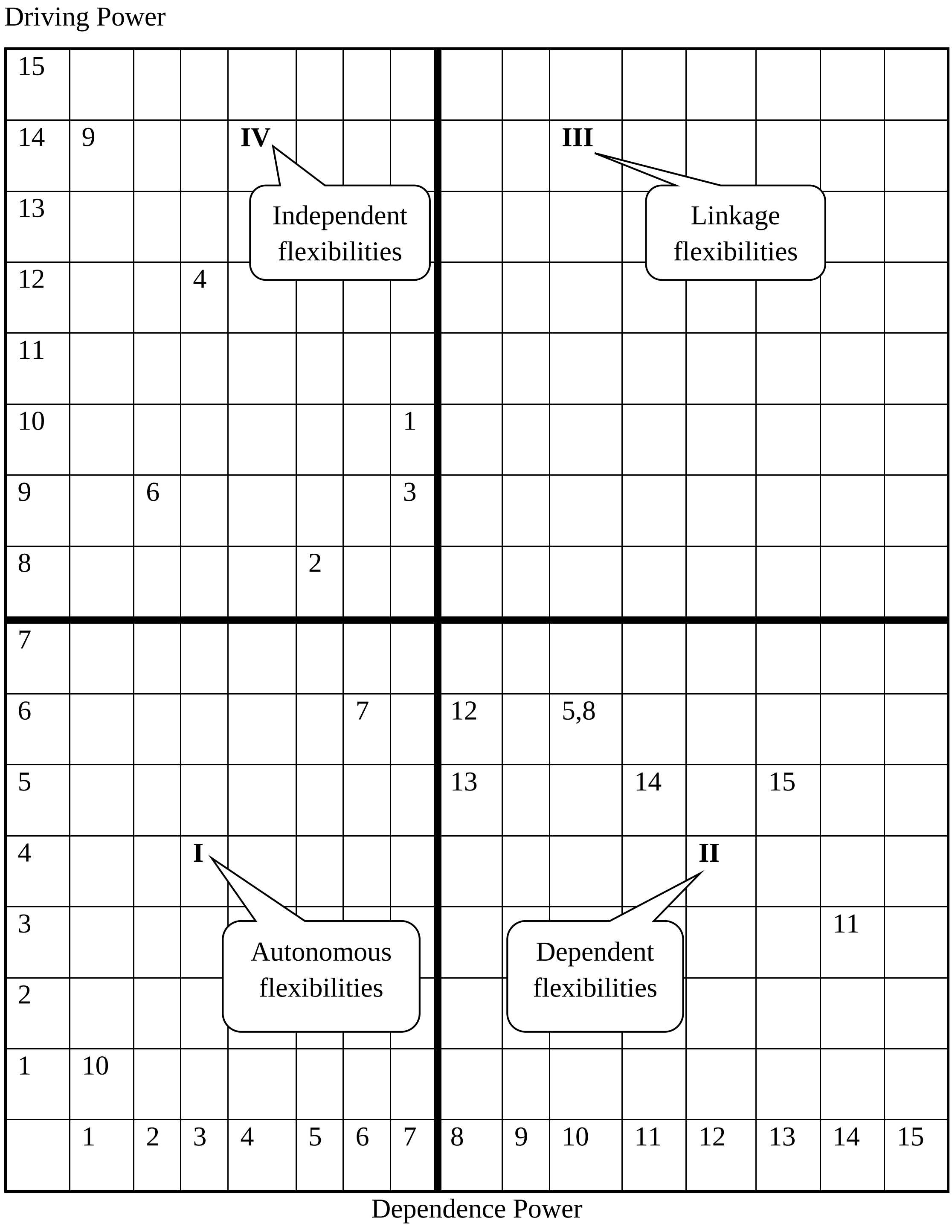

Figure 7.3 Clusters of flexibilities in FMS

7.3 RANKING OF FLEXIBILITIES BY MADM METHODS

In this chapter, methodology used for ranking of flexibilities are

i. Analytic hierarchy process (AHP)
ii. Technique for order preference by similarity to ideal situation (TOPSIS)
iii. Modified TOPSIS
iv. Improved preference ranking organization method for enrichment evaluations (Improved PROMETHEE)
v. VIKOR

7.3.1 Ranking of Flexibilities by AHP

In this section, the evaluation of flexibilities is carried out by AHP is described below:

Step 1: Objective is to find the ranking of flexibilities in flexible manufacturing system based on 15 attributes. The hierarchical structure is shown in Figure 7.4 as a ranking of flexibilities at the top level, 15 attributes at the second level and 15 alternatives at the third level.

Step 2: Relative importance of different attributes with respect to objective is find as under:

a) Pairwise comparison matrix using a scale of relative importance (as explained in AHP methodology) is shown in Table 7.6. All attributes are beneficial attributes so higher values are desired. The data given in Table 7.6 will be used as a matrix $A1_{15x15}$.
b) Calculating the geometric mean of i-th row and weights of the attributes, according to the step 2 of AHP methodology in chapter 2. The weights of the attributes will be used as the matrix A2. Weights of attributes are shown in Table 7.7.
c) The matrix A3 and A4 is calculate i.e. shown in Table 7.7.
d) Maximum eigenvalue λ_{max} is 17.2112 i.e. is the average of matrix A4.
e) The consistency index CI = (λ_{max} - M) / (M -1) = 0.158.
f) The random index (RI) for the 15 number of attributes=1. 59 is taken.
g) The consistency ratio (C.R) is calculated as C.R = CI/RI = 0.0993.
   C.R. = 0.0993 < 0.1
   C.R is less than or equal to 0.1 is acceptable.

Step 3: The attributes are expressed in linguistic term. These linguistic terms are converted into fuzzy scores as explained by the fuzzy MADM methodology. Table 7.8 presents the values in quantitative terms. The quantitative values of attributes are normalized and shown in Table 7.9.

Step 4: The overall or composite performance scores for the alternatives is obtained by multiplying the relative normalized weight (w_j) of each attribute with its corresponding normalized weight value for each alternative and summing over the attributes for each alternative. The overall or composite performance scores are shown in Table 7.10 and according this score ranking of flexibilities are also shown in Table 7.10.

7.3.2 Ranking of Flexibilities by TOPSIS

In this section, the evaluation of flexibilities is carried out by TOPSIS is described below:

Step 1: Objective is to find the ranking of flexibilities in a flexible manufacturing system based on 15 attributes is same as discussed in AHP ranking. All attributes the beneficial attributes i.e. higher values are desired.

Step 2: The next step is to represent all the information available for attributes (as in Table 7.7) in a decision matrix.

Step 3: The quantitative values of attributes are normalized and shown in Table 7.11 as $R_{15x15\ matrix}$.

Step 4: Relative importance matrix (i.e. weights) of different attributes with respect to the objective is taken as in AHP section (Table 7.7).

Step 5: The weighted normalized matrix, V_{15x15} is calculated and is shown below in Table 7.12.

Step 6: The next step is to obtain the ideal (best) and negative ideal (worst) solutions. ideal (best) and negative ideal (worst) solutions are shown in Table 7.13.

Step 7: The next step is to obtain the separation measures. Separation measures are shown in Table 7.14.

Step 8: The relative closeness of a particular alternative to the ideal solution is calculated and shown in Table 7.15 and according to this ranking of flexibilities are shown in Table 7.16.

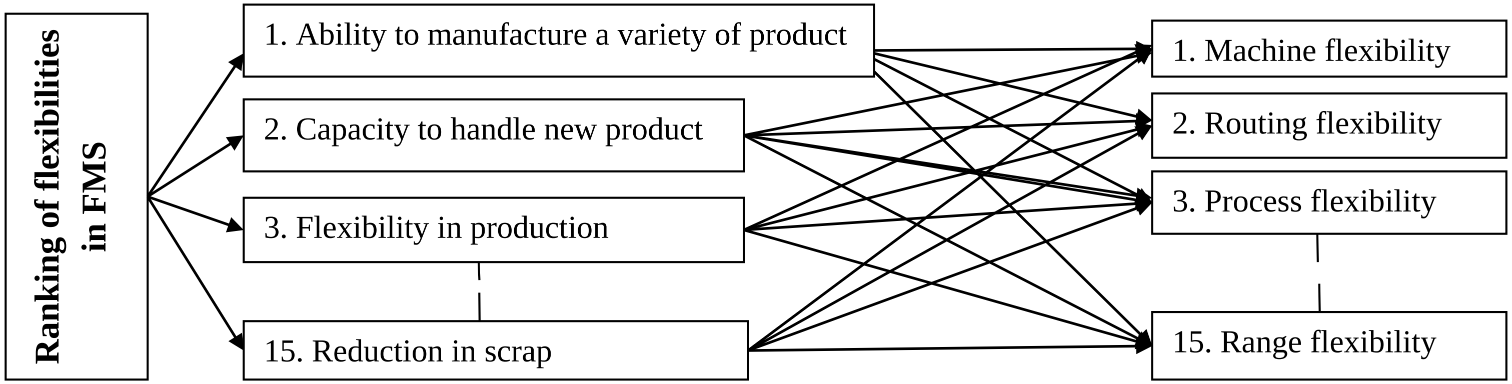

Figure 7.4 Hierarchical Structure

Table 7.7 Weights of the attributes

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Weight (w) i.e. A2	0.086	0.085	0.078	0.136	0.067	0.121	0.096	0.035	0.095	0.053	0.019	0.037	0.030	0.027	0.035
A3	1.591	1.478	1.435	2.378	1.215	2.085	1.943	0.610	1.624	0.928	0.305	0.572	0.479	0.424	0.545
A4=A3/A2	18.53	17.34	18.45	17.49	18.09	17.23	20.31	17.23	17.09	17.35	16.14	15.59	15.95	15.81	15.57

Table 7.6 Pairwise matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1	2	3	1/3	1/3	1/3	3	3	1/3	3	5	2	3	3	2
2	1/2	1	3	1/3	2	1/3	2	3	1/3	3	3	3	3	3	2
3	1/3	1/3	1	1/3	3	½	3	3	1/3	3	3	3	3	3	2
4	3	3	3	1	3	3	1/3	3	2	3	3	3	3	3	3
5	3	½	1/3	1/3	1	1/3	1/3	3	1/3	3	3	2	3	3	3
6	3	3	2	1/3	3	1	1/3	3	3	2	7	3	3	3	3
7	1/3	½	1/3	3	3	3	1	3	1/3	3	5	3	3	3	3
8	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1	1/3	1/2	1/3	2	3	2	2
9	3	3	3	1/2	3	1/3	1/3	3	1	1/2	3	3	3	3	3
10	1/3	1/3	1/3	1/3	1/3	½	1/3	2	2	1	3	2	3	3	2
11	1/5	1/3	1/3	1/3	1/3	1/7	1/5	1/3	1/3	1/3	1	1/3	1/3	1/3	1/2
12	1/2	1/3	1/3	1/3	½	1/3	1/3	1/2	1/3	1/2	3	1	1	2	2
13	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/3	3	1	1	2	1/2
14	1/3	1/3	1/3	1/3	1/3	1/3	1/3	1/2	1/3	1/3	3	1/2	1/2	1	1/2
15	1/2	½	1/2	1/3	1/3	1/3	1/3	1/2	1/3	1/2	2	1/2	2	2	1

Table 7.8 Fuzzy or crisp value of attributes

No.	Attributes Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Machine	0.865	0.665	0.665	0.5	0.59	0.5	0.41	0.59	0.665	0.665	0.59	0.335	0.255	0.5	0.41
2	Routing	0.41	0.41	0.665	0.5	0.255	0.5	0.59	0.59	0.41	0.41	0.665	0.59	0.5	0.41	0.5
3	Process	0.665	0.5	0.59	0.59	0.5	0.5	0.41	0.59	0.5	0.5	0.59	0.5	0.5	0.41	0.5
4	Product	0.745	0.865	0.665	0.59	0.41	0.5	0.41	0.59	0.59	0.5	0.665	0.41	0.41	0.5	0.41
5	Volume	0.41	0.41	0.41	0.5	0.5	0.59	0.59	0.5	0.5	0.665	0.5	0.41	0.41	0.41	0.41
6	Material	0.255	0.255	0.41	0.41	0.5	0.59	0.745	0.41	0.41	0.59	0.59	0.5	0.41	0.335	0.255
7	Operation	0.335	0.255	0.41	0.5	0.41	0.5	0.41	0.41	0.59	0.5	0.41	0.335	0.335	0.255	0.255
8	Expansion	0.41	0.335	0.665	0.5	0.5	0.41	0.5	0.665	0.745	0.745	0.5	0.335	0.255	0.41	0.255
9	Production	0.665	0.59	0.59	0.59	0.5	0.665	0.59	0.665	0.865	0.41	0.41	0.255	0.335	0.5	0.135
10	Programme	0.255	0.255	0.335	0.255	0.135	0.5	0.59	0.335	0.41	0.335	0.59	0.255	0.255	0.135	0.135
11	Market	0.5	0.59	0.5	0.335	0.255	0.665	0.135	0.255	0.59	0.255	0.5	0.255	0.135	0.5	0.135
12	Response	0.5	0.59	0.665	0.59	0.335	0.745	0.59	0.41	0.5	0.335	0.5	0.255	0.41	0.665	0.5
13	Product mix	0.59	0.5	0.665	0.5	0.5	0.59	0.5	0.5	0.5	0.59	0.5	0.59	0.41	0.5	0.5
14	Size	0.665	0.59	0.5	0.5	0.5	0.5	0.59	0.5	0.59	0.665	0.5	0.41	0.335	0.335	0.255
15	Range flexibility	0.5	0.5	0.59	0.5	0.41	0.5	0.59	0.41	0.5	0.5	0.59	0.335	0.255	0.255	0.135

Table 7.9 Normalized value of attributes

No.	Attributes Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Machine	1.000	0.769	1.000	0.847	1.000	0.671	0.550	0.887	0.769	0.893	0.887	0.568	0.510	0.752	0.820
2	Routing	0.474	0.474	1.000	0.847	0.432	0.671	0.792	0.887	0.474	0.550	1.000	1.000	1.000	0.617	1.000
3	Process	0.769	0.578	0.887	1.000	0.847	0.671	0.550	0.887	0.578	0.671	0.887	0.847	1.000	0.617	1.000
4	Product	0.861	1.000	1.000	1.000	0.695	0.671	0.550	0.887	0.682	0.671	1.000	0.695	0.820	0.752	0.820
5	Volume	0.474	0.474	0.617	0.847	0.847	0.792	0.792	0.752	0.578	0.893	0.752	0.695	0.820	0.617	0.820
6	Material handling	0.295	0.295	0.617	0.695	0.847	0.792	1.000	0.617	0.474	0.792	0.887	0.847	0.820	0.504	0.510
7	Operation	0.387	0.295	0.617	0.847	0.695	0.671	0.550	0.617	0.682	0.671	0.617	0.568	0.670	0.383	0.510
8	Expansion	0.474	0.387	1.000	0.847	0.847	0.550	0.671	1.000	0.861	1.000	0.752	0.568	0.510	0.617	0.510
9	Production	0.769	0.682	0.887	1.000	0.847	0.893	0.792	1.000	1.000	0.550	0.617	0.432	0.670	0.752	0.270
10	Programme	0.295	0.295	0.504	0.432	0.229	0.671	0.792	0.504	0.474	0.450	0.887	0.432	0.510	0.203	0.270
11	Market	0.578	0.682	0.752	0.568	0.432	0.893	0.181	0.383	0.682	0.342	0.752	0.432	0.270	0.752	0.270
12	Response	0.578	0.682	1.000	1.000	0.568	1.000	0.792	0.617	0.578	0.450	0.752	0.432	0.820	1.000	1.000
13	Product mix	0.682	0.578	1.000	0.847	0.847	0.792	0.671	0.752	0.578	0.792	0.752	1.000	0.820	0.752	1.000
14	Size	0.769	0.682	0.752	0.847	0.847	0.671	0.792	0.752	0.682	0.893	0.752	0.695	0.670	0.504	0.510
15	Range	0.578	0.578	0.887	0.847	0.695	0.671	0.792	0.617	0.578	0.671	0.887	0.568	0.510	0.383	0.270

Table 7.10 Composite performance scores and ranking of flexibilities by AHP

Sr. No.	Alternatives	Composite performance scores	Ranking
1	Machine flexibility	0.799	2
2	Routing flexibility	0.703	10
3	Process flexibility	0.763	6
4	Product flexibility	0.803	1
5	Volume flexibility	0.712	8
6	Material handling flexibility	0.654	12
7	Operation flexibility	0.605	13
8	Expansion flexibility	0.710	9
9	Production flexibility	0.789	3
10	Programme flexibility	0.470	15
11	Market flexibility	0.562	14
12	Response flexibility	0.774	4
13	Product mix flexibility	0.772	5
14	Size flexibility	0.742	7
15	Range flexibility	0.672	11

7.3.3 Evaluation of Flexibilities by Modified TOPSIS

In this section, the evaluation of flexibilities is described by Modified TOPSIS as given below:

Step 1: Objective is to evaluate the flexibilities in FMS based on 15 attributes. All these attributes the beneficial attributes, so, taken higher values of attribute.

Step 2: The next step is to represent all the information available for attributes in the form of a decision matrix. The data given in Table 7.8 are represented as the matrix $A1_{15x15}$. But the matrix is not shown here as it is nothing but the repetition of data given in Table 7.8. The quantitative values of attributes, given in Table 7.8, are given in fuzzy crisp values.

Step 3: In this step, the positive ideal solution (R^+) and the negative ideal solution (R^-) which is not dependent on the weighted decision matrix, are given in Table 7.17.

Step 4: Weights of different attributes are taken by AHP methodology and the weights as given in Table 7.7. The value of λ_{max} is 17.2112 and CR= 0.0993, it should be less than 0.1. Thus, there is good consistency in the judgment made.

Step 5: The weighted Euclidean distances are calculated and shown in Table 7.18.

Step 6: The relative closeness of a particular alternative to the ideal solution, $P_{i\text{-}mod}$, is calculated and shown in Table 7.19.

Step 7: The alternative flexibilities in FMS are arranged in descending order based on relative closeness. It is shown in Table 7.20.

7.3.4 Ranking of Flexibilities by Improved PROMETHEE

In this section, the evaluation of flexibilities is carried out by improved PROMETHEE is described below:

Step1: Objective is to find the ranking of flexibilities in a flexible manufacturing system based on 15 attributes is same as discussed in AHP ranking.

Step2: Relative importance matrix (i.e. weights) of different attributes with respect to the objective is taken as in AHP section and shown in Table 7.7.

Step 3: The next step is to have the information on the decision maker preference function P_i, for comparing the contribution of the alternatives in terms of each separate criterion. The pairwise comparison of criterion 'ability to manufacture a variety of product' gives the matrix given in Table 7.21. Ability to manufacture a variety of products is a beneficial criterion and higher values are desired. Flexibility having a comparatively high value of Ability to manufacture a variety of products is said to be 'better' than the other. Another criterion is followed same as the ability to manufacture a variety of products.

Step 4: After specifying a preference function P_i and weight w_i for each criterion, the multiple criteria preference index, Π_{a1a2} is calculated.

The leaving flow, entering flow and the net flow for different alternatives are calculated and these are given in Table 7.22. According to this net flow ranking of flexibility is shown in Table 7.23.

Table 7.11 Normalized value of attributes

No.	Attributes Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Machine	0.409	0.333	0.303	0.259	0.349	0.232	0.200	0.300	0.301	0.324	0.279	0.216	0.182	0.302	0.302
2	Routing	0.194	0.206	0.303	0.259	0.151	0.232	0.288	0.300	0.185	0.200	0.315	0.380	0.358	0.248	0.369
3	Process	0.314	0.251	0.269	0.305	0.296	0.232	0.200	0.300	0.226	0.244	0.279	0.322	0.358	0.248	0.369
4	Product	0.352	0.434	0.303	0.305	0.242	0.232	0.200	0.300	0.267	0.244	0.315	0.264	0.293	0.302	0.302
5	Volume	0.194	0.206	0.187	0.259	0.296	0.274	0.288	0.254	0.226	0.324	0.237	0.264	0.293	0.248	0.302
6	Material handling	0.121	0.128	0.187	0.212	0.296	0.274	0.364	0.208	0.185	0.288	0.279	0.322	0.293	0.202	0.188
7	Operation	0.158	0.128	0.187	0.259	0.242	0.232	0.200	0.208	0.267	0.244	0.194	0.216	0.240	0.154	0.188
8	Expansion	0.194	0.168	0.303	0.259	0.296	0.190	0.244	0.338	0.337	0.363	0.237	0.216	0.182	0.248	0.188
9	Production	0.314	0.296	0.269	0.305	0.296	0.308	0.288	0.338	0.391	0.200	0.194	0.164	0.240	0.302	0.100
10	Programme	0.121	0.128	0.153	0.132	0.080	0.232	0.288	0.170	0.185	0.163	0.279	0.164	0.182	0.082	0.100
11	Market	0.236	0.296	0.228	0.173	0.151	0.308	0.066	0.130	0.267	0.124	0.237	0.164	0.097	0.302	0.100
12	Response	0.236	0.296	0.303	0.305	0.198	0.345	0.288	0.208	0.226	0.163	0.237	0.164	0.293	0.402	0.369
13	Product mix	0.279	0.251	0.303	0.259	0.296	0.274	0.244	0.254	0.226	0.288	0.237	0.380	0.293	0.302	0.369
14	Size	0.314	0.296	0.228	0.259	0.296	0.232	0.288	0.254	0.267	0.324	0.237	0.264	0.240	0.202	0.188
15	Range	0.236	0.251	0.269	0.259	0.242	0.232	0.288	0.208	0.226	0.244	0.279	0.216	0.182	0.154	0.100

Table 7.12 Weighted normalized (R_{ij})

No	Attributes Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Machine	0.035	0.028	0.024	0.035	0.023	0.028	0.019	0.010	0.029	0.017	0.005	0.008	0.005	0.008	0.011
2	Routing	0.017	0.017	0.024	0.035	0.010	0.028	0.028	0.010	0.018	0.011	0.006	0.014	0.011	0.007	0.013
3	Process	0.027	0.021	0.021	0.042	0.020	0.028	0.019	0.010	0.021	0.013	0.005	0.012	0.011	0.007	0.013
4	Product	0.030	0.037	0.024	0.042	0.016	0.028	0.019	0.010	0.025	0.013	0.006	0.010	0.009	0.008	0.011
5	Volume	0.017	0.017	0.015	0.035	0.020	0.033	0.028	0.009	0.021	0.017	0.004	0.010	0.009	0.007	0.011
6	Material handling	0.010	0.011	0.015	0.029	0.020	0.033	0.035	0.007	0.018	0.015	0.005	0.012	0.009	0.005	0.007
7	Operation	0.014	0.011	0.015	0.035	0.016	0.028	0.019	0.007	0.025	0.013	0.004	0.008	0.007	0.004	0.007
8	Expansion	0.017	0.014	0.024	0.035	0.020	0.023	0.023	0.012	0.032	0.019	0.004	0.008	0.005	0.007	0.007
9	Production	0.027	0.025	0.021	0.042	0.020	0.037	0.028	0.012	0.037	0.011	0.004	0.006	0.007	0.008	0.003
10	Programme	0.010	0.011	0.012	0.018	0.005	0.028	0.028	0.006	0.018	0.009	0.005	0.006	0.005	0.002	0.003
11	Market	0.020	0.025	0.018	0.024	0.010	0.037	0.006	0.005	0.025	0.007	0.004	0.006	0.003	0.008	0.003
12	Response	0.020	0.025	0.024	0.042	0.013	0.042	0.028	0.007	0.021	0.009	0.004	0.006	0.009	0.011	0.013
13	Product mix	0.024	0.021	0.024	0.035	0.020	0.033	0.023	0.009	0.021	0.015	0.004	0.014	0.009	0.008	0.013
14	Size	0.027	0.025	0.018	0.035	0.020	0.028	0.028	0.009	0.025	0.017	0.004	0.010	0.007	0.005	0.007
15	Range	0.020	0.021	0.021	0.035	0.016	0.028	0.028	0.007	0.021	0.013	0.005	0.008	0.005	0.004	0.003

Table 7.13 Ideal (best) solutions (V^+) and Ideal (worst) solutions (V^-)

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Ideal(best) (V^+)	0.035	0.037	0.024	0.042	0.023	0.042	0.035	0.012	0.037	0.019	0.006	0.014	0.011	0.011	0.013
Ideal(worst) (V^-)	0.010	0.011	0.012	0.018	0.005	0.023	0.006	0.005	0.018	0.007	0.004	0.006	0.003	0.002	0.003

Table 7.14 Separation measures

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
(S^+)	0.027	0.041	0.030	0.027	0.036	0.046	0.046	0.039	0.023	0.058	0.048	0.031	0.030	0.030	0.104
(S^-)	0.047	0.036	0.047	0.048	0.038	0.037	0.028	0.038	0.050	0.022	0.026	0.046	0.041	0.045	0.042

Table 7.15 The relative closeness of a particular alternative to the ideal solution

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
(P_i)	0.640	0.471	0.610	0.643	0.512	0.447	0.378	0.492	0.681	0.279	0.354	0.596	0.575	0.601	0.285

Table 7.16 Ranking of flexibilities by TOPSIS

Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Flexibility	9	4	1	3	14	12	13	5	2	8	6	7	11	15	10

Table 7.17 Positive ideal solutions (R^+) and negative ideal solutions (R^-)

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
(R^+)	0.865	0.865	0.665	0.590	0.590	0.745	0.745	0.665	0.865	0.745	0.665	0.590	0.500	0.665	0.500
(R^-)	0.255	0.255	0.335	0.255	0.135	0.410	0.135	0.255	0.410	0.255	0.410	0.255	0.135	0.135	0.135

Table 7.18 Weighted Euclidean distances

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
(D^+)	0.179	0.285	0.213	0.185	0.255	0.326	0.325	0.269	0.177	0.402	0.335	0.231	0.211	0.204	0.260
(D^-)	0.334	0.252	0.306	0.332	0.255	0.253	0.178	0.271	0.335	0.149	0.182	0.301	0.284	0.278	0.236

Table 7.19 The relative closeness of a particular alternative to the ideal solution ($P_{i-\mathrm{mod}}$)

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
($P_{i-\mathrm{mod}}$)	0.650	0.469	0.588	0.6414	0.5	0.437	0.354	0.501	0.654	0.271	0.352	0.566	0.573	0.576	0.475

Table 7.20 Ranking of flexibilities by modified TOPSIS

Ranking	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Flexibility	9	1	4	3	14	13	12	8	5	15	2	6	7	11	10

Table 7.21 Pairwise comparison of criterion 'Ability to manufacture a variety of product'

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	-	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	0	-	0	0	0	1	1	0	0	1	0	0	0	0	0
3	0	1	-	0	1	1	1	1	0	1	1	1	1	0	1
4	0	1	1	-	1	1	1	1	1	1	1	1	1	1	1
5	0	0	0	0	-	1	1	0	0	1	0	0	0	0	0
6	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	1	-	0	0	1	0	0	0	0	0
8	0	0	0	0	0	1	1	-	0	1	0	0	0	0	0
9	0	1	0	0	1	1	1	1	-	1	1	1	1	0	1
10	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
11	0	1	0	0	1	1	1	1	0	1	-	0	0	0	0
12	0	1	0	0	1	1	1	1	0	1	0	-	0	0	0
13	0	1	0	0	1	1	1	1	0	1	1	1	-	0	1
14	0	1	0	0	1	1	1	1	0	1	1	1	1	-	1
15	0	1	0	0	1	1	1	1	0	1	0	0	0	0	-

Table 7.22 Leaving flow, entering flow and the net flow

Alternatives	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	$\boldsymbol{\varphi^{+}(a)}$	$\boldsymbol{\varphi^{-}(a)}$	$\boldsymbol{\varphi(a)}$
1	-	0.346	0.424	0.234	0.492	0.697	0.580	0.440	0.460	0.734	0.852	0.477	0.440	0.432	0.561	7.16	3.39	3.77
2	0.217	-	0.230	0.198	0.234	0.568	0.528	0.423	0.199	0.688	0.519	0.174	0.180	0.261	0.261	4.68	5.54	-0.86
3	0.238	0.522	-	0.169	0.541	0.607	0.635	0.549	0.174	0.764	0.672	0.327	0.306	0.397	0.453	6.35	4.16	2.19
4	0.307	0.549	0.390	-	0.561	0.596	0.568	0.576	0.423	0.783	0.757	0.477	0.456	0.531	0.663	7.63	3.28	4.34
5	0.284	0.336	0.270	0.337	-	0.552	0.691	0.404	0.174	0.885	0.489	0.192	0.149	0.213	0.405	5.38	5.03	0.34
6	0.284	0.337	0.270	0.374	0.152	-	0.450	0.303	0.270	0.715	0.508	0.272	0.168	0.303	0.466	4.87	7.38	-2.51
7	0.030	0.215	0.095	0.000	0.095	0.317	-	0.151	0.125	0.679	0.489	0.252	0.095	0.000	0.160	2.70	7.85	-5.14
8	0.279	0.277	0.384	0.346	0.288	0.595	0.641	-	0.222	0.734	0.662	0.287	0.183	0.288	0.390	5.57	5.94	-0.37
9	0.513	0.625	0.432	0.414	0.636	0.636	0.799	0.649	-	0.786	0.703	0.363	0.681	0.465	0.655	8.35	2.9	5.45
10	0.096	0.000	0.096	0.096	0.019	0.000	0.115	0.236	0.019	-	0.233	0.019	0.115	0.019	0.000	1.06	10.60	-9.54
11	0.121	0.414	0.328	0.121	0.492	0.492	0.416	0.319	0.019	0.695	-	0.095	0.301	0.148	0.328	4.28	8.34	-4.05
12	0.445	0.617	0.407	0.279	0.568	0.663	0.713	0.616	0.310	0.795	0.678	-	0.465	0.427	0.512	7.49	3.76	3.73
13	0.319	0.534	0.412	0.409	0.348	0.614	0.769	0.421	0.252	0.885	0.653	0.278	-	0.328	0.569	6.79	4.06	2.72
14	0.163	0.386	0.329	0.216	0.344	0.568	0.583	0.455	0.144	0.764	0.575	0.373	0.415	-	0.550	5.86	3.90	1.95
15	0.096	0.386	0.096	0.096	0.268	0.480	0.364	0.407	0.109	0.699	0.551	0.176	0.115	0.097	-	3.94	5.97	-2.03

Table 7.23 Ranking of flexibilities by improved PROMETHEE

Ranking	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Flexibility	9	4	1	12	13	3	14	5	8	2	15	6	11	7	10

Table 7.24 The best values and the worst values for the 15 Attributes

Attributes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$(m_{ij})_{max}$	0.865	0.865	0.665	0.59	0.59	0.745	0.745	0.665	0.865	0.745	0.665	0.59	0.5	0.665	0.5
$(m_{ij})_{min}$	0.255	0.255	0.335	0.255	0.135	0.41	0.135	0.255	0.41	0.255	0.41	0.255	0.135	0.135	0.135

Table 7.25 Values of E_i

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
E_i	0.333	0.477	0.389	0.319	0.478	0.570	0.635	0.469	0.300	0.857	0.675	0.351	0.369	0.434	0.530

Table 7.26 Values of F_i

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
F_i	0.088	0.095	0.088	0.088	0.076	0.095	0.088	0.121	0.038	0.136	0.104	0.076	0.076	0.088	0.088

Table 7.27 Values of P_i

Alternatives	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
P_i	0.288	0.450	0.337	0.275	0.355	0.533	0.558	0.576	0.002	1.000	0.671	0.240	0.257	0.378	0.464

7.3.5 Evaluation of Flexibilities by VIKOR

In this section, the evaluation of flexibilities is carried out by VIKOR is described below:

Step 1: Objective is to rank the flexibilities in FMS based on 15 attributes. All attributes the beneficial attributes, i.e. higher values are desired.

Step 2: Qualitative attributes are converted to their corresponding fuzzy number and then converted to the crisp scores. The quantitative values of attributes are, given in fuzzy crisp values, given in Table 7.8.

Step 3: Relative importance matrix (i.e. weights) of different attributes with respect to the objective is taken with AHP methodology and shown in Table 7.7.

The value of λ_{max} is 17.2112 and CR= 0.0993, which is less than allowed CR value of 0.1. Thus, there is good consistency in the judgment made.

Step 4: The best, i.e., $(m_{ij})_{max}$ and the worst, i.e., $(m_{ij})_{min}$, values of all attributes are determined. It is indicated in Table 7.24.

Step 5: The values of E_i and F_i are calculated and shown in Table 7.25 and 7.26.

Step 6: The values of P_i are calculated as given below in Table 7.27

Step 7: Alternatives are arranged in the ascending order, according to the values of P_i, E_i and F_i separately. It is indicated in Table 7.28. It can be determined from the results of Table 7.28 that alternative 9 is the best ranked by the measure P_i. It is checked in the two conditions as follows:

Condition 1: 'Acceptable advantage':

DQ = 1/15-1 = 1/14 = 0.071.

Using equation 2.34, $P(A^{(2)}) - P(A^{(l)})$ = 0.275-0.002= 0.273 > 0.071, hence the condition $P(A^{(2)}) - P(A^{(l)}) \geq DQ$ is satisfied.

Condition 2: 'Acceptable stability in decision making' alternative:

Since alternative 9 is also best ranked by E_i and F_i (considering the 'by consensus rule v = 0. 5'), therefore it is finally chosen and ranked as the best flexibility in FMS.

Step 8: The alternative flexibilities in FMS are arranged in descending order based on the values of P_i, E_i and F_i as shown in Table 7.29.

Table 7.28 Values of P_i, F_i and E_i for the 15 attributes

Sr. No.	P_i	Value	F_i	Value	E_i	Value
1	P9	0.002	F9	0.038	E9	0.300
2	P4	0.240	F4	0.076	E4	0.319
3	P1	0.257	F1	0.076	E1	0.333
4	P12	0.275	F12	0.076	E12	0.351
5	P13	0.288	F13	0.088	E13	0.369
6	P3	0.337	F3	0.088	E3	0.389
7	P14	0.355	F14	0.088	E14	0.434
8	P8	0.378	F8	0.088	E8	0.469
9	P2	0.450	F2	0.088	E2	0.477
10	P5	0.464	F5	0.088	E5	0.478
11	P15	0.533	F15	0.095	E15	0.530
12	P6	0.558	F6	0.095	E6	0.570
13	P7	0.576	F7	0.104	E7	0.635
14	P11	0.671	F11	0.121	E11	0.675
15	P10	1.000	F10	0.136	E10	0.857

Table 7.29 Ranking of flexibilities by VIKOR

Ranking	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Flexibility	9	4	1	12	13	3	14	8	2	5	15	6	7	11	10

7.4 SPEARMAN COEFFICIENT

In this case, the rankings obtained by the different MADM methods for alternative i.e. FMS flexibility ranking are consistent but not the same. To check the consistency in the rankings given by different methods, Spearman's rank correlation coefficients are calculated and shown in Table 7.30 and Figure 7.5 also. It can be observed that the rankings by different methods are consistent and all the methods can be considered for averaging of the ranks to find the adjusted ranks of alternative FMSs. Higher the coefficient, more consistent the rankings proposed by two MADM methods. From the values of correlation coefficients, it can be seen that all five MADM methods have good rank correlation with each other, hence the rankings given by any of the five MADM methods considered here has good similarity with the rankings given by other methods. Hence, ranking on the basis of average ranking values of all methods is carried out. As per the adjusted ranking the alternative FMS flexibility ranking, production flexibility (9) is chosen as the first rank and FMS flexibility, programme flexibility (10) as the last ranking. Therefore, averaging the rankings obtained by these five methods leads to the rank orders given in M and M* columns of Table 7.31 and Figure 7.6.

Table 7.30 Spearman's rank correlation coefficients between different MADM methods for ranking of flexibilities in flexible manufacturing system

	AHP	**TOPSIS**	**MODIFIED TOPSIS**	**Improved PROMETHEE**	**VIKOR**
AHP	1.000	0.936	0.946	0.986	0.979
TOPSIS	0.936	1.000	0.943	0.943	0.936
MODIFIED TOPSIS	0.946	0.943	1.000	0.954	0.954
Improved PROMETHEE	0.986	0.943	0.954	1.000	0.986
VIKOR	0.979	0.936	0.954	0.986	1.000

Table 7.31 Comparison of rankings obtained by AHP, TOPSIS, Modified TOPSIS, Improved PROEMTHEE and VIKOR methods for the ranking of flexibilities in flexible manufacturing system

Sr. No.	FLEXIBILITY	AHP	TOPSIS	MODIFIED TOPSIS	Improved PROMTEE	VIKOR	M	M*
1	Machine Flexibility	2	3	2	3	3	2.60	3
2	Routing Flexibility	10	9	11	10	9	9.80	10
3	Process Flexibility	6	4	4	6	6	5.20	5
4	Product Flexibility	1	2	3	2	2	2.00	2
5	Volume Flexibility	8	8	9	8	10	8.60	8
6	Material handling Flexibility	12	11	12	12	12	11.80	12
7	Operation Flexibility	13	12	13	14	13	13.00	13
8	Expansion Flexibility	9	10	8	9	8	8.80	9
9	Production Flexibility	3	1	1	1	1	1.40	1
10	Programme Flexibility	15	15	15	15	15	15.00	15
11	Market Flexibility	14	13	14	13	14	13.60	14
12	Response Flexibility	4	6	7	4	4	5.00	4
13	Product mix Flexibility	5	7	6	5	5	5.60	6
14	Size Flexibility	7	5	5	7	7	6.20	7
15	Range Flexibility	11	14	10	11	11	11.40	11

M average of the all five methods; and M* adjusted rank of M

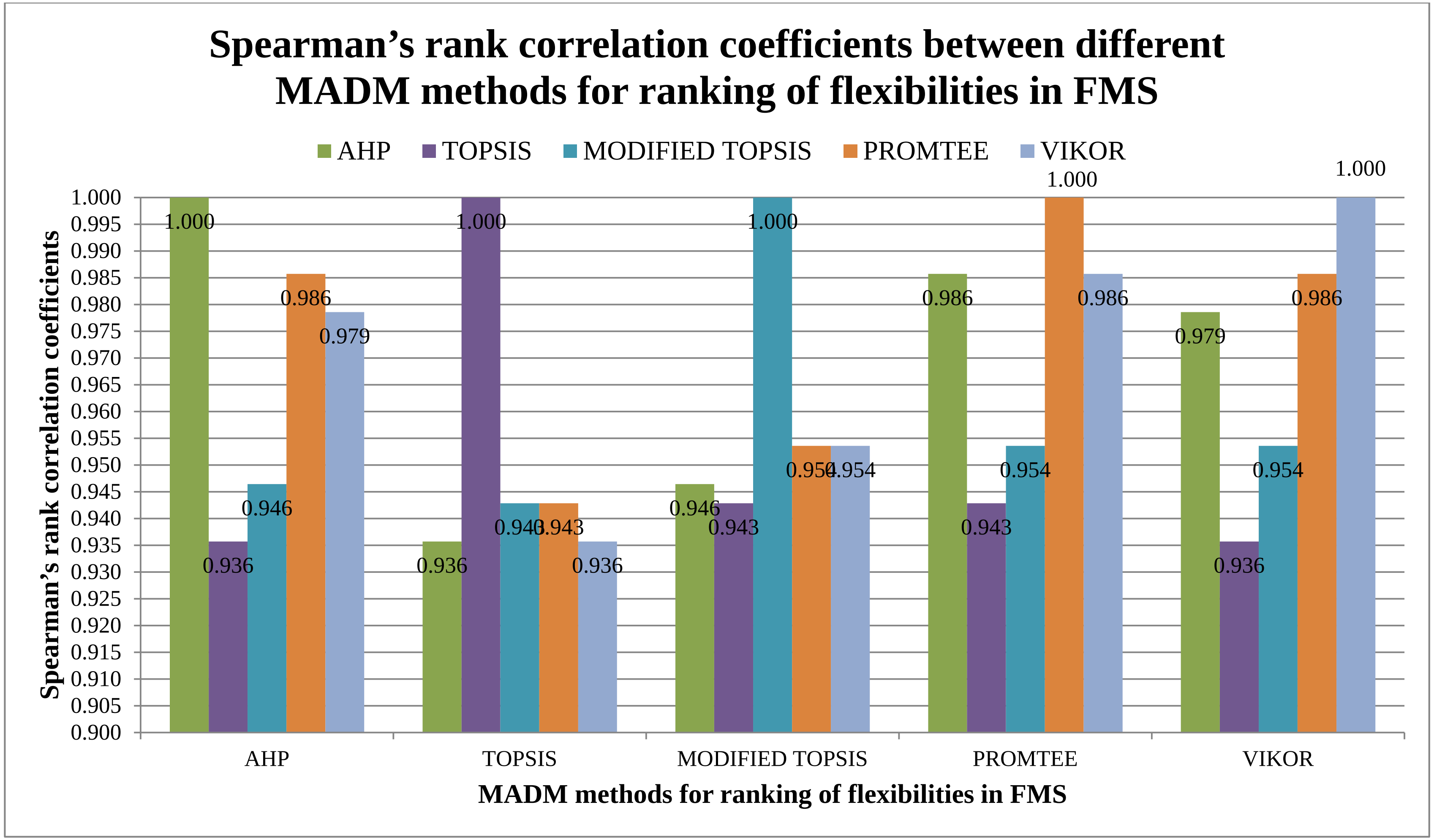

Figure 7.5 Spearman's rank correlation coefficients

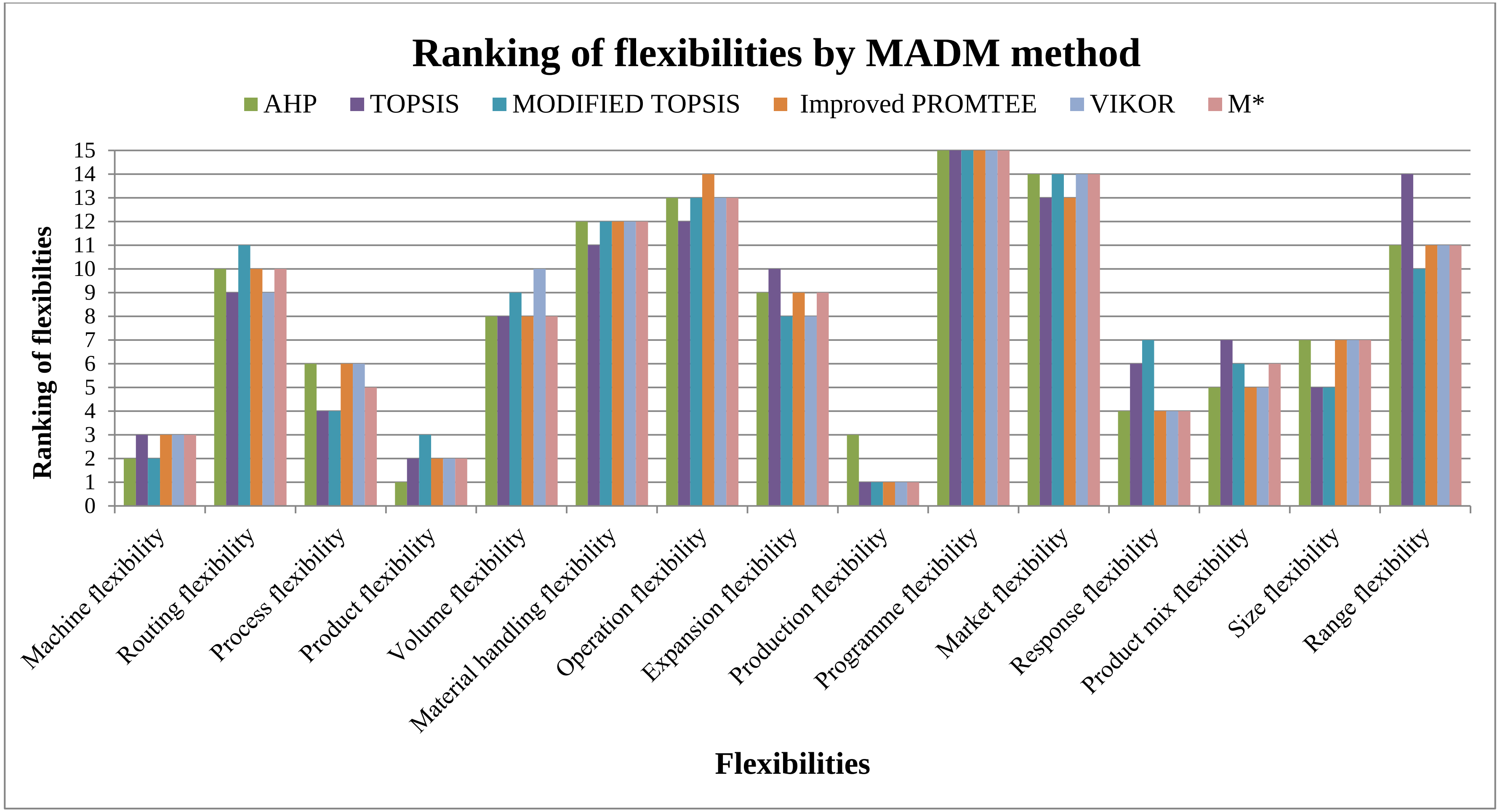

Figure 7.6 Ranking of flexibility by MADM method

7.5 DISCUSSION AND CONCLUSION

The aim of this chapter is to evaluate the flexibility which significantly affects the flexible manufacturing system (FMS) so that the management of any industry may effectively deal with these variables. Two distinct modelling approaches have been employed to examine the contextual relationship between the flexibilities and to evaluate them with some variables, which affect the flexibility in FMS. Flexibility and variables are identified through literature review and a relationship is established in the opinion of experts from industries and academia. Interpretive structural modelling has been developed to analyse the interactions in different types of flexibilities in FMS. It identifies the hierarchy of actions to be taken in handling different flexibilities, which affect the FMS. The managers can get an insight of these flexibilities and understand their relative importance and interdependence. The driving power dependence matrix gives some valuable insights about the relative importance and interdependence among the FMS flexibilities.

The management should therefore accord high priority in tackling these flexibilities. Besides tackling these flexibilities, management should also understand the dependence of these flexibilities on other levels in the ISM. This model has not been statistically validated. Structural equation modelling (SEM), also commonly known as linear structural relationship approach, has the capability of testing the validity of such a hypothetical model. But in this chapter, flexibility is evaluated by the different MADM methods like as AHP, TOPSIS, Modified TOPSIS, Improved PROMETHEE and VIKOR based on some variables. Ranking of flexibilities is found out by a different methodology of combined multiple attribute decision making method such as an AHP, TOPSIS, Modified TOPSIS, Improved PROMETHEE and VIKOR.

1. Ranking of flexibilities by AHP is 4-1-9-12-13-3-14-5-8-2-15-6-7-11-10.
2. Ranking of flexibilities by TOPSIS is 9-4-1-3-14-12-13-5-2-8-6-7-11-15-10.
3. Ranking of flexibilities by modified TOPSIS is 9-1-4-3-11-13-12-8-5-15-2-6-7-11-10
4. Ranking of flexibilities by improved PROMETHEE is 9-4-1-12-13-3-14-5-8-2-15-6-11-7-10.
5. Ranking of flexibilities by VIKOR is 9-4-112-13-314-8-2-5-15-6-7-11-10

Final ranking of flexibility in a flexible manufacturing system based on AHP, TOPSIS, Modified TOPSIS, Improved PROMETHEE and VIKOR is 9-4-1-12-3-13-14-5-8-2-15-6-7-11-10. According to these rankings, no. 9 i.e. production flexibility has the top ranking, i.e. the most impact on flexible manufacturing system and no.10 i.e. programme flexibility has lower most ranking i.e. the least impact on flexible manufacturing system. Ranking of flexibilities is shown in Figure 7.6. ISM model also concludes that production flexibility has the more driving power than other flexibilities. So, the practicing manager can focus on this flexibility in FMS. Now, practicing manager can conclude on which flexibility he should focus and up to which extent in FMS.

CHAPTER VIII

MAKESPAN ESTIMATION OF FMS ASSEMBLY SHOP

8.1 INTRODUCTION

Many large industries have tried to introduce flexible manufacturing systems (FMS) in today's manufacturing environment as their strategy. It enables them to adapt to the ever-changing competitive market requirements based on quality of machining products and to reduce the machining costs and to enhance the machining effectiveness [273]. A Flexible manufacturing system assembly shop (FMSAS) schedule is one in which all jobs must visit all machines in the same sequence. Processing of the job should be started on a succeeding machine before completing processing of a job on a current machine. This means that initially all jobs are available and that each machine is confined to processing only one job at any particular time [350]. In the facility arrangement the first machine to be visited first by each job and leaving other machines as idle queued by other jobs. Although queuing of jobs is prohibited in just-in-time manufacturing environments, production flow-shop manufacturing continues to find applications in manufacturing [351] and has attracted much research work [263, 352-355].

Scheduling an *n*-job *m*-machine with the constraint that all machines process jobs in the same order causes to the permutation situation due to which *n*! possible sequences to be considered and this easily leads to a combinatorial explosion in large numbers of jobs. Most of the researchers studied one-machine and two-machines flow-shop scheduling and used technique as branch and bound [356, 357] and others have resorted to heuristic techniques [358, 359] for seeking optimal solutions. An important aspect of scheduling is sequencing. The order in which jobs visit a machine is the process of sequencing. Johnson [354] stated that Johnson's algorithm is well suited for a two-machine problems and can be extended to three-machine cases by splitting machines into two pseudo machines which have processing times equal to the sum of the processing times on the actual machines. A generalization of Johnson's algorithm is that proposed by Campbell et al. [355] for solving general *n*-jobs *m*-machine problems in which *m*-1 two-machine problems are solved and the sequence having the least makespan is selected. Nawaz et al. [263] proposed a Nawaz, Enscor and Ham (NEH) algorithm to construct a jobs sequence in an iterative manner. The production flow shop scheduling of assembly problem is the problem of defining order over a set of jobs as they proceed from one machine (processor) to another in minimum time i.e. makespan of the jobs or assembly.

Scheduling outputs are generally graphically displayed by Gantt charts. Machine processing times for each job is used to draw them. It is also ensured that delay times are taken into consideration. A minimum makespan, which represents the minimum time required to complete all the jobs, is not found, this process is repeated for different sequences. The obtained sequence is considered to be optimal. The manual method for scheduling is tedious and prone to error. So, soft computing technique is used to find the makespan of the production flow shop. The makespan of the jobs can be calculated by neuro and fuzzy system.

An adaptive neuro fuzzy inference system for makespan estimation of FMSAS for five to ten jobs and five machines is presented by this research work. A FMSAS processes multiple part types and assemblies processed parts using various resources according to a specific sequence. The manufacturing sequences of parts are flexible. Alternative sets of resources may be selected for a manufacturing operation. The characteristics such as resource sharing, concurrency, routing flexibility, mutual exclusion, lot sizes and synchronization which are difficult to study [360].

The main objectives of this chapter are as follows:

- To find the makespan of the FMS assembly shop.
- To make a model with the help of neural network and fuzzy rules i.e. ANFIS model.
- To discuss the ANFIS model verification.

8.2 PROBLEM DESCRIPTION

The production shop of flexible manufacturing system assembly shop problem can be formulated as follows. Each of n jobs from the jobs set i = [1,2….,n], for n > 1, has to processed on m machine j = [1,2,….m] in the order given by the indexing of the machine being $t_{i,j}$ to find the minimum makespan and make a model to predict or estimate the makespan of the assembly jobs.

The following assumptions are considered in this problem:

1. Jobs are independent and available at time zero.

2. Machines are available at time zero.

3. Processing time of jobs is formerly specified.

4. No job has priority over any other job.

5. The transportation time between machines and set up time are included in the processing time.

6. Assembly of parts is also included in the processing time.

7. One job can only be processed on one machine at a time.

8. One machine can only process one job at a time.

9. No preemption is allowed, i.e. the processing of a job i on a machine j cannot be interrupted.

In this study, the operations set-up times are assumed to be independent of the job sequences and hence is added to the operation times. The performance of the proposed heuristic algorithm is studied in terms of minimum makespan.

Here, a case study of flexible manufacturing system assembly shop has been considered. This is the case of a large multi nation organization X engaged in the manufacture of a wide variety of automobile components in India, with an estimated turnover of Rs. 350 crores per year. That is one of the largest automobile component supplier in the country. The product range includes different car manufacturing company like Maruti Suzuki, Hyundai, Honda, Toyota etc. with different models. The organization has to increase the good quality and supply the product with variations of models with minimum time frame.

So, a model is prepared to predict the makespan of the components with different variants (i.e. five to ten jobs) on five machines or workstations including machining and assembly processes. A sample assembly shop line is shown in Figure 8.1. The final assembly is completed to pass five machines or workstations including machining and assembly process.

In this chapter, the framework of the proposed ANFIS-based soft computing intelligent system is described in the ANFIS methodology section for consisting of five machines which are capable of handling a five to ten numbers of jobs.

8.3 MAKESPAN CALCULATION BY NEH ALGORITHM

Considering 5 machine and 5 jobs for calculation of makespan by NEH algorithm.

Table 8.1 Processing time of jobs

	J_1	J_2	J_3	J_4	J_5
M_1	66	52	98	65	81
M_2	46	44	83	9	14
M_3	18	40	84	81	7
M_4	40	53	42	66	63
M_5	30	44	2	99	17

Step 1 Calculate total process times for each job i

Table 8.2 Total processing time of jobs

	J_1	J_2	J_3	J_4	J_5
M1	66	52	98	65	81
M2	46	44	83	9	14
M3	18	40	84	81	7
M4	40	53	42	66	63
M5	30	44	2	99	17
Processing Time	200	233	309	320	182

Step 2 Arranged in the decreasing order of processing times

Table 8.3 Descending order of total processing time of jobs

J_4	J_3	J_2	J_1	J_5
320	309	233	200	182

Step 3 Take J_4 and J_3

Iteration 1

Possible combinations: J_4-J_3 and J_3-J_4.

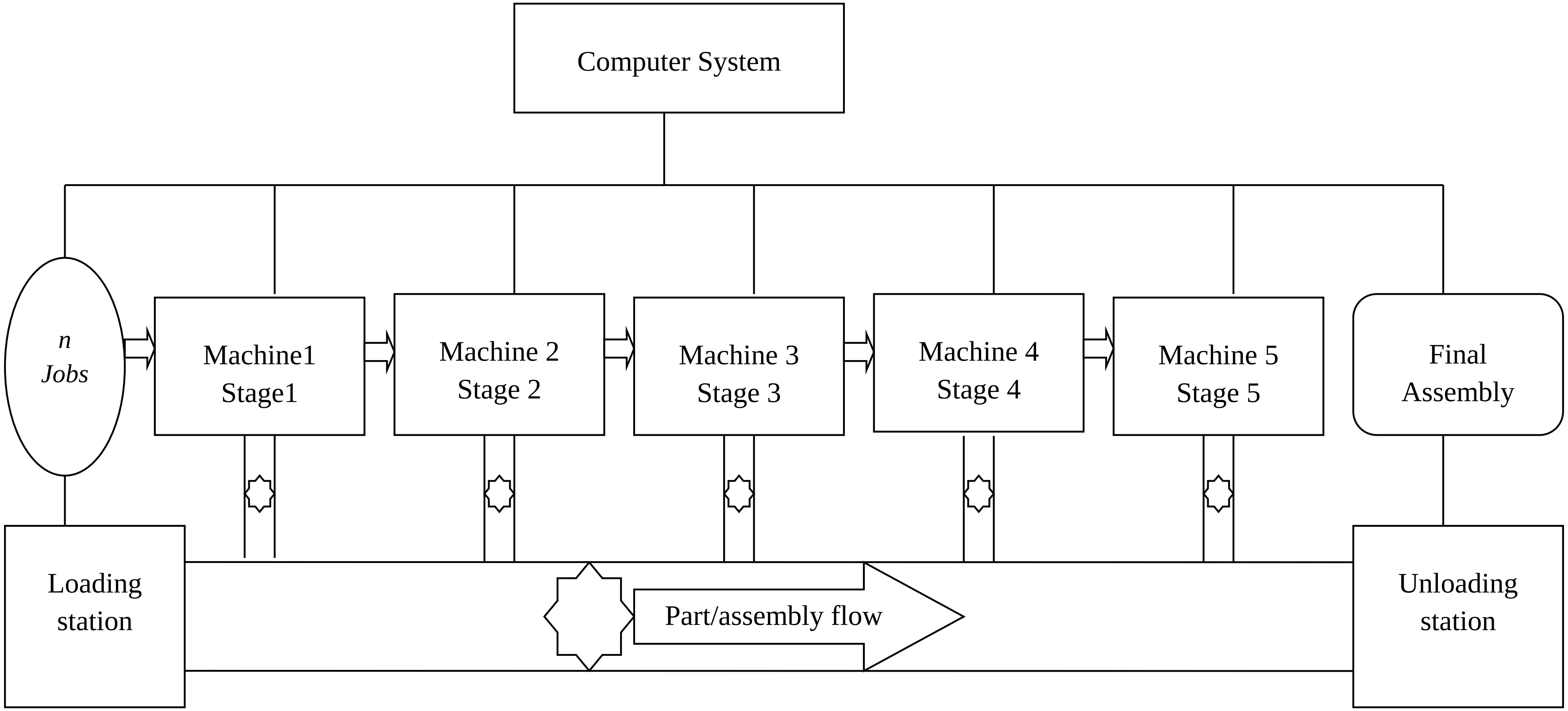

Figure 8.1 Five machine FMS assembly shops

For J_4-J_3:

Table 8.4 Makespan for partial sequence 4-3 jobs

	J_4	J_3	C_4	C_3	C_{max}
M_1	65	98	65	163	
M_2	9	83	74	246	
M_3	81	84	155	330	
M_4	66	42	221	372	
M_5	99	2	320	374	374

where C is makespan

For J_3-J_4:

Table 8.5 Makespan for partial sequence 3-4 jobs

	J_3	J_4	C_3	C_4	C_{max}
M_1	98	65	98	163	
M_2	83	9	181	172	
M_3	84	81	265	253	
M_4	42	66	307	319	
M_5	2	99	309	418	418

C_{max} for J_4-J_3 < J_3-J_4, therefore we choose J_4-J_3.

Step 4 Then take the next job in the sequence i.e., J_2.

Now J_2 can be squeezed in three ways i.e., J_2-J_4-J_3, J_4-J_2-J_3, J_4-J_3- J_2

Iteration 2

For J_2-J_4-J_3:

Table 8.6 Makespan for partial sequence 2-4-3 jobs

	J_2	J_4	J_3	C_2	C_4	C_3	C_{max}
M_1	52	65	98	52	117	215	
M_2	44	9	83	96	126	298	
M_3	40	81	84	84	207	382	
M_4	53	66	42	93	273	424	
M_5	44	99	2	97	372	426	426

For J_4-J_2-J_3:

Table 8.7 Makespan for partial sequence 4-2-3 jobs

	J_4	J_2	J_3	C_4	C_2	C_3	C_{max}
M_1	65	52	98	65	117	215	
M_2	9	44	83	74	161	298	
M_3	81	40	84	90	201	382	
M_4	66	53	42	147	254	424	
M_5	99	44	2	165	298	426	426

For J_4-J_3-J_2:

Table 8.8 Makespan for partial sequence 4-3-2 jobs

	J_4	J_3	J_2	C_4	C_3	C_2	C_{max}
M_1	65	98	52	65	163	215	
M_2	9	83	44	74	246	259	
M_3	81	84	40	90	330	299	
M_4	66	42	53	147	372	352	
M_5	99	2	44	165	374	396	396

C_{max} for J_4-J_3-J_2 < J_4-J_2-J_3, J_2-J_4-J_3 J_3-J_4, therefore we choose J_4-J_3-J_2.

Step 5:- Then take the next job in the sequence i.e., J_1.

Now J_1 can be squeezed in 4 ways i.e., J_1-J_4-J_3-J_2, J_4-J_1-J_3-J_2, J_4-J_3-J_1-J_2, J_4-J_3-J_2-J_1.

Iteration 3

For J_1-J_4-J_3-J_2:

Table 8.9 Makespan for partial sequence 1-4-3-2 jobs

	J_1	J_4	J_3	J_2	C_1	C_4	C_3	C_2	C_{max}
M_1	66	65	98	52	66	131	229	281	
M_2	46	9	83	44	112	140	312	325	
M_3	18	81	84	40	130	221	396	365	
M_4	40	66	42	53	170	287	438	418	
M_5	30	99	2	44	200	386	440	462	462

For J_4-J_1-J_3-J_2:

Table 8.10 Makespan for partial sequence 4-1-3-2 jobs

	J_4	J_1	J_3	J_2	C_4	C_1	C_3	C_2	C_{max}
M_1	65	66	98	52	65	131	229	281	
M_2	9	46	83	44	74	177	312	325	
M_3	81	18	84	40	155	195	396	365	
M_4	66	40	42	53	221	235	438	418	
M_5	99	30	2	44	320	265	440	462	462

For J_4-J_3-J_1-J_2:

Table 8.11 Makespan for partial sequence 4-3-1-2 jobs

	J_4	J_3	J_1	J_2	C_4	C_3	C_1	C_2	C_{max}
M_1	65	98	66	52	65	163	229	281	
M_2	9	83	46	44	74	246	275	325	
M_3	81	84	18	40	155	330	293	365	
M_4	66	42	40	53	221	372	333	418	
M_5	99	2	30	44	320	374	363	462	462

For J_4-J_3-J_2-J_1:

Table 8.12 Makespan for partial sequence 4-3-2-1 jobs

	J_4	J_3	J_2	J_1	C_4	C_3	C_2	C_1	C_{max}
M_1	65	98	52	66	65	163	215	281	
M_2	9	83	44	46	74	246	259	327	
M_3	81	84	40	18	155	330	299	345	
M_4	66	42	53	40	221	372	352	385	
M_5	99	2	44	30	320	374	396	415	415

C_{max} for J_4-J_3-J_2-J_1 < J_1-J_4-J_3-J_2, J_4-J_1-J_3-J_2, J_4-J_3-J_1-J_2, therefore we choose J_4-J_3-J_2-J_1.

Step 6:- Then take the next job in the sequence i.e., J_5.

Now J_5 can be squeezed in 5 ways i.e., J_5-J_4-J_3-J_2-J_1, J_4-J_5-J_3-J_2-J_1, J_4-J_3-J_5-J_2-J_1, J_4-J_3-J_2- J_5-J_1, J_4-J_3-J_2-J_1-J_5.

Iteration 4

For J_5-J_4-J_3-J_2-J_1:

Table 8.13 Makespan for partial sequence 5-4-3-2-1 jobs

	J_5	J_4	J_3	J_2	J_1	C_5	C_4	C_3	C_2	C_1	C_{max}
M_1	81	65	98	52	66	81	146	244	296	362	
M_2	14	9	83	44	46	95	155	327	340	408	
M_3	7	81	84	40	18	102	236	411	380	426	
M_4	63	66	42	53	40	165	302	453	433	466	
M_5	17	99	2	44	30	182	401	455	477	496	496

For J_4-J_5-J_3-J_2-J_1:

Table 8.14 Makespan for partial sequence 4-5-3-2-1 jobs

	J_4	J_5	J_3	J_2	J_1	C_4	C_5	C_3	C_2	C_1	C_{max}
M_1	65	81	98	52	66	65	146	244	296	362	
M_2	9	14	83	44	46	74	160	327	340	408	
M_3	81	7	84	40	18	155	167	411	380	426	
M_4	66	63	42	53	40	221	230	453	433	466	
M_5	99	17	2	44	30	320	247	455	477	496	496

For J_4-J_3-J_5-J_2-J_1:

Table 8.15 Makespan for partial sequence 4-3-5-2-1 jobs

	J_4	J_3	J_5	J_2	J_1	C_4	C_3	C_5	C_2	C_1	C_{max}
M_1	65	98	81	52	66	65	163	244	296	362	
M_2	9	83	14	44	46	74	246	258	340	408	
M_3	81	84	7	40	18	155	330	265	380	426	
M_4	66	42	63	53	40	221	372	328	433	466	
M_5	99	2	17	44	30	320	374	345	477	496	496

For J_4-J_3-J_2- J_5-J_1:

Table 8.16 Makespan for partial sequence 4-3-2-5-1 jobs

	J_4	J_3	J_2	J_5	J_1	C_4	C_3	C_2	C_5	C_1	C_{max}
M_1	65	98	52	81	66	65	163	215	296	362	
M_2	9	83	44	14	46	74	246	259	310	408	
M_3	81	84	40	7	18	155	330	299	317	426	
M_4	66	42	53	63	40	221	372	352	380	466	
M_5	99	2	44	17	30	320	374	396	397	496	496

For J_4-J_3-J_2-J_1-J_5:

Table 8.17 Makespan for partial sequence 4-3-2-1-5 jobs

	J_4	J_3	J_2	J_1	J_5	C_4	C_3	C_2	C_1	C_5	C_{max}
M_1	65	98	52	66	81	65	163	215	281	362	
M_2	9	83	44	46	14	74	246	259	327	376	
M_3	81	84	40	18	7	155	330	299	345	383	
M_4	66	42	53	40	63	221	372	352	385	446	
M_5	99	2	44	30	17	320	374	396	415	463	463

C_{max} for J_4-J_3-J_2-J_1-J_5 < J_5-J_4-J_3-J_2-J_1, J_4-J_5-J_3-J_2-J_1, J_4-J_3-J_5-J_2-J_1, J_4-J_3-J_2-J_5-J_1, therefore we choose J_4-J_3-J_2-J_1-J_5 and final makespan is 463.

Table 8.18 Makespan for five machine and jobs from five to ten

N	M_1	M_2	M_3	M_4	M_5	MAKESPAN
10	478	704	454	440	458	946
10	529	541	432	402	389	901
10	518	410	594	488	618	941
10	576	417	520	508	420	834
10	491	494	394	429	562	905
10	445	396	420	380	590	820
10	503	524	461	632	520	924
10	493	596	654	570	536	932

10	624	432	523	511	388	888
10	606	388	494	561	434	925
10	543	581	431	541	533	907
10	421	532	509	500	463	835
10	612	456	751	536	405	932
10	359	475	609	524	445	926
10	524	586	673	423	493	948
10	673	466	460	605	554	998
10	468	509	478	574	517	852
10	471	517	601	369	613	887
10	419	319	539	418	487	814
10	486	472	678	619	611	985
9	447	596	342	399	593	916
9	492	302	491	454	429	816
9	547	453	348	363	471	813
9	518	504	630	442	557	904
9	517	482	510	410	361	767
9	407	476	548	609	350	858
9	515	445	348	432	517	907
9	380	343	465	560	437	844
9	528	530	522	500	425	821
9	350	560	481	548	401	799
9	535	409	406	585	526	894
9	467	581	282	298	308	769
9	454	437	395	441	362	779
9	381	663	414	576	540	990
9	414	430	499	478	461	935
9	399	531	485	280	361	798
9	507	551	499	455	465	792
9	301	404	491	411	455	839
9	433	366	296	580	493	850
9	362	551	412	514	521	817

8	525	455	422	388	249	748
8	343	278	294	503	417	741
8	444	424	470	315	266	740
8	345	367	461	415	345	698
8	444	366	499	426	326	741
8	347	399	453	478	399	739
8	416	419	190	273	436	672
8	303	339	337	339	415	635
8	349	254	577	493	303	738
8	275	314	421	390	273	652
8	442	266	423	211	305	659
8	540	295	315	443	495	747
8	295	418	547	446	481	767
8	468	614	241	484	455	828
8	438	354	502	384	322	699
8	569	223	413	377	445	822
8	447	341	370	501	461	822
8	334	455	331	365	401	718
8	381	510	506	459	373	870
8	614	320	404	407	311	905
7	371	375	381	261	358	692
7	324	252	393	452	351	664
7	444	277	329	261	298	637
7	400	330	402	328	406	787
7	394	459	175	229	494	688
7	420	150	413	293	331	669
7	430	446	374	438	381	806
7	226	341	304	480	387	658
7	375	356	443	453	291	678
7	200	326	431	311	256	646
7	324	321	349	432	434	765
7	595	309	310	244	305	791

7	408	199	412	382	333	653
7	327	300	325	486	316	696
7	469	299	357	361	343	734
7	341	414	334	368	406	736
7	410	251	434	352	286	666
7	393	305	371	255	440	718
7	307	389	377	303	324	658
7	402	227	352	357	391	689
6	187	324	420	235	157	551
6	350	184	296	314	406	753
6	239	383	260	341	272	643
6	337	342	246	298	310	600
6	202	344	254	371	370	649
6	309	180	386	382	346	601
6	333	180	319	198	261	548
6	405	413	327	220	389	676
6	243	189	311	293	340	549
6	312	411	406	331	351	737
6	355	288	463	297	355	703
6	271	345	197	390	412	632
6	251	347	224	363	186	597
6	229	145	368	252	321	536
6	358	406	204	351	297	712
6	341	362	262	334	339	630
6	191	370	306	372	413	721
6	258	323	263	279	234	547
6	255	390	388	234	194	612
6	350	293	283	289	212	578
5	362	196	230	264	192	594
5	272	162	290	313	214	502
5	234	392	290	255	222	634
5	305	252	194	348	198	545

5	144	338	306	180	297	581
5	292	304	181	328	265	608
5	202	329	339	251	209	519
5	290	270	319	232	328	618
5	336	260	197	190	190	519
5	217	218	206	238	255	491
5	292	249	341	200	234	573
5	137	327	263	392	230	627
5	262	206	293	266	231	533
5	297	216	282	229	321	587
5	263	263	265	304	308	618
5	237	165	149	247	183	411
5	172	311	244	298	279	573
5	247	238	310	282	176	629
5	327	222	255	192	274	615
5	187	252	217	238	307	512

8.4 ANFIS METHODOLOGY

MATLAB is used for ANFIS model development. ANFIS command window is used for training and testing. Gaussian bell membership function was used in input and output. In ANFIS a hybrid learning method is applied for updating the FIS parameters. The training process continues till the desired number of training steps (epochs) or the desired root mean squared error (RMSE) between the desired and the generated output is achieved.

Steps of ANFIS model for makespan estimation of FMSAS are explained as follows:

Step 1: Normalize the training and test data.

Because the range of data is different, so normalized the data as

$$x_i' = \frac{x_i - x_{i,\min}}{x_{i,\max} - x_{i,\min}} \quad [262] \qquad (8.1)$$

Where $x_{i,\min}$ and $x_{i,\max}$ are the minimum and maximum values of ith input data.

Step 2: Input training data and test data loaded into the ANFIS model.

Input data are a number of jobs, summation of processing times for one to five machines, whereas the output data is the makespan or the completion time of jobs.

Step 3: Set the input and output parameters and membership function.

The output and input parameters for ANFIS are defined. Membership function i.e. gaussian bell shape is defined and used evalfis command for this.

Step 4: The optimal parameter values for optimization are defined.

The parameters are optimized in which radii parameter is most important.

Step 5: The epochs of the fuzzy inference system for training are defined.

The epochs are set for the training of the model.

Step 6: Train the ANFIS model.

The training of the model is started.

Step 7: Test the ANFIS model.

The model is tested after the training.

Step 8: The test output of the ANFIS model are recorded.

Table 8.19 shows the parameter values used in testing with the output of the model. Finally, the obtained test output results with ANFIS model are compared with the measured values.

Step 9: Plot correlation coefficient between measured and predicted makespan.

Correlation coefficient is a statistical process for estimating the relationships among variables, i.e. prediction of ANFIS model and the measured data used for the testing. Correlation coefficient is widely used for prediction. After obtaining the output of ANFIS model, a plot is drawn between the predicted data of ANFIS model and measured data set. Correlation coefficient of ANFIS model is shown in Figure 8.2.

8.5 MODEL VERIFICATION

Twenty-four random readings were used as the testing data set (Table 8.19). The plot of 24 measured makespan values versus predicted makespan using the ANFIS model is shown in Figure 8.3. This Figure presents a comparison of the measured makespan

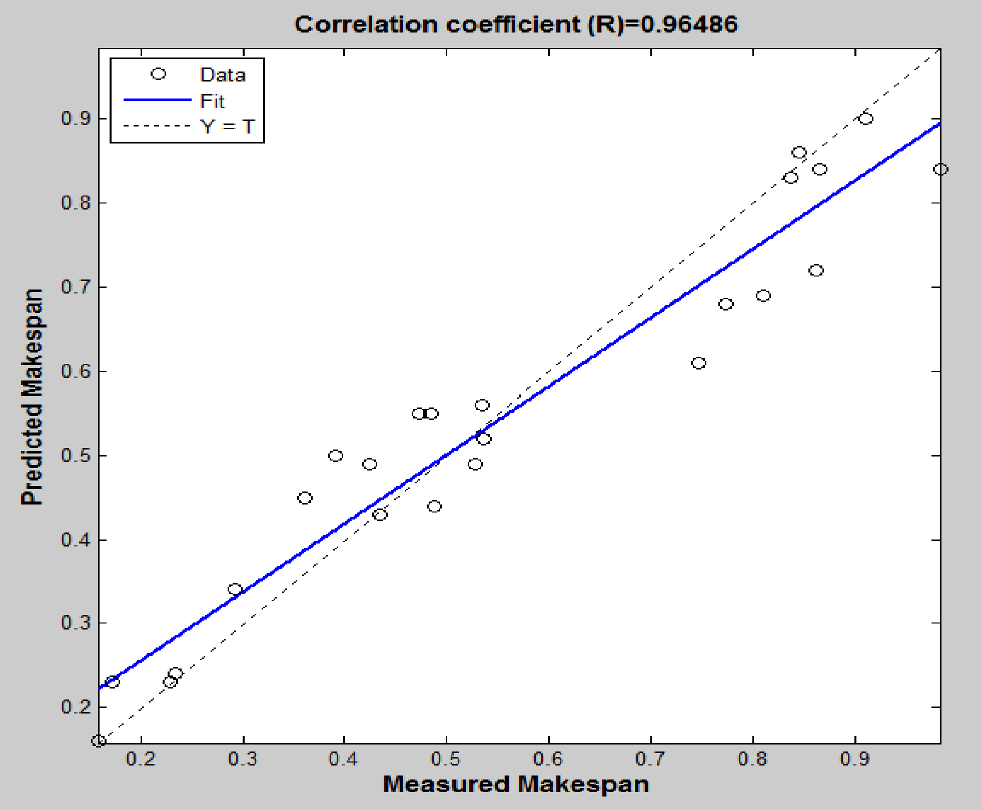

Figure 8.2 Correlation coefficient (R) of ANFIS data

and predicted makespan of the testing data set of 24 following training using ANFIS. Appropriate assent is evident between the measured and ANFIS-predicted makespan values. This close assent obviously displays that the ANFIS model can be used to predict the makespan under consideration. Thus, the proposed ANFIS model offers a promising solution to predicting makespan values in the specific range of parameters. To assess the ANFIS model, the percentage error E_i and average percentage error E_{av} defined in equations (8.2) and (8.3) [361], respectively, were used.

$$E_i = \frac{|measured\ \ makespan - predicted\ \ makespan|}{measured\ \ makespan} \times 100 \quad (8.2)$$

$$E_{av} = \frac{1}{m}\sum_{i=1}^{m} E_i \quad (8.3)$$

Where E_i is the percentage error of sample number I; and E_{av} is the average percentage error of m sample data.

From Table 8.19 and Figure 8.4 show that the average percentage error for predicting makespan is 4.03%. Figure 8.4 presents the percentage error between the predicted and measured makespan. The highest percentage of error for ANFIS model prediction is 9.7 %. The low error level signifies that the makespan results predicted by ANFIS are very close to the actual results. The error and accuracy values mean that the proposed model can predict makespan satisfactorily.

Table 8.19 Comparison of measured and predicted makespan

Sr. No.	Actual	Calculated	Error in %	Accuracy in %
1	901	894	-0.78	99.22
2	941	923	-1.91	98.09
3	834	904	8.39	91.61
4	905	884	-2.32	97.68
5	916	912	-0.44	99.56
6	816	879	7.72	92.28
7	813	857	5.41	94.59
8	904	956	5.75	94.25
9	767	824	7.43	92.57
10	698	751	7.59	92.41
11	741	742	0.13	99.87
12	672	691	2.83	97.17
13	696	665	-4.45	95.55
14	734	679	-7.49	92.51
15	736	729	-0.95	99.05
16	666	657	-1.35	98.65
17	718	724	0.84	99.16
18	548	552	0.73	99.27
19	676	633	-6.36	93.64
20	549	558	1.64	98.36
21	703	652	-7.25	92.75
22	502	506	0.80	99.20
23	545	521	-4.40	95.60
24	608	549	-9.70	90.30

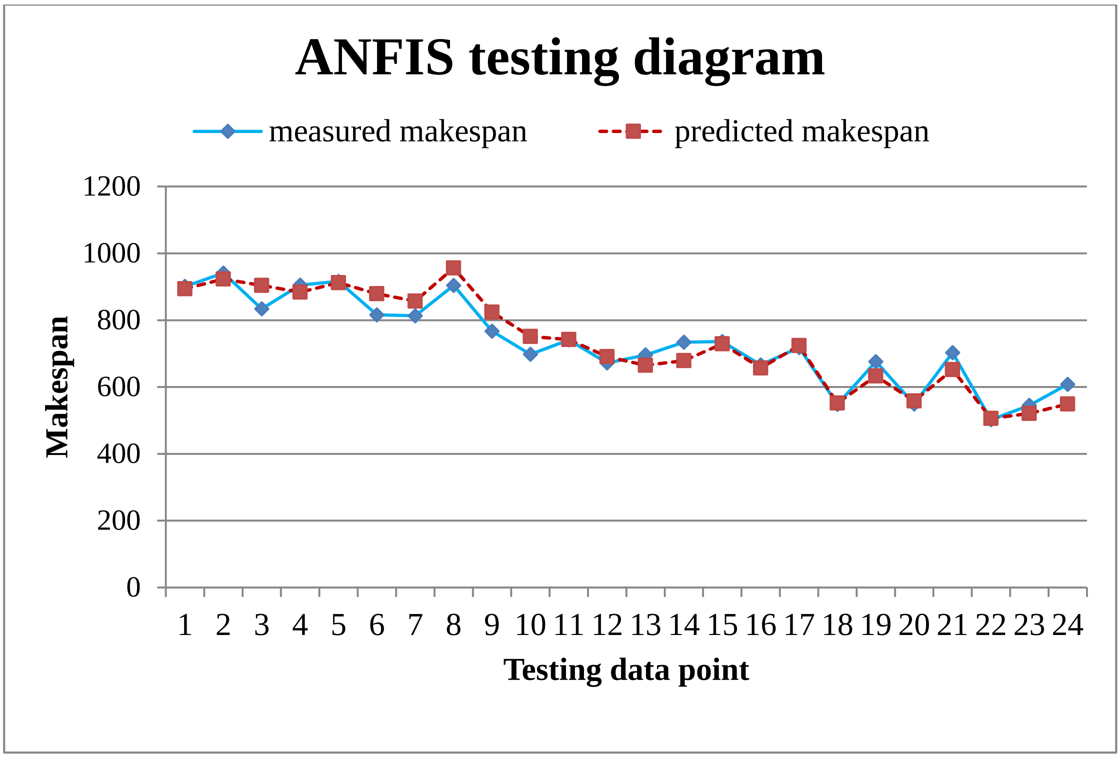

Figure 8.3 Measured makespan versus predicted makespan

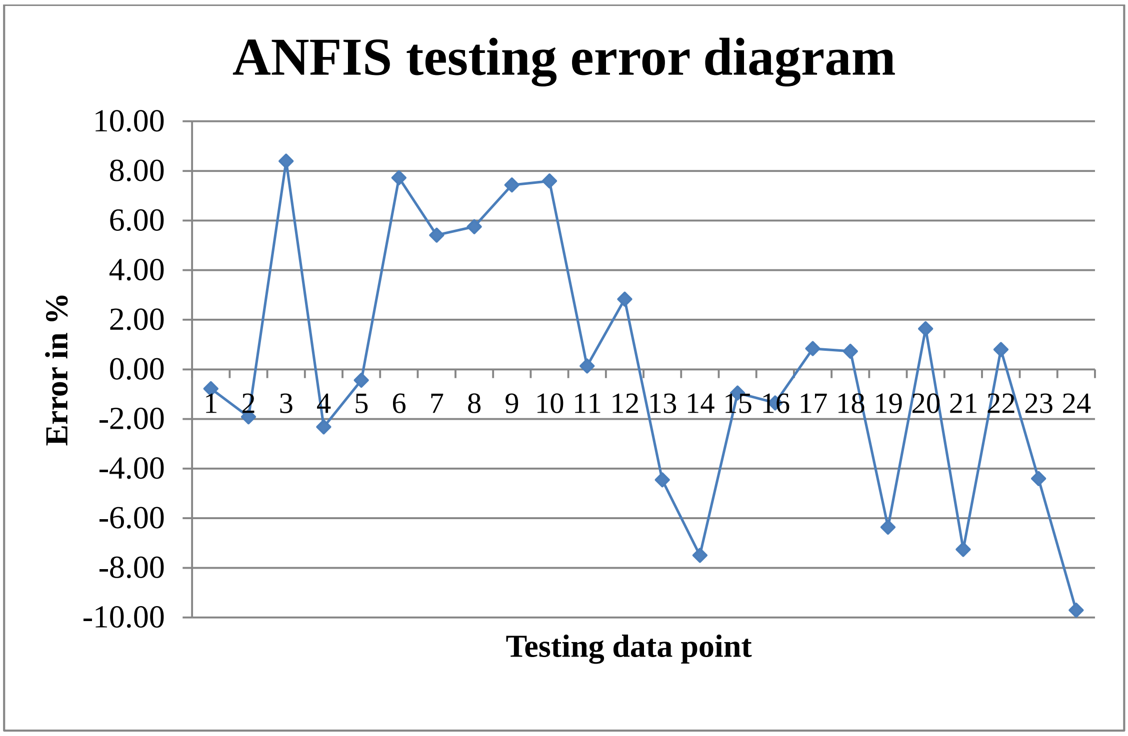

Figure 8.4 The error percentage

8.6 CONCLUSION

In this study, ANFIS has been used to develop an empirical model for predicting the makespan of FMSAS jobs in a manufacturing plant. An ANFIS model has been developed based on NEH heuristics for makespan calculation as a scheduling problem. The ANFIS model was developed in two phases, namely training phase and test phase. In the training phase, about 90 values, i.e. 79% of the problems are used and 24 values, i.e. 21% of the problems used for the testing phase. This model is verified by test data and the 95.97 average percentage of accuracy is achieved. Therefore, it can be concluded that makespan calculation of the production system, by the proposed ANFIS with NEH heuristic rules can be used as a reliable approach in estimating the job completion time of the problem studied. ANFIS shows a good performance with a coefficient of determination (R^2) is 0.9310 and RMSE of 0.0731. The root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed and coefficient of determination, describes how much of the variance between the two variables is described by the linear fit. Coefficient of determination of 0.9310 means that 93.10 percent of the variance is predictable. Regression analysis between measured and predicted makespan is also shown in a graphical way (Figure 8.2). The value of correlation coefficient (R) is 0.9649. The results mutually differ less than ± 10%. The correlation coefficient is close to 1 i.e. 0.9649, it would indicate that the variables are positively linearly related and the scatter plot falls almost along a straight line with positive slope.

CHAPTER IX

STUDY OF TOOL LIFE MANAGEMENT, ESPECIALLY FOR UNMANNED PRODUCTION SYSTEM

9.1 INTRODUCTION

In today's manufacturing environment, many large industries have attempted to introduce flexible manufacturing systems (FMS) as their strategy to adapt to the ever-changing competitive market requirements [273]. To ensure the quality of machining products and to reduce the machining costs and increase the machining effectiveness, it is very important to select the machining parameters in machining process. A FMS is an integrated, computer-controlled complex arrangement of automated material handling devices and numerically controlled (NC) machine tools that can simultaneously process medium sized volumes of a variety of part types. The main goal of development of monitoring systems is to increase productivity and finally enhance the performance of manufacturing system by maximizing tool life, minimizing down time, reducing scrappage and preventing damage.

The traditional ability of the operator to determine the condition of the tool based on his experiences and senses is now the expected role of the monitoring system in the manual system but in unmanned production system it is not possible. The demand for reducing production costs has driven manufacturers to automate most operations previously controlled by skilled operators. Therefore, the FMS has been developed. In such automated and unmanned machining system, a computerized system must have capabilities for monitoring and controlling the machining process to perform the role of a human operator.

One of the most important components in a machining system is the tool. If tool's condition is good than it increases the productivity of the manufacturing system and

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From this chapter the following papers have been published.

V. Jain and T. Raj, "Tool life management of unmanned production system based on surface roughness by ANFIS," *International Journal of System Assurance Engineering and Management,* 2016. Doi: 10.1007/s13198-016-0450-2.

scrap will be less. If a cutting tool is used within its design limits and does not fracture as a result of defects in the cutting tool material, its useful life can be estimated. The term tool life does not necessarily mean the length of time from when it is first used until the tool is finally scrapped, but refers to the length of time that a cutting edge will continue to cut before it needs to be resharpened [362]. As tool is damaged, by wear or fracture, it increases the surface roughness and consequently accuracy of the machined surface deteriorates. Eventually the tool must be changed. Some criteria must be developed to decide when to do this. In factories there is a tendency to adopt flexible criteria according to the needs of a particular operation, while in laboratories inflexible criteria are adopted to evaluate tool and work material machining capabilities [363]. The algebraic relationship between tool life and cutting speed is known as Taylor's tool life equation and is defined in equation (9.1) as:

$$\mathrm{VT}^{\mathrm{n}} = \mathrm{C} \tag{9.1}$$

Where *V* is the linear cutting speed of the tool (m/min), *T* is tool life (min) and *n* and *C* are constants. The most important conclusion to be drawn from Taylor's relationship is that tool life is mainly a function of cutting speed rather than either depth of cut or feed rate. If cutting speed is significantly increased tool life shortens dramatically. However, Taylor's equation has a drawback for example, it ignores the process parameters such as the depth of cut and the feed. From equation 9.2, it is found cutting speed is the most important process variable associated with tool life, followed by depth of cut and feed. For turning, equation (9.1) can be modified to equation (9.2)

$$VT^{n} d^{x} f^{y} = C \tag{9.2}$$

where d is the depth of cut and f is the feed in mm/rev, as shown in Figure 9.1. The exponents x and y must be determined experimentally for each cutting condition. Taking n = 0.15, x = 0.15 and y = 0.6 as typical values encountered in machining practice [364].

A cutting tool should be used at the optimum cutting conditions till failure. If the tool failure is based on the maximum flank wear, the tool cannot be reused. However, if it is based on the maximum surface roughness, there is a possibility to reuse it by changing the cutting conditions [104]. Gorczyca [365] studied that cutting force increased rapidly as tool life finished or over and it is shown in Figure 9.2.

Cutting parameters are optimized by the soft computing or metaheuristics technique, i.e. genetic algorithm (GA) and teaching-learning based optimization (TLBO) algorithm. An ANFIS model of cutting force is developed from a set of data obtained during actual machining tests. The data are divided into training and testing set. The training set is used for learning purposes while the testing set is used for testing the model. In this chapter, an attempt to solve tool life management of unmanned production system by using the ANFIS is done to predict the cutting force as the indicator of the tool life management.

The main objectives of this chapter are as follows:

1. To develop an ANFIS model for cutting force prediction regarding tool life.
2. To optimize cutting force by GA and TLBO.
3. To discuss the ANFIS model result.

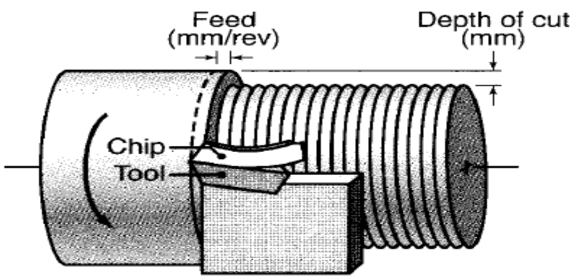

Figure 9.1 Illustration of feed and depth of cut in turning [364]

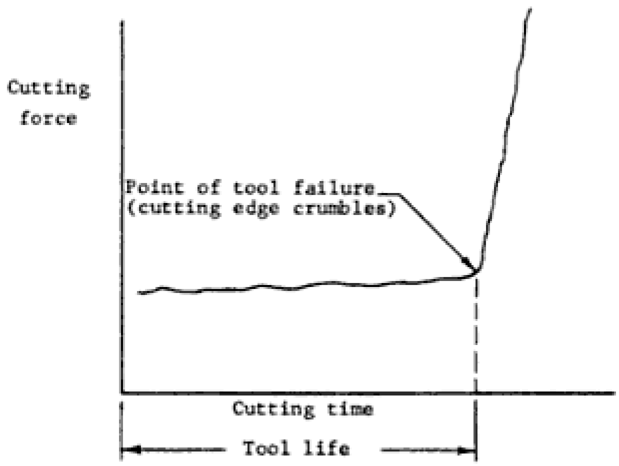

Figure 9.2 Relation between cutting force and tool life [365]

9.2 MACHINING PARAMETER FOR ANFIS MODELING

The Lathe is a machine tool that removes material by rotating a workpiece against a single point cutting tool. The various motions involved in the turning operation are illustrated in Figure 9.1.

These are the parameters of ANFIS model:

1. Cutting speed: The rotating motion of the workpiece is called cutting motion. It is found that an increase of cutting speed generally improves surface finish.

2. Depth of cut: The turning tool is set to the desired depth of cut and the thickness of the layer of metal removed in one cut is called depth of cut. It is always perpendicular to the direction of the feed motion. Increasing the depth of cut increases the cutting resistance and the amplitude of vibrations. As a result temperature also rises. Therefore, it is expected that surface quality deteriorates.

3. Feed: The cutting tool moves forward at a uniform rate, causing a continuous removal of chips. This motion is known as feed motion and feed is the amount or tool advancement per revolution of job parallel to the surface being machined. It is expressed in millimeter per revolution. Low feed rate is used for finishing cuts, hard work materials and weak cutters. Normally feed rate varies from 0.1 to 1.5 mm for medium cuts [366].

4. Cutting force: The input machining parameters depth of cut, feed and speed may be used to predict cutting forces and may be adjusted to optimum value to achieve the desired goods cost and minimum time of machining. Cutting force is one of important characteristic variables to be monitored in the cutting processes. The cutting forces are normally increased by wear of the tool. The cutting forces generated in metal cutting have a direct influence on generation heat, tool wear, quality of machined surface and accuracy of the work- piece [367]. The literature results show that tool breakage, tool wear and workpiece deflection are strongly related to cutting force [368, 369]. A cutting force dynamometer have been used to measure cutting force accurately [370].

Surface roughness (R_a): it is the output parameter of ANFIS modeling. There are many different roughness parameters in use, but R_a is the most common. The surface finish produced in a machining operation usually deteriorates as the tool life is over or nearly over. The machining parameters speed, feed, depth of cut and cutting forces were taken as input parameters and the response parameter R_a was considered as output response.

9.3 REGRESSION ANALYSIS

Regression analysis is a statistical process for estimating the relationships among variables. Regression analysis is widely used for prediction. Minitab software has been used for regression analysis. Various scatter plots are drawn i.e. scatter plot of cutting force vs cutting speed, feed and depth of cut and shown in Figures 9.3-9.5. It is very clear from all the graphs that optimum value for speed, feedand depth of cut for which cutting force is minimum is very difficult to identify by the graph. These graphs are merely showing the variation of different input parameter with cutting force, but not giving any optimum value. In order to get optimum value regression analysis completed and then it is optimized by various soft computing techniques.

In linear regression analysis general form of the equation is

$$C = p_1x_1 + p_2x_2 + p_3x_3 + \text{constant.}$$

An experiment conducted and data collected and based on the experimental data regression equation developed by Minitab software and obtained the value of p_1, p_2, p_3 and the constant.

$$\text{Cutting Force (C)} = -31.3 + 0.0141\ s + 296\ f + 394\ d \tag{9.3}$$

In this analysis, this equation is very strongly representing the relationship between input and output variable. This equation is very accurate and prediction will be very easy and it gives near optimal solutions.

9.4 OPTIMIZATION OF CUTTING FORCE BY METAHEURISTICS

In this study, optimum turning parameters at the lowest possible cutting force value was calculated using GA. Equation 9.3 derived by Minitab software was taken as the objective function to be minimized for the lowest cutting force value. The flowchart of the basic GA was given in Figure 2.10. In this study, although it can be seen as simple study, optimum turning parameters for minimum cutting force was obtained and equation 9.3 would provide turning parameter condition by using GA for the selected material.

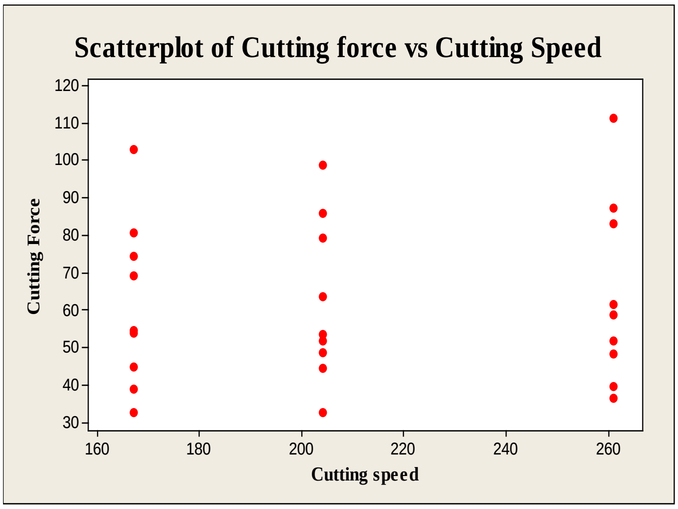

Figure 9.3 Scatterplot of cutting force vs speed

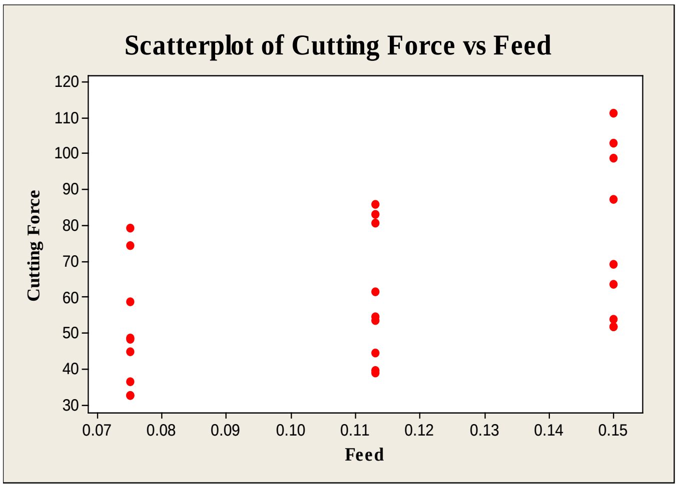

Figure 9.4 Scatterplot of cutting force vs feed

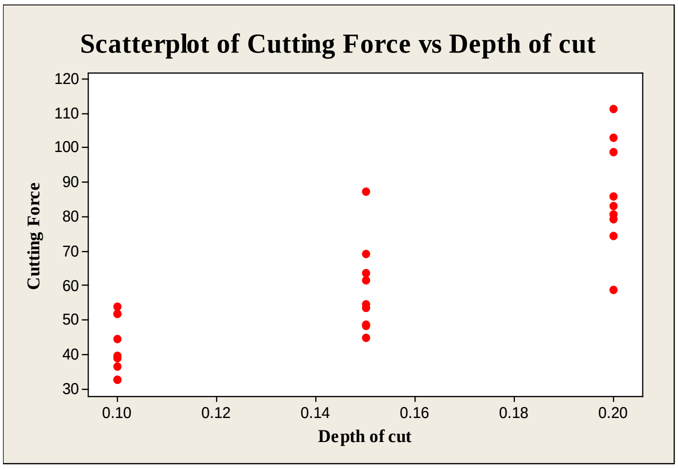

Figure 9.5 Scatterplot of cutting force vs depth of cut

Taking the minimum and the maximum values of turning parameters into account, boundary conditions for the objective function are given in equation 9.4 - 9.6.

$$167 \quad \leq s \leq 261.1 \tag{9.4}$$

$$0.075 \leq f \leq 0.15 \tag{9.5}$$

$$0.10 \quad \leq d \leq 0.2 \tag{9.6}$$

Equation 9.3 was also taken as the fitness function for the optimization of cutting force value obtained from turning. The algorithm given in Figure 2.10 (chapter 2) was run in Matlab optimization toolbox by using single point, double point, uniform crossover, intermediate and different mutation operators. The best result for minimum cutting force was obtained by using intermediate crossover. Also, various values were examined for mutation and crossover possibilities. The input turning parameter levels were fed to the GA program. Taking population size 50 with 100 iteration numbers. Considering the optimum turning parameters in the GA, the minimum cutting force (C = 32.916 N) value was obtained at s = 181.559 m/min, f = 0.075 mm/rev and d = 0.1 within 300 iteration. It was show that the results found by GA were in conformity with the experimental and theoretical ones. Fitness value and individual values of parameters found by GA is shown in Figure 9.6. GA tool window is used for this and it is shown in Figure 9.7.

The TLBO algorithm is also applied in this optimization problem which is given in equation 9.3. Boundary conditions are taken into consideration as given by equations (9.4-9.6). Taking a population size of 50 with three numbers of design variables. The obtained results are less than 100 generations. Considering the optimum turning parameters in the TLBO, the minimum cutting force (C = 32.6547 N) value was obtained at s = 167 m/min, f = 0.075 mm/rev and d = 0.1. Fitness value found by TLBO is shown in Figure 9.8.

9.5 ANALYSIS OF ANFIS MODELING

Bartarya and Choudhury [371] found the effect of cutting parameters on cutting force and surface roughness during finish hard turning AISI52100 grade steel. They developed a force prediction model on a heavy duty Lathe, make of HMT by using hone edge uncoated cubic boron nitride (CBN) tool during finish machining of EN31 steel (equivalent to AISI 52100 steel) hardened to 60±2 HRC. A Kistler, piezoelectric lathe tool dynamometer was used to measures cutting forces. MATLAB is used for ANFIS

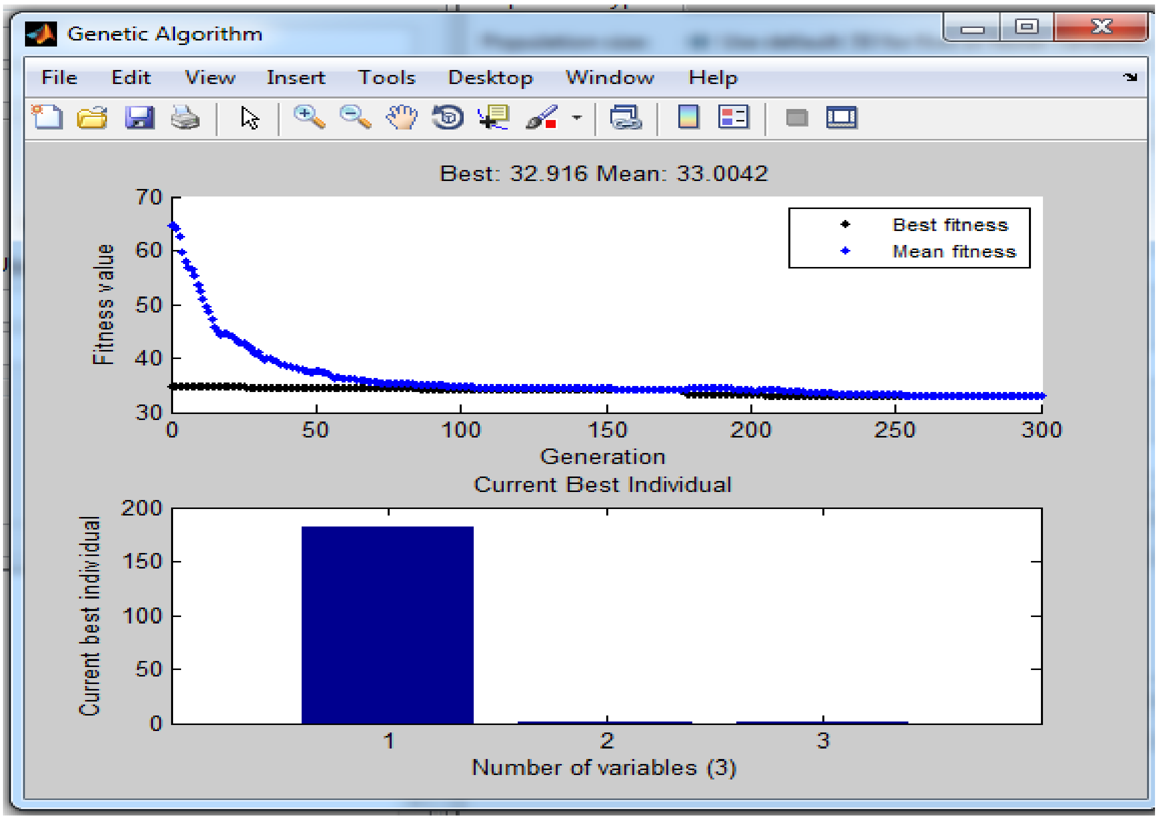

Figure 9.6 Fitness value from GA

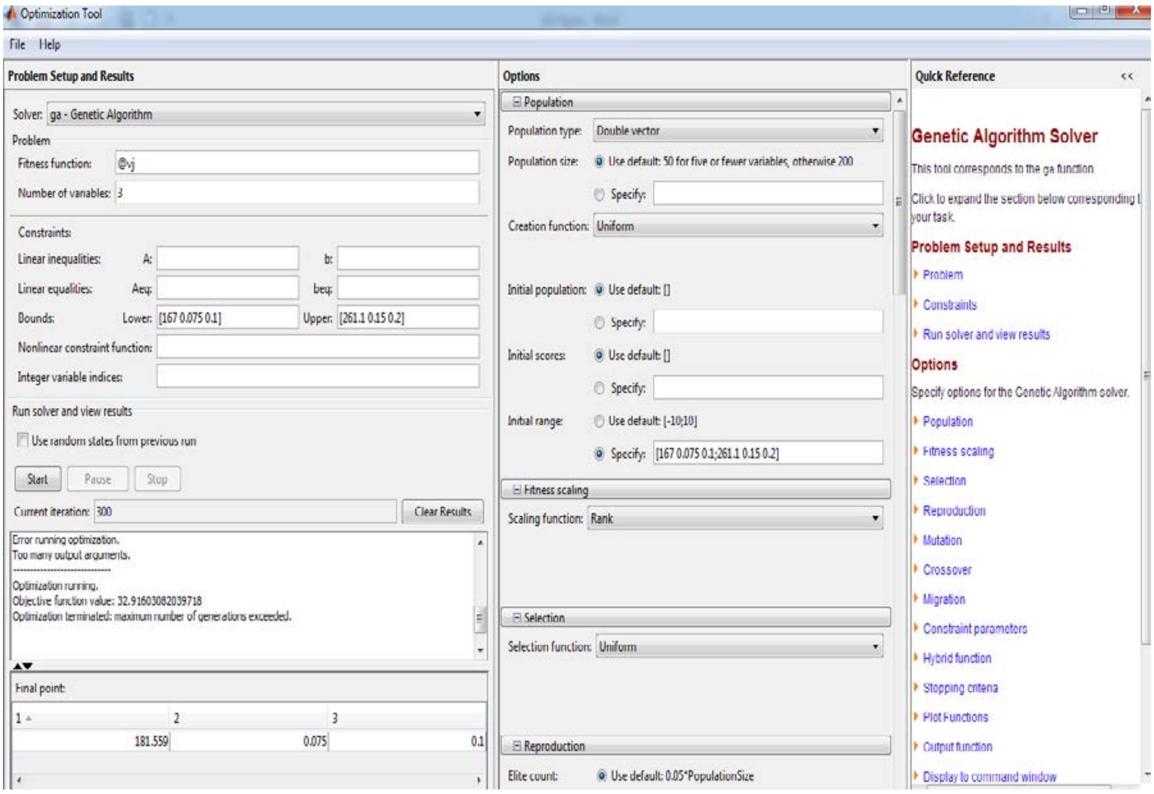

Figure 9.7 GA tool window

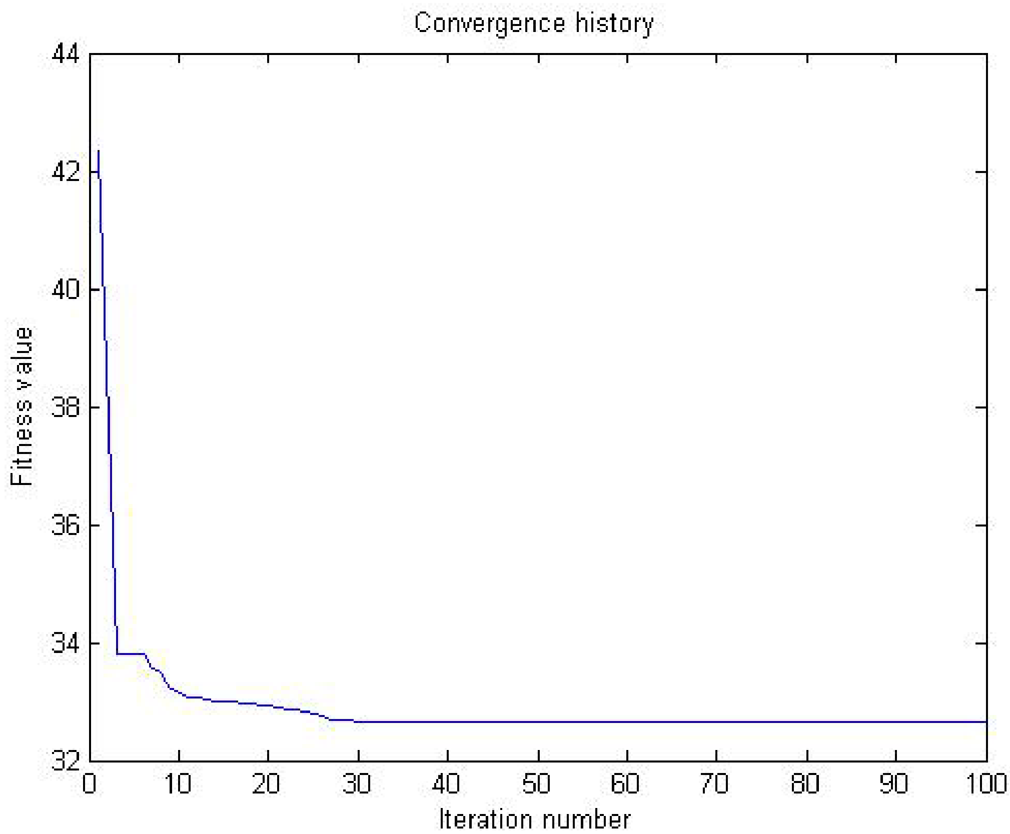

Figure 9.8 TLBO fitness value

model development. ANFIS graphical user interface (GUI) is used for training and testing. Gaussian combination membership function was used in input and constant membership functions were used in output. ANFIS applies a hybrid learning method for updating the FIS parameters. The training process continues till the desired number of training steps (epochs) or the desired root mean squared error (RMSE) between the desired and the generated output is achieved.

9.5.1 Analysis of Modeling of ANFIS for Cutting Force

The analysis for the cutting force prediction by ANFIS model is as follows:

Step 1: The architecture of ANFIS model is defined and shown in Figure 9.9.

Step 2: The turning data sets summarized and used for training data into the ANFIS model.

Step 3: In the turning process, the gaussian membership function with three membership function is used for distribution of the input variable. The Figure 9.10 shows the initial membership function of the input parameter 'cutting speed' in turning. Figure 9.11 shows the fuzzy rule architecture of ANFIS when the gaussian membership function is adopted. The architectures shown in Figure 9.12 consist of 27 fuzzy rules. ANFIS applies hybrid learning method for updating parameters. The input and output parameters are shown in Table 9.1.

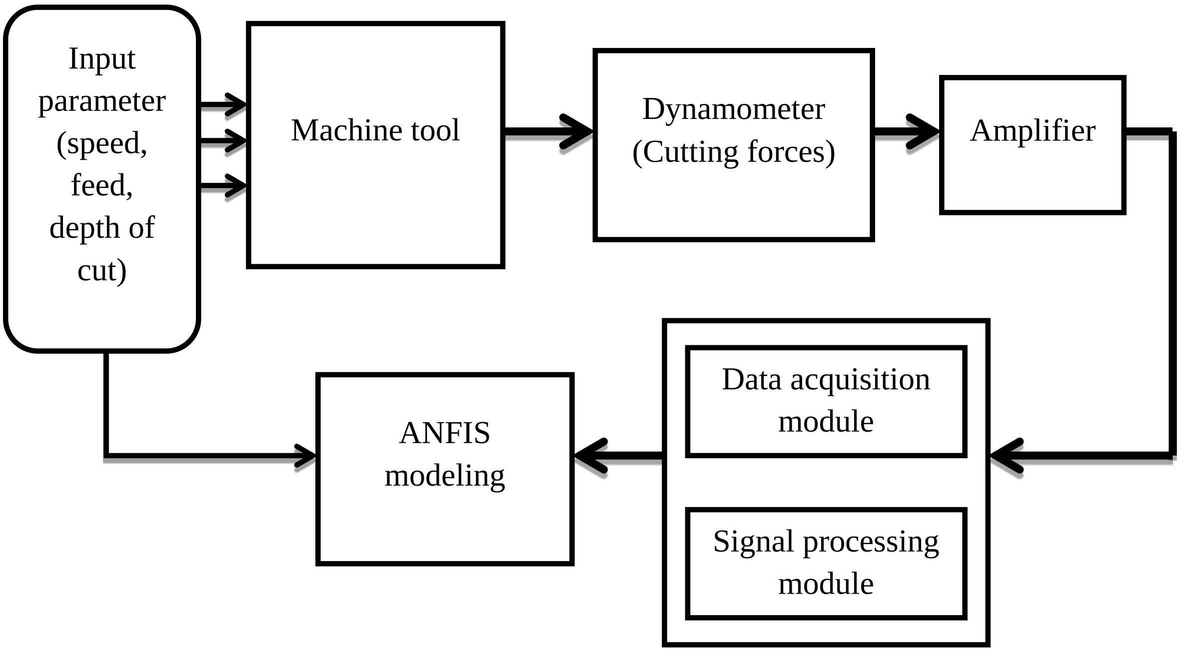

Figure 9.9 Architecture of ANFIS modeling

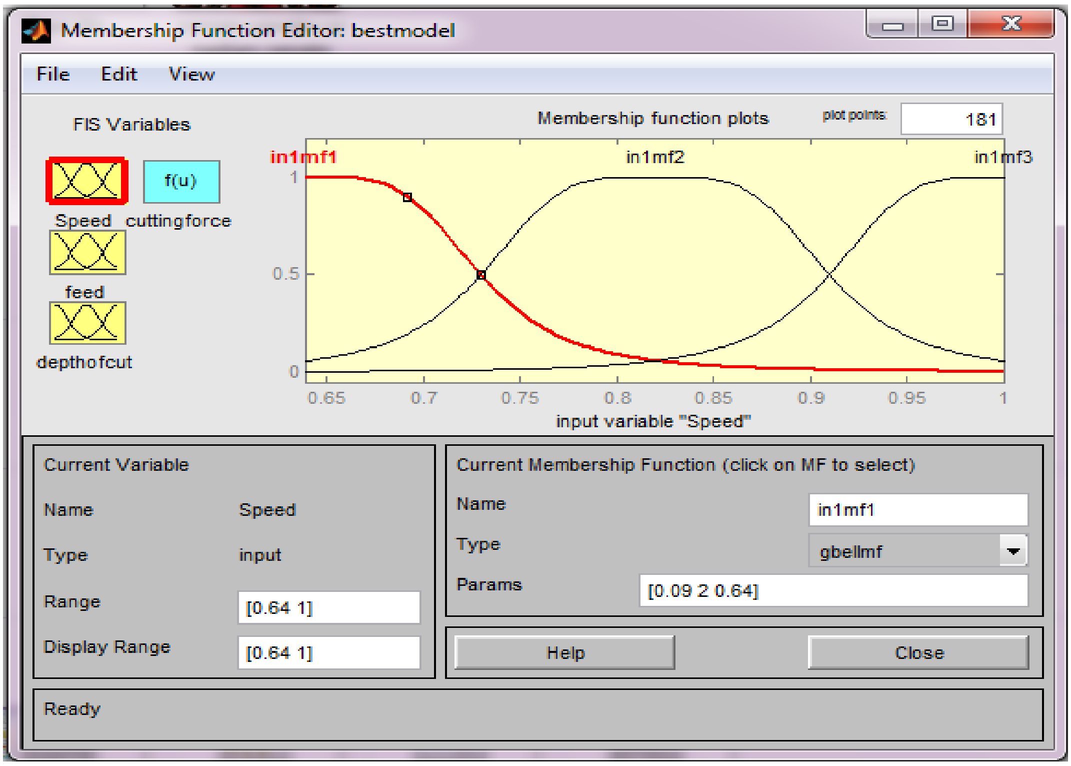

Figure 9.10 Initial membership function plot for 'cutting speed'

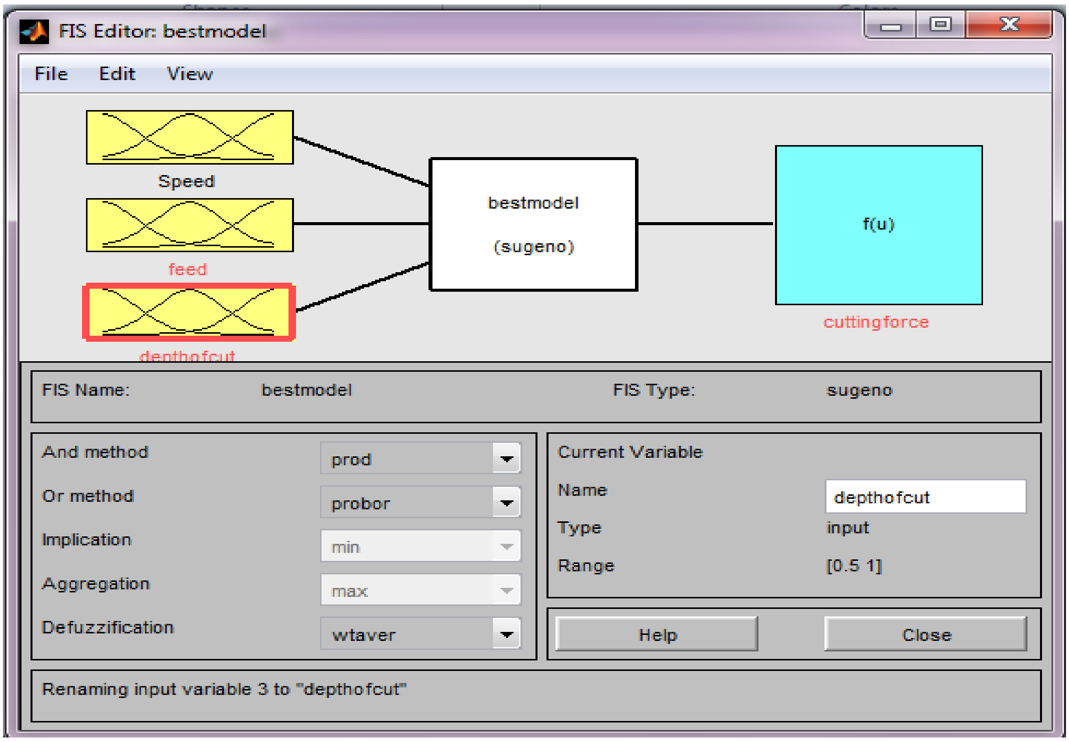

Figure 9.11 FIS (Sugeno)

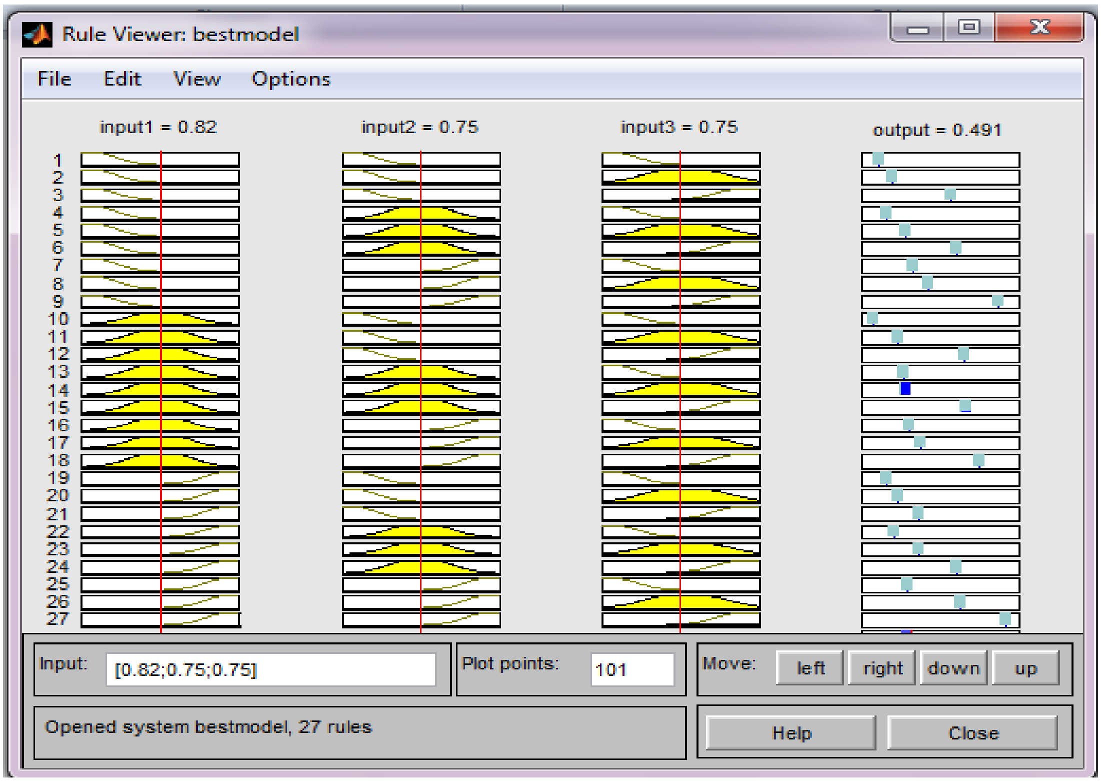

Figure 9.12 FIS rules

Table 9.1 Input and output parameters

Process parameter	Input /output
Cutting speed(V) 167-261 m/min	Input
Feed rate (F) 0.075-0.15 mm/rev	Input
Depth of cut (D) 0.1-0.2 mm	Input
Cutting force (F) N	Output

Step 4: The grid partition method is often chosen in designing a fuzzy controller, which usually involves only several state variables as the input to the controller. This partition method needs only a small amount of membership functions for each input.   ANFIS model structure is shown in Figure 9.13.

Step 5: During the training of ANFIS model in turning, seventy five sets of experimental data were used to conduct of learning.

The ANFIS learning scenario for prediction of the cutting force in turning is followed.

No. of input : 03

No. of output : 01

Number of training data pairs : 75

Number of fuzzy rules : 27

Epoch : 20

The training error performance of ANFIS based on gaussian membership function is shown in Figure 9.14.

Step 6: The turning data sets summarized and used for testing data into the ANFIS model.

Step 7: During the testing of ANFIS model for the cutting force prediction in turning, experimental data were used to check the validity of the model. Table 9.1 shows also the parameter values used in testing.

Step 8: Finally, the test output results obtained with ANFIS model are compared with the experimental results are shown in Table 9.2.

Step 9: This analysis is a statistical process for estimating the relationships among variables, i.e. output of ANFIS model and the actual data used for the testing. It is widely used for prediction. After the obtaining the output of ANFIS model, a plot is drawn between the outputs of ANFIS model and actual data set. Correlation coefficient of ANFIS model is shown in Figure 9.15. It uses training examples as input and constructs the fuzzy if - then rules and the membership functions (MF) of the fuzzy sets involved in these rules as output. This process is called a training phase. In this model, two different types of membership functions have been adopted for analysis in ANFIS training. Their difference regarding the accuracy rate of the cutting force prediction were compared. After training the model, its performance was tested under various cutting conditions. For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equation, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning.

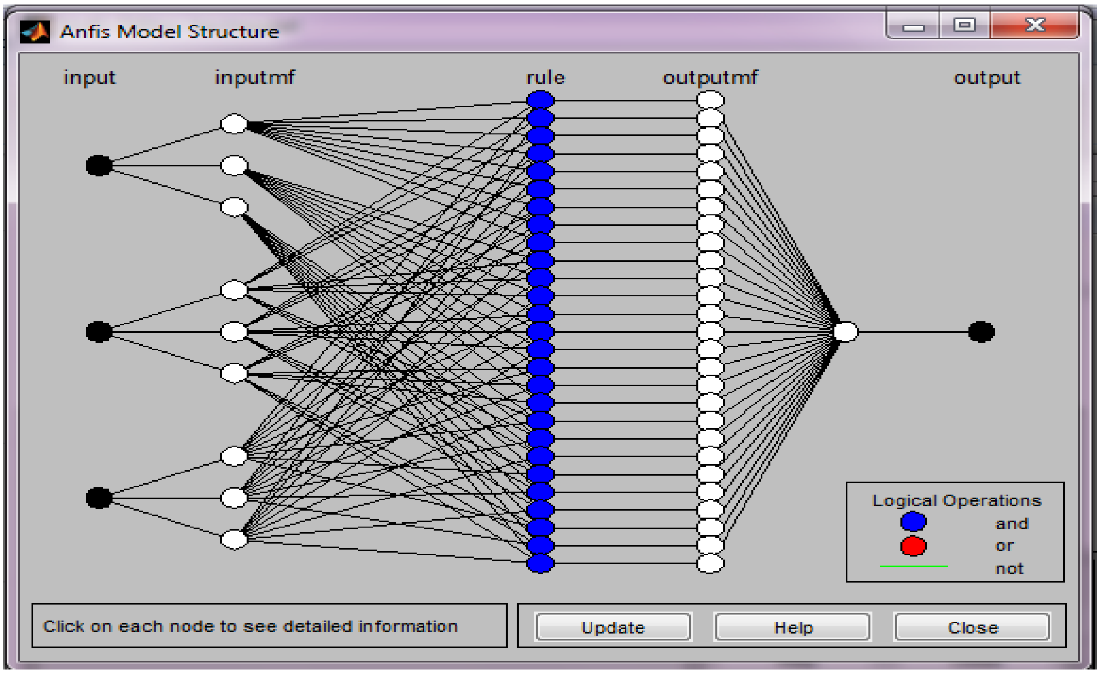

Figure 9.13 ANFIS model structure

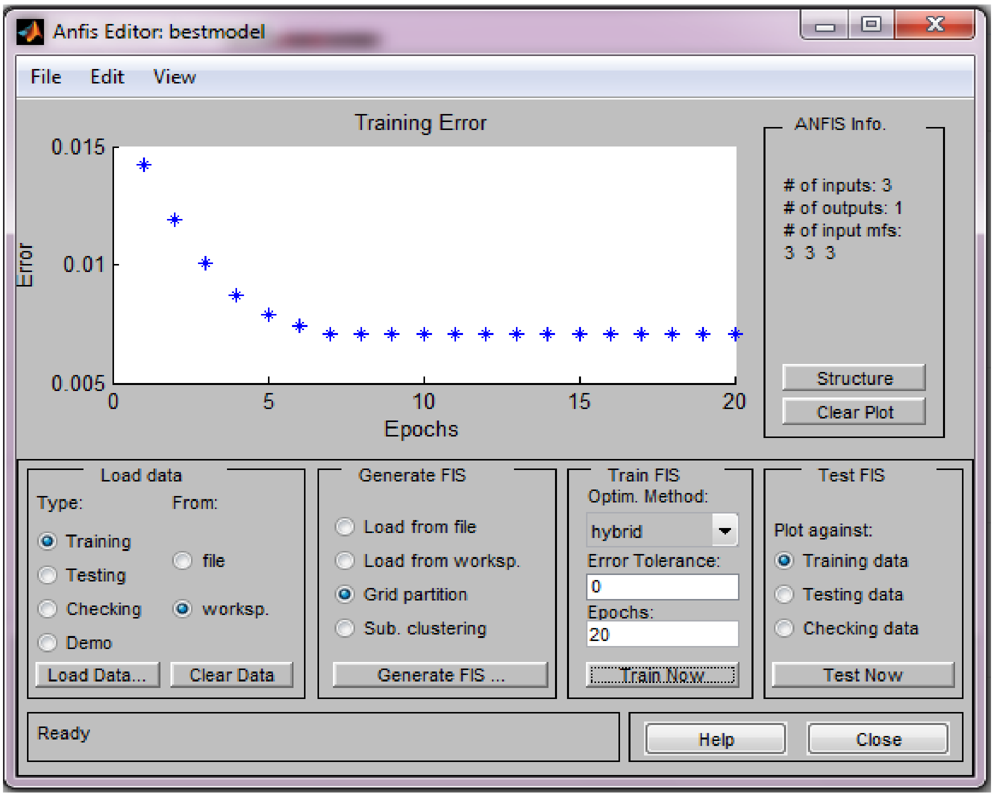

Figure 9.14 Training error

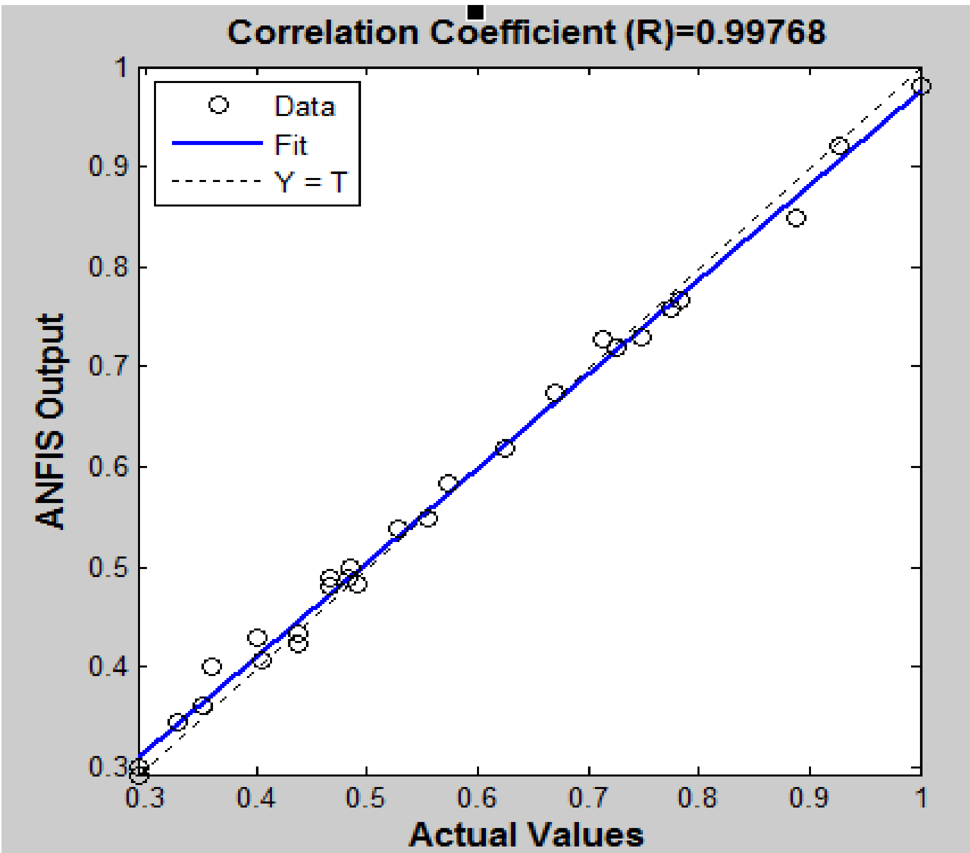

Figure 9.15 Correlation coefficient of ANFIS model for cutting force

Table 9.2 Partial results of ANFIS modeling

Cutting speed(*V*) m/min	Feed rate (*F*) mm/rev	Depth of cut (*D*) mm	Cutting force (F) N (actual)	Cutting force (F) N (output)	Error in %	Accuracy in %
167	0.075	0.10	32.63	33.45	2.51	97.49
167	0.075	0.15	45.00	45.26	0.58	99.42
167	0.075	0.20	74.50	74.90	0.54	99.46
167	0.113	0.10	39.10	40.27	2.99	97.01
167	0.113	0.15	54.55	53.70	-1.56	98.44
167	0.113	0.20	80.55	79.93	-0.77	99.23
167	0.150	0.10	53.90	55.54	3.04	96.96
167	0.150	0.15	69.30	68.83	-0.68	99.32
167	0.150	0.20	103.00	102.32	-0.66	99.34
204	0.075	0.10	32.60	32.55	-0.15	99.85
204	0.075	0.15	48.50	48.24	-0.54	99.46
204	0.075	0.20	79.30	80.75	1.83	98.17
204	0.113	0.10	44.50	47.71	7.21	92.79
204	0.113	0.15	53.70	54.34	1.19	98.81
204	0.113	0.20	86.00	84.19	-2.10	97.90
204	0.150	0.10	51.90	53.35	2.79	97.21
204	0.150	0.15	63.60	64.96	2.14	97.86
204	0.150	0.20	98.70	94.35	-4.41	95.59
261	0.075	0.10	36.50	38.36	5.10	94.90
261	0.075	0.15	48.50	47.05	-2.99	97.01
261	0.075	0.20	58.60	59.85	2.13	97.87
261	0.113	0.10	39.86	44.53	11.72	88.28
261	0.113	0.15	61.50	61.03	-0.76	99.24
261	0.113	0.20	83.20	80.98	-2.67	97.33
261	0.150	0.10	51.84	54.26	4.67	95.33
261	0.150	0.15	87.10	85.08	-2.32	97.68
261	0.150	0.20	111.09	108.95	-1.93	98.07

9.5.2 Analysis of Modeling of ANFIS for Surface Roughness

The analysis for the R_a prediction by ANFIS model is as follows:

Step 1: The architecture of ANFIS model was shown in Figure 9.9.

Step 2: The turning data sets summarized and used for training data into the ANFIS model.

Step 3: In the turning process, the gaussian combination - constant membership function is used for distribution of the input variable. Number of data should be greater than the number of modifiable parameters, so, two membership function is taken for each input in the model. With more than two membership function to each input, a warning message shown, i.e. number of data is smaller than the number of modifiable parameters. The Figure 9.16 shows the initial membership function of the input parameter 'cutting speed' in turning. Figure 9.17 shows the fuzzy rule architecture of ANFIS when the gaussian combination - constant function is adopted. The architectures shown in Figure 9.18 consist of 16 fuzzy rules. ANFIS applies hybrid learning method for updating parameters. The input and output parameters are shown in Table 9.3.

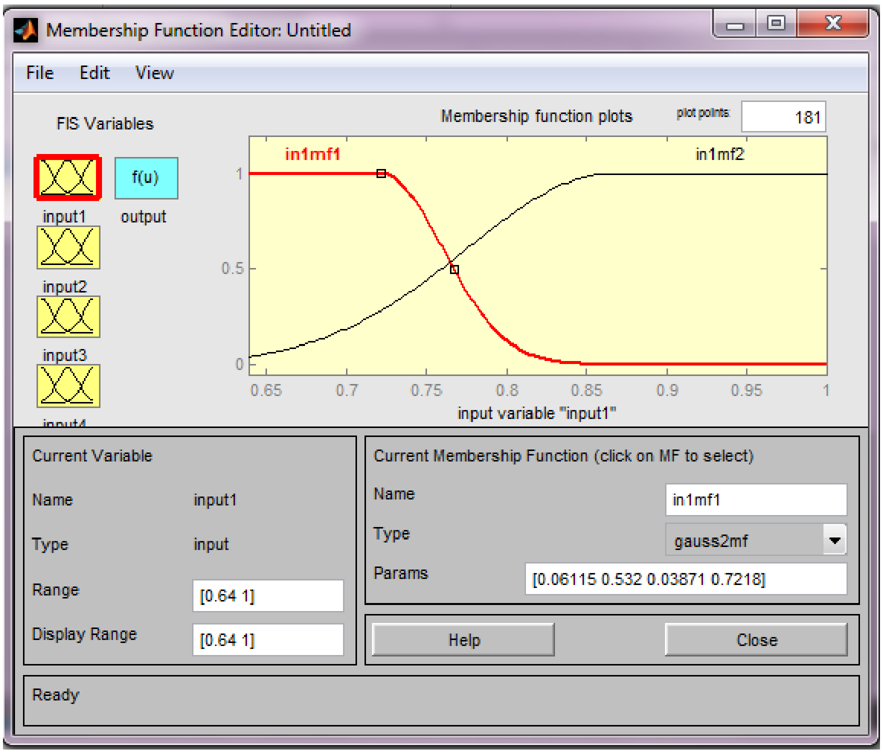

Figure 9.16 Initial membership function plot for 'cutting speed'

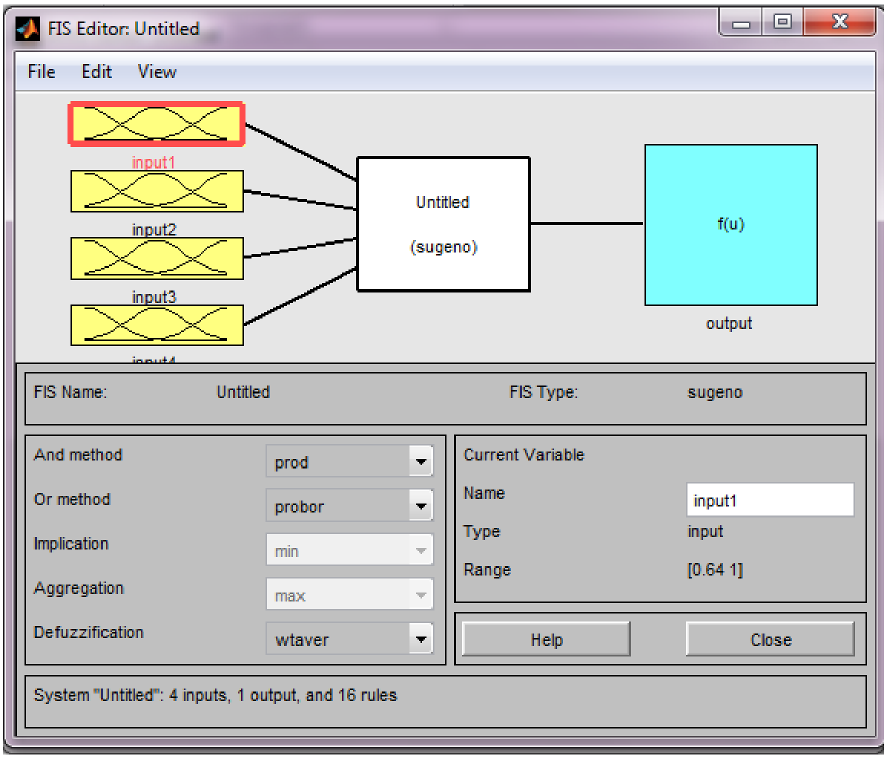

Figure 9.17 FIS (Sugeno)

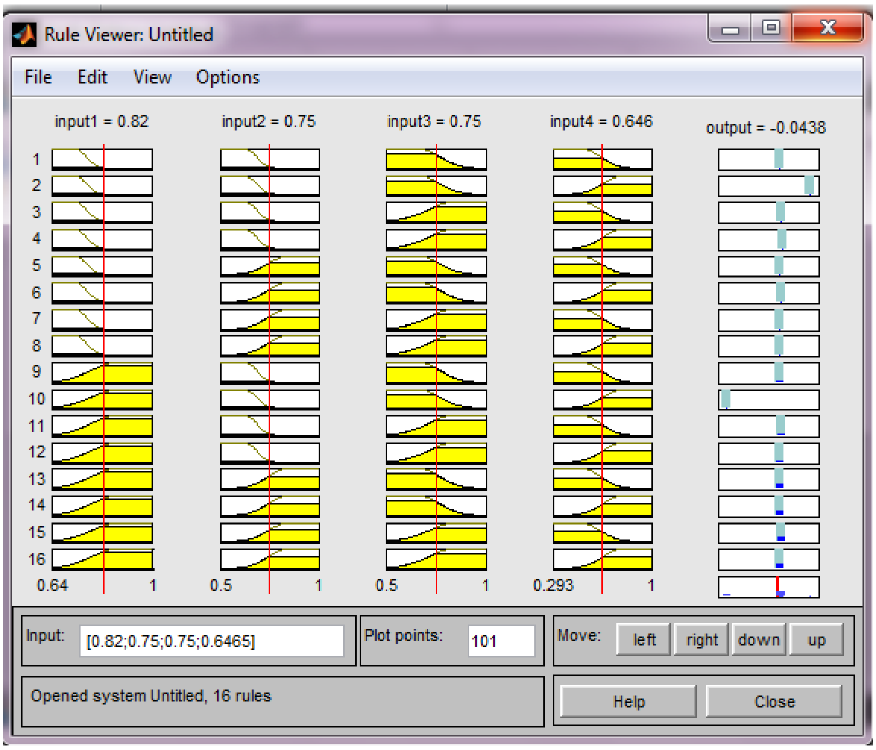

Figure 9.18 FIS rules

Table 9.3 Input and output parameters

Process parameter	Input /output
Cutting speed(V) m/min	Input
Feed rate (F) mm/rev	Input
Depth of cut (D) mm	Input
Cutting force (F) N	Input
Surface roughness (Ra)µm	Output

Step 4: The grid partition method is often chosen in designing a fuzzy controller, which usually involves only several state variables as the input to the controller. This partition method needs only a small amount of membership functions for each input. ANFIS model structure is shown in Figure 9.19.

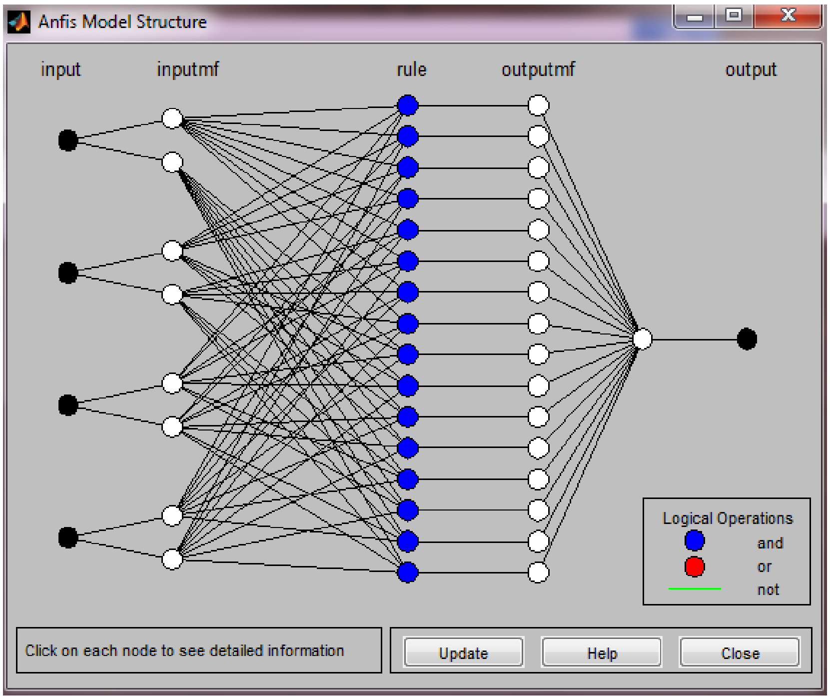

Figure 9.19 ANFIS model structure

Step 5: During the training of ANFIS model in turning, seventy five sets of experimental data were used to conduct of learning.

The ANFIS learning scenario for prediction of the surface roughness (R_a) in turning is followed.

Number of nodes	: 55
Number of linear parameters	: 16
Number of nonlinear parameters	: 32
Total number of parameters	: 48
Number of training data pairs	: 75
Number of fuzzy rules	: 16
Epoch	: 20
Training error	: 0.02824

The training and checking error performance of ANFIS based on gaussian combination - constant membership function is shown in Figure 9.20 and 9.21.

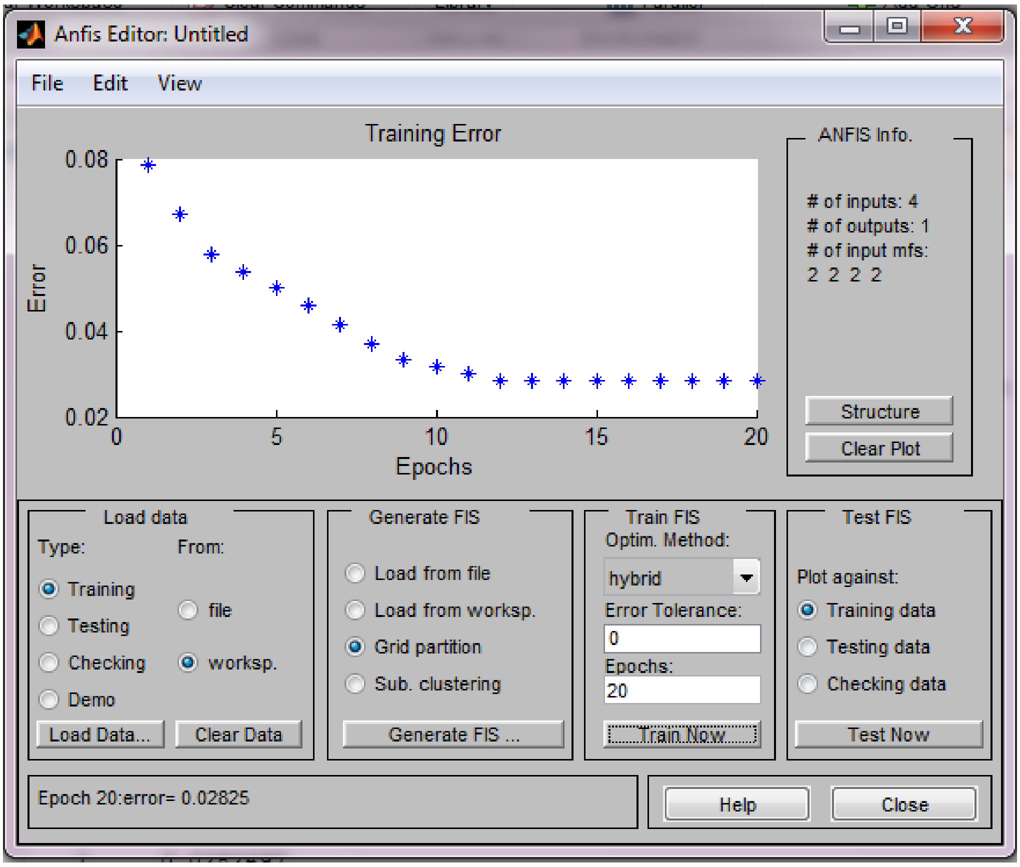

Figure 9.20 Training error

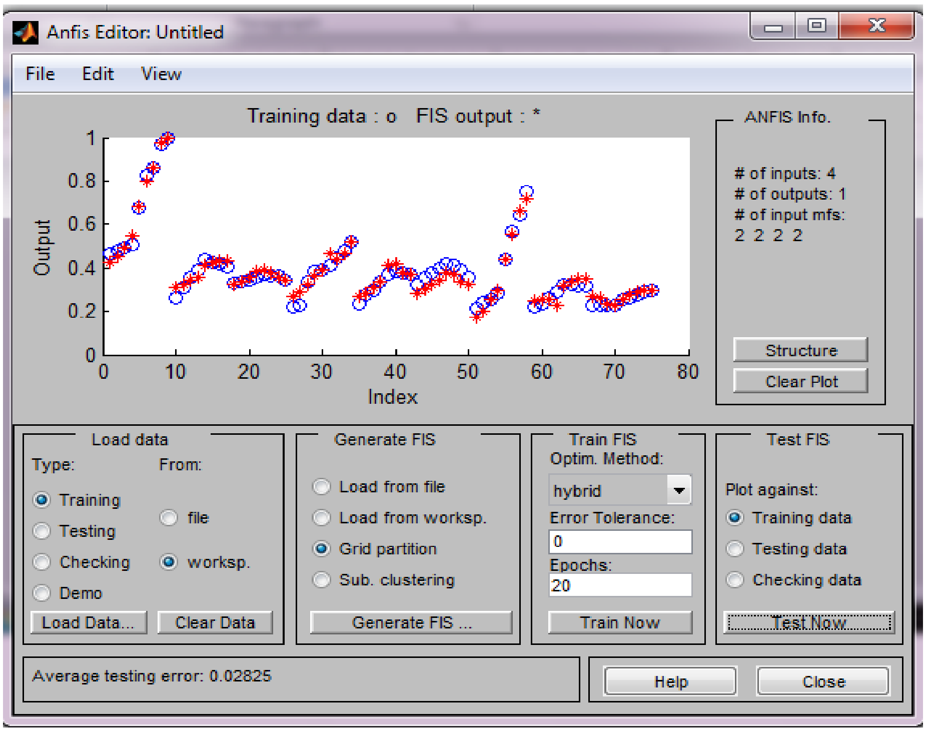

Figure 9.21 Training and checking Error of ANFIS

Step 6: The turning data sets summarized and used for testing data into the ANFIS model.

Step 7: During the testing of ANFIS model for the surface roughness (R_a) prediction in turning, experimental data were used to check the validity of the model. Table 9.4 shows the parameter values used in testing.

Step 8: Finally, the test output results obtained with ANFIS model are compared with the experimental results.

Table 9.4 Parameters used in testing

Process parameter	Values
Cutting speed(V) m/min	167-261
Feed rate (F) mm/rev	0.075-0.15
Depth of cut (D) mm	0.1-0.2

Step 9: Regression analysis is a statistical process for estimating the relationships among variables, i.e. output of ANFIS model and the actual data used for the testing. Regression analysis is widely used for prediction. After the obtaining the output of

ANFIS model, a plot is drawn between the output of ANFIS model and actual data set. Regression analysis of ANFIS model is shown in Figure 9.22.

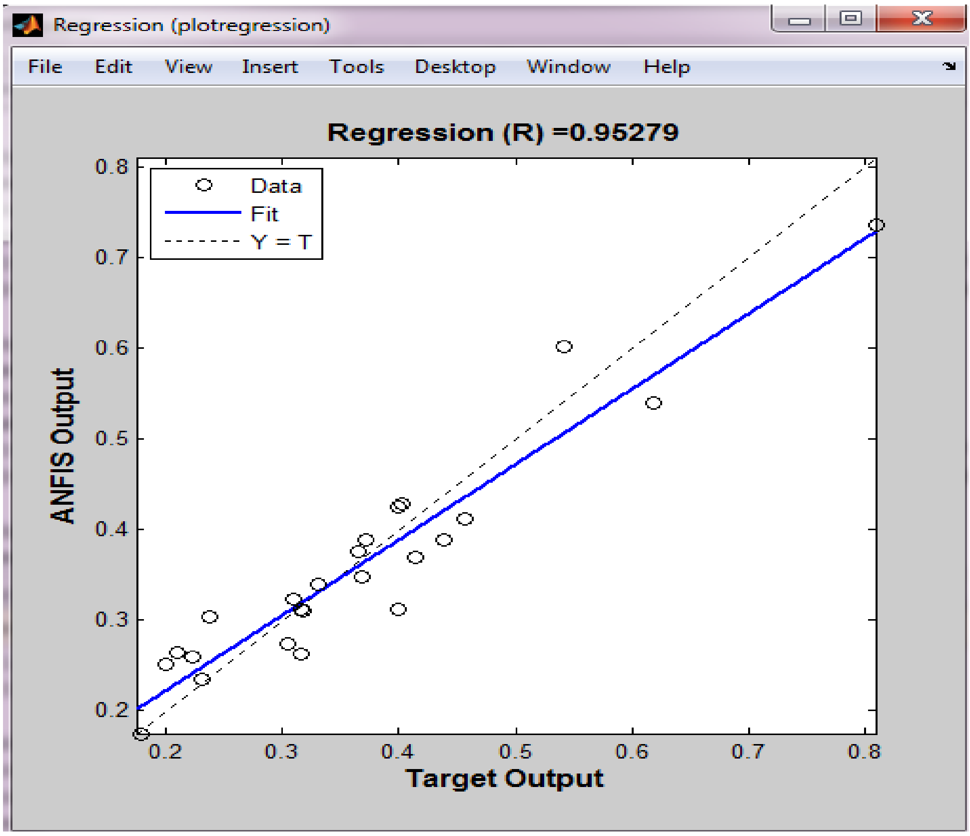

Figure 9.22 Regression analysis of ANFIS model for surface roughness

9.6 ANFIS MODEL VERIFICATION

9.6.1 ANFIS Model Verification for Cutting Force

Twenty-seven random readings were used as the testing data set (Table 9.2). The plot of 27 actual cutting force values versus output cutting force values using the ANFIS model is shown in Figure 9.23. The figure presents a comparison of the actual cutting force values and output cutting force values of the testing data set of 27 following training using ANFIS. Appropriate assent is evident between the actual and ANFIS-output cutting force values. This close assent obviously displays that the ANFIS model can be used to predict the cutting force values under unmanned production system consideration.

To assess the ANFIS model, the percentage error E_i and average percentage error E_{av} defined in equations (9.7) and (9.8) [361], respectively, were used.

$$E_i = \frac{|\text{actual value} - \mathit{output\ of\ ANFIS\ value}|}{\text{actual value}} \times 100 \tag{9.7}$$

$$E_{av} = \frac{1}{m}\sum_{i=1}^{m} E_i \tag{9.8}$$

Where E_i is the percentage error of sample number i; and E_{av} is the average percentage error of *m* sample data.

From Table 9.2 and Figure 9.24 show that the average percentage error for predicting cutting force values is 2.59%. Figure 9.24 presents the percentage error between the predicted and actual cutting force values. The error and accuracy values mean that the proposed model can predict cutting force values satisfactorily.

9.6.2 ANFIS Model Verification for Surface Roughness

Twenty random readings were used as the testing data set (Table 9.5). The plot of 20 actual surface roughness values versus output surface roughness values using the ANFIS model is shown in Figure 9.25. The figure presents a comparison of the actual surface roughness values and output surface roughness values of the testing data set of 20 following training using ANFIS. Appropriate assent is evident between the actual and ANFIS-output cutting force values. This close assent obviously displays that the ANFIS model can be used to predict the cutting force values under unmanned production system consideration.

To assess the ANFIS model, the percentage error E_i and average percentage error E_{av} defined in equations (9.7) and (9.8), respectively, were used.

From Table 9.5 and Figure 9.26 show that the average percentage error for predicting surface roughness values is 7.38%. Figure 9.26 presents the percentage error between the predicted and actual cutting force values. The error and accuracy values mean that the proposed model can predict cutting force values satisfactorily.

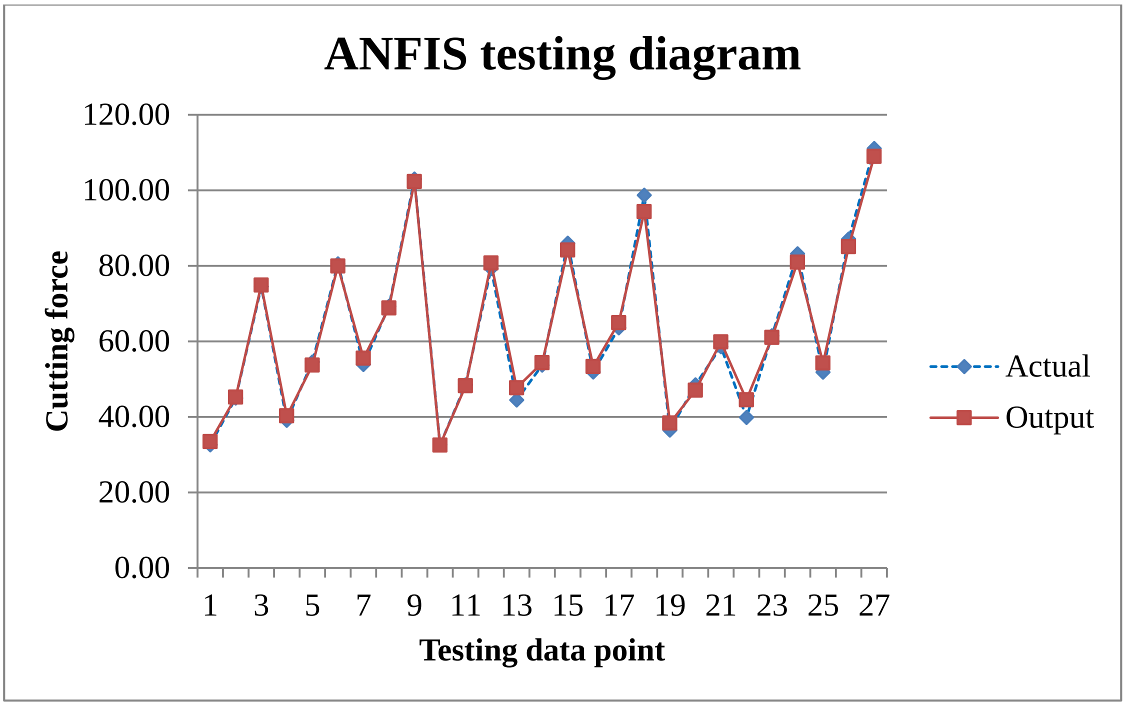

Figure 9.23 ANFIS testing diagram

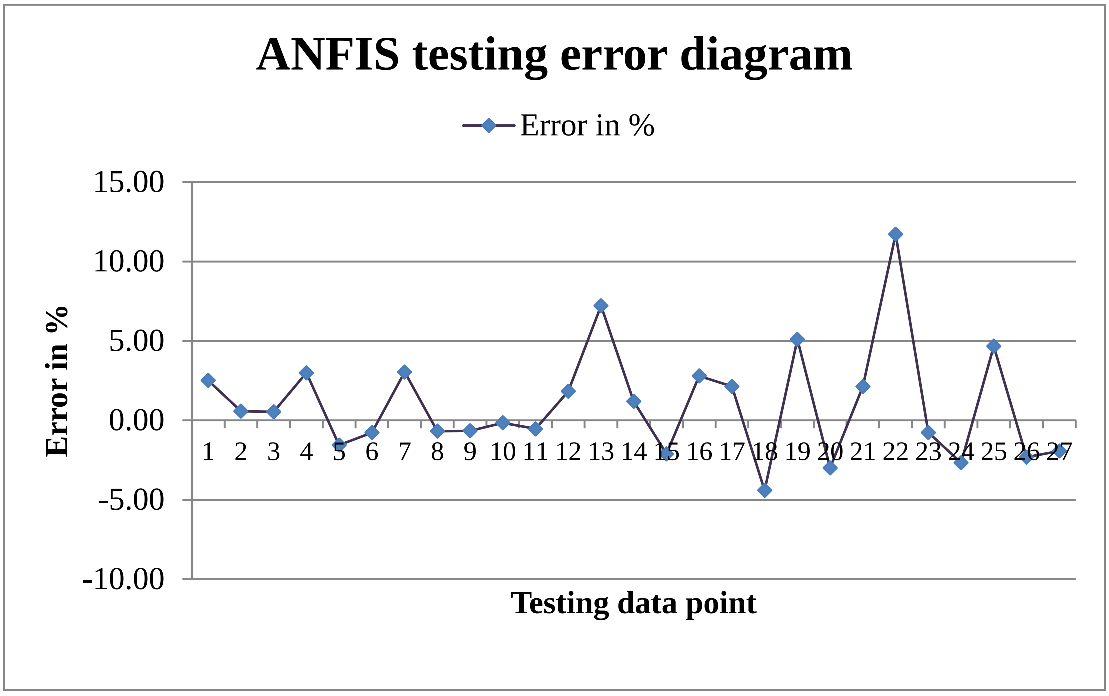

Figure 9.24 The error percentage

Table 9.5 Partial results of ANFIS modeling

Cutting speed(*V*) m/min	Feed rate (*F*) mm/rev	Depth of cut (*D*) mm	Cutting force (F) N	Surface roughness (R_a) µm (actual)	Surface roughness (R_a) µm (output)	Error in %	Accuracy in %
167	0.075	0.10	32.66	2.83	2.55	-10.0	90.00
167	0.075	0.15	44.99	3.35	3.72	11.10	88.90
167	0.113	0.15	54.55	2.72	2.41	-11.3	88.62
167	0.113	0.20	80.54	2.47	2.62	6.24	93.76
167	0.150	0.10	53.88	1.97	1.92	-2.46	97.54
167	0.150	0.15	69.32	2.30	2.41	4.65	95.35
167	0.150	0.20	102.98	2.05	2.10	2.53	97.47
204	0.075	0.15	48.55	2.49	2.65	6.43	93.57
204	0.075	0.20	79.32	3.83	3.34	-12.9	87.07
204	0.113	0.15	53.66	2.26	2.32	2.83	97.17
204	0.113	0.20	85.98	2.28	2.15	-5.47	94.53
204	0.150	0.10	51.88	1.89	1.70	-10.0	90.00
204	0.150	0.15	63.65	2.56	2.29	-10.6	89.31
204	0.150	0.20	98.65	1.95	1.93	-0.82	99.18
261	0.075	0.10	36.55	1.11	1.08	-2.63	97.37
261	0.075	0.20	58.66	5.01	4.55	-9.06	90.94
261	0.113	0.15	61.54	1.95	1.62	-16.7	83.24
261	0.113	0.20	83.21	1.92	2.00	4.06	95.94
261	0.150	0.10	51.88	1.38	1.60	16.26	83.74
261	0.150	0.15	87.09	1.43	1.45	1.37	98.63

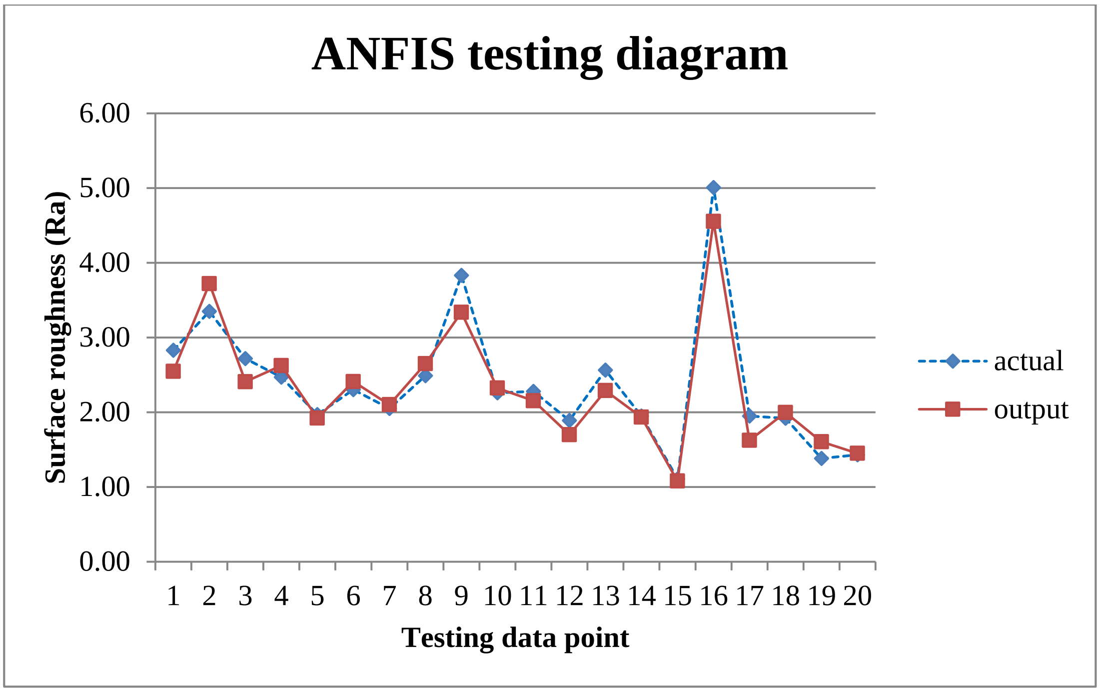

Figure 9.25 ANFIS testing diagram

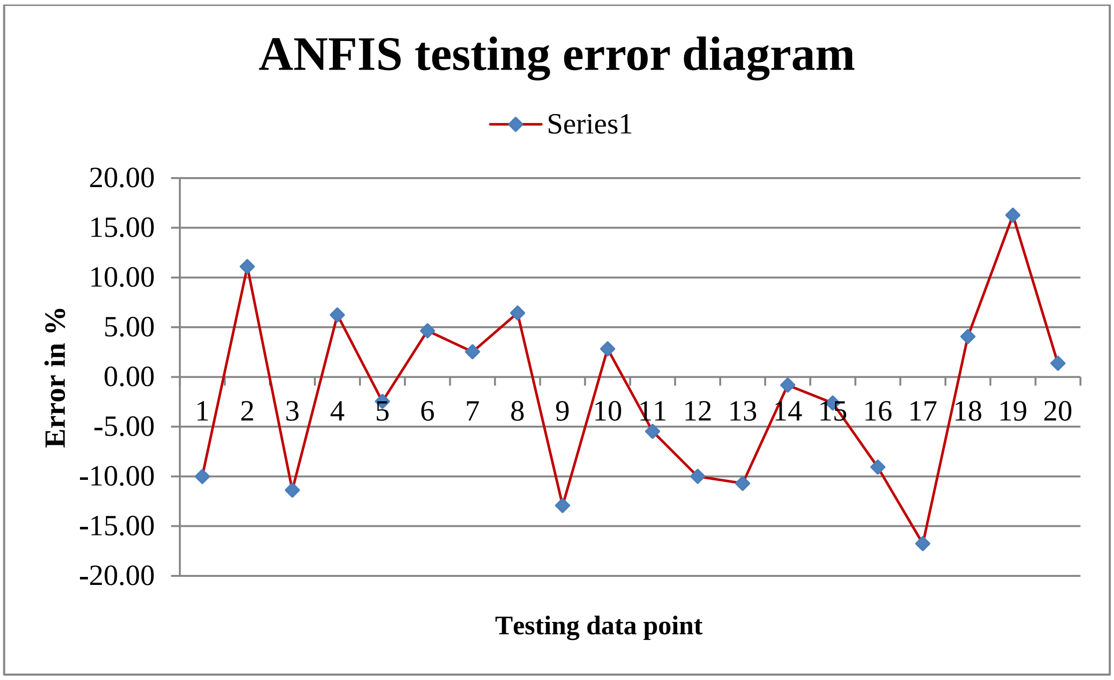

Figure 9.26 The error percentage

9.7 RESULT AND DISCUSSION

This section presents the analysis of results between the experimental data and ANFIS model output depending on the cutting parameters. The values of cutting parameters actual (experimental) and output of ANFIS are shown in Table 9.2. Figure 9.23 shows an ANFIS testing diagram of the actual and output of ANFIS cutting force values. This Figure shows that the online predicted values are a close match of the actual ones. Adaptive neuro-fuzzy interference system shows a good performance with a coefficient of determination (R^2) is 0.9952 and RMSE of 0.0167. The root-mean-square error (RMSE) is a frequently used measure of the differences between values predicted by a model or an estimator and the values actually observed and coefficient of determination, describes how much of the variance between the two variables is described by the linear fit. Coefficient of determination of 0.9952 means that 99.52 percent of the variance is predictable. Regression analysis between actual and output cutting force is also shown in a graphical way in Figure 9.15. The value of correlation coefficient (R) is 0.9976. The results mutually differ less than ± 10%. The correlation coefficient is close to 1 i.e. 0.9976, it would indicate that the variables are positively linearly related and the scatter plot falls almost along a straight line with positive slope.

ANFIS modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and testing data sets. Training data constitutes a set of input and output data. The data is normalized in order to make it suitable for the training process. This normalized data was utilized as the inputs (machining parameters) and outputs (cutting force) to train the ANFIS. In other words, two types of data are formed in order to train the ANFIS. Input data are cutting speed, feed and depth of cutting. The output data is cutting force. So, tool life for unmanned production system is analyzed on the basis of cutting force. The increasing cutting force means the deterioration and the wearing of the tool.

Figure 9.25 shows an ANFIS testing diagram of the actual and output of ANFIS surface roughness values. The figure shows that the online predicted values are a close match of the actual ones. Adaptive neuro-fuzzy interference system shows a good performance with a coefficient of determination (R^2) is 0.9078 and RMSE of 0.0443. Coefficient of determination of 0.9078 means that 90.78 percent of the variance is predictable. Regression analysis between actual and output surface roughness is also shown in a graphical way in Figure 9.22. The value of Correlation coefficient (R) is

0.9528. The results mutually differ less than ± 10%. The correlation coefficient is close to 1 i.e. 0.9528, it would indicate that the variables are positively linearly related and the scatter plot falls almost along a straight line with positive slope. ANFIS modeling process starts by obtaining a data set (input-output data pairs) and dividing it into training and testing data sets. Training data constitutes a set of input and output data. The data is normalized in order to make it suitable for the training process. This normalized data has been utilized as the inputs (machining parameters) and outputs (surface roughness) to train the ANFIS. In other words, two types of data are formed in order to train the ANFIS. Input data are cutting speed, feed, depth of cut and cutting forces. The output data is surface roughness. So, tool life for unmanned production system is analyzed on the basis of surface finish. If the surface finish deteriorates, it means tool is going to wear out. The advantages of ANFIS system over the traditional estimation methods are simple complementing of the model by new input parameters without modifying the existing model structure, automatic searching for the non-linear connection between the inputs and outputs. After training, its performance was found satisfactory under various cutting conditions.

9.8 CONCLUSION

In this chapter, a model for tool life for unmanned production system by using an adaptive neuro-fuzzy inference system (ANFIS) is made to predict the cutting force and surface roughness as the cutting forces increases tool life and surface finish deteriorates. This model offers ability to estimate tool life for the unmanned production system related to cutting force and surface roughness.

(1) It enables monitoring of unmanned production for tool life.

(2) ANFIS model can predict ± 10% of output and it can achieve more accurate.

(3) This modeling can estimate the cutting force and surface roughness, very fast and accurately on the basis of input cutting parameters like speed, feed and depth of cut and cutting force.

(4) With reference to this model, any model can be designed to predict the data.

CHAPTER X

SYNTHESIS OF THE RESEARCH WORK

10.1 INTRODUCTION

It is evident that performance enhancement is required in all manufacturing industries. So, there are some factors which effect the performance of a manufacturing system. Productivity, flexibility and quality are the three main factors of FMS which have been identified. Some variables are also identified from literature review which affect performance, productivity and flexibility of FMS. Evaluation of flexibility in FMS focus the impact of flexibilities in manufacturing system. Study of tool life for unmanned production system is necessary for manufacturing system. FMS assembly shop makespan estimation help the production manager for better planning and schedule of assembly.

In this chapter, synthesis of research work mentioned in the previous chapters have been presented. The main objectives of this chapter are:

i. To present overall picture of the research work.
ii. To discuss different studies done in previous chapters.
iii. To establish a link among all the studies carried out in this research work.

10.2 SYNTHESIS OF THE RESEARCH WORK

Research reported in this thesis concerns the investigation of some performance, productivity and flexibility variables of FMS. The research was carried out with objectives specified in the first chapter. The achieved objectives are as follows:

i. The literature existing on FMSs has been studied, some issues of FMS constraint are discussed.
ii. Major variables of performance, productivity and flexibility have been identified.
iii. ISM model has been developed for performance variables and the driving and dependence power of performance variables has been found by MICMAC analysis.

iv. ISM model has been developed for productivity variables and the driving and dependence power of productivity variables has been found by MICMAC analysis.

v. TISM model has been developed for flexibility variables and the driving and dependence power of flexibility variables has been found by fuzzy MICMAC analysis.

vi. ISM model of performance variables has been validated by structural equation modeling and the FMS performance index has been found by GTMA.

vii. ISM model of productivity variables has been validated by structural equation modeling and the FMS productivity index has been found by GTMA.

viii. TISM model of flexibility variables has been validated by structural equation modeling and the FMS flexibility index has been found by GTMA.

ix. ISM model has been developed for types of flexibility of FMS and the driving and dependence power of flexibility has been found by MICMAC analysis.

x. Evaluation of flexibility based on variables which affect the flexibility of FMS by combined MADM methods.

xi. FMS assembly shop makespan is calculated by NEH algorithm and its estimation is done by soft computing technique i.e. ANFIS.

xii. Tool life management of unmanned production system is also done by soft computing technique i.e. ANFIS.

xiii. Cutting parameter optimized by metaheuristics i.e. GA and TLBO.

For achieving the objectives, the methodologies used in the present research are presented in Table 10.1 and briefly discussed below:

10.2.1 Literature Review

An extensive literature review carried out through which some variables of FMS and some issues of FMS have been considered. A large number of research paper were studied to find the variables of performance, productivity and flexibility of FMS. Issues related to constraints of FMS are also studied. A detailed study of these are discussed in chapter 2. Methodologies which are used in this research to achieve the research objectives have also been discussed in this chapter.

10.2.2 Questionnaire Administration

To understand the perception of FMS variables a questionnaire is developed and it is discussed in chapter 3. Questionnaire is developed separately for performance, productivity and flexibility variables. Fifteen variables for performance, twenty variables for productivity and fifteen variables for flexibility of FMS have been considered. According to survey result, automation has been ranked as the top most variable for performance of FMS. Use of automated material handling device has been ranked as top most variable for productivity of FMS. Flexible fixturing has been ranked as top most variable for flexibility of FMS. Performance, productivity and flexibility variables of FMS have been used for further modeling and analysis.

10.2.3 Development of ISM Model

Separate ISM models have been prepared for performance and productivity variables of FMS and flexibility of FMS in chapter 4, 5and 7 respectively. Through ISM model of performance variables it is found that automation, effect of tool life, use of automated material handling devices and rework percentage are placed in the bottom of model which are the key variables for performance of FMS. From the MICMAC analysis it is found that these are also independent variables which have strong driving power and less dependence power.

Through ISM model of productivity variables it is found that training, financial incentive, trained worker and effect of tool life are placed in the bottom of model which are the key variables for productivity of FMS. From the MICMAC analysis it is found that training, trained worker, effect of tool life, automation and reduction in rework percentage are having high driving power. From this modeling, it is concluded that effect of tool life, automation and reduction in rework percentage are the common variables for performance and productivity of FMS. So, focus on these variables will increase productivity followed by the increase in the performance of FMS.

Through ISM model of flexibility variables of FMS it is found that production flexibility, product flexibility, machine flexibility and material handling flexibility are placed in the bottom of model which are the key flexibility of FMS. From the MICMAC analysis found that these are also independent variables which have strong driving power and less dependence power.

Table 10.1 Methodologies used in the research

Objectives	Methodology	Study No.
To identify variables which affect FMS and constraints of FMS with some issues.	Literature review and expert opinion	1
To understand the perception of FMS variables	Questionnaire based survey	2
Modeling and analysis of performance variables of FMS	Interpretive structural modeling, Structural equation modeling and Graph theory matrix approach	3
Modeling and analysis of productivity variables of FMS	Interpretive structural modeling, Structural equation modeling and Graph theory matrix approach	4
Modeling and analysis of flexibility variables of FMS	Total interpretive structural modeling, Structural equation modeling and Graph theory matrix approach	5
Ranking of flexibility in FMS	Interpretive structural modeling, Combined multiple attribute decision making methods, i.e. AHP, TOPSIS, Modified TOPSIS, Improved PROMETHEE and VIKOR.	6
Makespan estimation of FMS assembly shop	NEH Algorithm, ANFIS	7
Tool life management for unmanned production system	ANFIS, GA, TLBO, Regression analysis	8

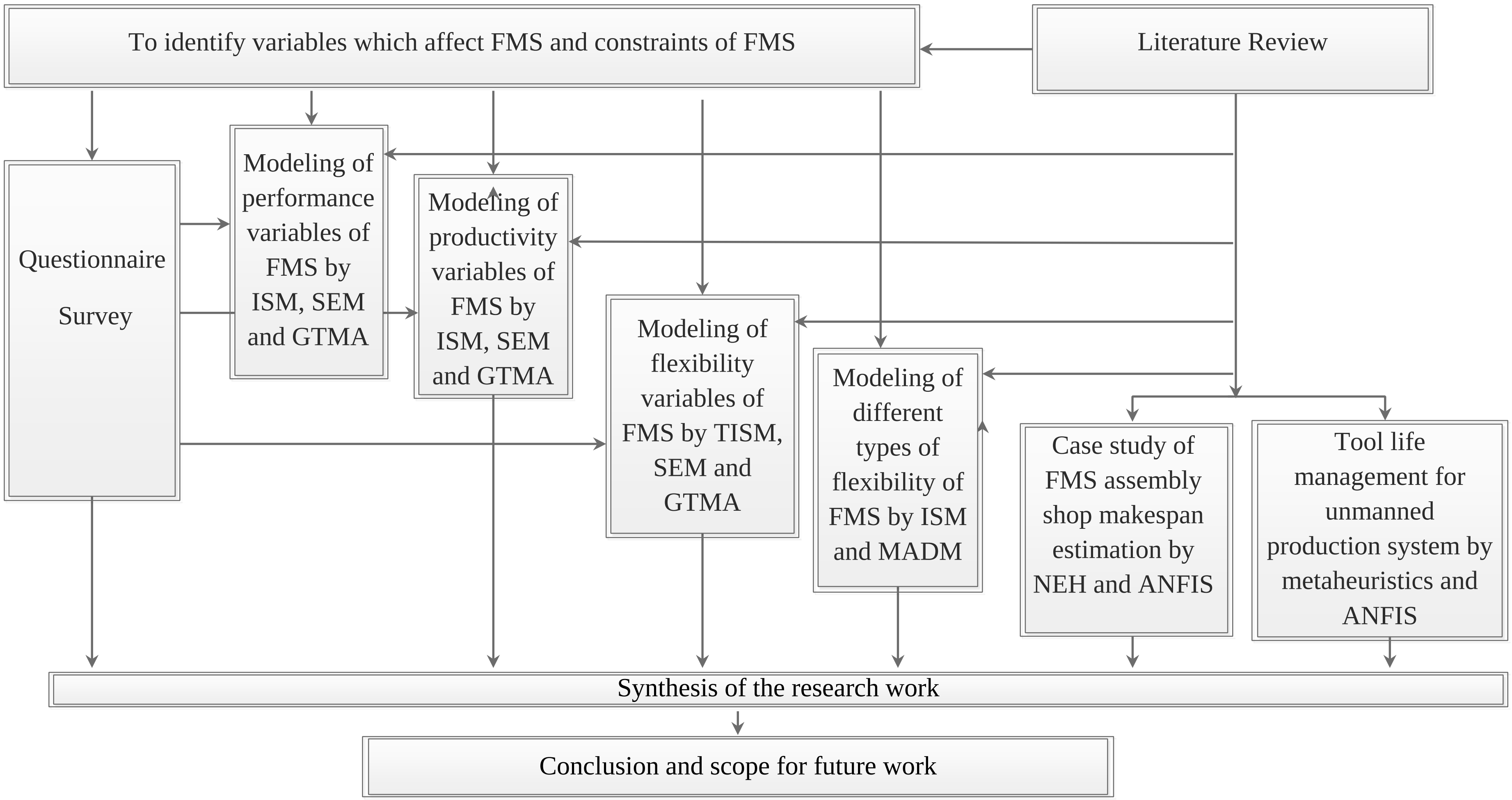

Figure 10.1 Integration of methodologies used in this research

10.2.4 Development of TISM Model

TISM model for flexibility variables has been discussed in chapter 6. Fifteen variables are taken for this modeling. Interpretation of the mutual relationship of variables is comparatively weak in ISM. Thus, an upgraded version of ISM i.e. Total interpretive structural modeling (TISM) methodology is used to develop the model and the mutual relationship of variables is identified in the TISM. This research is an application of TISM to interpret the mutual relationship with the ISM using the tool of interpretive matrix and leads to evolving the framework and find out driving and the dependence power of variables, using fuzzy MICMAC analysis. The result shows that use of reconfigurable machine tool, automation and flexible fixturing have strong driving power and weak dependence power and are at the lowest levels in hierarchy in the TISM model. Hence, superior performance of FMS can be achieved by improving the driving variables of flexibility.

10.2.5 Development of SEM Model

ISM and TISM model developed for performance, productivity and flexibility of FMS has a limitation that these models are not statistically validated. So, structural equation modeling is used to validate these models in chapter 4, 5 and 6 respectively for performance, productivity and flexibility modeling. Data analysis in SEM proceeds in two steps. First the Exploratory factor analysis (EFA) is used to identify the underlying dimensions of variables in FMS. Next is confirmatory factor analysis (CFA) to confirm the factor structure of the dimensions in FMS. Both are powerful statistical techniques. By performing EFA, factor structure is placed, whereas CFA verified the factor structure of a set of observed variables. CFA is carried by SEM statistical technique. EFA is applied to extract the factors in FMS by The statistical package for social sciences (SPSS) software and confirming these factors by CFA through analysis of moment structures (AMOS) software.

The fifteen performance variables are identified through literature and three factors are extracted, which involves the performance of FMS. The three factors are quality, productivity and flexibility. SEM using AMOS was used to perform the first order three factor structure. Fit indices of this model show good model fit (CMIN ($\chi 2$) =185.888, df = 81, p =.000; CMIN/DF (χ 2/ DF) = 2.295 (< 5); CFI =0.964; TLI = 0.953; IFI = 0.964; NFI = 0.938; RFI=0.920; GFI=0.913; and RMSEA = 0.07). The result of this model was discussed in chapter four. Quality factor includes the effect of tool life, scrap percentage, rework percentage and automation. Productivity factor includes the variables unit manufacturing cost, unit labor cost, manufacturing lead time, throughput time, set up cost and setup time. Flexibility factor includes the equipment utilization, ability to manufacture a variety of product, capacity to handle new product, use of automated material handling devices and reduced work in process inventory.

The twenty productivity variables are identified through literature and four factors are extracted which involves the productivity of FMS. The four factors are people, quality, machine and flexibility. SEM using AMOS was used to perform the first order four factor structures. Fit indices of this model show good model fit (CMIN ($\chi 2$) =397. 350, df = 159, p =.000; CMIN/DF (χ 2/ DF) = 2.499 (< 5); CFI =0. 964; TLI = 0.957; IFI = 0.964; NFI = 0.941; RFI=0.930; GFI= 0.890; RMR= 0.05 and RMSEA = 0.069). The result of this model was discussed in chapter five. People factor include the training, financial incentive and unit labour cost. Quality factor include the effect of tool life, customer satisfaction, reduction in scrap percentage, reduction in rework percentage and reduction of rejection. Machine factor include the equipment utilization, trained worker, manufacturing lead time and setup time, unit manufacturing cost, throughput time and set up cost. Flexibility factor include the automation, use of automated material handling devices, reduction in material flow, reduced work in process inventory, capacity to handle new product and ability to manufacture a variety of product.

Fifteen variables are identified through literature and four factors are extracted, which affects the flexibility of FMS in production flexibility, machine flexibility, product flexibility and volume flexibility. Structural equation modeling (SEM) using AMOS was used to perform the first-order four-factor structure of the FMS flexibility. Fit indices of this model show good model fit (CMIN ($\chi 2$) = 154.638, df =84, p= 0. 000, CMIN/DF (χ 2/ DF) =1. 841 (< 2); GFI = 0.937; RMSEA= 0.05; AGFI = 0.909; RMR= 0. 03; NFI = 0.902; CFI = 0.924; TLI= 0.905; and IFI = 0.926). The result of this model was discussed in chapter six. Production flexibility factor include the combination of operation, reduced WIP inventories, reduction in material flow, use of reconfigurable machine tool and reduction in scrap. Machine flexibility factor include the increase machine utilization, ability to manufacturing a variety of product, manufacturing lead time and setup time reduction and quality consciousness. Product flexibility factor include the capacity to handle new product, flexible fixturing and flexibility in the design of production system. Volume flexibility factor include the automation, use of automated material handling devices and speed of response.

These structural models are further recommended for evaluation of index by graph theory matrix approach.

10.2.6 GTMA for Evaluation of FMS Index

Chapter 4, 5 and 6 presents a graph theory matrix approach to the FMS performance index, FMS productivity index and FMS flexibility index respectively.

Performance variables are identified by literature review and explored by EFA. These variables are grouped into three factors i.e. productivity, flexibility and quality. The GTMA approach correlate these factors and quantified based on mutual interdependencies of their variables. This study propose a numerical value of performance known as FMS performance index for any industry. By knowing the FMS performance index, manufacturing industry can enhance their performance.

Productivity variables are also identified by literature review and explored by EFA. These variables are grouped into four factors i.e. people, machine, flexibility and quality. The GTMA approach correlate these factors and quantified based on mutual interdependencies of their variables. This study propose a numerical value of productivity known as FMS productivity index for any industry. By knowing the FMS productivity index, manufacturing industry can enhance their productivity.

Flexibility variables are identified by literature review and explored by EFA. These variables are grouped into four dimensions i.e. production, product, machine and volume flexibility. The GTMA approach correlate these factors and quantified based on mutual interdependencies of their variables. This study propose a numerical value of performance known as FMS flexibility index for any industry. By knowing the FMS flexibility index, manufacturing industry can enhance their flexibility. The flexibility and the productivity of the system increase, the performance of the system also increases.

10.2.7 MADM for Ranking of Flexibility

Combined MADM methods like AHP, TOPSIS, Modified TOPSIS, Improved Promethean VIKOR is shown in chapter 7 for ranking of types of flexibility based on flexibility variables.

Ranking of flexibilities is found out by a different methodology of combined multiple attribute decision making method such as an AHP, TOPSIS, Modified TOPSIS, Improved PROMETHEE and VIKOR. According to AHP product flexibility; TOPSIS production flexibility; modified TOPSIS production flexibility; improved PROMETHEE production flexibility; and by VIKOR is production flexibility. In this case, the rankings obtained by the different MADM methods for alternative i.e. FMS flexibility ranking are consistent but not the same. So, spearman's rank correlation coefficients are calculated to check the consistency in the rankings given by different methods. It is observed that the rankings by different methods are consistent and all the methods can be considered for averaging of the ranks to find the adjusted ranks of alternative FMSs. All five MADM methods have good rank correlation with each other, hence the rankings given by any of the five MADM methods considered here has good similarity with the rankings given by other methods. Hence, ranking on the basis of average ranking values of all methods is carried out. The production flexibility is chosen as the top most FMS flexibility as per the FMS flexibility ranking.

10.2.8 ANFIS Modeling for Makespan Estimation and Tool Life Management for Unmanned Production System

ANFIS modeling is done for makespan estimation and tool life management for unmanned production system and shown in chapter 8 and 9 respectively. A case study for FMS assembly shop is discussed and found the makespan for assembly by NEH algorithm. Based on this, ANFIS model is developed to estimate the makespan for assembly shop in advance. So, production manager can plan and schedule the assembly accordingly.

Secondly, two ANFIS model i.e. cutting force ANFIS model and surface roughness ANFIS model for tool life management is developed. Cutting force are based on cutting speed, feed and depth of cut. Surface roughness are based on cutting speed, feed, depth of cut and cutting force. Cutting force and surface roughness are predicted from these models and these are the indicators of tool life. Tool life cannot be predicted directly for unmanned production system so cutting force and surface roughness are used to indicate tool life for unmanned production system.

10.2.9 Metaheuristic Optimization of Cutting Parameters

Metaheuristics are used to optimize the cutting parameter like speed, feed and depth of cut to optimize cutting force in chapter 9. Two metaheuristics technique are used i.e. genetic algorithm and teacher learning based optimization. The optimum turning parameters in the GA, the minimum cutting force (C = 32.916 N) value was obtained at s = 181.559 m/min, f = 0.075 mm/rev and d = 0.1. The TLBO algorithm is also applied in this optimization problem. The optimum turning parameters in the TLBO, the minimum cutting force (C = 32.6547 N) value was obtained at s = 167 m/min, f = 0.075 mm/rev and d = 0.1. Fitness value and individual values of parameters found by GA and TLBO are discussed in chapter nine. Both techniques have almost similar results. Objective function for optimization is created by regression analysis by Minitab software. The results of metaheuristics are also verified by ANFIS modeling. So, it is future direction for production manager to optimize cutting force to get better tool life.

10.3 CONCLUSION

This chapter focuses on the synthesis of the research reported in this thesis. The synthesis indicates that there is an agreement in the outcomes of different methodologies used in the present research work. Figure 10.1 illustrates the integration of methodologies used in this research. Further, the conclusion, key findings, implications and scope for future research have been presented in the next chapter.

CHAPTER XI

SUMMARY, KEY FINDINGS, SCOPE FOR FUTURE WORK AND CONCLUSION

11.1 INTRODUCTION

The major causes to implement FMS in manufacturing firms are regularly changing customer demands, cut throat competition and globalization. During past few decades various issues of FMSs are extensively explored by the researchers but their capabilities are not fully exhausted. The reason behind this is the wide gap existing between the theoretical research and practical expectations of the manufacturing industries. The alternate forms of FMSs can be developed by pursuing the researcher to research in exploring and analyzing the FMSs in Indian context.

11.2 SUMMARY OF THE WORK DONE

The present research has developed and justified the FMSs for Indian industrial environment. In this section, the research carried out for achieving the research objectives is presented. The main work undertaken in this research includes the following

i. Exhaustive literature review was conducted to identify some relevant issues and variables in the field of FMSs.

ii. On the basis of the literature review and discussion with industry personnel and academicians, a questionnaire was designed to elicit responses from the manufacturing experts. The responses to the questionnaire-based survey helped to understand the inclination of the Indian industries towards performance, productivity and flexibility of FMSs.

iii. Different issues handled in the questionnaire included for performance, productivity and flexibility of FMSs.

iv. The questionnaire was analyzed for descriptive statistics testing.

v. The statistical analysis of the questionnaire is followed by development of three models with the ISM methodology. This study has been focused on finding the driving and dependence power of the variables of performance, productivity and flexibility of FMS by MICMAC analysis. The developed ISM models also help in understanding the mutual relationship of the variables.

vi. SEM analysis is carried out for performance, productivity and flexibility variables of FMS.

vii. The GTMA based framework was developed to quantify the performance, productivity and flexibility variables of FMS.

viii. Ranking of flexibility is done by combined multiple attribute decision making methods, i.e. AHP, TOPSIS, Modified TOPSIS Improved PROMETHEE and VIKOR.

ix. Makespan estimation of FMS assembly shop is done by NEH algorithm and ANFIS.

x. Tool life management for unmanned production system is done by two ANFIS model

a) Tool life management of unmanned production system based on surface roughness by ANFIS.

b) Tool life management of unmanned production system based on cutting force by ANFIS and metaheuristics.

11.3 MAJOR CONTRIBUTIONS OF THE RESEARCH

The major contributions made through this research are given below

i. The present research provides a comprehensive review of the literature and identifies the variables which affect performance of FMS.

ii. Fifteen variables are identified which effect the performance of FMS.

iii. Twenty variables which effect the productivity of FMS are recognized.

iv. Fifteen variables which are the cause of the flexibility of FMS are detected.

v. The driving and dependence power of variables have been analyzed and found the main variables which affect the FMS.

vi. Major factors affecting the performance, productivity and flexibility of FMS have been identified.

vii. The driving and dependence power of flexibilities have been analyzed by ISM.

viii. FMS performance index, FMS productivity index and FMS flexibility index has been proposed by GTMA framework which help any industry to know its own index value to upgrade them.

ix. Combined multiple attribute decision making methods are used for ranking of flexibility based on fifteen variables. Spearman's rank correlation coefficients observed that the rankings by different methods are consistent.

x. NEH algorithm found the makespan and made a model by ANFIS for industry to predict the makespan of FMS assembly shop.

xi. Optimization of cutting parameters by metaheuristics i.e. G.A and TLBO and discussed the method to optimize parameters.

xii. ANFIS model is proposed for surface roughness and cutting force for tool life management in industries.

11.4 KEY FINDING OF THE RESEARCH

The key finding, emerge from this research are as follows

i. Mainly responding companies are interested to enhance the performance, productivity and flexibility of FMS.

ii. Survey result showed that automation is the most important as a performance variable of FMS. Use of automated material handling devices is the most important as a productivity variable of FMS. Flexible fixturing is the most important as a flexibility variable of FMS.

iii. An insight into the ISM model of performance variables of FMS indicates that automation, effect of tool life, use of automated material handling devices and rework percentage are the highest driving power. It means automation and effect of tool life plays a significant role for affecting performance of FMS.

iv. With the ISM modeling and MICMAC analysis of productivity variables of FMS training, trained worker and effect of tool life variables have the most driving power. These are the key variables to enhance the productivity of FMS.

v. Flexibility variables of FMS are evaluated by TISM and found that use of reconfigurable machine tool variable is main variable. Focusing on this variable increase the flexibility of the manufacturing system.

vi. Use of reconfigurable machine tool, automation and flexible fixturing have the highest driving power and it is evaluated by fuzzy MICMAC analysis. Therefore focuses on the said variable will increase the flexibility of system.

vii. The framework developed by graph theory matrix approach suggests a numerical value of feasibility which is termed as FMS performance index for any industry. By evaluating FMS performance index value for different industries, their manufacturing system can be compared for their suitability to FMS environment.

viii. Another framework is also developed by graph theory matrix approach to quantify productivity variables of FMS. This study suggests the way to evaluate productivity variables of FMS. A framework for flexibility variables of FMS is also developed by graph theory matrix approach to quantify flexibility variables of FMS.

ix. The three main factors are identified for FMS performance like quality, productivity and flexibility.

x. The four main factors are evaluated for FMS productivity like quality, machine, people and flexibility.

xi. Four flexibility i.e. production, machine, product and volume flexibility are identified as dimensions in FMS.

xii. Exploratory factor analysis (EFA) identify factors from all available variables of performance, productivity and flexibility.

xiii. To confirm the relationships between variables, structural equation modelling (SEM) is used. This is used for specification and estimation of direct as well as indirect relationship between variables.

xiv. Ranking of flexibility is identified by combined MADM methods and concluded that production flexibility is the most important flexibility of FMS. So, production manager can analyze their organization.

xv. FMS assembly shop makespan estimation is done by soft computing technique. Makespan represents the minimum time required to complete all the jobs. A model based on ANFIS is used for estimation of makespan. With this model, production manager can plan the production schedule.

xvi. Tool life management for unmanned production system is also done by soft computing technique. Two model are prepared one for cutting force and another for surface roughness.

xvii. Cutting force is estimated on the three parameters - speed, feed and depth of cut. In this cutting force is the indicator of tool life. The cutting forces are normally increased by wearing of tool. As per literature also, tool breakage or tool wear are strongly related to cutting force.

xviii. Optimization of cutting force, based on speed, feed and depth of cut takes place by metaheuristics i.e. G.A and TLBO. The optimum values are the mostly same. Production manager can find the optimum parameters values to find the optimum value of cutting force.

xix. Surface roughness is estimated on the four parameters like speed, feed, depth of cut and cutting force. In this surface roughness is the indicator of tool life. The surface finish produced in a machining operation usually deteriorates as the tool life gets over or nearly over.

xx. ANFIS as soft computing technique, enables the production system to monitor the unmanned production system tool life.

11.5 IMPLICATION OF THE RESEARCH

The findings of this research have made some important contributions to the literature. These findings deal with some important issues related to the performance of FMSs in Indian industrial environment.

Other major contribution of this research are as follows:

i. An important contribution of this research to the literature is the identification of gaps in this present research in the areas of FMS. To the best of our knowledge such a consolidated list of gaps in research area of FMS has not been reported earlier.

ii. A large number of performance variables have been identified and analyzed in this research work.

iii. A large number of productivity variables have been identified and analyzed in this research work.

iv. A large number of flexibility variables have been identified and analyzed in this research work.

v. The perceptions of Indian companies towards the variables of performance, productivity and flexibility of FMS have been captured by administering questionnaire.

vi. Variables of performance, productivity and flexibility of FMS are developed by ISM model and MICMAC analysis.

vii. These models are statistical validated by SEM and highlighted the finding of performance, productivity and flexibility of FMS.

viii. Evaluation of flexibility done by MADM methods and found the ranking of flexibility based on some variables.

ix. FMS performance index, FMS productivity index and FMS flexibility index have been proposed in this research through which any industry can calculate its index to their organization. Such type of numerical values have not been reported earlier.

x. FMS assembly shop makespan can be estimated in advance for the planning of production schedule.

xi. Tool life management for unmanned production system judged by cutting force and surface roughness values because there is no direct measurement of tool life. So, with the help of ANFIS cutting force and surface roughness model tool life can be predicted on line monitoring purpose for unmanned production system.

xii. Cutting parameter can be optimized by metaheuristics to find the optimum values.

11.5.1 Implications for the Managers

Some important managerial implications have also been emerged from this research. Managers in the area of manufacturing may drive useful insight from the empirical study presented in this research. Production Manager often feels handicapped in differentiating machine flexibility, process flexibility, product flexibility, operation flexibility and production flexibility. They also face problems in manufacturing system like how to measure the level of flexibility and how to quantify them. Researchers have not been able to develop any universally accepted technique on which the manufacturing people can rely. Though a lot of research work has been reported regarding flexibility in the FMS, yet its real-life implications are not encouraging. In this research, the definitions of different flexibilities are tried to define as given in the literature. The research work concluded that production flexibility has the most impact on flexible manufacturing system. It is helpful to the production manager for analyzing this for their organization. Based on this ranking, they can conclude that on which flexibility should focus to reduce costs or increase the performance of the manufacturing system. As the flexibility increases, the result productivity of the system increases. Flexibility is not a strictly defined phenomenon and consequently any measure proposed for it will be inapplicable in many situations. Managers should study the measures carefully and modify them, or possibly reconstruct them, to best suit their needs. However, in the specific case, the type and amount of flexibility needed to be established, as well as the means for achieving that type of flexibility, focusing on the specific sales, cost and asset issues that are relevant to the company and manufacturing situation. Practicing manager should ensure the driving and dependence power of variables to enhance the flexibility, productivity and performance of FMS. To ensure better tool life, optimum parameters should be used.

The GTMA methodology has very high industrial relevance in its application like quantification of the factors. In advance, industries can know the strength of various variables which affect the performance/productivity/flexibility of FMS and steps can be taken to increase it. Industries should calculate their index according to their requirements in FMSs. Intensity of flexibility/ performance/productivity will be different for different organizations because some organization may be simple implanted FMS or others may be complicated (fully) FMS.

11.5.2 Implications for the Industries

The present research is beneficial for all sorts of Indian manufacturing industry. FMS use robots and AGVs for material handling purposes. This will boost the employee for safe working like as robots are used for hazardous and complicated work like painting and welding of assembly shop. The GTMA methodology has very high industrial relevance in its application like quantification of the factors. In advance, industries can know the strength of various variables which affect the performance / productivity / flexibility of FMS and steps can be taken to increase it. Industries should calculate their index according to their requirements in FMSs. Intensity of flexibility / performance / productivity will be different for different organizations because some organization may be simple implanted FMS or others may be complicated (fully) FMS. To improve the performance, productivity and flexibility of FMS certain variables and factors are discussed. So, management should focus the key variables to enhance the performance, productivity and flexibility of FMS.

Industries can schedule their production plan as the estimation of makespan of assembly shop is done by ANFIS modeling in advance. So, they can schedule the production plan effectively.

Industries can optimized the cutting parameters like speed, feed and depth of cut to get the optimum cutting force. Cutting force mainly effect the tool life while tool life is important variable in FMS to increase the productivity and performance of FMS. Tool life can be managed for unmanned production system by using ANFIS modeling because directly online monitoring of tool life is not possible.

11.5.3 Implications for the Academicians

There are some important implications in the present research which are for the academicians. The study on various issues related to FMS and identified gaps from the literature will be helpful to the researcher carried out future research in this area. The questionnaire presented in this research can be used as an instrument to carry out future research in the area of performance, productivity and flexibility of FMS. The developed ISM and TISM model help to impose model and the mutual relationship of variables and find out driving and the dependence power of variables, using fuzzy MICMAC analysis. It is further analyzed by structural equation modeling, but it may be extended for higher degree analysis. Graph theory matrix approach motivate the researcher to develop the framework to indicate the numerical index of variables. MADM method motivates evaluation of any variable in FMS. To predict the values, ANFIS model can be designed according to their requirement.

11.6 LIMITATIONS AND SCOPE FOR FUTURE WORK

This research has provided substantial insights into the FMS performance issues. There is a need to further explore the role of these variables in a flexible manufacturing system and carry out case studies to examine the impacts of these variables in different practical situations. For the sake of simplicity the sub-systems within each system of risks were not considered. This is one of the major limitations in the present work. In the present study, limited implication have been identified for their analysis. Experts help can be sought to develop the contextual relationships for the ISM model, which may have introduced some element of bias.

However, the research work can be extended to following directions:

i. The initial model has been generated using ISM methodology for performance, productivity and flexibility of FMS. The ISM models generated in the present research work are validated by using structural equation modeling (SEM) as it has a capability to validate such ISM models. The SEM has a capability to utilize the already existing model as ISM and SEM are complimentary in nature. But SEM model used in this research has some limitation as:
   a) The present study applies SEM to a first order three factor structure for fifteen performance variables. SEM could be applied to a more advanced model incorporating a greater number of variables.
   b) The present study applies SEM to a first order four factor structure for twenty productivity variables. SEM could be applied to a more advanced model incorporating a greater number of variables.
   c) The present study applies SEM to a first order three factor structure for fifteen flexibility variables. SEM could be applied to a more advanced model incorporating a greater number of variables.

ii. More number of variables affecting the FMS's performance, productivity and flexibility can be identified to develop ISM and GTMA based models

iii. ISM has been developed to analyse the interactions in different flexibilities in FMS. It identifies the hierarchy of actions to be taken in handling different flexibilities, which affect the FMS. This model has not been statistically validated. Structural equation modelling (SEM), also commonly known as linear structural relationship approach, has the capability of testing the validity of such a hypothetical model.

iv. The ranking of flexibility is based on fifteen variables using the MADM. But the relative importance of the outcomes should be discussed with some case study, because it could be a major concern in decision making. The present study applies only fifteen factors for ranking of flexibility, a greater number of factors may be considered for this purpose.

v. Research is further required in this area to further explore these outcomes in practical scenarios and by different more MADM methods.

vi. Case study is carried out to estimate the makespan of FMS assembly shop with ANFIS. But it may be required more training to find the correlation coefficients of the makespan of assembly shop.

vii. Tool life management of unmanned production system is based on cutting force and surface roughness. There are some limitations of this research like there can be more than three variables to predict the tool life of unmanned production system. Secondly, this model cannot be optimal for another cutting force because further re-training may be necessary for other model.

11.7 CONCLUSION

This research, focuses on the performance analysis of FMS. The aim of this study is to recognize some factors which effect performance, productivity and flexibility of FMS. A comprehensive literature review and issues of constraints of FMS like machine tool, tool management, material handling system, robots and fixtures have been addressed. A questionnaire has been developed and survey of Indian industries has been conducted to understand the perspective and inclination of Indian industries towards the FMS. Variables affecting the performance, productivity and flexibility of FMS are included in the questionnaire.

In the present research work, two ISM model of variables affecting the performance and productivity of FMS and one model for types of flexibilities have been prepared. After analysis of two model of variable of performance and productivity it is found that variables such as automation, effect of tool life, use of automated material handling system, rework percentage, setup time and scrap percentage are the key variables affecting the performance and variables such as automation, effect of tool life, reduction in rework percentage, training and trained worker are the key variables for productivity of FMS. It is observed that automation, effect of tool life and rework percentage are the common key variables affecting the performance and productivity of FMS. Therefore industrial manager should focus on these variables for effective utilization of FMS. From the third ISM model of flexibility, it is observed that production flexibility, product flexibility, material handling flexibility, machine flexibility, process flexibility and routing flexibility are the key flexibilities which are affecting the utilization of FMS.

Another framework of variable of flexibility of FMS has been prepared by TISM. From this framework it is observed flexible fixturing, automation, use of the reconfigurable machine tool, use of automated material handling devices and flexibility in production are the key variables which affect the flexibility of FMS. From the above models of ISM and TISM, it can be concluded that automation is the major variable which affect the performance, productivity and flexibility of FMS. Hence, industrial expert should focus on the automatic operation of all component of FMS and it is also main requirement in unmanned operation especially for the third shift of manufacturing industries.

Further ISM and TISM model prepared for performance, productivity and flexibility of FMS have been validated by SEM. Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are used for SEM. EFA is applied to extract the factors in FMS by SPSS software and three factors are identified which effect performance of FMS i.e. productivity, flexibility and quality. These factors are confirmed by CFA through AMOS software. Four factors are identified by EFA through SPSS software which effect the productivity of FMS i.e. people, machine, flexibility and quality and these factors are confirmed by CFA through AMOS software. Four dimensions are clearly defined i.e. production, product, machine and volume flexibility by EFA through SPSS software and confirmed by CFA through AMOS software. Quantification is done by GTMA for performance, productivity and flexibility factors of FMS. In this quantitative analysis of performance of FMS, it is found that productivity factor has the maximum index value which means that these variables are the major variables affecting the performance of FMS and some of these variables are aligned with the qualitative analysis of performance of FMS. In this quantitative analysis of productivity of FMS, it is found that flexibility factor has the maximum index value which means that these variables are the major variables affecting the productivity of FMS and some of these variables are aligned with the qualitative analysis of productivity of FMS. In this quantitative analysis of flexibility of FMS, it is found that production flexibility has the maximum index value which means that these variables are the major variables affecting the flexibility of FMS and some of these variables are aligned with the qualitative analysis of flexibility of FMS.

Another framework for ranking the different types of flexibilities of FMS has been prepared by combined MADM methods. From the framework, production flexibility is the major flexibility affecting the performance of FMS. This is also confirmed with the

ISM model of types of different flexibilities in which production flexibility is the key flexibility in FMS.

FMS assembly shop makespan is calculated by NEH algorithm and makespan estimation is done by soft computing technique i.e. ANFIS. ANFIS model is a combination of neural network and fuzzy rules. The purpose of this research is to gain the advantage of the capabilities of both Fuzzy systems, which is a rule-based approach well as neural network which focus on the network training. This model has been verified and the good average percentage accuracy achieved. Therefore, it is concluded that makespan calculation of the production system, by the proposed ANFIS with NEH heuristic rules can be used as a reliable approach in estimating the job completion time of the problem studied.

As the tool life has been found one of the major variables affecting the performance and productivity of FMS (as depicted from the ISM model of performance and productivity of FMS). Therefore tool life management for unmanned production system is analyzed by two ANFIS models taking into the account of effects of cutting force and surface roughness on tool life. Cutting force is one important characteristic variable to be monitored in the cutting processes to determine tool life regarding tool breakage, tool wear and surface roughness (R_a) of the workpiece. The principal presumption was that the cutting forces are normally increased by the wear of the tool. Surface roughness is also the indicator of tool life. The surface finish produced in a machining operation usually gives higher finish with a good tool and it deteriorates as the tool life gets over or nearly to be over. ANFIS method is used to extract the features of tool states from cutting force signals. ANFIS model for cutting force shows a good performance with a good correlation coefficient and average percentage error for predicting cutting force. The ANFIS model for surface roughness also achieved good correlation coefficient and average percentage error for predicting surface roughness. Hence these models provide ability to estimate tool life for the unmanned production system related to cutting force and surface roughness. Tool life of tool is good at the optimized parameters of cutting force. Optimization of cutting forces based on speed, feed and depth of cut is taken by GA and TLBO algorithm and found the optimum parameter values. The same parameters values are examined in ANFIS model and the results are appropriate. So, production manager can design any model to predict the data based on these models.

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APPENDIX-A

QUESTIONNAIRE

Mechanical Engineering Department

YMCA University of Science and Technology, Faridabad

Sub: - Filling questionnaire for Dissertation (Ph.D.) work on Performance analysis of Flexible manufacturing System.

Dear Sir/Madam,

I am pursuing for research degree (Ph.D.) in Mechanical Engineering under the guidance of Prof. (Dr.) Tilak Raj, Professor in Mechanical Engineering at YMCA University of Science and Technology, Faridabad.

A flexible manufacturing system (FMS) is an integrated, computer-controlled complex arrangement of automated material handling devices and numerically controlled (NC) machine tools that can simultaneously process medium-sized volumes of a variety of part types. FMS can be very rapidly adjusted to part variety according to the changing market demands. It can respond quickly and smoothly to unexpected changes in the market and recently, it is setting new trends in the manufacturing world. The purpose of my present research work under-taken is to develop a hierarchical model and to establish a methodology for modeling and analysis of performance, productivity and flexibility variables.

In this regard a questionnaire covering issues related to Performance, Productivity and flexibility variables of the Flexible Manufacturing system is being sent to your reputed organization. As the answers to these questions provided by you, will be of utmost value towards achieving the objective, we earnestly request you to kindly spare some of your valuable time for giving answers to various questions as observed in your organization. The purpose of the survey is purely academic. Therefore, all responses will be kept strictly confidential and will be used only for this academic work.

I request you to kindly spare your valuable time to fill up this questionnaire and return through the email / post as per your convenience. I assure you that it will be kept strictly confidential.

Thanks with warm regards

Yours Sincerely,

Vineet Jain (Research Scholar)

QUESTIONNAIRE

Section 1: Organisation Profile

1. (A) Name of organization…………………………………….

   (B) Type of business………………………………………….

2. Please indicate the number of employees at your organization:

   (A) Less than 100 [] (B) 101 to 500 [] (C) 501 to 1000 []

   (D) 1001 to 3000 [] (E) More than 3000 []

3. Please indicate the total turnover of your organization in US$ millions:

   (A) Less than 10 [] (B) 10 to 50 [] (C) 50 to 100 []

   (D) 100 to 500 [] (E) 500 to 1000 [] (D) More than 1000 []

Section II: FMS Performance Variables

4. Please indicate the level of following variables which affect the Performance of FMS in your company (1- strongly disagree, 2 - disagree, 3- slightly disagree, 4 - neither disagree nor agree, 5 - slightly agree, 6- agree, 7 - strongly agree):

Sr. No	Performance Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Unit manufacturing cost							
2	Unit labor cost							
3	Manufacturing lead time							
4	Effect of tool life							
5	Throughput time							
6	Set up cost							
7	Scrap percentage							
8	Rework percentage							
9	Setup time							
10	Automation							
11	Equipment utilization							
12	Ability of manufacturing of variety of product							
13	Capacity to handle new product							
14	Use of automated material handling devices							
15	Reduced work in process inventory							

Section III: FMS Productivity Variables

5. Please indicate the level of following variables which affect the productivity of FMS in your company (1- strongly disagree, 2 - disagree, 3- slightly disagree, 4 - neither disagree nor agree, 5 - slightly agree, 6- agree, 7 - strongly agree):

Sr. No	Productivity Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Training							
2	Financial incentive							
3	Unit labor cost							
4	Effect of tool life							
5	Customer satisfaction							
6	Reduction in scrap percentage							
7	Reduction in rework percentage							
8	Reduction of rejection							
9	Equipment utilization							
10	Trained worker							
11	Manufacturing lead time and setup time							
12	Unit manufacturing cost							
13	Throughput time							
14	Set up cost							
15	Automation							
16	Use of automated material handling devices							
17	Reduction in material flow							
18	Reduced work in process inventory							
19	Capacity to handle new product							
20	Ability of manufacturing of variety of product							

Section IV: FMS Flexibility Variables

6. Please indicate the level of the following factors which affect the flexibility of FMS in your company (1- strongly disagree, 2 - disagree, 3- slightly disagree, 4 - neither disagree nor agree, 5 - slightly agree, 6- agree, 7 - strongly agree):

Sr. No	Performance Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	Ability to manufacture a variety of products							
2	Capacity to handle new products							
3	Flexibility in production							
4	Flexible fixturing							
5	Combination of operation							
6	Automation							
7	Use of automated material handling devices							
8	Increase machine utilization							
9	Use of the reconfigurable machine tool							
10	Manufacturing lead time and set up-time reduction							
11	Speed of response							
12	Reduced WIP inventories							
13	Reduction in material flow							
14	Quality consciousness							
15	Reduction in scrap							

Respondent Profile

1. Name (If you please):
2. Designation:

(a) CEO [] (b) Sr. Manager [] (c) Manager [] (d) Supervisor []

(e) Junior staff []

3. Your functional area:

(a) Production [] (b) Marketing [] (c) Maintenance [] (d) Quality Control []

(e) Any other [] *(please specify)*

4. Your association in years with current organization:

(a) Less than 5 [] (b) 5-7 [] (c) 8-10 [] (d) More than 10 []

Thank you very much for your valuable feedback

APPENDIX-B

BRIEF PROFILE OF THE RESEARCH SCHOLAR

NAME : Vineet Jain

ADDRESS : 141/ 9, Shiv Puri, Gurgaon-122001.
Mobile: 08901510570; E-Mail: vjdj2004@gmail.com

WORK EXPERIENCE: Total : 17 years
Industry : 05 years
Teaching : 12 years

EDUCATIONAL QUALIFICATION:

- Pursuing Ph. D in Mechanical Engineering from YMCA University of Science and Technology Faridabad.
- M. Tech in Mechanical Engineering (Manufacturing & Automation) with 73.78 % (Hons.) from Y.M.C.A. Institute of Engineering, Faridabad in 2008
- B.E (Mechanical) with 74.67% (Hons.) from Regional Engineering College, Kurukshetra Haryana in 2002. (Now *National Institute of Technology* , *Kurukshetra*)
- Diploma in Mechanical Engineering with 69.82% from Govt. Polytechnic, Ambala in 1996.

COMPUTER PROFICIENCY:

- M.S Office, Matlab, Pro/Engineer, SPSS, AMOS and Internet Application.

BOOK PUBLISHED:

- A book on “Basics of Mechanical Engineering” (for First year engineering students) published by Dhanpat Rai Publications Pvt.Ltd. in 2009 and a second edition is published in 2011.
- A book on “Strength of Material -1” (for second year engineering students) published by Dhanpat Rai Publications Pvt. Ltd. in 2012.
- A book on “Elements of Mechanical Engineering” (for First year engineering students) published by Dhanpat Rai Publications Pvt. Ltd. in 2012.

JOURNAL PUBLICATIONS:

- Raj, T., Attri, R., & Jain, V. (2012). Modelling the factors affecting flexibility in FMS. *International Journal of Industrial and Systems Engineering*, 11 (4), 350-374.
- Jain, V. & Raj, T. (2013) 'Evaluation of flexibility in FMS using SAW and WPM', *Decision Science Letters*, 2 (4), 223-230.
- Jain, V. & Raj, T. (2013). Ranking of flexibility in flexible manufacturing system by using a combined multiple attribute decision making method. *Global Journal of Flexible System Management*, 14(3), 125-141.
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- Jain, V.& Raj, T. (2015). Evaluating the intensity of variables affecting flexibility in FMS by graph theory and matrix approach. *International Journal of Industrial and Systems Engineering*,19 (2), 137-154.
- Jain, V. & Raj, T. (2015). A hybrid approach using ISM and Modified TOPSIS for the evaluation of flexibility in flexible manufacturing system. *International Journal of Industrial and Systems Engineering*, 19 (3), 389-406.
- Jain, V. & Raj, T. (2015). Modelling and analysis of FMS flexibility factors by TISM and fuzzy MICMAC. *International Journal of System Assurance Engineering and Management*, 6(3), 350-371.doi 10.1007/s13198-015-0368-0.
- Jain, V. & Raj, T. (2016). Modelling and analysis of FMS performance variables by ISM, SEM and GTMA Approach. *International Journal of Production Economics*, 171(1), 84-96.
- Jain, V. & Raj, T. (2016). Tool life management of unmanned production system based on surface roughness by ANFIS. *International Journal of System Assurance Engineering and Management*, doi 10.1007/s13198-016-0450-2.

APPENDIX-C

THE LIST OF PUBLICATION OUT OF THESIS

List of Published Papers

Sr. No.	Title of the paper	Name of Journal where published	No.	Volume & Issue	Year	Pages
1	Modelling and analysis of FMS performance variables by ISM, SEM and GTMA Approach	ELSEVIER(International Journal of Production Economics)	ISSN: 0925-5273	171(1)	2016	84-96
2	Modelling and Analysis of FMS Productivity Variables by ISM, SEM and GTMA Approach	SPRINGER(Frontier of Mechanical Engineering)	ISSN: 2095-0241 (Online)	9 (3)	2014	218-232
3	Modelling and analysis of FMS flexibility factors by TISM and fuzzy MICMAC	SPRINGER(International Journal of System Assurance Engineering and Management)	ISSN: 0976-4348 (Online)	6(3)	2015	350-371
4	Evaluating the variables affecting flexibility in FMS by Exploratory and Confirmatory factor analysis	SPRINGER(Global Journal of Flexible System Management)	ISSN: 0974-0198 (Online)	14 (4)	2013	181-193

5	Evaluating the intensity of variables affecting flexibility in FMS by Graph Theory and Matrix Approach	INDERSCIENCE(International Journal of Industrial and Systems Engineering)	ISSN: 1748-5045(Online)	19 (2)	2015	137-154
6	A hybrid approach using ISM and Modified TOPSIS for the evaluation of Flexibility in Flexible Manufacturing System	INDERSCIENCE(International Journal of Industrial and Systems Engineering)	ISSN: 1748-5045(Online)	19 (3)	2015	389-406
7	Ranking of flexibility in Flexible Manufacturing System by using a Combined Multiple Attribute Decision Making Method	SPRINGER(Global Journal of Flexible System Management)	ISSN: 0974-0198 (Online)	14(3)	2013	125-141
8	Evaluation of Flexibility in FMS by VIKOR Methodology	INDERSCIENCE(International Journal of Industrial and Systems Engineering)	ISSN: 1748-5045(Online)	18 (4)	2014	483-498
9	Evaluation of flexibility in FMS using SAW and WPM	GROWING SCIENCE (Decision Science Letters)	ISSN 1929-5812 (Online)	2 (4)	2013	223-230
10	Tool life management of unmanned production system based on surface roughness by ANFIS	SPRINGER(International Journal of System Assurance Engineering and Management)	ISSN: 0976-4348 (Online)	DoI: 10.1007/s13198-016-0450-2	2016	

List of Accepted Papers

Sr. No.	Title of the paper	Name of Journal where accepted	No.	Volume & Issue	Year
11	Identification of performance variables which affect the FMS: a state of art review	INDERSCIENCE (International Journal of Process Management and Benchmarking)	ISSN: 1741-816X (Online)	Accepted	2016

List of Communicated Papers

Sr. No.	Title of the paper	Name of Journal where published	Present Status	Year
12	An adaptive neuro-fuzzy inference system for makespan estimation of FMS assembly shop: a Case study (manuscript number IJSA-D-16-00135R1)	SPRINGER(International Journal of System Assurance Engineering and Management)	Under second revision	2016
13	Prediction of cutting force by using ANFIS (manuscript number IJSA-D-16-00242)	SPRINGER(International Journal of System Assurance Engineering and Management)	Under review	2016
14	Study of issues related to constraints in FMS by ISM, fuzzy ISM and TISM (manuscript number TJCI-2016-0150)	Taylor & Francis (Journal of Industrial and Production Engineering)	Under review	2016
15	Optimization of cutting force by using metaheuristics (manuscript number IJISE-151872)	INDERSCIENCE(International Journal of Industrial and Systems Engineering)	Under review	2016