Multi Attribute Decision Making Approaches in New Product Design and Development

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By

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DECLARATION

I, Mahesh Mohan Caisucar hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau.
Date: 27-07-2022 Mahesh Mohan Caisucar

CERTIFICATE

I hereby certify that the work was carried out under my supervision and may be placed for evaluation.

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ABSTRACT

The trend of the industry is to move towards the design and manufacturing of more sophisticated products so as to bring about customer satisfaction and to remain competitive in local as well as global market. The sophistication involves product with higher and safer performance, more environmental friendliness, better quality and reliability and shorter product life cycle. New product development is a complex process involving number of stages and thorough research has to be carried out at each of the phases. Idea generation is the first phase in the product development process and contains considerable amount of uncertainty causing elements. Selecting the best feasible alternatives from among set of alternatives is important for the success and growth of the industry. Using brain storming a number of ideas or concepts are listed down. Since a structured approach is required to take care of the uncertainty, MCDM methods are used to select the best idea among the chosen few. The research gap identified through the literature review carried out, shows that the effect of alternative rating variables of all alternatives taken together are not considered in ranking of alternatives during the idea screening. To address this gap three novel methods have been proposed wherein all the data involved i.e., criteria weightages data and alternative rating data are arranged in a hierarchical form and then ranking is carried out taking in to account effect of alternatives with respect to criteria variables of other alternatives to make decision for a particular alternative. The first method is based on hybrid combination of hierarchical structure and Fuzzy TOPSIS. The send method is based on hybrid combination of hierarchical structure and SNSS TOPSIS. The third method is based on score function of SNNS TOPSIS. A case study is carried out in a manufacturing industry for finding the best alternative using all the three methods and COPRAS G and Fuzzy TOPSIS method were used to validate the result. The data was collected in linguistic form so that the decision makers can express them in a better way. These linguistic variables are converted to triangular fuzzy number or single value neutrosophic number. Another research gap which came out during literature review was that design for manufacturability factors are not considered for during the decision-making process of new product development. Consideration of design for manufacturability factors during product design shortens the product life cycle thus minimizing production and manufacturing time, ensuring smooth flow of product, minimize cost etc. On the other hand, 34 % of the India's output in manufacturing is through SMEs. SMEs involved in manufacturing contribute towards 90% of all the industrial unit in India. It was paradoxical to see that, although the SMEs are important for the socio-economic development of the country, there is neglect towards them and the research carried out on new product development is more towards the larger units. Small and medium enterprises face difficulties in terms of limited technical know-how and financial capabilities, when they go for a new product development. A model has been proposed for selection of best alternative for NPD for SMEs based on factors affecting design for manufacturability. 38 factors affecting the idea selection phase of NPD for SMEs from DFM consideration were listed. These 38 low level factors were arranged under their respective high-level factors. Analytical hierarchical process was used to carry out pair wise comparison between high- and low-level factors respectively. A unique ranking method was formulated to get the relative importance of all 38 factors with respect to each other. The ranking method was then validated by comparing it with standard ranking method and finding the Spearmen coefficient. Cronbach's alpha method was modified to suit the collected data and for checking consistency of the data. The model proposes various scenario's which can arise during NPD in SMEs and provides solution as to how to go ahead with the decision-making process. The proposed model was validated using standard MCDM methods such as COPRAS G and GA-ANN.

Keywords: New Product Development, Small and Medium Enterprises, Design for Manufacturability, Hierarchical Ranking, Multi Criteria Decision Making, AHP, Fuzzy TOPSIS, COPRAS G, Genetic Algorithm, Artificial Neural Network, Single Value Neutrosophic-Set.

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List of Abbreviations, Notations and Nomenclature

Abbreviations

AHP	: Analytical Hierarchical Process
MADM	: Multi Attribute Decision Making
TFN	: Triangular Fuzzy Number
TOPSIS	: Technique of Order Preference Similarity to the Ideal Solution
COPRAS	: Complex Proportional Assessment
FAHP	: Fuzzy Analytical Hierarchical Process
ANP	: Analytical Network Process
ER	: Evidential Reasoning
QFD	: Quality Function Deployment
IT	: Information Technology
R&D	: Research & Development
SMEs	: Small & Medium Scale Enterprise
MSME	: Micro, small and medium enterprises
SVNS	: Single Valued Neutrosophic set
GDP	: Gross Domestic Product
GA	: Genetic Algorithm
ANN	: Artificial Neural Network
ANP	: Analytic Network Process
DFM	: Design for Manufacturability
MD	: Managing Directors
FERA	: Foreign Exchange Regulation Act
SVM	: Support Vector Machine
ARIMA	: Autoregressive Integrated Moving Average
LCSA	: Life Cycle Sustainability Assessment
GC	: Group Consensus
GDA	: Group Decision Analysis
VoC	: Voice of Customer
EIA	: Environmental Impact Assessment

VL	: Very Low
L	: Low
M	: Medium
H	: High
VH	: Very High
VP	: Very Poor
P	: Poor
F	: Fair
G	: Good
VG	: Very Good
CI	: Consistency Index
CR	: Consistency Ratio
DM	: Decision Maker
FPIS	: Fuzzy Positive Ideal Solution
FNIS	: Fuzzy Negative Ideal Solution
CC	: Closeness Coefficient
C1	: Criteria 1
C2	: Criteria 2
C3	: Criteria 3
C4	: Criteria 4
C5	: Criteria 5
A1	: Alternative 1
A2	: Alternative 2
A3	: Alternative 3
MAX	: Maximum
MIN	: Minimum
SCEA	: Safety and critical effect analysis

Notations

Σ	: Summation
$\forall$	: For all

Nomenclature

$\mu_A(x)$	: Membership function of fuzzy set A

$\tilde{p}$	: Triangular fuzzy number
(p^L, p^M, p^U)	: Triangular fuzzy number as a triplet
r_i	: Fuzzy geometric value
w_i	: Fuzzy weights
ρ	: Spearman rank correlation coefficient
d_i	: Difference between ranks of corresponding variables
m	: Number of alternatives
n	: Number of criteria
r_{ij}	: Alternative rating against criteria
R_i	: Summation of the ratings given by rater to the subject
$\propto$	: Cronbach's Alfa
k	: Number of decision makers
$\tilde{\omega}_j$	: Weight of the criteria
$\tilde{x}_j$	: Rating of alternative given by k^{th} decision maker
D	: Matrix of the alternatives
$\tilde{v}_{ij}$	: Weighted normalized decision matrix
$\tilde{r}_{ij}$	: Elements of the normalized fuzzy decision matrix
S^+	: Separation from the positive ideal solution
S^-	: Separation from the negative ideal solution
d_v	: Distance between two fuzzy numbers
C_i^*	: Closeness coefficient
U_i^*	: Utility Value

Chapter 1

Introduction

1.1 General

New Product Development (NPD) converts the opportunity present in the market in the form of a product which can be sold. It involves introducing an existing product with modification or launching a totally new product in the market. Regular introduction of new product leads to increase in the market share of the company. Development of new product satisfying quality, performance and cost is the necessity of the hour. This becomes more important for companies having shorter product life cycle. In most cases the data available for developing a new product might be limited, uncertain or not reliable. This creates difficulties in conducting assessment at early design stage. Uncertainty may arise from sources which are internal as well as external including technical, management and commercial issues. A structured approach is required to be used that can facilitate practitioners and decision-makers to evaluate the relative importance among various elements and factors that affect NPD decisions. The research identifies factors which affect the performance of new product and proposes a model to take care of the issues faced particularly by the small and medium enterprises. New hierarchical methods have been proposed which helps in the decision-making process.

1.2 Product Development Process

Product development process can be caried out in various forms, but there are certain stages which are common to all the processes.

Fuzzy Front End: It involves all those activities before the specification of the product is finalized. Specification caters to the way the product should be made to satisfy the customer requirements or market need.

Product Design: In this stage the designing process for the product is carried out in detail so as to meet the specifications of the customers or new requirements of the customers.

Product Implementation: It involves making of the prototype design and testing it for the specifications and user requirements.

Fuzzy Back End Process: It is also known as commercialization phase wherein the production process will start and the product will be launched in the market.

The front-end process involves the idea generation and idea selection, which are the most unpredictable processes. Idea generation involves brain storming activities so as to generate ideas regarding the new product. Idea selection involves reducing these ideas to a very few and then selecting the best idea or alternative. Many models have been conceptualized to carry out the NPD process, but the model proposed by Booz, Allen and Hamilton [31] known as the BAH model still stands as the most useful model for the industries.

1.3 Factors affecting New Product Development

The stages of New Product Development involve consideration of many decision factors which are shown in Figure 1. Most of these decision factors require MADM approach, some of which are listed below:

1. Design concept evaluation
2. New product portfolio selection
3. Product project screening
4. New product design Assessment
5. Sustainable product development
6. Quality function deployment
7. Group decision
8. System reliability
9. Material selection

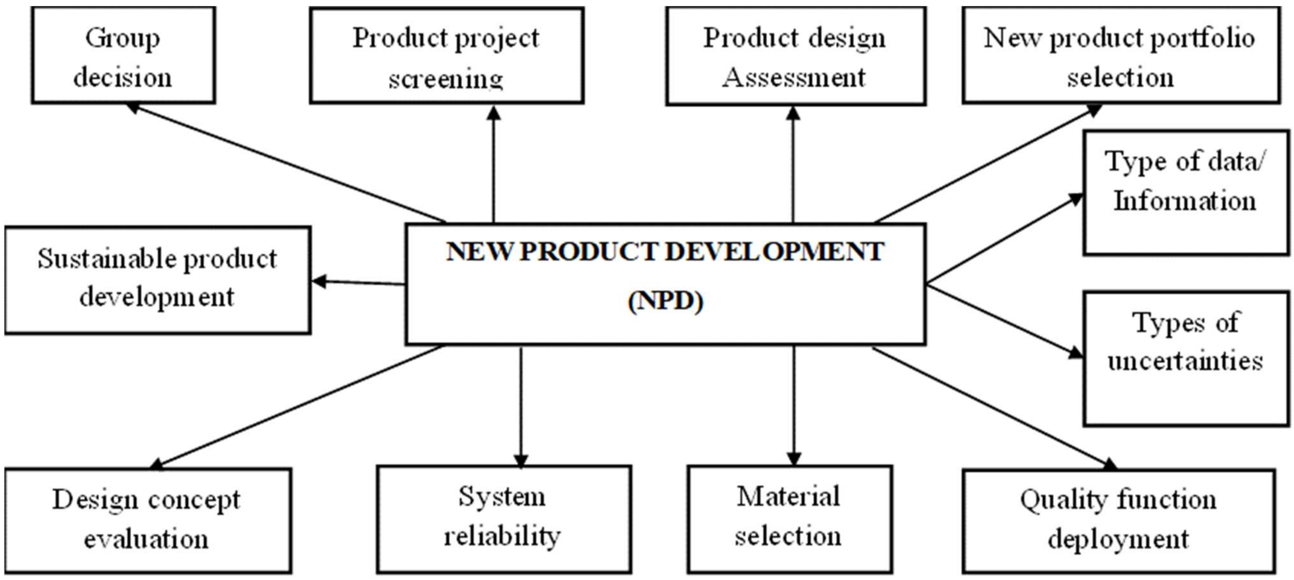

Figure 1.1: Factors affecting NPD.

1.3.1 Design concept evaluation

A poor design concept can rarely be compensated at the later stages. Hence one of the most critical decision points when managing NPD is design concept evaluation. At early design stages, up to 70% of the overall product development cost is committed. Successful design concept evaluation results in saving cost and time of product development. Design concept evaluation is a complex multi-criteria decision making (MADM) problem which involves many factors ranging from task-related factors (e.g., product complexity, initial customer requirements impreciseness and information scarcity) to decision related factors (e.g., the expertise and diversity of decision makers (DM), and the method of aggregating judgments). At the same time design concept evaluation is also a group decision-making problem. The required data and information come from design knowledge and experience at the earlier design stages and subjective judgments of DM. Design information is deficient and imprecise at the earlier design stages. Lack of precision and the confidence levels on DMs' judgments contribute to various degrees of uncertainty. Coping with uncertain and vague characteristics of information is critical to the effectiveness of decision-making. Furthermore, the aggregation method of individual judgments in group decision making and the alternatives ranking method in the evaluation model are critical to the accuracy and effectiveness of design concept evaluation [1].

1.3.2 New product portfolio selection

New-product portfolio selection is a crucial and vital decision for successful new-product development. Selecting a new-product portfolio for the future is an important problem faced by all companies that engage in NPD. Since a vast amount of information is incomplete and selection criteria are interdependent and often conflicting in nature, portfolio decisions are difficult, because of the combinatorial complexity of allocating a limited resource over a multiplicity of new products. Portfolio management decision is usually made on the basis of product value, project risk and business strategies. The decision maker must allocate a limited set of resources to projects in a manner that balances risk, reward, and alignment with their respective strategies which may have non-numerical values. Due to both the nature and timing of new product development, portfolio selection is associated with uncertainty and complexity, and conventional evaluation methods cannot handle such decisions suitably and effectively [2].

1.3.3 Product project screening

The rate of NPD project failure is around one-third or even higher, although it varies from industry to industry. There are usually numerous new product ideas during the early stage of project development. Some of the ideas have high probability of success, while majority of them could be unfeasible. Project screening helps to eliminate the ideas that have high probability of failure. Thus, it is imperative to conduct project screening, as selecting a right project for commercialization, is the first step to the success of NPD. NPD project screening helps to eliminate projects that have high potential of failure and allocate the development resources to the projects that have the highest potential of success. As a result, the growth of companies can be sustained and the overall NPD failure rate can be reduced. Ranking, checklists, scoring models, and numerical weighting methods are some of the methods available for NPD project screening. However, the methods are too simple to tackle complex problems. Hence the growing complexity of NPD requires the use of more sophisticated management science decision support techniques [3]. Incomplete data or lack of data and imprecise judgments are the two ways by which uncertainty are induced at project screening. A very little reliable information is available to make judgments against screening criteria. Examples such as, the lack of financial and engineering data, make decision making difficult and unreliable. Most of the screening approaches are based on judgments of managers. Inability of human in making reliable judgments is another cause of uncertainty. The experience of the managers may be limited to a small number of projects, and the managers' ability to judge the importance of screening criteria and compare potential projects may also be limited. The involvement of multidisciplinary NPD team members in the decision-making process is an additional characteristic of NPD. Team members from different functional units jointly make decisions to screen and select projects. However, the members usually do not have expertise or knowledge in all the aspects of the screening criteria. Hence in the given situation, they may not be able to make accurate judgments on some aspects that are not related to their functional expertise. Since NPD always involves new issues including new design, new manufacturing processes, new suppliers, etc., it is not practical to make judgments based fully on past experience or information. It is therefore a big challenge for product managers and experts, to move from experience-based decision making to scientific NPD project screening decision making. MADM methodology helps manufacturers in handling uncertainties and group-based decisions in the early NPD project screening stage [3, 4].

1.3.4 New product design assessment

Researchers and practitioners have emphasized the need to enhance product design assurance in early design stages. Determining the best product design among a lot of feasible alternatives is a key issue in successful new product development. It is advocated that the entire product attributes of performance, quality, reliability, safety, maintainability, serviceability, manufacturability, etc., are built during the product design process. Hence, the product design process becomes an increasingly complex decision-making problem. One must simultaneously cater, for many interrelated criteria of both quantitative and qualitative nature. The design decision analysis has to be conducted on the basis of both precise numbers and subjective judgments, which are imprecise and vague (fuzzy) in nature. These uncertainties are incurred due to a lack of evidence and understanding or human's inability of providing accurate judgments at early design stage of novel new products. This reveals that a better decision-making methodology is needed to facilitate product design assessment in situations where several performance measures like product functions and features, manufacturability and cost, quality and reliability, maintainability and serviceability, etc., must be accounted for, but conventional approaches cannot be applied with confidence [5].

1.3.5 Sustainable product development

Environmental Impact Assessment (EIA) problems are characterized by environmental factors that are qualitative in nature and can be assessed only on the basis of human judgments. Such judgements inevitably involve various types of uncertainties such as ignorance and fuzziness. Hence EIA problems have to be modelled and analyzed using methods that can handle uncertainties [6]. The framework which aims at the integration of economic, environmental and social considerations into product development is known as Sustainable Product Development. The major challenge is the holistic analysis and improvement of products regarding their impact on surrounding systems. The product needs to be analyzed along its complete lifecycle for a valid assessment. The principle of sustainable development requires the consideration of multiple design targets at the same time. For example, reduction of hazardous waste against higher material cost. Design engineers need to foresee diverse interrelations between a product's characteristics and its economic, social and environmental impacts while developing sustainable products. A wide range of design methods have been developed in order to support this complex task. Life Cycle Sustainability Assessment (LCSA), which is a retrospective analytical method, requires a large amount of information and is thus utilized when important design decisions are already made, whereas prospective methods are rather generic and too broad to be helpful in concrete design decisions. For shifting multi-criteria quantitative analysis to earlier development, the integration of discrete decision trees with LCSA is used. [7, 20].

1.3.6 Quality function deployment

Quality function deployment (QFD) is a method to help transform customer needs (Voice of the Customer [VoC]) into engineering characteristics (and appropriate test methods) for a product or service. It helps create operational definitions of the requirements, which may be vague when first expressed. It often involves a group of cross-functional team members from marketing, design, quality, finance and production and a group of customers. Each member and customer demonstrate significantly different behavior from the others and generates different assessment results which may be complete and incomplete, precise and imprecise, known and unknown, leading to great uncertainty in the QFD process. Significant number of subjective judgments is required from both customers and QFD team members for the successful implementation of QFD. Selected customers assess the relative importance of customer expectations or requirements (WHATs). The QFD team is set up to identify customer wants, map them into relevant engineering requirements, which are often called the HOWs, develop the relationship matrix between WHATs and HOWs and the interrelationship matrix between HOWs, and prioritize the HOWs [8, 21]. The analytic hierarchy process (AHP), a well-known and commonly used multi-criteria decision-making method, and its variants: fuzzy AHP, analytic network process (ANP) and fuzzy ANP have been suggested and widely applied to prioritize customer requirements (WHATs). The weighted sum method, fuzzy weighted average (FWA), fuzzy outranking approach and grey model have all been suggested for prioritizing engineering design requirements [8, 9]. Since fuzziness is involved in the process of QFD, MADM techniques are required to deal with it and also to address the issue of how to deal with incomplete, imprecise and missing (ignorance) information in QFD, which is essentially inherent and sometimes inevitable in human being's subjective judgments.

1.3.7 Group decision

The process of NPD is multidisciplinary in nature. It requires the participation of a group of people from different departments in making decisions. A problem of judgment synthesis arises because of this group approach. Each group members may present different judgments about project screening decisions because of differences in technical backgrounds, departmental goals and constraints etc. The reliability of the decisions may depend on the way the diverse judgments are synthesized [3]. Group decision involves reduction of different individual preferences on a given set to a single collective preference. The most important characteristic of group decision is that all individuals involved in decision making belong to some organization (family, firm, government). Their opinions may differ in their perception of the problem and they may have different interest, but they are all responsible for the organization's well-being and share responsibility for the implemented decision [10]. The group discussion involves focusing on what actions and criteria to be considered, what weights and other necessary parameters will be appropriate. Once all the individual information has been gathered and the discussion is closed, a technique is used for obtaining values of these model parameters which represents the collective opinion. With this information, the multicriteria decision model gives us the group ranking. Group consensus (GC) is a pivotal factor, to reach a final solution accepted by almost all or at least most of the group, in the group decision analysis (GDA) [11].

1.3.8 System reliability

Reliability analysis aims at the quantification of the probability of failure of the system and focuses on safety. Many researchers have developed various reliability prediction techniques. An accurate product reliability prediction model can offer useful information for managers to take follow- up actions to improve the quality and cost of system. Most of these models are developed using the following: Bayesian Statistical, Linear or Nonlinear Multiple Regression, Neural Networks, Support Vector Machine (SVM) and Autoregressive Integrated Moving Average (ARIMA). But these models suffer from number of drawbacks, such as lack of suitable models, exceptional assumptions of prediction model, and difficulty to validate. Also, accuracy and speed are hampered [14]. A fundamental issue in reliability analysis based on the failure data is the uncertainty in the failure occurrence and consequence. For a complex engineering system, many reliability analysis problems involve quantitative data and qualitative information, as well as various types of uncertainties such as incompleteness and fuzziness. Under these circumstances, there is a need to develop a new reliability analysis method, using multiple attribute decision analysis (MADA), which can deal with various types of uncertainties efficiently [12, 13].

1.3.9 Material selection

For diverse engineering applications, selection of proper materials for different components is a challenging task in the design and development of new products. During the entire design and manufacturing process, materials play a crucial and important role. A wrongly selected material results in huge cost involvement. It may even lead to premature component or product failure. New materials are available to meet the demands of cost reduction and better performance which now a days are been used to replace older materials. Normally a trial-and-error method based on previous experimentation are used while choosing a new material. Large number of factors such as mechanical, electrical and physical properties and cost considerations of the materials are required for the selection. The designers and engineers have to take into account a large number of material selection criteria. A large number of available alternative materials, having complex relationships with various selection parameters (criteria), make the material selection process a challenging task. Decision making in the presence of multiple, generally conflicting criteria requires the use of multiple criteria decisions making (MADM) [15, 16, 17].

1.4 Fuzziness in New Product Decision Making

The decision-making process in new product development involves qualitative as well as quantitative data. The qualitative data in linguistic terms helps the decision maker to express his perception in a better way. To tackle the uncertainty and fuzziness in data due to individual perception, the linguistic variable can be converted to triangular fuzzy number or single value neutrosophic (SVN) number. This helps to retain maximum original information, thus leading to reliable final decision solution [21]. It is observed that in new product development the quantitative data may not always be available for all the factors, the reason being past historical data not being available because of a totally new concept. In this given scenario, it is always better to express the quantitative data also in linguistic form and convert the linguistic variable in terms of fuzzy number to take care about the fuzziness in the data.

1.5 Organisation of Report

There are eight chapters in the report. The first chapter deals with the introduction of new product development, the various factors affecting the new product development and the need for fuzziness in new product development. A detailed literature review is carried out in the second chapter regarding new product development, small and medium enterprises, design for manufacturability, various MADM methods such as AHP, Fuzzy TOPSIS, COPRAS-G, GA-

ANN, SVNS TOPSIS and also crisp set theory, fuzzy set theory and neutrosophic set theory. Problem identification & scope and the proposed methodologies to address the research problem are discussed in the third chapter. The aim and the objectives are presented at the end. The fourth chapter deals with commonly used MADM methods such as Fuzzy TOPSIS and COPRAS-G with a case study in manufacturing unit and sensitivity analysis was performed over the input data. Since Evidential Reasoning is a powerful method which takes care of uncertainty and input data in linguistic form is normal to the new product development, two methods have been proposed so that Fuzzy scale and Grey scale can be used in ER. The fifth chapter involves proposing a hybrid MADM method using the hierarchical structure and Fuzzy TOPSIS, to deal with the one of the literature gaps identified. The validation of the proposed method is carried out by solving a case study using COPRAS-G. Chapter six deals with two new methods which have been proposed, based on neutrosophic logic and have advantage over the original method. The methods have been validated by solving the case study problem from chapter five. The seventh chapter deals with the problems faced by the SME's. The higher-level and lower-level factors of design for manufacturability affecting the idea generation stage of NPD are listed. Data is collected from equal number of manufacturing and design personnel and data consistency is checked using spearmen co-relation co-efficient and Cronbach alpha. All the factors are then ranked on a common scale to get their relative importance. A self-assessment model is proposed to take care of the difficulties faced by the SME's. A case study is carried out to validate the model using COPRAS-G and GA-ANN method. Chapter eight presents the discussion and conclusion and talks about scope for further research.

Chapter 2

Literature Review

2.1 General Discussion

Globalisation has resulted in a stiff competition in the market and customer satisfaction is one of the most important factors now a days. For survival of the industries, developing new products satisfying quality, performance and cost and launching them in the market is the need of the hour as it helps the industries to remain competitive. The project idea screening phase is the most important phase in the new product development process. There are usually numerous new product ideas during the screening stage. Most of the ideas are not feasible to implement whereas some of them have a high probability of success. Ideas having high probability of failure are eliminated during the project screening. The failure rate of NPD project is very high and it varies based on the types of industries. Since there are lot of uncertainty causing elements present during the new product development process, a structured approach such as MADM methods are required. In many research papers fuzzy TOPSIS and COPRAS-G are used in finding the best alternatives. The fuzzy and grey scale helps in tackling the uncertainty in the data. Another scale known as neutrosophic scale is highly being researched as it can take care of impreciseness, inaccuracy and incompleteness in the data by considering truth function, indeterminacy function and falsity function. A lot of research has been carried out in the area of new product development and articles have been published, but mostly in large enterprises. SMEs are the backbone engine for socio-economic development of a state as well as the country. In India, the SMEs roughly employ around 46 crores people. NPD helps SMEs to cater to customer satisfaction and remain competitive in the market, but they suffer from lack of experienced people either at the technical or managerial level and restricted funding for research activity. Also, consideration of DFM factors during the new product development can help in shortening the life cycle of the product and at the same time minimize manufacturing time, thus ensuring smooth flow of product at minimize cost. The literature review considers all such aspect which would help in the research work. Figure 2.1 shows the flow of the literature review in this chapter which includes literature survey on NPD, SMEs and MADM. The MADM methods along with the type of data used during the research work is also shown in the figure.

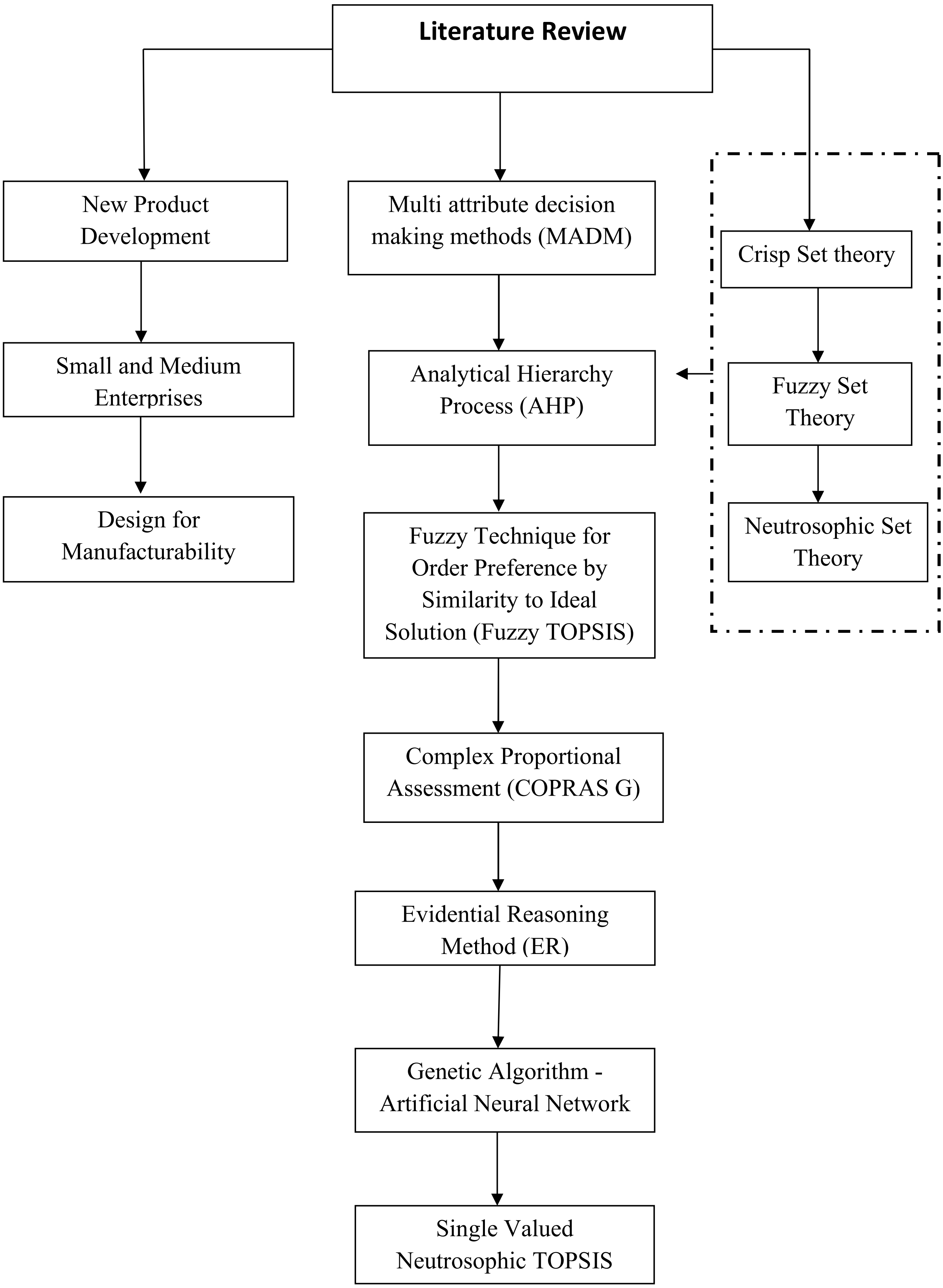

Figure 2.1: Flow of Literature Review.

2.2 New Product Development

Economists suggests that NPD performance affects the rise of economy and wealth of any country [22]. The NPD process starts when a firm wants to launch a new product. Launch of a new product act as a competitive tool and provides a differential advantage in the competitive market. There are many characteristics of the product which plays an important role during customer evaluation and finally choosing the product [23]. New market can be created and improvement in growth is possible through introduction of new product. Because of the uncertainty in the process a high amount of risk is associated with the launch of new products. Two types of errors are possible during the development process: the firm decides to go ahead with a potentially unsuccessful idea or the firm decides not to go ahead with a successful idea. In the former case the firm will have investment losses and in the latter case the firm will have to reflect on the missed investment opportunity [24, 25]. NPD has become the core function of many industries as stiff competition, requirement of reduced product life cycle, faster development time, reduced cost and better product quality does not allow a firm to outsource the NPD activity to the suppliers [26]. Brand sustainability and business sustainability of any firm is dependent on how the NPD is managed and to what extent it is successful. Locating the driving forces and the key success factors are important for the brand image in the market. The brand image becomes more vital, if the brand is for global market [27]. Cooper [28] an expert in the area of product development practices, in his published book has talked about accelerating the launching process of new product from the inception stage.

The stages of NPD process have been modelled by many researchers. Some of the commonly used models are IDEO process model, Scorecard-Markov model and new product development process [29]. The most commonly used model is the one developed by Booz, Allen and Hamilton [30]. The BAH model, as it is called, reflects correctly to a very large extent the practices followed in the industries for NPD. It provides a systematic framework for reducing the risk component associated with product development activities. The BAH model has seven stages. The first stage is new product strategy development, followed by idea generation as the second stage and screening and evaluation as the third stage. The fourth stage is business analysis and the fifth stage is product development. Testing of the prototype and commercialisation of the final product forms the sixth and seventh stage.

In all the models proposed, the idea generation and screening phase is considered as the most important phase of NPD. The idea generation and screening phase involves, first listing down the alternatives or ideas to meet the company objective. Employees, customers and vendors are part of the idea generation. Having a large pool of ideas is the objective of the idea generation phase. All potential ideas should be welcomed. Through initial screening and evaluation process, most of the ideas having higher rate of failure are eliminated and those having the greatest potential for succeeding are kept for further evaluation [32]. In this stage the number of ideas is few but the cost associated with the development process increases and this trend remains for the other stages. Ulrich [31] has talked about design for environment (DFE) so as to minimize the harmful impact on the environment while going for a new product. The correct DFE decision allows environmental and economic decision to be compatible and at the same time have better product quality and reduced cost. The impact on the environment could be in the form of natural depletion of resources, consumption of energy, discharges or waste generation in from of liquid, gas or solids. This impact has to be considered during the early stages of the NPD, as once the design is finalised any changes will result in increase in the product life cycle time as well as the cost. An interdisciplinary approach is required to carry out the activities of DFE. A major share of company's profit comes from sale of new products, but failure rate of the product after launch and consequent cost of failure is high. Hence a high risk is associated with NPD strategy. Decision aids can be used to reduce the uncertainties and complexity and thus improve the accuracy of the judgement. [33, 34].

NPD process consists of significant uncertainty causing elements arising from technical, management or commercial issues. Uncertainties or ambiguities can come because of individual heterogeneity. Sometimes the task associated with a new product might be very simple but, the decision makers can interpret them as complex if the instructions are not clear. Certain characteristics of instructions such as confusion, misunderstanding, misinterpretation or misleading have to be avoided. Hence all the instructions should be clear or ambiguous in nature [35]. NPD process involves team members from various interdisciplinary departments. Commitment is required while selecting the different decision makers. Each criterion may be given different importance by the decision makers involved. The decision makers themselves might be from different disciplines and may have their own perceptions of the problem in hand [36]. The expertise and diversity of the decision makers play an important role in the decision-making process. Although a diverse group may bring about accuracy in the evaluation process, but there are chances that the group might not be able to perform effectively because of the difference in opinion and working background. If we consider R&D and manufacturing as two groups associated with new product, both these groups will have different perceived importance with respect to the product and this can lead to error in judgement. While R & D people might lay more stress on the application of the new product, manufacturability will be a major concern for manufacturing people. A fear that the new product development will require the individuals to upgrade their skills to suit the new applications, may also results in individual biasing their opinion to achieve the perceived goal [37]. Group decision making has its own advantage as it can improve the accuracy by involving people having diversified knowledge in the decision-making process. Also, studies have shown that individuals are reluctant or are not accurate when giving decision on outside domain. Aggregation of the decisions of the decision makers play an important role in the success of the new product [38].

The deployment of resources e.g., capital, human, machine and time, for NPD has to be rational. Also as compared to traditional market strategies, viral product design can be more effective in the new product getting adopted [39]. Decision made during the design phase have a significant influence on the product resources. This influence is there over the entire life cycle of the product. It is not easy to evaluate and express the decision made during the design stage and the life cycle phase. Only after the product has been produced, we can access the efficiency of the resources. A potential saving in resources can be obtained if the impact of decisions during the design phase are not neglected [40]. Attribute values in linguistic terms helps the decision maker to express his perception in a better way. To tackle the uncertainty and fuzziness in data due to individual perception, the linguistic variable can be converted to triangular fuzzy number or trapezoidal fuzzy number or single value neutrosophic number. This helps to retain maximum original information, thus leading to reliable final decision solution [41]. Hence to evaluate the alternatives consisting of various elements and factors, a structured approach is required to carry out the decision-making process. MADM is one such structured approach which helps the decision makers in making the best decision.

2.3 Small and Medium Enterprises

The role of SME's in contributing to the economy of the nation and the world cannot be under estimated. In the new millennium, SMES are looked upon as engine for growth, centres for innovations and solution to age old problem of unemployment. In fact, SMES contribute more towards job creation than the large industries. An argument has been proposed which states that, if the small businesses have scarcity of resources, as is normally the case, then they should utilise these finite resources so that they can contribute to a better growth [42]. Industrial economy is dependent on SME's. E-business diffusion in SMEs have been induced in the system as it can provide a competitive advantage to the SMEs but the SMEs have not been successful in fully adopting the technology [43]. The GDP of a country and employment are dependent on SME's. Due to dynamic change required in the product features, the development process and the associated supply chain have become increasingly complex. Data was collected in the form of web-based survey form from the industries located in Malaysia and Iran and a measurement model was constructed to reflect the role of information technology in product development [44]. Economists believe that performance of NPD is directly linked to the growth of economy and the wealth of a nation [45]. SMES are the one which brings about the stability to the economy of either developing or developed country. They act as shock absorbers to dampen the shocks of dynamic changes in economic cycle. Based on a case study in South Korea, it was observed that small businesses have increased in the value they add and the number of employments they employ. SMEs are also the main force behind equalizing the differences in income among the workers [46]. SMEs are the backbone engine for stabilizing the socio-economic development of a state as well the country and they are an important part of any industry. But at the same time small businesses are associated with higher birth rate and death rate as compared to the large-scale industries. Over a period of time, if the SMES survive than they tend to grow in terms of labour, capital and sales [47].

Presently India ranks ahead among the fastest growing economic countries. In India, SMEs provide a large number of job opportunities and act as a source of employment for lakhs of people living in villages and semi urban towns. Roughly 46 crore people are employed by SMEs in India. Ministry of Micro, Small and Medium Enterprises (MSME) have laid procedures for declaring a unit to be small or medium. As per MSME, if an enterprise invests 10 crores in plant and machinery and the turnover at the end of the year is less than 50 crores, then that unit is termed as small enterprise. For medium enterprise these values are 50 crores for plant and machinery and 250 crores for turnover at the end of the year. SME's have recorded a better growth rate compared to the general industrial scenario but are plagued with greater challenges in the post liberalization era. Heterogeneity of the SME sector comes from the different capacity of the enterprise, the types of products and services offered and the technical knowhow used. The growth of SME's is hampered due to lack of experienced personnel either at the technical or managerial level and restricted capital allocation for carrying out research. The highly sophisticated and rapidly changing market demands product life cycle to be reduced to satisfy the ever-changing customer demand. Selecting the best possible alternative at the idea generation phase of the NPD is very critical for survival and success of the industry. At the same time SME's will always suffer from limited technical and monitorial capabilities [48, 49].

One important observation is that, critical factors affecting the NPD often lie locally in the company or around it. Enterprises have realized that developing all the required technology inhouse is next to impossible and hence technological support has to be taken from external outside sources [50, 51, 52]. NPD includes generation of ideas, selection of ideas and then designing a new product as per the selected ideas. The NPD personnel involved requires knowledge, from within the firm and outside the firm to execute the above three stages. Since knowledge from external source is required to be acquired by the SMEs, this knowledge has to be identified first. NPD requires knowledge from customer or market, like what the product should do. It requires technological knowledge, so as to decide about the features of the product. Finally, to realize the product, it requires organizational knowledge. Under customer knowledge, firm requires knowledge of new product ideas, design criteria and specifications, knowledge of the market, government and socio-economy. In case of technological knowledge, firm might require technical process knowledge, research and design competence, research and design instrumentalities, practical experience, experimental and test procedures, knowledge of manufacturing, knowledge of support processes, production and manufacturing competence, knowledge of location and availability of certain information [22. 53].

Although SMEs help in creating and providing jobs to weaker section of the society, they have to overcome certain challenges, such as fast response to market situation, rapid and feasible solution to complex industrial problems and reducing cost [54]. Troy [55] has talked about introducing cross functional integration in small businesses to increase the success, but to what extent integration has to be carried out remains a mystery as it involves a great deal of variance. Cooper [56] discussed steps to successfully accelerate the new product launch in SMEs from the idea stage. He showed that only 80% of the NPD success is achieved by 20% of the top companies. On the same ground, the 20% of the bottom companies have only 38% of success rate. There is also parity in the profit making among these two groups, with the top group having double or more profit as compared to the bottom group. A review paper on new product development with respect to past research, present findings and directions for the future was published by Brown [57]. He reflected that changes in the technical component and market fluctuation cannot be controlled fully and suggested that proactive steps be taken during the development process. A decision support system for identifying initial idea from cross domain analysis during the screening phase was carried out in SMEs [58]. Work has been carried out in small and medium pharma industry on challenges in decision making models for new product development [59, 60]. Wai [61] has talked about effect of government intervention on the manufacturing systems and business approaches of SMEs in China, Hong Kong and Taiwan. The approach involved detailed personal interviews with selected people from these three regions. Similarities and differences were noted and they were compared with the western counterparts. Gilson [62] provided an evaluation tool based on lean and green approach for developing environment friendly new product involving small and medium enterprises. A business model was proposed after analyzing 233 SMEs in Taiwan which helped in developing a stable and environment friendly new product [63]. A similar business model was proposed by Rauter [64] by analyzing SMEs in Austria. It was seen that the innovations in terms of NPD in SMEs are not the first of its kind, especially in the technological field and they tend to be, adoption of new production method or modifying and developing improved products [65, 66]. It is paradoxical to see that, although the SMEs are important for the socio-economic development of the country, there is neglect towards them and the research carried out on new product development is more towards the larger units. Another observation which came out through research analysis was that, irrespective of whether large enterprises or small and medium enterprises, studies have mostly taken place in countries such as United States, European countries and China. Very less research has been carried out on SMEs in India.

2.4 Design for Manufacturability

Design for manufacturability talks about actively designing of products to optimize the manufacturing process. DFM process occurs even before production or manufacturing starts. Based on the product and its features, the DFM process will vary. The manufacturing process may involve procuring, manufacturing, assembling, testing, delivering, after sales and servicing and repair, at the same time ensuring optimal cost and quality, better safety and compliance and most important of all customer satisfaction. The DFM concept was developed to bridge the gap between design stage and its effect on manufacturing, resulting in comprehensive product development process [67]. The DFM concept is present in almost all the enterprises, but to what extent the implementation is carried out depends on the manufacturing technology available. It has been observed that 80% of the total cost of the product is incurred till the design of the product gets determined, as this design determines the manufacturing factors required, which in turn affects the overall production cost. Hence DFM has an important role in reducing the product cost and plays a vital role in the new product development.

Consideration of DFM factors during product design, shortens the product life cycle, thus minimizing production and manufacturing time, ensuring smooth flow of product, minimize cost etc. Quality issues resulting from part interaction can be reduced by selecting better parts and proper matching of parts [67]. DFM can be used for bench marking of competitor's product also. SMEs involved in manufacturing contribute towards 90% of all the industrial unit in India. They have a tendency of going on introducing new products, without checking for existing compatible products, resulting in having a large number of product portfolios [68]. Another reason for this large product portfolio is the tendency of the SMEs to satisfy each and every potential customer [69]. Inability to maintain or lack of formal product history and database, results in frequent changes in product design, instead of using or modifying existing design [70]. Ranjan [71] used the concept of graph-based approach for applying DFM in additive manufacturing. DFM has been used in steel furniture industries, to reduce the final cost of the product and hence improve the productivity of the company, by considering the needs and desires of the customer and trying to optimize the design. DFM helps in overcoming the traditional reason for design failure and erroneous interpretation [72]. Electrostatic drives such as comb actuators involves complex manufacturing process. They have been successfully developed, based on consideration of design for manufacturability [73]. Integration of DFM and product development process can be more effective as compared to traditional development process. Traditional development processes involve a higher risk and are relatively expensive [74]. Study was carried out on 127 NPD projects in a consumer electronic firm, having global presence to study the effect of NPD team members throughout the development process. Also, the effect of team membership on manufacturability was studied [75]. Stiff global competition has resulted in industries across the globe, trying to reduce the product price and at the same time provide a higher quality. An important strategy for continuous survival and growth require that the design and manufacturing activities are properly integrated. DFM helps in bringing about integration and effective collaboration of product design and process design. Constraints which are present during the implementation of DFM are non-flexible organisation structure, unreliable manufacturing cost data and scarce interaction between design and manufacturing personnel [76]. Research on using DFM factors, for selecting the best alternative among set of alternatives during the idea screening phase, has not been taken up so far and presents a research gap which can be worked upon.

2.5 Multi Attribute Decision Making

Globalisation has led industries to increase their product diversity and variety, thus forcing industries to go for new product development. When there are number of choices (alternatives), and decision has to be made on these choices, based on some parameters (criteria), which might be beneficial type (e.g., profit) or non-beneficial type (e.g., cost), and at the same time having different dimensions or units, having non-biased transparent decisions might be difficult [77]. The approach required to solve the issue should be structured in nature and MADM methods are able to do so. As per Hwang and Masud [77], all MADM methods have the following characteristics:

- There is more than one alternative available for decision making
- There are more than one attributes (criteria) i.e., multi-attribute. For calculating the final ranking, relevant information between each alternative and each criterion is required.
- There are always conflicts between the attributes either because they are beneficial or non-beneficial type or having different units.
- Normalization of data is required to be carried out on the different units, so that they can be compared.
- The final output is to rank the best alternative, by considering all the given data.

Many MADM methods have been used for idea screening in NPD [78, 79]. Some of them are simple additive weighting [80], analytical hierarchical process [81], technique for order preference by similar to ideal solution [82, 83], artificial neural network [84]. Brown [85] have published article which shows the research work done in the past, the ongoing present situation and steps and direction for the future. Robert, 2019 in his article has laid down the drivers required for the success in new-product development [86]. Work has been carried out using cross functional research [87] and cross domain analysis to increase the success rate of NPD [88]. Zadeh [89] introduced the fuzzy theory which is an extension of the classical set theory. Triangular fuzzy number (TFN) is most commonly used in many of the research papers [90, 91]. Fuzzy multi attribute decision making models (FMCDM), involving fuzzy concept, have been used for project selection process [92, 93]. Fuzzy AHP based simulation approach [94], fuzzy linguistic approach based on linguistic representation model [95], fuzzy inference process using concept evolution and convergence process [96], hybrid AHP and fuzzy DEA method [97], heterogeneous axiomatic design method using distance measure [98] have been applied to find the best alternative during the idea screening stage. A methodology based on logarithmic fuzzy preference programming (LFPP) has been proposed, wherein pairwise comparison has been expressed as a logarithmic nonlinear programming, leading to crisp values [99]. Fuzzy multiple criteria decision-making approach has been used for evaluating government websites [100]. Consistency and determinacy of linguistic variables used in decision making were treated using fuzzy set approach by Ma [101]. Approach involving consensus score, of combination of median score and median ranking has been used in checking the quality of food [102]. Criteria weights have been calculated using fuzzy AHP and PROMETHEE has been used for ranking alternatives [103]. Rahmani [104] presented a model to evaluate effectiveness of knowledge management using fuzzy AHP. Muduli and Barve [105] have used fuzzy AHP to improve the effectiveness of green supply chain management (GSCM) practices. Selecting best alternative has been carried out using AHP and goal programming [106]. Fuzzy AHP and Fuzzy TOPSIS have been used to carry out the evaluation of knowledge management model [107].

2.6 Analytical Hierarchical Process

Analytic Hierarchical process (AHP) proposed by Saaty [108], is based on multilevel hierarchical structure. A complicated multi attribute decision making problem is broken down in to criteria and alternatives using this structure. AHP is the best method when the data is subjective in nature, and helps to find out the best alternative, from a given set of alternatives, by determining the relative importance at each level of hierarchical structure, using the pair wise comparison method. AHP includes three steps: first, converting the given problem in to a hierarchical structure; second, pairwise comparison of criteria and alternatives; third, solving for priorities. A number of researchers have proposed new or modified quantitative scales. AHP, Fuzzy AHP and hybrid AHP are widely used by researchers in various multi attribute decision making applications till date. Green product designs have been suggested using extended Fuzzy-AHP [109]. Intuitionistic fuzzy analytic hierarchy process has been used extensively in product development [110]. Fuzzy analytic hierarchy process has been compared with fuzzy cognitive network process for new product strategy [111]. Pornwasin and Tossapol [112] have used fuzzy AHP-TOPSIS approach, for prioritizing new product solutions. Integrated Fuzzy AHP, VIKOR and DEA methodology have been used for multi criteria evaluation of sectoral investments for sustainable development [113]. Chen [114] utilized AHP and TOPSIS to evaluate uncertainty in demand observed in supply chain. Similarly, integrated AHP-TOPSIS and GIS have been used for solving an ammunition distribution network design problem, using multi-objective mathematical modelling [115] and decision making on the state of transformers [116]. AHP, along with particle swarm optimization, has been used for solving capacitated military logistic depot location problem [117]. Benitez [118] dealt with probabilistic concepts in management of uncertain pairwise comparisons using AHP. Vikor and AHP [119], utility theory with AHP [120], FMEA and AHP [121] have been used in selection problems. AHP along with Delphi method has been used for finding the effects of factors on academic integrity in e-learning [122]. Ercan [123] evaluated the performance of proposed method, based on moment integrated concept of physics, by comparing it with AHP and solving many numerical. Hammadi [124] proposed an integrated model for assessing risk in supply chain, using extended fuzzy AHP. Standard AHP preference table is shown in Table 2.1.

Table 2.1: Standard AHP preference table.

Equally preferred	1
Equally to moderately preferred	2
Moderately preferred	3
Moderately to strongly preferred	4
Strongly preferred	5
Strongly to very strongly preferred	6
Very strongly preferred	7
Very strongly to extremely preferred	8
Extremely preferred	9

2.7 Fuzzy TOPSIS

Zadeh [125] introduced the fuzzy theory, which is an extension of the classical set theory. Hwang & Yoon [126] were the first to develop the TOPSIS (technique for order preference by similarity to an ideal solution) method. It is the most commonly used MADM method because of its ease of understanding, computational efficiency and detailed mathematical concepts. The selection of the best alternative is done by considering the distance of the alternative from the positive ideal solution and the negative ideal solution. This method takes in to account the beneficial type criteria and non-beneficial types of criteria [127]. To tackle the fuzziness in real life problems, extension of TOPSIS known as Fuzzy TOPSIS has been widely and successfully used in wide range of real-world problems [128, 129, 130]. Here the linguistic variables are converted in to fuzzy number using the standard fuzzy scale. It has been used in number of research papers for getting the end objective, which is mostly the selection of alternatives such as supplier selection [131, 132], logistic service provider third part selection [133], plant location selection process [134, 135, 136], Robotics selection [137, 138], selection of computer integrated manufacturing technology [139]. Triangular fuzzy number (TFN) is the most commonly used in Fuzzy TOPSIS [140, 141]. Fuzzy TOPSIS has been used in metal composite selection process for structural applications. Here,tensile strength, melting point, hardness, density was taken as beneficial criteria and cost was taken as non-beneficial [142]. Weapon selection, using the AHP and TOPSIS methods under fuzzy environment, has been carried out for weapon manufacturer [143]. Housing quality based on adaptability attribute, has been evaluated using the method [144]. A hybrid Fuzzy AHP and Fuzzy TOPSIS was used to evaluate the capabilities of instructors for medical sciences [145], investigation in the e-Health tool utilisation by patients and clinical experts with regards to Canada [146], group decision making to carry out ranking of automotive manufacturing company scripts for investment in Tehran Stock Exchange (TSE) [147]. Behzad Ian [148] has carried out extensive studies and analysed 266 research papers for TOPSIS method based on 100 different journals since 2000. Similar extensive study on the application of fuzzy TOPSIS has been carried out by Barczewski [149] for the last decade. Portfolio allocation is an important aspect in new product development. If number of alternatives are available, then apportioning assets to them becomes a complex situation. Validation of portfolio allocation has been done using fuzzy TOPSIS [150].

2.8 COPRAS-G

The COPRAS method is used, for evaluating and selecting the alternative against the criteria, by adopting a stepwise ranking and evaluating procedure of the alternative, in terms of their significance and utility degree. Deng [151], talked about control problems on grey systems. Introduction to grey system theory was done by Deng [152]. Theory and applications on properties of relational space for grey system was published by Deng [153] in 1988. COPRAS-G method was introduced by Zavadskas [154]. Researchers have found good results using the grey systems and COPRAS for the past few decades. Lin [155] have used grey number in dynamic multi-attribute decision making model. COPRAS-G had been used in selection of best website [156], multi-criteria evaluation of container terminal technologies [157], cutting tool material selection [158]. Hybrid MADM methods involving COPRAS-G and other methods are also popular. AHP and COPRAS-G methods was used for selecting company [159] and prioritizing constructing projects of municipalities in Iran [160]. Fuzzy analytical hierarchy process and grey relational analysis was used for machine tool selection [161] and market segment evaluation and selection [162]. Mohammad [163] used SWARA and COPRAS-G methods for decision making in machine tool selection. A COPRAS-G-MODM hybrid approach was applied for strategy portfolio optimization [164]. Validation of portfolio allocation in new product development has been done using COPRAS-G [150]. This method has been used in finding solutions to numerous scientific problems. Key factors required for sustainable architecture have been analysed using a hybrid method made up of BWM and COPRAS [165]. In a recent publication, COPRAS-G was used to evaluate crisis reduction method in form of inter-basin water transfer projects. Integer, fuzzy scale and grey intervals were used in this evaluation [166].

2.9 Evidential Reasoning

Evidential reasoning is based on Dempster-Shafer theory and decision theory. It was developed by Yang for multi attribute decision making analysis involving uncertainty. The assessment is done using a belief structure to create a model. A MADM problem gets represented as a belief decision matrix. The important features of evidential reasoning are

(i) Use of belief decision matrix results in reliable assessment of an option as compared to conventional matrix.

(ii) All forms of data such as single value, probability distribution based, qualitative with their respective uncertainties can be taken care by the ER method.

(iii) The outcomes can be projected in a more informative manner.

Evidential reasoning method finds its use in wide number of application due to its ability in handling uncertainties. It has been used for analysing human reliability in maritime applications by modelling the relation between factors which lead to human error [167]. Handling customer issues and complaints is an important decision-making process. Evidential reasoning has been used for developing support tool for handling customer complaints [168]. Evidential reasoning has been used in decision making process of financial investment where input information is conflicting in nature and involvers qualitative inputs from the investors [169]. Waste water reuse involves assessing the waste water and the tertiary treatment methods and at the same time giving equal importance to sustainable development. It is a multi-attribute decision making problem as it involves various objectives and uncertainty creating element. Evidential reasoning method has been used to carry out the sustainability assessment [170]. Security is of prime importance in development of E-commerce. AHP and ER has been used to carry out the assessment of security in E-commerce facility [171]. Lot of complexities arise while selecting a R & D project since it involves many criteria and alternatives. Evidential reasoning based on data driven rule has been used to select the best alternative. It involves the use of experimental data and relation mapping in arriving at the final decision [172]. Decision making during emergency response without any command in case of maritime application was proposed using ER and TOPSIS. The influencing parameters were integrated using ER and decision making was carried out using TOPSIS [173]. Evidential reasoning has been used in face recognition algorithm [174], creating a stock trading expert system [175], solid waste assessment in hospitals [176], assessing building energy efficiency [177], weapon system capability assessment [178].

2.10 Genetic Algorithm – Artificial Neural Network

Artificial neural network (ANN) is best suited for application which are dynamic and practical in nature. A survey of neural network applications was carried out by Lisboa [179]. It can generalize and predict new output based on past inputs or trends. Software can be used and information can be processed at a higher speed. Genetic algorithm (GA) is an optimization technique based on Darwin's evolution theory. It was introduced by Holland [180] and detailed by Goldberg [181]. Genetic algorithm follows the natural phenomenon of selection, reproduction and mutation for finding optimal solution. Wang [182] used genetic algorithm method to solve scheduling problems while Wang [183] used it for bi-objective pump scheduling in water supply. The wide use of GA has resulted from its ability to solve multi-dimensional problems. Integrated artificial neural network and genetic algorithm provide a number of benefits in solving a multi attribute decision making problem A combination of ANN and GA methodology has been used by Lau [184] for performance benchmarking system to support supplier selection while Creese [185] have used it for supplier selection with performance index. ANN and GA methodology has been used for vendor selection by Kumar and Roy [186] and Lakshmanpriya [187]. Similarly, Ariffin [188] and Asthana and Gupta [189] have used hybrid method of ANN and GA for supplier selection. A drilling rate index (DRI) prediction model was proposed and validated using performing indices, such as variance, root mean square error, to predict the drilling ability on the rock [190]. Another model for prediction of bending force in hot strip rolling process was carried out using various input parameters such as incoming temperature, incoming and outgoing thickness, width of the strip, rolling force and speed [191]. Optimum machining parameters were found out using GA ANN technique to reduce the surface roughness to minimum and was validated using real machining experimental data [192]. Similar study was carried out for predicting the optimized paraments during pre-treatment process of bio diesel production [193] and prediction of spring back action during sheet metal forming process [194,195].

2.11 Single Valued Neutrosophic TOPSIS

Some novel theories are required as fuzzy systems and intuitionistic fuzzy systems [196, 197] are not enough when situation involves uncertainty, incompleteness, impreciseness and inconsistency in the input data or decision makers data. Fuzzy systems are defined with respect to membership function only and hence non-membership and indeterminacy is lost. In case of intuitionistic fuzzy set, the connectors are defined with respect to membership and non-membership, hence indeterminacy is lost. This loss is taken care by using the concept of neutrosophic sets developed and proposed by F. Smrarandache [198, 199]. As per Smarandache, neutrosophic means “knowledge of neutral thought”. The neutrosophic logic is very close to stimulating human thinking, as it reflects uncertainty of human life and is an extension of classic set, fuzzy set, intuitionistic fuzzy set and interval valued intuitionistic fuzzy set. The three basic components of neutrosophic sets are truth membership function, indeterminacy membership function and the falsity membership function. For example, an expert can give the following statement saying that possibility that the statement is true is 06, statement is false is 0.5 and statement is not sure is 0.3. All the three-membership function are independent of each other and their highest sum adds up to 3, which means that each function varies from 0 to 1. Neutrosophic logic characterizes each logical statement in a 3-D format wherein the three axes are made up of truth function, indeterminacy function and falsity function. The origin will have value (0, 0, 0) whereas the diagonally opposite point will have the value (1, 1, 1). Since neutrosophic sets are difficult to apply to real world problems, Wang [200] proposed the concept of single value neutrosophic set (SVNS). SVNS provides the set operators required for applying the neutrosophic logic. In new product development in particular, the decision makers are not able to have conviction in their statement, in terms of degree of truth or falsity, when there is lack of knowledge, lack of time, pressure. Neutrosophic logic has been compared with other well-known logical tools and stands out if there is uncertainty and vagueness in the data [201]. The concept of neutrosophic sets and its difference form the fuzzy sets have been well published [202, 203]. Uncertainties and inconsistencies because of experts evaluation and complexity of the process, are part of the risk assessment phase. Safety and critical effect analysis (SCEA) is a method that calculates the risk magnitude, based on attributes such as probability, severity, frequency, and detectability. Neutrosophic sets have been used to evaluate such occupational risk [204]. Research has been carried out on diabetic patients, using sugar analysing smart medical devices, by having group decision making framework based on neutrosophic TOPSIS [205]. Similar group decision making framework has been incorporated, by using Hamming distance, to get the weights of the decision makers [206]. Integrated neutrosophic TOPSIS has been used for personnel selection, to find the perfect applicant fulfilling the enterprise requirement [207], ranking of hotels based on sentiments and assessments on a standardized scale [208], supplier selection [209]. Trapezoidal neutrosophic number has been used in combination with TOPSIS and case study has been carried out to evaluate its efficacy [210]. The single value neutrosophic scale for criteria weightages and alternative rating against each criterion is shown in Table 2.2 and Table 2.3.

Table 2.2: SVNS Table for criteria weight calculation.

Linguistic variable	SVNS
Very important (VI)	(0.90, 0.10, 0.10)
Important (I)	(0.75, 0.25, 0.20)
Medium (M)	(0.50, 0.50, 0.50)
Unimportant (UI)	(0.35, 0.75, 0.80)
Very unimportant (VUI)	(0.10, 0.90, 0.90)

Table 2.3: SVNS Table for alternative ratings against criteria.

Linguistic terms	SVNS
Extremely good (EG) / extremely high (EH)	(1.00, 0.00, 0.00)
Very very good (VVG) / very very high (VVH)	(0.90, 0.10, 0.10)
Very good (VG) / very high (VH)	(0.80, 0.15, 0.20)
Good (G) / high (H)	(0.70, 0.25, 0.30)
Medium good (MG) / medium high (MH)	(0.60, 0.35, 0.40)
Medium (M) / fair (F)	(0.50, 0.50, 0.50)
Medium bad (MB) / medium low (ML)	(0.40, 0.65, 0.60)
Bad (B) / low (L)	(0.30, 0.75, 0.70)
Very bad (VB) / very low (VL)	(0.20, 0.85, 0.80)

2.12 Summary

The literature addresses many factors affecting the new product development. All the above listed factors show that MADM approach is a must for NPD process. The literature review shows that most of the published work does not consider all forms of data e.g., imprecise, vague, incomplete, uncertain etc. Like all decision problems, new product development decisions contain considerable amount of uncertainty causing elements. This can confuse the decision-maker to reach the targeted performance. Uncertainty arises from, both internal and external multiple sources including technical, management and commercial issues. A structured approach is required to be used, that can facilitate practitioners and decision-makers to evaluate the relative importance among various elements and factors that affect NPD decisions. For this, studying the existing MADM methods and checking whether group based MADM methods can give better result, is required. It is very difficult to get historical data for new product development. Hence mostly subjective data in qualitative form is considered. Incorporating this subjective data as input for traditionally superior MADM method is a very important requirement. Certain factors such as Design for Manufacturability (DFM), which also affect the new product development, have not been considered. Consideration of DFM factors during product design, shorten the product life cycle, minimizing production and manufacturing time, ensuring smooth flow of product, minimize cost etc... Quality issues resulting from part interaction can be reduced by selecting better parts and proper matching of parts. Lastly in today's competitive market, managing NPD becomes crucial for survival of small and medium sized enterprises (SMEs). Many SMEs face a dilemma in NPD. While the SMEs realize the need for NPD, focus to work in this area is frequently driven out by other immediate priorities. Understanding the key performance criteria of NPD for SMEs and devising a self-assessment model for NPD performance, is the need of the hour. Table 2.4 shows the research papers referred during the literature review process. Figure 2.2 gives the complete flow of the research work.

Table 2.4: Literature review breakdown for research process.

Topic	Literature review for sub topic
New Product Development	Design concept evaluation [1]
	New product portfolio selection [2]
	Product project screening [3 - 4]
	New product design assessment [5]
	Sustainable product development [6, 7, 20]

	Quality function deployment [8, 9, 21]
	Group decision [3, 10, 11]
	System reliability [12 - 14]
	Material selection [15 - 17]
	Fuzziness in new product decision making [20, 21, 41]
	New product process [22 - 28]
	Stages of NPD process [29 - 31]
	Failure rate of NPD [32 - 34]
	Uncertainty in NPD [35 - 36]
	NPD teams members [37 - 38]
	Deployment of resources [39 - 40]
Small and Medium Enterprises	Role of SMEs [42 - 44, 46 - 48]
	Difficulties faced by SMEs in NPD [49 - 53]
	Product development in SMEs [45, 54 - 60]
	Effect of government intervention on NPD in SMEs [61 - 66]
Design for Manufacturability	DFM in SMEs [67]
	DFM problems associated with SMEs [68 - 76]
Multi Attribute Decision Making	Idea screening in NPD [78 - 79]
	Simple additive weighting [80]
	Analytical hierarchical process [81]
	Technique for order preference by similar to ideal solution [82 - 83]
	Artificial neural network [84]
	Literature review on MADM [85]
	Cross functional domain research [86 - 88]
	Fuzzy theory and triangular fuzzy number [89 - 91]
	Fuzzy MADM [92 - 93, 100 - 102]
	Fuzzy AHP [94 - 101, 105 - 107]
Analytical Hierarchical Process	AHP method [108]
	Fuzzy AHP method and application [109 - 112]
	AHP – TOPSIS method and application [112 - 116]
	AHP with other methods [117 - 124]
Fuzzy TOPSIS	TOPSIS introduction and method [125 - 127]
	Fuzzy TOPSIS introduction and method [128 - 130]

	Fuzzy TOPSIS for supplier selection [131 - 132]
	logistic service provider [133]
	plant location selection [134 - 136]
	Robotics selection [137 - 138]
	Hybrid Fuzzy TOPSIS applications [139 - 150]
COPRAS-G	COPRAS method and grey theory [151 - 154]
	COPRAS-G applications [155 - 158]
	Hybrid COPRAS-G applications [159 - 166]
Evidential Reasoning	Evidential Reasoning applications [167 - 178]
Genetic Algorithm – Artificial Neural Network	Survey of ANN applications [179]
	Genetic algorithm method and application [180 - 183]
	GA – ANN applications [184 - 195]
Single Valued Neutrosophic TOPSIS	Limitations of fuzzy and intuitionistic fuzzy systems [196 - 197]
	Concept of neutrosophic sets [198 - 199]
	Single value neutrosophic set [200 - 201]
	Application of SVNS [202 - 203]
	Application of SVNS TOPSIS [204 - 210]
Ranking Method	Ranking method [215]
Cronbach's Alpha	Use of Cronbach's Alpha [216]

To summarize based on the research paper, review has been carried out in the area of factors affecting the idea screening phase of new product development. Review has been carried out on small and medium enterprises and the problems associated when SEMs go for product development. Since majority of SMEs deal with manufacturing and SMEs are the back bone for socio economic development of any country, literature survey has been done in the area of design for manufacturability. Decision making in new product development involves uncertainty causing elements. The data involved may be incomplete, imprecise, inconsistent in nature. A structured approach is required to take care of the uncertainty causing elements. MADM methods helps in this process. Hence the study has been carried out on most commonly used MADM methods. Another approach to tackle this uncertainty is to use fuzzy set theory and neutrosophic set theory. Papers have been reviewed in these areas also.

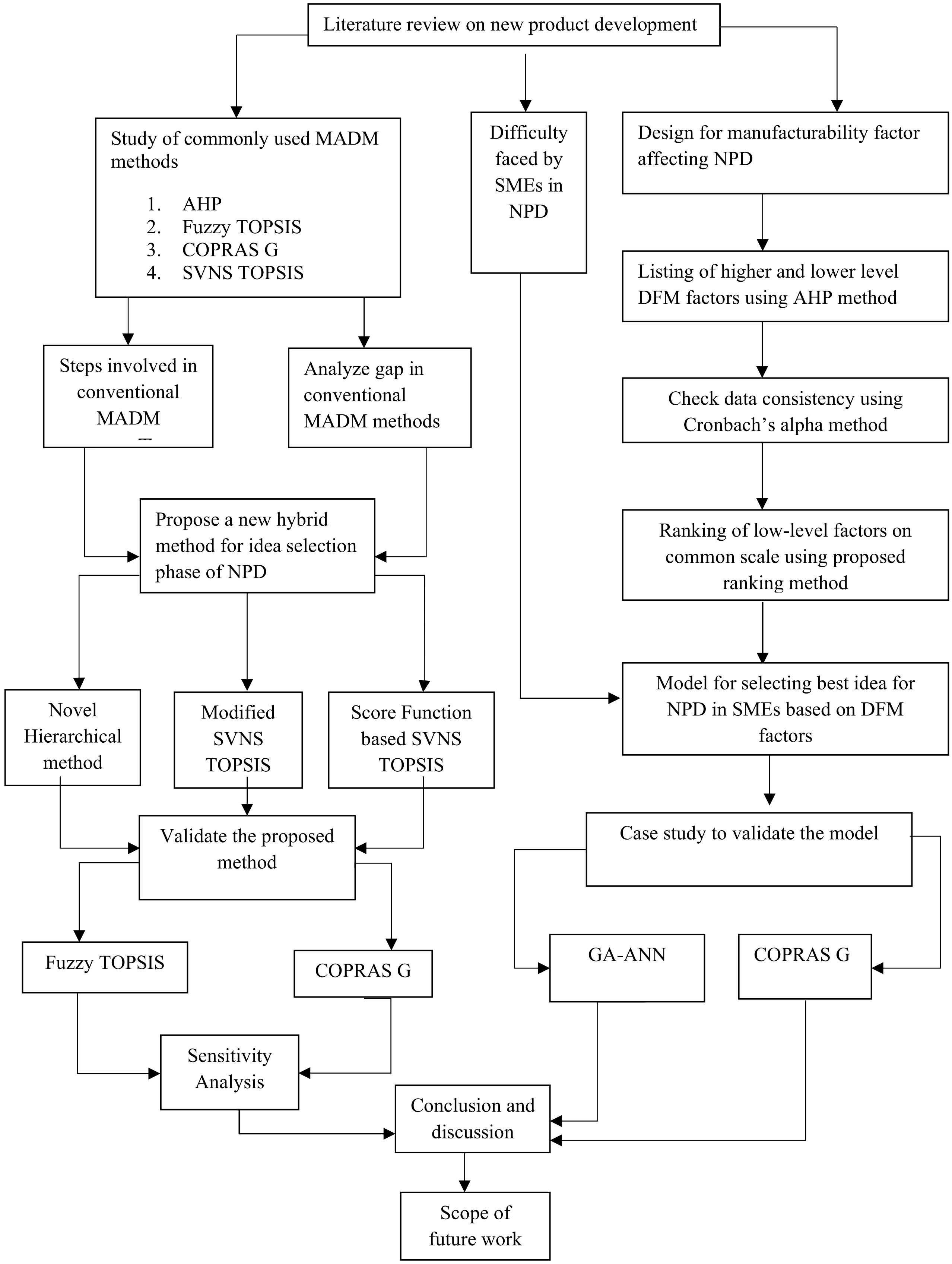

Figure 2.2: Flow of Research Work.

Chapter 3

Problem Description and Solution Methodologies

3.1 Introduction

In an increasingly competitive global market, companies must be better at developing new products. The trend of the industry is to move towards the design and manufacture of more sophisticated products because of the global competition involved. The sophistication involves products with better and safer performance, more environmental friendliness, higher quality and reliability, and shorter time. Particularly for the companies with short product life cycle, development of new products fulfilling reasonable quality demands, performance and cost is of prime importance. At the early product design stage such multiple criteria have to be considered and assessed. But because of the limited reliable data available to measure and evaluate decision criteria, there is always difficulty in conducting the assessment at early design stage. Like all decision problems, new product development decisions contain considerable amount of uncertainty causing elements. This can confuse the decision-maker to reach the targeted performance. Tackling these issues has become very important for the survival of the industry.

3.2 Motivation for the Research Work

SMEs are the backbone engine for socio-economic development of a state as well the country. Presently India ranks ahead among the fastest growing economic countries. In India, SMEs provide a large number of job opportunities and act as a source of employment for lakhs of people living in villages and semi urban towns. SME's have recorded a better growth rate compared to the general industrial scenario but are plagued with greater challenges in the post liberalization era. Heterogeneity of the SME sector comes from the different capacity of the enterprise, the types of products and services offered and the technical knowhow used. The growth of SME's is hampered due to lack of experienced personnel either at the technical or managerial level and restricted capital allocation for carrying out research. For SME's the survival in the global world requires, having a knowledge intensive relation inside and outside their borders [52]. Particularly in the area of new product development, their lack of technical knowhow and other resources have to be tackled by cooperation with the external resources in and around [53]. It was observed that significantly less amount of research was carried out in the area of critical design for manufacturing factors affecting NPD in SME's. Design for manufacturability talks about actively designing of products to optimize the manufacturing process. Consideration of DFM factors during product design shorten the product life cycle minimizing production and manufacturing time, ensuring smooth flow of product, minimize cost etc. Quality issues resulting from part interaction can be reduced by selecting better parts and proper matching of parts. In manufacturing scenarios, SME's usually have a tendency of going on introducing new products, without checking for existing compatible products, resulting in having a large number of product portfolios [67]. The literature review points out that substantial benefits have been realized by firms using design for manufacturability during product design or using existing product database and applying it to new product. Identifying the critical design for manufacturability factors, can substantially bring improvement in the success of new product development for small and medium enterprises, involved in manufacturing.

Idea screening is an important stage in the NPD process, involving lot of uncertainty causing elements and hence a structured approach like multi attribute decision making (MADM) techniques is required, to select the best alternative among available alternatives. A number of MADM methods are available to carry out the decision process. The research gap, identified through the literature review carried out, shows that the effect of alternative rating variables of all alternatives taken together have not been incorporated much in selecting the best idea during the idea screening. It is very difficult to get historical data for new product development. Hence mostly subjective data in qualitative form is considered. Incorporating this subjective data as input for traditionally superior MADM method is a very important requirement.

3.3 Problem Statement

The research problem is to propose a model for ranking critical factors affecting new product development from design for manufacturability consideration and validating the model using multi attribute decision making (MADM) methods and to propose a hybrid method to select the best alternative by taking in to account the effect of alternative rating data for all the alternatives.

The following below mentioned objectives forms the framework for the research problem identified:

1. Investigate the commonly used MADM approaches in NPD.
2. Check the Effectiveness of Group/ Hybrid based MADM Approach.
3. Consider Design and Development in the process of New Product Development.
4. Understand the key DFM Criteria of NPD for SMEs.
5. Devise a Self-Assessment Model for NPD Performance for SMEs.

3.4 General Assumptions

Design for manufacturability affects idea screening of NPD. Type of input data whether it is qualitative or quantitative also affects the final alternative ranking process. SMEs are the back bone of any country and a self-assessment model for SMEs is the need of the hour. Listed below are the general assumptions made for each of the topic mentioned above.

3.4.1 Design for manufacturability

Most of the SME's are involved in manufacturing and/or assembly of multiple products. The components and specification of these products normally have high level of similarity. Design for manufacturability is an important factor as SME's can realize significant benefits when a similar part is required in many products. SME's have the required database in terms of R&D know-how, design procedures, manufacturing capabilities and assembly layout for their existing product. A considerable time can be saved by shortening the life cycle for the newly developed product by using the technical know-how and capabilities in terms of men, machine, methods, materials already available with the SME's. It becomes easier to use the same men power and methods for the new product, if it is in tune with the existing product. Similarly processes and materials going in to making of the new product, if it is line with the existing products of the enterprise, it will lead to overall savings for the enterprise as a whole. Advantage can be taken of the already available manufacturing setup and assembly process layout. Design for manufacturability has various advantages such as:

1. Production capabilities can be identified by manufacturing team, thus helping in better selection of materials and processes, quality parameters can be achieved and reduction is possible in conflicts occurring during production.
2. Special purpose tooling which may require longer time for procuring can be easily made available. This can provide competitive advantage by shortening the development process.

3. Problems which can occur during production phase because of technical feasibility can be assessed on earlier.
4. Conflict resolution can be avoided and the focus can be towards problem solution.

This is the reason for considering design for manufacturability as an important factor for new product development.

3.4.2 Linguistic variables for quantitative factors

It is observed that in new product development the quantitative data may not always be available for all the factors, the reason being past historical data not being available because of a totally new concept. This might hold true for existing product also, which might be required for benchmarking, as some of the quantitative data might not be available e.g., trying to get quantitative information of a competitor's product. In this given scenario, it is always better to express the quantitative data also in linguistic form and convert the linguistic variable in terms of fuzzy number to take care about the fuzziness in the data. Since the linguistic variables are expressed with respect to a standard scale, errors as compared to actual quantitative data can be minimized. Wherever quantitative data is available the same data can be used as it is.

3.4.3 Linguistic variables for qualitative factors

The NPD process is multidisciplinary. Groups of people from different departments take part in decision making process. Judgment synthesis becomes very important because of this group approach. Based on differences in technical backgrounds, departmental goals and constraints etc., group members may present different judgments about project screening decisions. The accuracy of the decisions depends on the synthetization of these different judgments. To tackle the uncertainty and fuzziness in the data due to individual perception, the qualitative data is expressed as linguistic variable. This helps the decision maker to express his perception in a better way. The linguistic variable can then be converted to triangular fuzzy number. This helps to retain maximum original information, thus leading to reliable final decision solution

3.4.4 Research of SMEs in India

SMEs are the backbone engine for socio-economic development of any state or country, be it developed or developing country. It also plays a very important role in under-developed countries. Although the case study has been carried out in the state of Goa, the proposed model is generalised in nature and can be applied in any of the SMEs across the world. A few factors listed in the model either will have to be deleted or some might have to be added, but the majority of the factors will remain the same. The steps proposed in the model can be used as it is in any of the SME's.

3.5 Scope of the Problem

There is a wide scope for research on new product development as seen from the literature. The existing research on new product development process is mainly carried out in large industries, as they have the R&D for the technical know-how, experienced men power to take the required decision. For SME's the survival in the global world requires, having a knowledge intensive relation inside and outside their borders. Particularly in the area of new product development, their lack of technical knowhow and other resources have to be tackled by cooperation with the external resources in and around. SMEs are the backbone of any state as well as the country. Presently India ranks ahead among the fastest growing economic countries. A large number of job opportunities are provided by SMEs in India. India has lakhs of people living in villages and semi urban towns. SMEs acts as a source of employment for all these people. They help in developing the socio-economic conditions. The growth of SME's is hampered due to lack of experienced personnel either at the technical or managerial level and restricted capital allocation for carrying out research. Hence identifying the critical factors affecting the performance of new product development in SMEs has a wide scope. It is an added requirement to rank all these critical factors. A framework model for the SMEs to rely upon, while making decision during the idea screening phase, will be an added advantage to the SMEs. Also, the conventional MADM methods, while making decision during the idea screening phase, do not consider all the data available while selecting the best alternative. The research scope can be further expanded to provide a novel method, which will take in to consideration all the data available, in terms of alternative rating for various criteria, while deciding about the best alternative.

3.6 Solution Methodologies

There are five major objectives of the research problem. The first two objective involves investigating the commonly used MADM approaches in NPD and to check the effectiveness of group based MADM methods. The mathematical sets used during the MADM process can be either crisp set or fuzzy set or neutrosophic set. In order to satisfy the first objective, the most commonly used MADM method in NPD were studied, such as Fuzzy TOPSIS, COPRAS-G. For the second objective, fuzzy scale and grey scale were used with the Evidential Reasoning method to incorporate qualitative data in the ER method, a novel group based or hybrid methods was proposed, using fuzzy logic and another two methods were proposed using neutrosophic logic. The novel hybrid methods are a combination of Fuzzy TOPSIS and hierarchical structure, neutrosophic TOPSIS and hierarchical structure and the last one is based on score function. The commonly used MADM methods do not consider the effect of alternative rating variables of all alternatives taken together, while deciding about the best idea, during the idea screening phase. To address this gap, all the three novel methods have been proposed, wherein all the data involved i.e., criteria weightages data and alternative rating data, are arranged in a hierarchical form and ranking is carried out, taking in to account effect of alternatives with respect to criteria variables of other alternatives, to make decision for a particular alternative. A case study was carried out in a manufacturing industry for finding the best alternative, using all the proposed novel methods and COPRAS-G and Fuzzy TOPSIS method was used to validate the result. To check the superiority of proposed hierarchical method and modified SVNS TOPSIS method with respect to other MADM methods, two most commonly used methods i.e., fuzzy TOPSIS and COPRAS-G were used for comparison. A program was written with number of alternatives ranging from 2 to 10, number of criteria ranging from 2 to 10 and number of decision-makers between 2 to 5. Random data sets were generated in linguistic form using the code and some data was taken from published papers. More than 100 numerical were solved using all the five methods, i.e., fuzzy TOPSIS, COPRAS-G, proposed hierarchal method, modified SVNS TOPSIS method and score function based SVNS TOPSIS and alternative ranking was obtained for each of the method. Spearmen co-relation formula was used to get the co-relation coefficient. It was observed that the co-relation coefficient ranged from 0.88 to 0.91 when applied between the proposed hierarchical method and Fuzzy TOPSIS and COPRAS-G. Similarly, it was observed that the co-relation coefficient ranged from 0.85 to 0.90 when applied between the modified SVNS TOPSIS method and Fuzzy TOPSIS and COPRAS-G. These methods provide an improved solution, not only in selecting best idea during idea screening phase of NPD, but also can be applied to rank alternatives in various other MADM applications. The third method is based on converting the SVN number in to a single crisp number using the score function. This method also provided stable and consistent ranking of the alternatives. The last three objective involves considering design and development in the process of NPD, understanding the key design performance criteria and developing a self-assessment model for NPD performance. These objectives were defined based on the literature gap, which identified that design for manufacturability is a very important factor. A comprehensive study was carried out to list all the factors affecting NPD, from design for manufacturability consideration for SMEs. A novel method was proposed to rank all the listed factors. A self-assessment model was developed so that the SMEs on their own, with their limited know how, could take decision on the NPD performance. To validate the model, a case study in the motor industry located in Goa, India was taken up. COPRAS-Grey and hybrid method involving ANN-GA was used to solve the MADM problem. The input was taken from two sources (i) standard weights obtained for the DFM factors (ii) weights given by decision makers from the company. It was observed that the final solution using both the methods was same irrespective of the input data. The mathematical sets used in the various MADM methods and the solution methodologies used in the research are listed below.

3.6.1 Mathematical sets in MADM

The mathematical sets used in multi attribute decision making are listed below:

- Crisp set
- Fuzzy set
- Single valued neutrosophic set (SVNS)

3.6.1.1 Crisp set theory

Collection of all the data points or elements comprises a set. The information is available in quantitative form. These elements are either countable or discrete integers. The analysis is carried out as per the classical set theory.

If P and Q are two sets, then

P U Q = {x/ x ∈ P or x ∈ Q} indicates union between two sets.

P ∩ B = {x/ x ∈ P and x ∈ Q} indicates intersection between two sets.

P / B = {x/ x ∈ P or x ∉ Q} indicates difference between two sets.

3.6.1.2 Fuzzy set theory

The fuzzy set theory was introduced by Zadeh [125]. A lot of modified fuzzy MADM method have been proposed and successfully implemented to tackle real world problem [211, 212, 213]. If X is made up of number of collections represented by x ,a fuzzy set A in X is a set of pairs as shown in Equation 3.1 and certainty of x belongs to A increases for larger value of the membership function [214].

$$A = \{(x, \mu_A(x)) | x \epsilon X\}$$

$\mu_A(x)$ denotes a membership function of x in A.

- **3.6.1.3 Triangular fuzzy numbers**

The TFN is represented as follows: A = (a, b, c). The parameter a gives the smallest possible value, b gives the peak value and c gives the largest possible value of the membership function (Figure 3.1).

$$\mu_A(x) = \begin{cases} 0 & \text{for } x < a;\ x > c \\ \frac{x-1}{b-1} & \text{for } a \le x \le b \\ \frac{c-x}{c-b} & \text{for } b \le x \le c \end{cases} \tag{3.1}$$

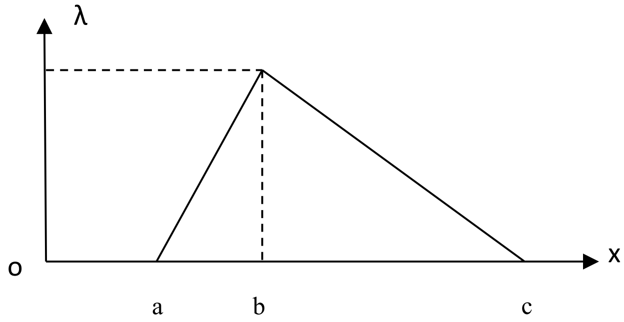

Figure 3.1: Triangular fuzzy number.

- **3.6.1.4 Arithmetic operations**

If $\tilde{P} = (p^1, p^2, p^3)$ and $\tilde{Q} = (q^1, q^2, q^3)$ two fuzzy numbers, then the basic arithmetic operations between them is represented as follows [22]:

- Addition

$$\tilde{P} + \tilde{Q} = (p^1, p^2, p^3) + (q^1, q^2, q^3) = (p^1 + q^1, p^2 + q^2, p^3 + q^3) \tag{3.2}$$

- Subtraction

$$\tilde{P} - \tilde{Q} = (p^1, p^2, p^3) - (q^1, q^2, q^3) = (p^1 - q^3, p^2 - q^2, p^3 - q^1) \tag{3.3}$$

- Multiplication

$$\tilde{P} \times \tilde{Q} = (p^1, p^2, p^3) \times (q^1, q^2, q^3) = (p^1 \times q^1, p^2 \times q^2, p^3 \times q^3) \tag{3.4}$$

- Division

$$\tilde{P} \div \tilde{Q} = (p^1, p^2, p^3) \div (q^1, q^2, q^3) = (p^1 \div q^3, p^2 \div q^2, p^3 \div q^1) \tag{3.5}$$

- Reciprocal

$$1/_{\tilde{P}} = 1/_{(p^1, p^2, p^3)} = \left(1/_{p^3}, 1/_{p^2}, 1/_{p^1}\right) \tag{3.6}$$

- Scalar

$$\widetilde{\lambda P} = \lambda(p^1, p^2, p^3) = (\lambda p^1, \lambda p^2, \lambda p^3) \quad (3.7)$$

- Euclidean distance

$$d(\tilde{P}, \tilde{Q}) = [(p^1 - q^1)^2 + (p^2 - q^2)^2 + (p^3 - q^3)^2]^{\frac{1}{2}} \quad (3.8)$$

Where $0 < p^1 \leq p^2 \leq p^3$ and $0 < q^1 \leq q^2 \leq q^3$

A standard fuzzy scale to convert linguistic variables to triangular fuzzy number is shown in Table 3.1.

Table 3.1: Standard fuzzy scale to convert linguistic variables to TFN.

Fuzzy number	Alternative assessment	Criteria weights
(1, 1, 3)	Very Poor (VP)	Very Low (VL)
(1, 3, 5)	Poor (P)	Low (L)
(3, 5, 7)	Fair (F)	Medium (M)
(5, 7, 9)	Good (G)	High (H)
(7, 9, 9)	Very Good (VG)	Very High (VH)

3.6.1.5 Neutrosophic Set Theory

Let X be point in the universe (objects) such that $x \in X$, then neutrosophic set A in X is given by

$$A = \{x, (T_A(x), I_A(x), F_A(x)), x \in X\} \quad (3.9)$$

Where $T_A(x)$ is the truth-membership function

$I_A(x)$ is the indeterminacy membership function

$F_A(x)$ is the falsity membership function

and $T_A(x), I_A(x), F_A(x)$: X - [0, 1]

$T_A(x) + I_A(x) + F_A(x) \leq 3$

- **3.6.1.6 Single valued neutrosophic set**

Let $P_1 = (p_1, q_1, r_1)$ and $P_2 = (p_2, q_2, r_2)$ be two SVN numbers,

- Addition

$$P_1 \oplus P_2 = (p_1 + p_2 - p_1 p_2, q_1 q_2, r_1 r_2) \quad (3.10)$$

- Multiplication

$$P_1 \otimes P_2 = (p_1p_2,\ q_1+q_2-q_1q_2,\ r_1+r_2-r_1r_2) \tag{3.11}$$

- Scalar multiplication

  Let λ be a positive real number.

$$\lambda A = (1-(1-p1)^{\lambda},\ q_1^{\lambda},\ r_1^{\lambda}),\ \lambda>0. \tag{3.12}$$

- Score function

  Based on truth degree, indeterminacy degree and falsity degree, the score value of SVN is given by

$$S(P_1) = \frac{1+p_1-2q_1-r_1}{2} \tag{3.13}$$

3.6.2 MADM method

Following are the steps in the MADM method:

Step 1: Identify the application for which the MADM method is required.

Step 2: List down all the alternatives and criteria along with the number of decision makers.

Step 3: Based on 'm' alternatives and 'n' criteria, make a (m*n) decision matrix. Let the alternatives be represented by A = {A_i, i = 1, 2, 3, ….m} and criteria be represented by C = {C_i, i = 1, 2, 3, …. n}. Table 3.2 shows the decision matrix. X_{ij} represents the relative rating of alternative against each criterion.

Table 3.2: MADM Decision Matrix.

Criteria / Alternatives	C_1	C_2	C_3	……..	C_n
A_1	X_{11}	X_{12}	X_{13}	……..	X_{1n}
A_2	X_{21}	X_{22}	X_{23}	……..	X_{2n}
A_3	X_{31}	X_{32}	X_{33}	……..	X_{3n}
……….	……..	……..	……..	……..	……..
A_m	X_{m1}	X_{m2}	X_{m3}	……..	X_{mn}

Step 4: Convert qualitative input data to quantitative data. Covert the linguistic data to crisp data.

Step 5: Carry out normalisation of matrix. Since each criterion will have different units, normalisation procedure has to be carried out to bring all data to one level.

Step 6: Calculate the criteria weights. Criteria weights can be found out using other MADM methods or from the decision makers opinion.

Step 7: Carry out ranking of all the alternatives. Using any of the conventional, commonly used MADM methods carry out the ranking of all the alternatives. The one having highest relative score among the alternatives is taken as the best alternative.

3.6.3 AHP method

Step 1: Develop a hierarchical structure with goal at top level, evaluation attribute at second level, followed by alternative at the last level.

Step 2: Using the scale provided by Saaty [108] create a matrix which will help in making decision based on relative positions of attributes and alternatives [108]. While comparing any two members, 1 indicate 'equal importance', 3 indicates 'slightly more important" as compared to the other member, 5 indicates strongly more important as compared to the other member, Similarly, 7 and 9 indicate demonstrably more important and absolutely more important. If there are n attributes and m alternatives, then we get a decision matrix of m*n as shown in Table 3.3.

Table 3.3: AHP Decision Matrix.

Alternatives	C_1	C_2	C_3	………..	C_n
A_1	A_{11}	A_{12}	$A_{1}3$	………..	A_{1n}
A_2	A_{21}	A_{22}	A_{23}	………..	A_{2n}
A_3	A_{31}	A_{32}	A_{33}	………..	A_{3n}
………..	………..	………..	………..	………..	………..
A_m	A_{m1}	A_{m2}	A_{m3}	………..	A_{mn}

Step 3: Calculate the weights of the attributes by finding the geometric mean of the i^{th} row and carrying out the normalisation of the decision matrix as shown in Equation 3.14.

$$GM_J = \left[\prod_{J=1}^{N} b_{ij}\ \right]^{1/n} \text{and } W_J = \left[\frac{GM_J}{\sum_{j=1}^{n} GM_J}\right]^{1/n} \tag{3.14}$$

Step 4: Get matrix A_3 such that $A_3 = A_1 * A_2$ and $A_4 = A_3/ A_2$ where $A_2 = [w_1, w_2, \ldots.w_j]$. Calculate the average of matrix A_4 which will give the maximum eigen value denoted by λ_{max}.

Step 5: Calculate the consistency index (CI) and consistency ratio (CR) using Equation 3.15 and Equation 3.16.

$$CI = \frac{(\lambda \max - \ )}{(n-1)} \tag{3.15}$$

$$CR = \frac{CI}{R1} \tag{3.16}$$

Where R1 indicates the average consistency index. If the consistency ratio is less than 0.1, i.e., CR ≤ 0.1, it indicates that decision matrix is consistent. Table 3.4 shows the standard random index (RI) for the AHP technique.

Table 3.4: Random index values for AHP technique.

Attribute	3	4	5	6	7	8	9	10
RI	0.52	0.89	1.11	1.25	1.35	1.4	1.45	1.49

Step 6: Use Equation 3.17 to calculate the overall performance score.

$$Pi = \sum_{j=1}^{n} Wj * xij \tag{3.17}$$

Step 7: Rank the alternatives based on the Pi score. The highest Pi score will give the best ranked alternative whereas the lowest Pi score will give the worst alternative.

3.6.4 Fuzzy TOPSIS method

The Fuzzy TOPSIS procedure is as follows:

Step 1: Identify the decision makers represented by 'k'. Decide on the criteria based on which evaluation will be made represented by 'n'. List down the feasible alternatives represented by 'm'.

Step 2: Let the decision makers decide on the linguistic variables to be used to represent the criteria weightages denoted by $\tilde{\omega}_j$. Similarly Let the decision makers decide on the linguistic variables to be used to represent alternative ratings with respect to each criterion denoted by $\check{x}_j$. Standard fuzzy scale is used to covert linguistic variable to triangular fuzzy numbers.

Step 3: Based on the 'k' decision makers, calculate the average criteria weights and average alternative ratings against each criterion, using Equation 3.18 and 3.19.

$$\widetilde{w}_j = \frac{1}{3}\left[\widetilde{w}_j^1 + \widetilde{w}_j^2 + \ldots + \widetilde{w}_j^k\right] \tag{3.18}$$

$$\tilde{x}_j = \frac{1}{3}\left[\tilde{x}_j^1 + \tilde{x}_j^2 + \ldots + \tilde{x}_j^k\right] \tag{3.19}$$

where $\tilde{\omega}j$ represent criteria weights, $\tilde{x}j$ represents alternative ratings against each criterion.

Step 4: Create fuzzy decision matrix (D) which will provide data given by the decision makers as shown in Equation 3.20.

$$D = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1m} \\ \vdots & \vdots & \vdots & \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & \tilde{x}_{nm} \end{bmatrix} \tag{3.20}$$

where $\tilde{x}_{ij}$, j = 1, 2,….m, are linguistic variables. Traingular fuzzy numbers are used to represent the variables. The triangular fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, cij)$.

Step 5: Normalize the fuzzy decision matrix (D). Use linear transformation to bring all the criteria scales to a single platform. Use Equations 3.21 and 3.22 to normalize the fuzzy decision matrix as given by:

$$\widetilde{r_{ij}} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right), \quad c_j^+ = \max_i c_{ij} \text{ (benefit criteria)} \tag{3.21}$$

$$\widetilde{r_{ij}} = \left(\frac{a_j^+}{c_{ij}}, \frac{a_j^+}{b_{ij}}, \frac{a_j^+}{a_{ij}}\right), \quad a_j^+ = \min_i a_{ij} \text{ (cost criteria)} \tag{3.22}$$

Step 6: Multiply the criteria weights ($\widetilde{w}_j$) to the elements ($\tilde{r}_{ij}$) to get the weighted normalized decision matrix ($\tilde{v}_{ij}$) as shown in Equation 3.23.

$$\tilde{v}_{ij} = \widetilde{r_{ij}} \times \widetilde{w_j} \tag{3.23}$$

Step 7: Decide about the best solution or the Fuzzy Positive Ideal Solution (FPIS) and the worse solution or the Fuzzy Negative Ideal Solution (FNIS).

For each alternative calculate the separation measures. For positive ideal solution (S+) the separation measures are given by Equation 3.24.

$$S_i^+ = \sum_{j=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^+) \tag{3.24}$$

Similarly, for negative ideal solution (S-) the separation measures from the negative ideal solution (S-) is given by Equation 3.25.

$$S_i^- = \sum_{i=1}^{n} d_v(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{3.25}$$

The vertex method is used to calculate the distances between any two fuzzy numbers. Here dv (.,.) represents the distance between two fuzzy numbers. According to the vertex method, the distance between two triangular fuzzy numbers A_1 (l_1, m_1, u_1) and A_2 (l_2, m_2, u_2) is calculated using Equation 3.26.

$$d(A_1, A_2) = \sqrt{\frac{1}{3}[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2]} \tag{3.26}$$

Step 8: Calculate the relative closeness to the ideal solution Ci* using equation 3.27 and Ci* closest to 1 will give the best solution.

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{3.27}$$

3.6.5 COPRAS-G method

Follow the steps below for the application of COPRAS:

The initial two steps of TOPSIS method and that of COPRAS method are the same. Get the aggregated weightages and the aggregated alternative rating against criteria ranking using the standard grey scale.

Step 1: Using the linear normalisation procedure get the normalized decision matrix

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \qquad (i = 1,2 \ldots\ldots, m; j = 1,2, \ldots\ldots, n) \tag{3.28}$$

Step 2: Multiply the aggregated weighted matrix to the normalised matrix to get the weighted normalised decision matrix (D).

$$D = [d_{ij}]_{mxn} = r_{ij} w_j \tag{3.29}$$

Step 3: For each of the beneficial and non-beneficial criteria, sum up the values of the weighted normalised decision Matrix.

$$S_{+i} = \sum_{j=1}^{n} d_{+ij} \qquad\qquad S_{-i} = \sum_{j=1}^{n} d_{-ij} \tag{3.30}$$

Step 4: The significances value for each of the alternative (Qi) are determined using the following formula:

$$\mathrm{Q_i} = \mathrm{S_{+i}} + \frac{\mathrm{S_{-min}} \sum_{i=1}^{m} \mathrm{S_{-i}}}{\mathrm{S_{-i}} \sum_{i=1}^{m} \left(\frac{\mathrm{S_{-min}}}{\mathrm{S_{-i}}}\right)} = \mathrm{S_{+i}} + \frac{\sum_{i=1}^{m} \mathrm{S_{-i}}}{\mathrm{S_{-i}} \sum_{i=1}^{m} \left(\frac{1}{\mathrm{S_{-i}}}\right)} \qquad (3.31)$$

Where S-min is the minimum value of S-i. The significance value indicates superiority of that alternative against the other alternatives. The alternative with the highest Q_i is the best alternative.

Step 5: The utility value for each alternative (U_i) is calculated by comparing the significance value of all the alternatives with the most efficient one and can be denoted as below:

$$\mathrm{U_i} = \left[\frac{\mathrm{Q_i}}{\mathrm{Q_{max}}}\right] * 100\% \qquad (3.32)$$

where Q_{max} is the maximum relative significance value. These range of utility values is from zero to 100%.

3.6.6 Evidential Reasoning method

Follow the steps below for the application of ER method:

Step 1: Consider L basic attributes e_i (i $= 1, \ldots,$ L) with respect to a system y. Let the L basic attributes have the evidence source as shown by Equation 3.33.

$$E = \{e_1, \ldots., e_L\} \qquad (3.33)$$

Let the attribute weights be $w = \{w_1, \ldots, w_i \ldots, w_L\}$ where w_i is the relative weight of the ith basic attribute e_1.

Step 2: Normalise the weights so conditions are satisfied as shown by Equation 3.34.

$$0 \leq w_i \leq 1 \text{ and } \sum_{i=1}^{L} w_i = 1 \qquad (3.34)$$

Step 3: Define the N distinct evaluation grades as given by Equation 3.35, where F_N is the evaluation coefficient of nth grade.

$$F = \{F_1, \ldots, F_n \ldots, F_N\} \qquad (3.35)$$

Step 4: Represent a given assessment for e_i (i $= 1, \ldots,$ L) mathematically as a distribution represented by Equation 3.36.

$$S(e_i) = \{(F_n, \beta_{n,i}), n = 1, \ldots, N\}, \qquad \mathrm{i} = 1, \ldots, \mathrm{L} \qquad (3.36)$$

where $\beta_{n,i}$indicates the degree of belief and

$$\beta_{n,i} \geq 0,\ \sum_{n=1}^{N} \beta_{n,i} \leq 1$$

Step 5: The basic probability mass is given by $m_{n,i}$ and the unassigned probability mass is given by $m_{F,i}$. The basic probability mass can be calculated using Equation 3.37 to 3.41.

$$m_{n,i} = w_i \beta_{ni}, \qquad n = 1, \dots, N, \quad i = 1, \dots, L \tag{3.37}$$

$$m_{F,i} = 1 - \sum_{n-1}^{N} m_{n,i} = 1 - w_i \sum_{n-i}^{N} \beta_{n,1}, \qquad i = 1,2, \dots, L \tag{3.38}$$

$$\tilde{m}_{F,i} = w_i (1 - \sum_{n-i}^{N} \beta_{n,1}), \qquad i = 1,2, \dots, L \tag{3.39}$$

$$\tilde{m}_{F,i} = 1 - w_i \qquad i = 1,2, \dots, L \tag{3.40}$$

$$m_{F,i} = \tilde{m}_{F,i} + \tilde{m}_{F,i} \tag{3.41}$$

Step 6: Aggregate the basic probability masses with respect to the L masses to get the combines probability ratings by using Equation 3.43 to 3.47.

$$\{F_n\} : \ m_n = K_L \left[\prod_{i=1}^{L} (m_{n,i} + \tilde{m}_{F,i} + \tilde{m}_{F,i}) - \prod_{i=1}^{L} (\tilde{m}_{F,i} + \tilde{m}_{F,i}) \right]$$
(3.42)

$$\{F\} : \ \tilde{m}_F = K_L \left[\prod_{i=1}^{L} (\tilde{m}_{F,i} + \tilde{m}_{F,i}) - \prod_{i=1}^{L} (\tilde{m}_{F,i} \right] \tag{3.43}$$

$$\{F\} : \ \tilde{m}_F = K_L \prod_{i=1}^{L} \tilde{m}_{F,i}, \ {\scriptstyle n=1,\dots,N} \tag{3.44}$$

With $K_L = \left[\sum_{n-1}^{N} \prod_{i=1}^{L} (m_{n,i} + \tilde{m}_{F,i} + \tilde{m}_{F,i}) - (N-1) \prod_{i=1}^{L} (\tilde{m}_{F,i} + \tilde{m}_{F,i}) \right]^{-1}$ (3.45)

$$\{F_n\} : \ \beta_n = \frac{m_n}{1 - \tilde{m}_F} \tag{3.46}$$

$$\{F\} : \ \beta_F = \frac{\tilde{m}_F}{1 - \tilde{m}_F} \tag{3.47}$$

where β_n and β_F are the degree of belief of the aggregated assessment. The attribute assessment is given by F_n and F .

Step 7: The combined assessment is represented by Equation 3.48.

$$S(y) = \{(F_n, \beta_n), n = 1,2, \dots, N\} \tag{3.48}$$

3.6.7 GA-ANN method

The procedure consists of two parts:

Part 1: A linear objective function of the type $\sum WiXi$ are formed using the criteria listed down for selecting the best alternative. Optimal function values for all the criteria are found out.

Part 2: The optimal value returned by the ANN model is used to find the relative importance of all the alternatives. The best alternative is the one which has the maximum score. A single layer feed forward neural network model is used. The procedure for finding the relative importance of alternatives is as follows:

Step 1: Using pair wise comparison of criteria, calculate the input layer weight of ANN. Also calculate output layer weight (W_i) by comparing the alternatives available with the listed criteria.

Step 2: Objective function with constraints is formulated as below:

$$\text{Maximize } \sum WiXi \text{ or Minimize } \sum WiXi \tag{3.49}$$

Subject to $W1 + W2 + W3 + \dots. + Wi = 1; \quad l < Xi < U$

where X_i are the criteria,

l is the lower bound

U is the upper bound for that criterion

Step 3: Using optimization toolbox of MATLAB, we find out the optimal function value for all the criteria for each alternative. The following parameters have to be:

- Population size
- Scaling function
- Selection
- Crossover fraction

- Mutation
- Stopping criteria

Step 4: The data obtained in the previous step becomes the input to the input layer of the feed forward network leading to calculation of the output of the input layer.

Step 5: The output value of the input layer becomes the input value for the output layer of the feed forward network. The output of this output layer gives the ranking of the alternatives.

3.6.8 SVNS – TOPSIS method

Single valued neutrosophic sets can be used as a part of extended TOPSIS method. Here the fuzzy scale is replaced by the neutrosophic scale. If all the alternatives are represented by A= $\{\rho 1,\ \rho 2,\ \ldots,\ \rho m\}$ and all the criteria are represented by G= $\{\beta 1,\ \beta 2,\ \ldots,\ \beta n\}$, then the procedure of SVNS TOPSIS is as follows:

Step 1: Get the relative weights for each of the decision makers.
Based on the linguistic data on the decision maker, using Table 2.2 we get the relative weights for the decision makers. If there are 'k' decision makers and the SVN number is given by A_t = (a_t, b_t, c_t), where the subscript 't' indicated the t^{th} decision maker, the relative weights for the t^{th} decision maker is given by:

$$\delta_t = \frac{a_t + b_t\left(\frac{a_t}{a_t+c_t}\right)}{\sum_{t=1}^{k} a_t + b_t\left(\frac{a_t}{a_t+c_t}\right)} \tag{3.50}$$

Where $\delta t \geq 0$ and $\sum_{t=1}^{k} \delta_t = 1$

Step 2: Based on the decision makers data, create an aggregated SVN decision matrix D.
D is given by D = $\sum_{t=1}^{k} \delta_t D^t$ where D = d_{ij} = (u_{ij}, r_{ij}, v_{ij})

$$\text{and } d_{ij} = \left(1 - \prod_{t=1}^{k}\left(1 - u_{ij}^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(r_{ij}^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(v_{ij}^{(t)}\right)^{\delta t}\right) \tag{3.51}$$

Hence D can be expressed as,

$$D = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{12} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2n} \\ \vdots & & & \vdots \\ \rho_{m1} & \rho_{m2} & \cdots & \rho_{mn} \end{pmatrix} \tag{3.52}$$

where ρij (i=1, 2, …, m; j=1, 2, …, n) denotes a single value neutrosophic number.

Step 3: Calculate the weights of each criterion.

Based on the decision given by each decision maker, the importance of each criterion will be different. The weights given by each decision makers for the criteria have to aggregated to get final weights of the criteria. Let W= (w_1, w_2, …, w_n) indicate the weights of the criteria where w_j indicates the relative importance of criterion β_j where j=1, 2, …, n. For criteria β_j the SVN number for the t^{th} decision maker be $wj^{(t)}$=($aj^{(t)}$, $bj^{(t)}$, $cj^{(t)}$). Therefore, the final criteria weights are given by Equation 3.37.

$$w_j = \delta_1 w_j^{(1)}, \delta_2 w_j^{(2)}, \ldots\ldots, \delta_k w_j^{(k)}$$

$$= \langle \left(1 - \prod_{t=1}^{k}\left(1 - a_j^{(t)}\right)^{\delta t}, \prod_{t=1}^{k} \left(b_j^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(c_j^{(t)}\right)^{\delta t}\right) \rangle \tag{3.53}$$

Step 4: Construct the aggregated weighted SVN decision matrix.

Multiply the aggregated weighted matrix (D) with criteria weight (W) to get the aggregated weighted SVN decision matrix. Assume that $D^* = \left(d_{ij}^*\right)$, therefore,

$$D^* = D \otimes W \tag{3.54}$$

where $d_{ij}^* = w_j \otimes d_{ij}$

$$\text{and, } D^* = \begin{pmatrix} \rho w_{11} & \rho w_{12} & \cdots & \rho w_{1n} \\ \rho w_{21} & \rho w_{22} & \cdots & \rho w_{2n} \\ \vdots & & & \vdots \\ \rho w_{m1} & \rho w_{m2} & \cdots & \rho w_{mn} \end{pmatrix}$$

Step 5: Calculate single valued positive-ideal solution (SVN-PIS) and single valued negative-ideal solution (SVN-NIS). SVN-PIS and SVN-NIS are defined as follows:

$$\rho^+ = \left(a_{\rho+w}\left(\beta_j\right), b_{\rho+w}\left(\beta_j\right), c_{\rho+w}\left(\beta_j\right)\right) \tag{3.55}$$

$$\rho^- = \left(a_{\rho-w}\left(\beta_j\right), b_{\rho-w}\left(\beta_j\right), c_{\rho-w}\left(\beta_j\right)\right) \tag{3.56}$$

where

$$a_{\rho+w}\ \left(\beta_j\right) = \begin{pmatrix} \max a_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \min a_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

$$b_{\rho+w}\ \left(\beta_j\right) = \begin{pmatrix} \min b_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \max b_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

$$c_{\rho+w}\ \left(\beta_j\right) = \begin{pmatrix} \min c_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \max c_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

and

$$a_{\rho-w}\ \left(\beta_j\right) = \begin{pmatrix} \min a_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \max a_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

$$b_{\rho-w}\ \left(\beta_j\right) = \begin{pmatrix} \max b_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \min b_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

$$c_{\rho-w}\ \left(\beta_j\right) = \begin{pmatrix} \max c_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \\ \min c_{\rho iw}\left(\beta_j\right), & if\ j\ \in G_1 \end{pmatrix}$$

Step 6: Measure the distance from the positive and negative ideal

Use Equation 3.41 and 3.42 to get the distances from SVN-PIS and SVN-NIS

$$S_i^- = \left(\frac{1}{3}\sum_{j=1}^{n}\left\{\left(\left|a_{ij} - a_j^+\right|\right)^2 + \left(\left|b_{ij} - b_j^+\right|\right)^2 + \left(\left|c_{ij} - c_j^+\right|\right)^2\right\}\right)^{\frac{1}{2}} \tag{3.57}$$

(i = 1, 2, …, m)

$$S_i^+ = \left(\frac{1}{3}\sum_{j=1}^{n}\left\{\left(\left|a_{ij} - a_j^-\right|\right)^2 + \left(\left|b_{ij} - b_j^-\right|\right)^2 + \left(\left|c_{ij} - c_j^-\right|\right)^2\right\}\right)^{\frac{1}{2}} \tag{3.58}$$

(i = 1, 2, …, m)

Step 7: Calculate the closeness coefficient (CC)

Get the closeness coefficient for each alternative from the ideal solutions by using equation

$$\rho_j = \frac{s^-}{s^+ + s^-} \text{ where } 0 \leq \rho_j \leq 1 \tag{3.59}$$

Step 8: Carry out the ranking of alternatives.

Lower value of closeness coefficient will result in the last rank and higher value of closeness coefficient will result in the highest ranking.

3.7 Summary

The research is aimed at proposing novel hybrid MADM method, which will take in to account all the data available, while deciding about the best new product alternative. Three novel methods have been proposed during the course of work. A case study was carried out in a manufacturing industry for finding the best alternative using the proposed novel method and the validation of the result was done using COPRAS-G. Further chapters deal with these novel methods and the case studies. Model for ranking critical factors affecting new product development, from design for manufacturability consideration for small and medium enterprises, is proposed in the further chapter and the validation is carried out using traditional method such as COPRS G and hybrid method such as GA-ANN.

Chapter 4

MADM and Hybrid-ER approaches in Screening of NPD in a Manufacturing Unit

4.1 General

The first objective of the research work was to investigate the commonly used MADM approaches in NPD. There are certain common characteristics in all the MADM, like the conflict between the multiple alternatives and multiple criteria. These multiple alternatives have to be ranked by the decision makers based on the criteria weights. There are many MADM methods used, for finding the best alternative among a set of alternatives, during the idea screening phase of NPD, but the most commonly used methods are Fuzzy TOPSIS, COPRAS-G. TOPSIS was originally developed by Hwang and Yoon [126]. In TOPSIS, the best alternative is the one, which is at the shortest distance from positive ideal solution or the best solution and at the same time it should be farthest away from the negative ideal solution or the worse solution. Since there is lot of impreciseness or inconsistency in the new product data and TOPSIS is a method of compensatory aggregation and there is incongruous dimension to the criteria selected, using fuzziness in TOPSIS make it simpler to take care of the above-mentioned problems. COPRAS-G method involves the use of significance factor and utility degree and provides a stepwise evaluation to rank the alternative. Deng [152, 153] proposed the grey system theory. The grey system theory requires smaller sample size and involves simpler calculation. Contradictory conclusions are avoided during the quantified outcomes using the grey relational analysis. The above two methods are explained stepwise using a case study carried out in automobile manufacturing unit. Since Evidential Reasoning is a powerful method which takes care of uncertainty and input data in linguistic form is normal to the new product development, two methods have been proposed so that fuzzy scale and grey scale can be used in ER. Incorporating the qualitative data as input for traditionally superior MADM method is a very important requirement of NPD as mostly historical data might not be available.

4.2 Ranking of Alternatives in a Manufacturing Unit

A case study was carried out in a bus body building industry to select the best concept to go ahead for building the final bus. Based on the customers' requirements, the company came up with three new product ideas. These ideas (alternatives) were:

Concept A - Dynamic and Fluidic (A1)
Concept B - Rugged-Robust-Loud & Bold Face (A2)
Concept C - Clean and Understated with Subtle Form (A3)
Brain storming was carried out among the stake holders and the criteria's which affected the decision making were listed as follows:
Aesthetics (C1)
Production process (C2)
Cost of product (C3)
Regulatory requirements (C4)
Market segment (C5).
It is to be noted here that the criteria C1, C2, C4 and C5 are of beneficial type i.e., we would always like to have a higher value for them, whereas criteria C3 which is in terms of cost i.e., non-beneficial type.

The decision-making process involved three decision makers namely:
Design manager (DM1)
Production manager (DM2)
Marketing manager (DM3).

4.2.1 Fuzzy TOPSIS method

The step wise procedure for fuzzy TOPSIS is listed in Section 3.6.4.

Step 1: There are three alternatives (A1, A2, A3), five criteria's (C1, C2, C3, C4, C5) and three decision makers (DM1, DM2, DM3).

Step 2: The three decision makers gave the weightages for each criterion as well as assigned the linguistic variable for each alternative against each criterion. Standard fuzzy scale is used to convert the linguistic data to triangular fuzzy number as seen in Table 4.1. Table 4.2 gives the criteria weightages of all the three decision makers. Table 4.3 gives the linguistic rating for alternatives against each criterion as given by decision makers

Table 4.1: Fuzzy ratings for linguistic variables.

Alternative Assessments				
Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
(1, 1, 3)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(7, 9, 9)
Criteria Weightages				
Very Poor (VP)	Poor (P)	Fair (F)	Good (G)	Very Good (VG)
(1, 1, 3)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(7, 9 ,9)

Table 4.2: Linguistic rating for criteria.

Criteria Weightages			
Criteria	DMI	DM2	DM3
C1	VH	H	H
C2	H	H	L
C3	M	M	H
C4	H	VL	M
C5	M	M	H

Table 4.3: Linguistic rating for alternatives against each criterion given by decision makers.

Criteria	A1			A2			A3		
	DMI	DM2	DM3	DMI	DM2	DM3	DMI	DM2	DM3
C1	G	G	F	VG	G	VG	G	G	F
C2	F	G	G	F	G	G	G	F	F
C3	G	F	G	G	F	G	G	F	G
C4	G	P	F	G	P	F	G	P	F
C5	G	F	F	G	G	F	G	F	P

Step 3: Get the average weights of criteria and ratings of alternatives given by the three decision makers. Here the linguistic variables are converted to their fuzzy number and simple aggregation formulas are used. This helps to capture the decisions of all the three decision makers into a single one.

Step 4: Construct the fuzzy decision matrix as shown in Table 4.4. It involves making a combined table of criteria weightages and alternative ratings against each criterion.

Table 4.4: Aggregated ratings for alternative against criteria.

Criteria	A1									Aggregation		
	DM1			DM2			DM3					
C1	5	7	9	5	7	9	3	5	7	4.333	6.333	8.333
C2	3	5	7	5	7	9	5	7	9	4.333	6.333	8.333
C3	5	7	9	3	5	7	5	7	9	4.333	6.333	8.333
C4	5	7	9	1	3	5	3	5	7	3	5	7
C5	5	7	9	3	5	7	3	5	7	3.667	5.667	7.667

Criteria	A2									Aggregation		
	DM1			DM2			DM3					
C1	7	9	9	5	7	9	7	9	9	6.333	8.333	9
C2	3	5	7	5	7	9	5	7	9	4.333	6.333	8.333
C3	5	7	9	3	5	7	5	7	9	4.333	6.333	8.333
C4	5	7	9	1	3	5	3	5	7	3	5	7
C5	5	7	9	5	7	9	3	5	7	4.333	6.333	8.333

Criteria	A3									Aggregation		
	DM1			DM2			DM3					
C1	5	7	9	5	7	9	3	5	7	4.333	6.333	8.333
C2	5	7	9	3	5	7	3	5	7	3.667	5.667	7.667
C3	5	7	9	3	5	7	5	7	9	4.333	6.333	8.333
C4	5	7	9	1	3	5	3	5	7	3	5	7
C5	5	7	9	3	5	7	1	3	5	3	5	7

Criteria	Criteria Weightages									Aggregation		
	DM1			DM2			DM3					
C1	7	9	9	5	7	9	5	7	9	5.667	7.667	9
C2	5	7	9	5	7	9	1	3	5	3.667	5.667	7.667
C3	3	5	7	3	5	7	5	7	9	3.667	5.667	7.667
C4	5	7	9	1	2	3	3	5	7	3	4.667	6.333
C5	3	5	7	3	5	7	5	7	9	3.667	5.667	7.667

Criteria			Alternatives								
			A1			A2			A3		
5.667	7.667	9	4.333	6.333	8.333	6.333	8.333	9	4.333	6.333	8.333
3.667	5.667	7.667	4.333	6.333	8.333	4.333	6.333	8.333	3.667	5.667	7.667
3.667	5.667	7.667	4.333	6.333	8.333	4.333	6.333	8.333	4.333	6.333	8.333
3	4.667	6.333	3	5	7	3	5	7	3	5	7
3.667	5.667	7.667	3.667	5.667	7.667	4.333	6.333	8.333	3	5	7

Step 5: Construct normalized fuzzy decision matrix as shown in Table 4.5

Table 4.5: Normalized fuzzy decision matrix.

CRITERIA	ALTERNATIVES								
	A1			A2			A3		
C1	0.481	0.704	0.926	0.704	0.926	1	0.481	0.704	0.926
C2	0.52	0.76	1	0.52	0.76	1	0.44	0.68	0.92
C3	1	0.684	0.52	1	0.684	0.52	1	0.684	0.52
C4	0.429	0.714	1	0.429	0.714	1	0.429	0.714	1
C5	0.44	0.68	0.92	0.52	0.76	1	0.36	0.6	0.84

Step 6: Calculate the weighted normalized decision matrix as shown in Table 4.6. The weighted normalized decision matric is obtained by multiplying the criteria weightages to the alternating ratings against each criterion.

Table 4.6: Weighted normalized fuzzy decision matrix.

Criteria	Alternatives								
	A1			A2			A3		
C1	2.728	5.395	8.333	3.988	7.099	9	2.728	5.395	8.333
C2	1.907	4.307	7.667	1.907	4.307	7.667	1.613	3.853	7.054
C3	3.666	3.877	3.986	3.666	3.877	3.986	3.666	3.877	3.986
C4	1.286	3.333	6.333	1.286	3.333	6.333	1.286	3.333	6.333
C5	1.614	3.855	7.056	1.907	4.308	7.67	1.321	3.401	6.443

Step 7: The FPIS is taken as: A* = (9.000, 9.000, 9.000) and the FNIS is taken as: A- = (1.000, 1.000, 1.000) as shown in Table 4.7. The distance separation formula is used to calculate the distance of each alternative from the fuzzy positive ideal solution and the fuzzy negative ideal solution.

Table 4.7: Separation measures for each alternative.

Criteria	A1		A2		A3	
	FPIS	FNIS	FPIS	FNIS	FPIS	FNIS
C1	4.194	5.036	3.095	6.059	4.194	5.036
C2	4.970	4.328	4.970	4.328	5.318	3.880
C3	5.158	2.846	5.158	2.846	5.158	2.846
C4	5.737	3.365	5.737	3.365	5.737	3.365
C5	5.317	3.882	4.969	4.330	5.682	3.440
$\sum$ d	25.377	19.457	23.930	20.929	26.089	18.567

Step 8: Finally, the closeness coefficient is calculated and the ranking was carried out. It was observed that alternative 2 was the best among the three alternatives as shown in Table 4.8. Figure 4.1 indicates the ranking of the alternatives using the fuzzy TOPSIS method.

Table 4.8: Relative closeness to the ideal solution.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.434	93.022	2
A2	0.467	100	1
A3	0.416	89.118	3

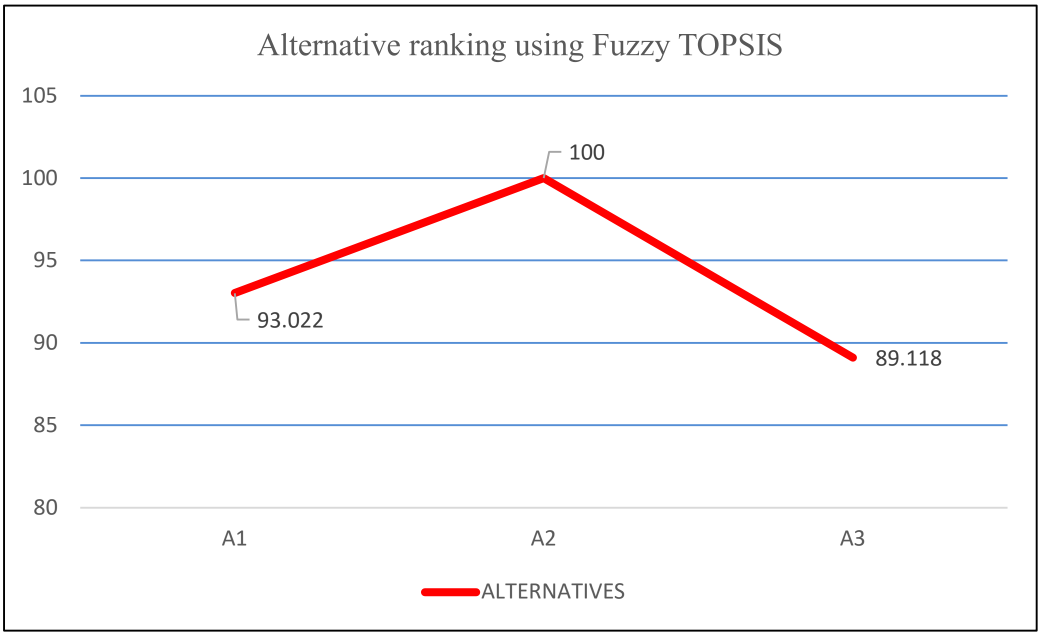

Figure 4.1: Ranking of the alternatives using the Fuzzy TOPSIS method.

4.2.2 COPRAS-G method

The step wise procedure for COPRAS-G is listed in section 3.6.5.

Step 1: Standard grey scale is used to convert the linguistic data to grey number. The grey scale is shown in Table 4.9.

Table 4.9: Standard Grey Scale.

Grey Scale	Very Good (VG)	Good (G)	Fair (F)	Poor (P)	Very Poor (VP)
	8 - 9	6 - 8	4 - 6	2 - 4	1 - 2

Step 2: Carry out the aggregation of criteria weights of all decision makers as shown in Table 4.10. Similarly carry out the aggregation of alternative ratings against each criterion as shown in Table 4.11.

Table 4.10: Aggregation of criteria weights for COPRAS-G.

C1		C2		C3		C4		C5	
8	9	6	8	4	6	6	8	4	6
6	8	6	8	4	6	1	2	4	6
6	8	2	4	6	8	4	6	6	8
20	25	14	20	14	20	11	16	14	20
6.667	8.333	4.667	6.667	4.667	6.667	3.667	5.333	4.667	6.667
7.500		5.667		5.667		4.500		5.667	
0.259		0.195		0.195		0.155		0.195	

Table 4.11: Aggregation of alternative ratings against each criterion for COPRAS-G.

Weights	C1		C2		C3		C4		C5	
	0.259		0.195		0.195		0.155		0.195	
Alternative	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2
A1	5.333	7.333	5.333	7.333	5.333	7.333	4	6	4.667	6.667
A2	7.333	8.667	5.333	7.333	5.333	7.333	4	6	5.333	7.333
A3	5.333	7.333	4.667	6.667	5.333	7.333	4	6	4	6
	18	23.33	15.33	21.33	16	22	12	18	14	20
	41.33		36.67		38.00		30.00		34.00	

Step 3: Calculate the normalized decision-making matrix as shown in Table 4.12.

Table 4.12: COPRAS-G normalized decision-making matrix.

Weights	C1		C2		C3		C4		C5	
	0.259		0.195		0.195		0.155		0.195	
Alternative	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2

A1	0.129	0.177	0.145	0.200	0.140	0.193	0.133	0.200	0.137	0.196
A2	0.177	0.210	0.145	0.200	0.140	0.193	0.133	0.200	0.157	0.216
A3	0.129	0.177	0.127	0.182	0.140	0.193	0.133	0.200	0.118	0.176

Step 4: Calculate weighted normalized decision-making matrix as shown in Table 4.13. The weighted normalized decision matric is obtained by multiplying the criteria weightages to the alternating ratings against each criterion.

Table 4.13: COPRAS-G weighted normalized decision-making matrix.

Weights	C1		C2		C3		C4		C5	
	0.259		0.195		0.195		0.155		0.195	
Alternative	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2
A1	0.033	0.046	0.028	0.039	0.027	0.038	0.021	0.031	0.027	0.038
A2	0.046	0.054	0.028	0.039	0.027	0.038	0.021	0.031	0.031	0.042
A3	0.033	0.046	0.025	0.036	0.027	0.038	0.021	0.031	0.023	0.034

Step 5: The weighted normalized values are summed for both beneficial and non-beneficial criteria. For maximization, alternatives with larger values are preferable. For minimization, alternatives with lower values are preferable. Refer Table 4.14

Table 4.14: Distance separation Table.

Alternative	S_i+	S_i-
A1	0.132	0.033
A2	0.146	0.033
A3	0.124	0.033
	∑S_i	0.098

Step 6: The relative significances or priorities of each alternative are determined. The relative significance value of an alternative shows the degree of satisfaction attained by that alternative. The greater the value, the higher is the priority of the alternative. The alternative with the highest relative significance value is the best choice among the alternatives. Refer Table 4.15

Table 4.15: Utility values for each alternative.

Alternative	Q_i
A1	0.164
A2	0.179
A3	0.157

Step 7: The quantitative utility for each alternative is calculated. The degree of an alternative's utility, which leads to a complete ranking of the alternatives, is determined by comparing the priorities of all the alternatives with the most efficient one. It is observed that alternative 2 is the best alternative followed by alternative 1 and then alternative 3. Table 4.16 gives the ranking of alternative as per COPRA-G. Figure 4.2 indicates the ranking of the alternatives using the COPRAS-G method.

Table 4.16: Final ranking of alternative as per COPRAS-G method.

Alternative	Ui	Ranking
A1	92.017	2
A2	100	1
A3	87.883	3

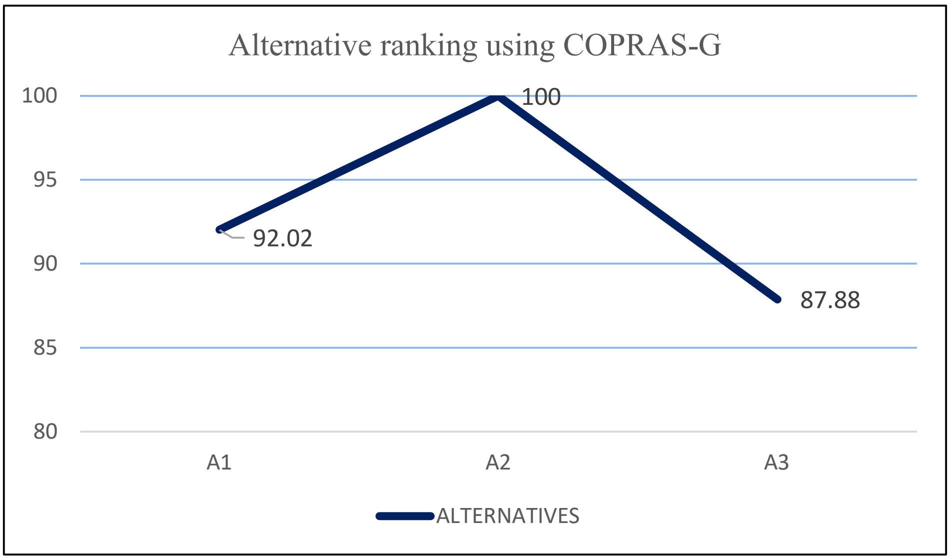

Figure 4.2: Ranking of the alternatives using the COPRAS-G method.

4.3 Sensitivity Analysis

Sensitivity analysis is the last step in the decision-making process. It should be carried out to check for the vulnerability of the data. In the sensitivity analysis procedure, we tend to change certain parameters and the effect on the final outcome is observed, while doing so we tend to create additional analysis, which might not be the best situation. This new analysis might produce different outcomes which may call for further investigation into the decision-making process. If the outcome does not change, the process is said to be robust or stable. But if the outcome changes, then the process is said to be sensitive. The most commonly used sensitivity analysis method is, the single direction sensitivity analysis method, as it is easier to interpret. In this method, one of the solitary information variables is changed and its effect on the final outcome of the decision-making process is studied. Sensitivity analysis allows us to understand which criteria has major effect on the decision-making process. It allows the decision maker to choose the correct MADM method based on the sensitivity analysis. In this chapter sensitivity analysis is carried out on fuzzy TOPSIS and COPRAS-G. The procedure involves changing the criteria weightages of any individual criteria to a higher value and keeping the weightages of rest of the criteria to a very low value. For example, the first criteria might be assigned the highest triangular fuzzy number and all the other criteria will be assigned the lowest triangular fuzzy number. With this data the entire problem is solved again and the ranking of alternative is carried out. In the next step the second criteria is assigned the highest triangular fuzzy number and all the other criteria including the first criteria will be assigned the lowest triangular fuzzy number. Again, the same problem will be solved and ranking of alternative will be observed. Sometimes all the benefit criteria are assigned the highest triangular fuzzy number and the cost type are assigned the lowest possible triangular fuzzy number. Similarly, vice versa all the cost criteria will be assigned the highest triangular fuzzy number and the benefit type criteria will be assigned the lowest triangular fuzzy number. All the ranking outcome of the decision-making process will be observed. If the ranking outcome in majority of the cases remains same, then we can say that the decision-making process is stable and the obtained ranking is the best ranking possible.

4.3.1 Sensitivity analysis on fuzzy TOPSIS

In the fuzzy TOPSIS method since we use the fuzzy scale, the highest triangular fuzzy number is 7, 7, 9 and the lowest triangular fuzzy number is 1, 1, 3.

Case 1: Maximize criteria 1 of Fuzzy TOPSIS method

In this case criteria 1 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages are assigned fuzzy number 1, 1, 3 as shown Table 4.17.

Table 4.17: Maximize criteria 1 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	7, 7, 9
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

Refer Table 4.18 for closeness coefficient value, utility value and alternative ranking

Table 4.18: Ranking of alternatives by Fuzzy TOPSIS method for case 1.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.582	80.116	2
A2	0.727	100	1
A3	0.492	67.703	3

Case 2: Maximize criteria 2 of Fuzzy TOPSIS method

In this case criteria 2 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1 are assigned fuzzy number 1, 1, 3 as shown Table 4.19.

Table 4.19: Maximise criteria 2 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	7, 7, 9
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.20

Table 4.20: Ranking of alternatives by Fuzzy TOPSIS method for case 2.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.816	85.895	2
A2	0.950	100	1
A3	0.761	80.105	3

Case 3: Maximize criteria 3 of Fuzzy TOPSIS method

In this case criteria 3 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1and 2 are assigned fuzzy number 1, 1, 3 as shown Table 4.21.

Table 4.21: Maximise criteria 3 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	7, 7, 9
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.22

Table 4.22: Ranking of alternatives by Fuzzy TOPSIS method for case 3.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.330	60.120	3
A2	0.549	100	1
A3	0.465	84.715	2

Case 4: Maximize criteria 4 of Fuzzy TOPSIS method

In this case criteria 4 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 4 are assigned fuzzy number 1, 1, 3 as shown Table 4.23.

Table 4.23: Maximize criteria 4 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	7, 7, 9
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.24

Table 4.24: Ranking of alternatives by Fuzzy TOPSIS method for case 4.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.799	89.254	2
A2	0.895	100	1
A3	0.688	76.877	3

Case 5: Maximize criteria 5 of Fuzzy TOPSIS method

In this case criteria 5 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 5 are assigned fuzzy number 1, 1, 3 as shown Table 4.25.

Table 4.25: Maximize criteria 5 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	7, 7, 9

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.26

Table 4.26: Ranking of alternatives by Fuzzy TOPSIS method for case 5.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.799	89.254	2
A2	0.895	100	1
A3	0.688	76.877	3

Table 4.27: Utility value in all the sensitivity analysis cases.

	C1	C2	C3	C4	C5
A1	80.116	85.895	60.120	89.254	81.966
A2	100	100	100	100	100
A3	67.703	80.105	84.715	76.877	76.209

We can see from the sensitivity analysis that alternative 2 is the best alternative followed by alternative 1 and the last preference goes to alternative 3. But in case 3, wherein criteria 3 is made the best, it is observed that alternative 2 still remains the best, but it is followed by alternative 3 and then alternative 1. This has happened because criteria 3 is cost type. In general, sensitivity analysis has proved that the decision-making process is stable and alternative 2 is the best alternative to go ahead for manufacturing. Table 4.27 shows the utility value in all the cases. Figure 4.3 shows the outcome of the sensitivity analysis wherein alternative 2 is the best alternative. In the Figure the red colour line indicates alternative 2. As seen the red colour line touches 100 % for all the criteria.

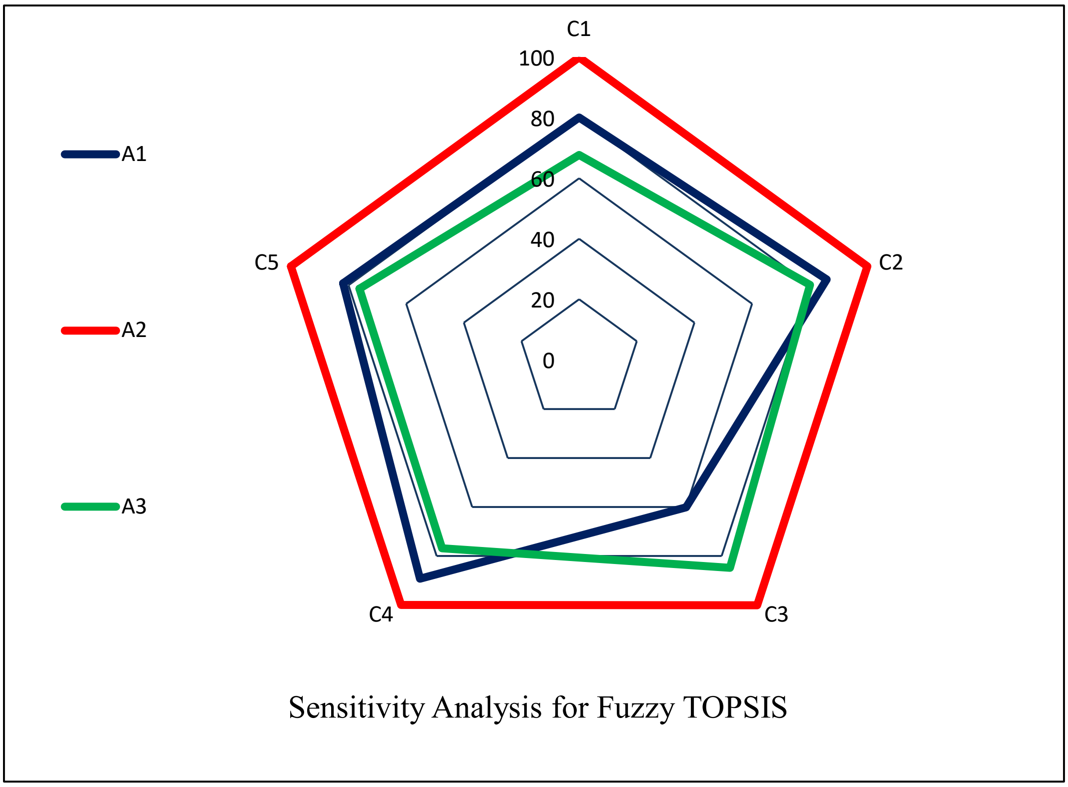

Figure 4.3: Outcome of sensitivity analysis showing alternative 2 to be the best alternative.

4.3.2 Sensitivity analysis on COPRAS-G

In the COPRAS-G method since we use the grey scale, the highest grey number is 8, 9 and the lowest triangular fuzzy number is 1, 2.

Case 1: Maximize criteria 1 of COPRAS-G method

In this case criteria 1 is assigned the fuzzy number 8, 9 and rest all the criteria weightages are assigned fuzzy number 1, 2 as shown Table 4.28.

Table 4.28: Maximize criteria 1 of COPRAS-G method.

Criteria	Weightage
C1	8, 9
C2	1, 2
C3	1, 2
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.29

Table 4.29: Ranking of alternatives by COPRAS-G method for case 1.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.329	97.626	2
A2	0.337	100	1
A3	0.323	95.846	3

Case 2: Maximize criteria 2 of COPRAS-G method

In this case criteria 2 is assigned the fuzzy number 8, 9 and rest all the criteria weightages including criteria 1 are assigned fuzzy number 1, 2 as shown Table 4.30.

Table 4.30: Maximize criteria 2 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	8, 9
C3	1, 2
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.31

Table 4.31: Ranking of alternatives by COPRAS-G method for case 2.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.335	91.781	2
A2	0.365	100	1
A3	0.292	80.000	3

Case 3: Maximize criteria 3 of COPRAS-G method

In this case criteria 3 is assigned the fuzzy number 8, 9 and rest all the criteria weightages including criteria 1and 2 are assigned fuzzy number 1, 2 as shown Table 4.32.

Table 4.32: Maximise criteria 3 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	8, 9
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.33

Table 4.33: Ranking of alternatives by COPRAS-G method for case 3.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.321	95.821	3
A2	0.335	100	1
A3	0.322	96.119	2

Case 4: Maximize criteria 4 of COPRAS-G method

In this case criteria 4 is assigned the fuzzy number 8, 9 and rest all the criteria weightages excluding 4 are assigned fuzzy number 1, 2 as shown Table 4.34.

Table 4.34: Maximize criteria 4 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	1, 2
C4	8, 9
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.35

Table 4.35: Ranking of alternatives by COPRAS-G method for case 4.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.348	91.579	2
A2	0.380	100	1
A3	0.324	85.263	3

Case 5: Maximize criteria 5 of COPRAS-G method

In this case criteria 5 is assigned the fuzzy number 8, 9 and rest all the criteria weightages excluding 5 are assigned fuzzy number 1, 2 as shown Table 4.36.

Table 4.36: Maximize criteria 5 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	1, 2
C4	1, 2
C5	8, 9

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 4.37

Table 4.37: Ranking of alternatives by COPRAS-G method for case 5.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.332	89.973	2
A2	0.369	100	1
A3	0.290	78.591	3

The sensitivity analysis points out that alternative 2 is the best alternative followed by alternative 1 and then by alternative 3. But in case 3, wherein criteria 3 is made the best, it is observed that alternative 2 still remains the best, but it is followed by alternative 3 and then alternative 1. This has happened because criteria 3 is cost type. This same phenomenon was observed in sensitivity analysis of fuzzy TOPSIS. In general, sensitivity analysis has proved that the decision-making process is stable process with alternative 2 being the best alternative for manufacturing. Table 4.38 shows the utility value in all the cases. Figure 4.4 shows the outcome of the sensitivity analysis wherein alternative 2 is the best alternative. In the Figure the red colour line indicates alternative 2. As seen the red colour line touches 100 % for all the criteria.

Table 4.38: Utility value in all the sensitivity analysis cases.

	C1	C2	C3	C4	C5
A1	97.626	91.781	95.821	91.579	89.973
A2	100	100	100	100	100
A3	95.846	80.000	96.119	85.263	78.591

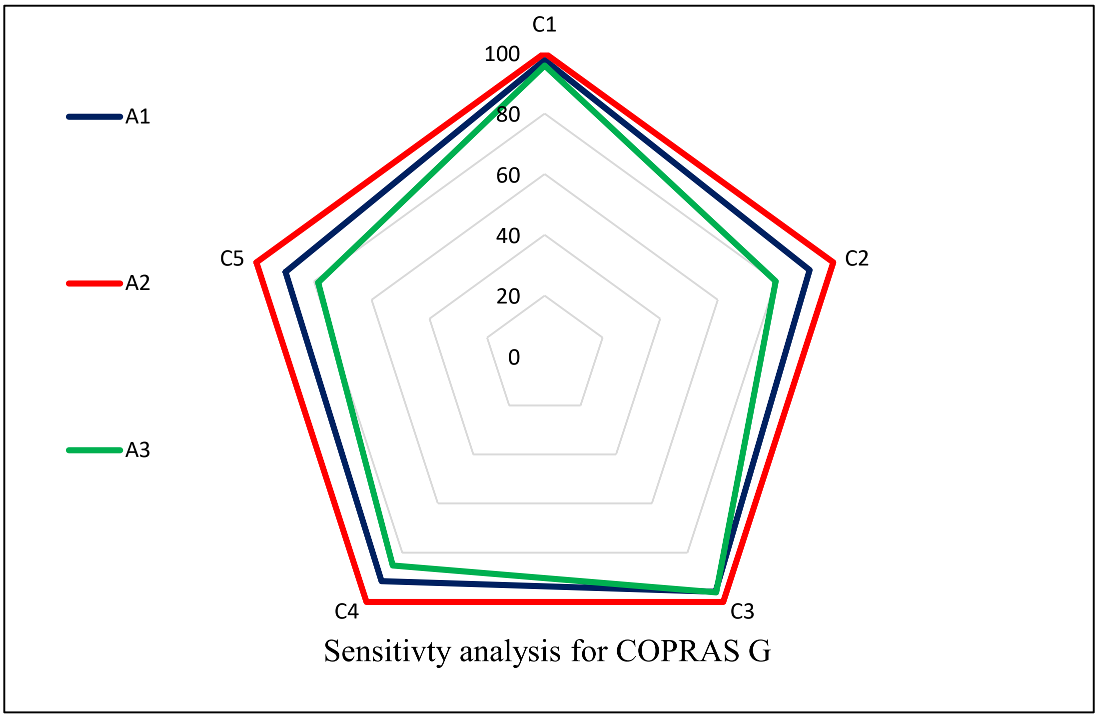

Figure 4.4: Outcome of sensitivity analysis showing alternative 2 to be the best alternative.

4.4 Hybrid Evidential Reasoning method

It is very difficult to get historical data for new product development. Hence mostly subjective data in qualitative form is considered. Incorporating this subjective data as input for traditionally superior MADM method is a very important requirement. At the same time, the NPD process is multidisciplinary in nature. Groups of people from different departments take part in decision making process. Judgment synthesis becomes synonymous with this group approach. The differences can be in various forms such as departmental goals, technical backgrounds and constraints etc. Group members may have individually different opinion about project screening decisions. Hence accuracy of the decisions and synthetization are directly proportional to the final decision-making outcome. To tackle the uncertainty and fuzziness in the data due to individual perception, the qualitative data is expressed as linguistic variable. This helps the decision maker to express his perception in a better way. Use of fuzzy scale or grey scale helps to convert the linguistic variables to either fuzzy numbers or grey numbers while still retaining the maximum original information, thus leading to reliable final decision solution. Evidential reasoning is based on Dempster-Shafer theory and decision theory. It was developed by Yang for multi attribute decision making analysis involving uncertainty. Evidential reasoning method finds its use in wide number of application due to its ability in handling uncertainties. Two hybrid methods have been proposed to bring together the effectiveness of fuzzy scale and grey scale along with the evidential reasoning algorithm. In both the methods the input data is taken in linguistic form to take in to account the advantage associated with it and also the fact that for NPD historical data in quantitative form might not be available. The evidential reasoning method is then applied to get the final decision.

4.4.1 Hybrid Grey ER

The case study which was considered in Section 4.2 is taken again for solving using hybrid grey ER method.

Step 1: The problem consists of three decision makers, five criteria and three alternatives. Here all the decision makers are having equal say in the decision-making process and hence each of them has equal weightage.

Step 2: Normalise the weights so that conditions are satisfied as shown by Equation 3.34. Refer Table 4.39 and Table 4.40.

Table 4.39: Normalised weights.

	DM1	DM2	DM3	SUM	Averaged Weights	Weights
C1	8 (VH)	4 (M)	8 (VH)	20/3	7.33	0.25
	9 (VH)	6 (M)	9 (VH)	24/3		
C2	6	8	2	16/3	6.17	0.21
	8	9	4	21/3		
C3	4	2	8	14/3	5.5	0.19
	6	4	9	19/3		
C4	6 (H)	1	4	11/3	4.5	0.16
	8 (H)	2	6	16/3		
C5	4	2 (L)	8	14/3	5.5	0.19
	6	4 (L)	9	19/3		

Table 4.40: Alternative rating against each criteria value.

A1	A2	A3
6.33	6.16	6.33
6.33	7.00	5.00
7.00	7.00	6.33
5.00	5.67	5.67
5.50	6.33	4.33

Step 3: Define the N distinct evaluation grades as given by Equation 3.35. Refer Table 4.41.

Table 4.41: Standard Evaluation Grade.

Worse	Poor	Average	Good	Excellent
1.5	3	5	7	8.5

Step 4: Represent a given assessment for e_i (i $=$ $1, \dots, $L) mathematically as a distribution represented by Equation 3.36. Refer Table 4.42 – 4.44.

Table 4.42: Belief table for Alternative 1.

Criteria	W	P	A	G	E
I	0	0	0.335	0.665	0
II	0	0	0.335	0.665	0
III	0	0	0	1	0
IV	0	0	1	0	0
V	0	0	0.75	0.25	0

Table 4.43: Belief table for Alternative 2.

Criteria	W	P	A	G	E
I	0	0	0.42	0.58	0
II	0	0	0	1	0
III	0	0	0	1	0
IV	0	0	0.665	0.335	0
V	0	0	0.335	0.665	0

Table 4.44: Belief table for Alternative 3.

Criteria	W	P	A	G	E
I	0	0	0.335	0.665	0
II	0	0	1	0	0
III	0	0	0.335	0.665	0
IV	0	0	0.665	0.335	0
V	0	0.335	0.665	0	0

Step 5: Calculate the basic probability mass is given by $m_{n,i}$ and the unassigned probability mass is given by $m_{F,i}$. Use Equation 3.37 to 3.41. Refer Table 4.45 – 4.47.

Table 4.45: Basic probability mass and unassigned probability mass for Alternative 1.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0838	0.1663	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0704	0.1397	0.0000	0.7900	0.0000	0.7900

m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0000	0.1900	0.0000	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.1600	0.0000	0.0000	0.8400	0.0000	0.8400
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0000	0.1425	0.0475	0.0000	0.8100	0.0000	0.8100

Table 4.46: Basic probability mass and unassigned probability mass for Alternative 2.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.1050	0.1450	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0000	0.2100	0.0000	0.7900	0.0000	0.7900
m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0000	0.1900	0.0000	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.1064	0.0536	0.0000	0.8400	0.0000	0.8400
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0000	0.0637	0.1264	0.0000	0.8100	0.0000	0.8100

Table 4.47: Basic probability mass and unassigned probability mass for Alternative 3.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0838	0.1663	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.2100	0.0000	0.0000	0.7900	0.0000	0.7900
m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0637	0.1264	0.0000	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.1064	0.0536	0.0000	0.8400	0.0000	0.8400
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0637	0.1264	0.0000	0.0000	0.8100	0.0000	0.8100

Step 6: Aggregate the basic probability masses with respect to the L masses to get the combines probability ratings by using Equation 3.43 to 3.47. Refer Table 4.48 – 4.50.

Table 4.48: Aggregated basic probability mass and unassigned probability mass for Alternative 1.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0838	0.1663	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0704	0.1397	0.0000	0.7900	0.0000	0.7900
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.1278	0.2655	0.0000	0.6067	0.0000	0.6067
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.1061	0.3903	0.0000	0.5037	0.0000	0.5037
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.1991	0.3496	0.0000	0.4512	0.0000	0.4512
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0000	0.2700	0.3415	0.0000	0.3885	0.0000	0.3885

Table 4.49: Aggregated basic probability mass and unassigned probability mass for Alternative 2.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.1050	0.1450	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0000	0.2100	0.0000	0.7900	0.0000	0.7900
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.0848	0.3093	0.0000	0.6059	0.0000	0.6059
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.0698	0.4314	0.0000	0.4988	0.0000	0.4988
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.1254	0.4338	0.0000	0.4409	0.0000	0.4409
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0000	0.1439	0.4828	0.0000	0.3733	0.0000	0.3733

Table 4.50: Aggregated basic probability mass and unassigned probability mass for Alternative 3.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0838	0.1663	0.0000	0.7500	0.0000	0.7500
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.2100	0.0000	0.0000	0.7900	0.0000	0.7900
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.2500	0.1361	0.0000	0.6139	0.0000	0.6139
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.2683	0.2136	0.0000	0.5181	0.0000	0.5181
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.3209	0.2271	0.0000	0.4520	0.0000	0.4520
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0307	0.3819	0.1964	0.0000	0.3910	0.0000	0.3910

Step 7: The combined assessment is represented by Equation 3.48. Refer Table 4.51.

Table 4.51: Final utility value for all three alternatives for grey ER method.

Alternatives	W	P	A	G	E	UA	U_min	U_average	U_max	Final Rank	Utility Value
	beta 1	beta 2	beta 3	beta 4	beta 5	beta H					
Alternative 1	0.000	0.000	0.442	0.558	0.000	0.000	0.640	0.640	0.640	II	92.349
Alternative 2	0.000	0.000	0.230	0.770	0.000	0.000	0.693	0.693	0.693	I	100
Alternative 3	0.000	0.050	0.627	0.322	0.000	0.000	0.568	0.568	0.568	III	82.010

It is observed that alternative 2 was the best among the three alternatives as shown in Table 4.51. The results were same as obtained with the Fuzzy TOPSIS and COPRAS G method.

4.4.2 Hybrid Fuzzy ER

The case study which was considered in Section 4.2 is taken for solving using hybrid fuzzy ER method.

Step 1: The problem consists of three decision makers, five criteria and three alternatives. Here all the decision makers are having equal say in the decision-making process and hence each of them has equal weightage.

Step 2: Normalise the weights so that conditions are satisfied as shown by Equation 3.34. The values are obtained using standard distance formula. Refer Table 4.52.

Table 4.52: Alternative rating against each criteria value.

A1	A2	A3
6.54	6.26	6.54
6.26	7.19	5.26
7.19	7.19	6.54
5.26	5.90	5.90
5.62	6.54	4.63

Step 3: Define the N distinct evaluation grades as given by Equation 3.35. Refer Table 4.53.

Table 4.53: Standard Evaluation Grade.

Worse	Poor	Average	Good	Excellent
1.5	3	5	7	8.5

Step 4: Represent a given assessment for e_i $(\mathrm{i} = 1, \dots, \mathrm{L})$ mathematically as a distribution represented by Equation 3.36. Refer Table 4.54 – 4.56.

Table 4.54: Belief table for Alternative 1.

Criteria	W	P	A	G	E
I	0	0	0.23	0.77	0
II	0	0	0.36	0.64	0
III	0	0	0	0.9	0.1
IV	0	0	0.87	0.13	0
V	0	0	0.69	0.31	0

Table 4.55: Belief table for Alternative 2.

Criteria	W	P	A	G	E
I	0	0	0.36	0.64	0
II	0	0	0	0.9	0.1
III	0	0	0	0.9	0.1
IV	0	0	0.54	0.46	0
V	0	0	0.23	0.77	0

Table 4.56: Belief table for Alternative 3.

Criteria	W	P	A	G	E
I	0	0	0.23	0.77	0
II	0	0	0.87	0.13	0
III	0	0	0.23	0.77	0
IV	0	0	0.54	0.46	0
V	0	0.18	0.82	0	0

Step 5: Calculate the basic probability mass is given by $m_{n,i}$ and the unassigned probability mass is given by $m_{F,i}$. Use Equation 3.37 to 3.41. Refer Table 4.57 – 4.59.

Table 4.57: Basic probability mass and unassigned probability mass for Alternative 1.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0568	0.1902	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0763	0.1357	0.0000	0.7880	0.0000	0.7880
m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0000	0.1710	0.0190	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.1401	0.0209	0.0000	0.8390	0.0000	0.8390
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0000	0.1311	0.0589	0.0000	0.8100	0.0000	0.8100

Table 4.58: Basic probability mass and unassigned probability mass for Alternative 2.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0889	0.1581	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0000	0.1908	0.0212	0.7880	0.0000	0.7880
m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0000	0.1710	0.0190	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.0869	0.0741	0.0000	0.8390	0.0000	0.8390
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0000	0.0437	0.1463	0.0000	0.8100	0.0000	0.8100

Table 4.59: Basic probability mass and unassigned probability mass for Alternative 3.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0568	0.1902	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.1844	0.0276	0.0000	0.7880	0.0000	0.7880
m13	m23	m33	m43	m53	mH,3-	mH,3~	mH3
0.0000	0.0000	0.0437	0.1463	0.0000	0.8100	0.0000	0.8100
m14	m24	m34	m44	m54	mH,4-	mH,4~	mH4
0.0000	0.0000	0.0869	0.0741	0.0000	0.8390	0.0000	0.8390
m15	m25	m35	m45	m55	mH,5-	mH,5~	mH5
0.0000	0.0342	0.1558	0.0000	0.0000	0.8100	0.0000	0.8100

Step 6: Aggregate the basic probability masses with respect to the L masses to get the combines probability ratings by using Equation 3.43 to 3.47. Refer Table 4.60 – 4.62.

Table 4.60: Aggregated basic probability mass and unassigned probability mass for Alternative 1.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0568	0.1902	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0763	0.1357	0.0000	0.7880	0.0000	0.7880
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.1090	0.2842	0.0000	0.6069	0.0000	0.6069
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.0907	0.3928	0.0118	0.5047	0.0000	0.5047
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.1694	0.3701	0.0106	0.4499	0.0000	0.4499
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0000	0.2325	0.3705	0.0091	0.3879	0.0000	0.3879

Table 4.61: Aggregated basic probability mass and unassigned probability mass for Alternative 2.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0889	0.1581	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.0000	0.1908	0.0212	0.7880	0.0000	0.7880
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.0717	0.3052	0.0163	0.6068	0.0000	0.6068
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.0594	0.4123	0.0256	0.5027	0.0000	0.5027
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.1033	0.4329	0.0225	0.4413	0.0000	0.4413
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0000	0.1117	0.4976	0.0190	0.3717	0.0000	0.3717

Table 4.62: Aggregated basic probability mass and unassigned probability mass for Alternative 3.

m11	m21	m31	m41	m51	mH,1-	mH,1~	mH1
0.0000	0.0000	0.0568	0.1902	0.0000	0.7530	0.0000	0.7530
m12	m22	m32	m42	m52	mH,2-	mH,2~	mH2
0.0000	0.0000	0.1844	0.0276	0.0000	0.7880	0.0000	0.7880
m1,I(2)	m2,I(2)	m3,I(2)	m4,I(2)	m5,I(2)	mH,I(2)-	mH,I(2)~	mH,I(2)
0.0000	0.0000	0.2015	0.1826	0.0000	0.6159	0.0000	0.6159
m1,I(3)	m2,I(3)	m3,I(3)	m4,I(3)	m5,I(3)	mH,I(3)-	mH,I(3)~	mH,I(3)
0.0000	0.0000	0.2067	0.2750	0.0000	0.5183	0.0000	0.5183
m1,I(4)	m2,I(4)	m3,I(4)	m4,I(4)	m5,I(4)	mH,I(4)-	mH,I(4)~	mH,I(4)
0.0000	0.0000	0.2461	0.3013	0.0000	0.4526	0.0000	0.4526
m1,I(5)	m2,I(5)	m3,I(5)	m4,I(5)	m5,I(5)	mH,I(5)-	mH,I(5)~	mH,I(5)
0.0000	0.0166	0.3299	0.2612	0.0000	0.3924	0.0000	0.3924

Step 7: The combined assessment is represented by Equation 3.48. Refer Table 4.63.

Table 4.63: Final utility value for all three alternatives.

Alternatives	W	P	A	G	E	UA	U_min	U_average	U_max	Final Rank	Utility Value
	beta 1	beta 2	beta 3	beta 4	beta 5	beta H					
Alternative 1	0.000	0.000	0.380	0.605	0.015	0.000	0.659	0.659	0.659	II	92.381
Alternative 2	0.000	0.000	0.178	0.792	0.030	0.000	0.713	0.713	0.713	I	100
Alternative 3	0.000	0.027	0.543	0.430	0.000	0.000	0.601	0.601	0.601	III	84.232

It is observed that again alternative 2 is the best among the three alternatives followed by alternative 1 and then alternative 3 as shown in Table 4.63. The results were same as obtained with the Fuzzy TOPSIS and COPRAS G method. Hence both the proposed methods are verified.

4.5 Summary

In this chapter commonly used MADM approaches are presented for selecting the best new product idea for a bus body building industry under fuzzy environment using Fuzzy TOPSIS and COPRAS-G. The approach consists of three steps. In step 1, the new product ideas (alternatives) and criteria, based on which decision are to be taken were identified. These alternatives were: Concept A - Dynamic and Fluidic (A1), Concept B - Rugged-Robust-Loud & Bold Face (A2), Concept C - Clean and Understated with Subtle Form (A3). The criteria's which affected the decision making were: Aesthetics (C1), Production process (C2), Cost of product (C3), Regulatory requirements (C4) and Market segment (C5). In step 2, decision makers who can contribute meaningfully, provided the linguistic ratings for criteria weightages as well as linguistic ratings for alternatives against each criterion. The decision-making process involved three decision makers namely: Design manager (DM1), Production manager (DM2) and Marketing manager (DM3). In step 3, fuzzy TOPSIS and COPRA G was applied to aggregate the ratings and generate an overall performance score for selecting the best new product idea. The highest score alternative is selected. In the case study, Alternative 2 (Concept B - Rugged-Robust-Loud & Bold Face) was the best among the three alternatives, followed by alternative 1(Concept A - Dynamic and Fluidic). The utility value in terms of numbers also express the level of confidence in the selected alternative. It is observed that in TOPSIS and COPRAS method when utility value of alternative 2 was taken as 100%, alternative 1 had the score as 93.02% and 92.07% respectively and alternative 3 had the values as 89.11 and 87.88 respectively. These values can be taken as an indicator as to what extend the preferred alternative is better over the other alternatives. Sensitivity analysis was carried out by taking maximum weightage for one of the criterion and minimum weightage for all the other criteria. Result of sensitivity analysis indicate that the final obtained result was stable and consistent. Two new hybrid methods were proposed so that the input data could be taken in linguistic form and grey scale and fuzzy scale was used to convert the linguistic variables either in to grey numbers or fuzzy numbers. The same manufacturing case study data was considered and Evidential reasoning method was used to find the best alternative assessment. It was observed that in both the methods i.e., Hybrid Grey ER and Hybrid Fuzzy ER, the alternative ranking turned out to be the same as the one obtained with Fuzzy TOPSIS and COPRAS G methods. The validation proved that the proposed method can be used to combine linguistic data with the evidential reasoning method using either grey scale or fuzzy scale.

Chapter 5

A Proposed Ranking Method for Idea Screening in NPD

5.1 General

There are lot of uncertainty causing element during the idea screening phase which is an important phase of new product development. This uncertainty requires a structured approach which can be provided by the multi attribute decision making methods. There are lot many MADM methods available to carry out the decision process of selecting the best alternative or idea from a given set of ideas. The drawback observed during the literature review was that the conventional MADM methods do not consider the effect of all alternative ratings while deciding about a given alternative. The importance of selecting the best MADM method to evaluate the alternative cannot be undermined, as the failure rate of NPD is very high and along with that the cost of failure is high. The research proposes a novel hierarchical ranking method for idea screening, which takes care of the limitations of the conventional MADM methods.

5.2 Proposed Method

The proposed method takes the criteria weightages and alternative rating in linguistic form from the decision makers so as to retain maximum original information. This linguistic data is then converted to fuzzy number, to tackle the uncertainty in the data. The criteria weightage data and the alternative rating data are then aggregated and normalized. The separation measure of both the data from the fuzzy positive ideal solution is obtained. The separation measure is than converted to maximization value so that higher value will result in a better solution. Both the maximization matrix is then normalized. The elements of criteria weightages maximization vector are considered as first level factors and elements of the alternative ratings maximization matrix are considered as the second level factors. The elements of both the matrix are arranged in hierarchical structure by placing the alternative rating values for a given criteria under that particular criteria weight. The uniqueness of the method lies in the fact t hat, the global weightage for a given alternative rating is expressed as a ratio of product of alternative rating for that criteria and criteria weight in the numerator and the sum of all the alternative rating, except for the alternative ratings of the criteria under consideration, in the denominator. The higher the denominator value, which will happen if the other second level factors have higher weights, will significantly reduce the global weights of those local factors which are under consideration. On the other hand, if the denominator value is less, it will significantly increase the global weights of those local factors which are under consideration. Hence each global weight is obtained by taking in to account the effect of all the other alternative rating values. This process either undermines or inflates the value of the global weight for that alternative rating based on its overall relationship with respect to the other data points. The flow chart for the proposed methos is shown in Figure 5.1.

5.3 Mathematical Model

The procedure for the proposed method is as follows:

Step 1: Feasible alternatives should be generated; evaluation criteria should be decided and the decision makers are to be identified. Let say there are “m” alternatives, “n” criteria and “k” decision makers.

Step 2: Allow the decision makers to choose the appropriate linguistic variables to decide about the weightages for the criteria. Similarly let the decision makers choose the linguistic variables for each alternative with respect to each criterion i.e., alternative ratings. The linguistic scale is converted to the fuzzy scale in terms of TFN using the standard Table shown below:

Table 5.1: Fuzzy ratings for linguistic variables.

Fuzzy number	Alternative assessmen	Criteria weights
(1, 1, 3)	Very Poor (VP)	Very Low (VL)
(1, 3, 5)	Poor (P)	Low (L)
(3, 5, 7)	Fair (F)	Medium (M)
(5, 7, 9)	Good (G)	High (H)
(7, 9, 9)	Very Good (VG)	Very High (VH)

Step 3: Get the average weights of criteria and ratings of alternatives given by the ‘k’ decision makers, using Equations 5.1 and 5.2.

$$\tilde{\omega}_j = \frac{1}{k}\left[\tilde{\omega}_j^1 + \tilde{\omega}_j^2 + \ldots\ldots + \tilde{\omega}_j^k\right] \qquad (5.1)$$

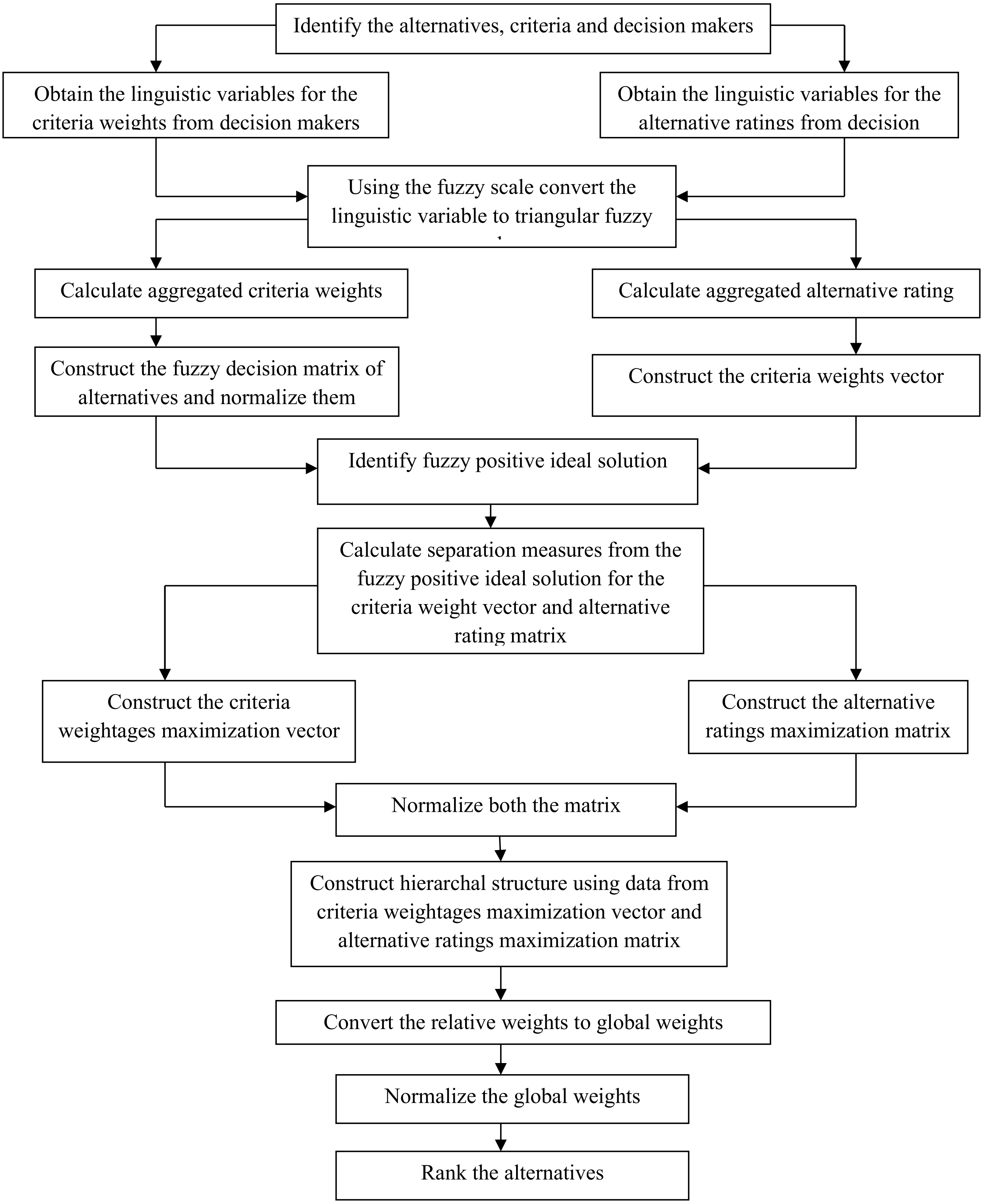

Figure 5.1: Flow chart proposed method.

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^{1} + \breve{x}_{ij}^{2} + \ldots\ldots + \breve{x}_{ij}^{k}\right] \tag{5.2}$$

i = 1, 2,…….m; j = 1, 2,…….n.

where $\breve{\omega}_j$ stands for the weight of criteria and $\check{x}_{ij}$ stands for the rating of alternative given by k^{th} decision maker.

Step 4: Next step is to make the fuzzy decision matrix of the alternatives (D). This gives the subjective ratings given by a set of decision makers as shown in Equation 5.3.

$$D = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \vdots & & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{5.3}$$

where i = 1, 2,…….m; j = 1, 2,…….n.

The variables are represented by triangular fuzzy numbers, $\tilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$.

Step 5: Normalized fuzzy decision matrix should be constructed using matrix (D). The various scales are transformed to comparable scale using linear scale transformation. The normalized fuzzy decision matrix is given by Equations 5.4 and 5.5.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^{+}}, \frac{b_{ij}}{c_j^{+}}, \frac{c_{ij}}{c_j^{+}}\right) \tag{5.4}$$

where $c_j^{+} = max_i c_{ij}$ (benefit criteria)

$$\tilde{r}_{ij} = \left(\frac{a_j^{+}}{c_{ij}}, \frac{a_j^{+}}{b_{ij}}, \frac{a_j^{+}}{a_{ij}}\right) \tag{5.5}$$

where $a_j^{+} = min_i a_{ij}$ (Cost criteria)

Step 6: Identify the Fuzzy Positive Ideal Solution ($\breve{v}_j^{+}$). Calculate the separation measures for each alternative rating from the fuzzy positive ideal solution using Equation 5.6 and form the alternative rating matrix (l_{ij}). Similarly calculate separation measure for criterion weightages from the fuzzy positive ideal solution using Equation 5.7 to get the criteria weightage vector (u_j).

$$l_{ij} = \sum_{j=1}^{n} d_v\left(\tilde{r}_{ij}, \breve{v}_j^{+}\right) \tag{5.6}$$

$$u_j = \sum_{j=1}^{n} d_v\left(\widetilde{\omega}_j, \breve{v}_j^{+}\right) \tag{5.7}$$

Here $d_v(.,.)$ represents the distance between two fuzzy numbers using the vertex method. According to the vertex method, the distance between two triangular fuzzy numbers D_1 (a_1, a_2, a_3) and D_2 (b_1, b_2, b_3) is calculated using Equation 5.8.

$$(D_1, D_2) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{5.8}$$

$$l_{ij}^{M} = 1 - c_{ij} \quad \text{(Benefit criteria)} \tag{5.9}$$

$$l_{ij}^{M} = c_{ij} \quad \text{(Cost criteria)} \tag{5.10}$$

Similarly convert criteria weightage vector to maximization criteria weightage vector (u_j^M) by using equation Equations 5.11 and 5.12.

$$u_j^M = 1 - c_{ij} \quad \text{(Benefit criteria)} \tag{5.11}$$

$$u_j^M = c_{ij} \quad \text{(Cost criteria)} \tag{5.12}$$

Step 8: Normalize the alternative rating maximization matrix and criteria weightages maximization vector.

Step 9: Consider the elements of the criteria weightage maximization vector as first level factors (u_j^M) and the elements of the alternative rating maximization matrix as second level factors (l_{ij}^M). Structure the first level factor and the second level factor in such a way so as to get a hierarchical order. This is done by placing the second level factors for particular criteria under the first level factor for those criteria.

Step 10: Transform the relative weightages associated with each factor in to global level weightages(W_{ij}) using Equation 5.13. Carry out the normalization of the global weights using Equation 5.14.

$$W_{ij} = \frac{u_j^M * l_{ij}^M}{\sum l_{ij}^M} \tag{5.13}$$

i = 1, 2, 3 ………….. m
j = 1, 2, 3……………n
k = 1, 2, 3……………m and k ≠ j

$$W_{ij}^{N} = \frac{W_{ij}}{\sum W_{ij}} \tag{5.14}$$

W_{ij}^{N} = Normalized global weights
i = 1, 2, 3 ………….. m
j = 1, 2, 3……………n

Step 11: The ranking of the alternative (Ai) is obtained by summing up all the global weightages for that alternative as shown in Equation 5.15. The highest sum gives the best alternative.

$$\mathrm{A_i} = \sum_{i=}^{n} W_{ij}^{N} \quad \text{for j= 1, 2,…….n} \tag{5.15}$$

Step 12: Calculate the quantitative utility for all alternatives (Ui) using Equation 5.16. The alternative with the highest value is the best alternative.

$$\mathrm{U_i} = \left[\frac{\mathrm{A_i}}{\mathrm{A_{imax}}}\right] * 100\% \tag{5.16}$$

where A_{imax} is maximum value of A_i.

5.4 Validation of Proposed Ranking Method

The research work was caried out for the best new product idea for an X-ray manufacturing company. A new X-ray machine had to be launched in the market which would cover all clinical applications, have better image quality, better ergonomics, consistent performance, easy and fast to learn and operate. Based on the customers' requirements and market survey, the company came up with three new product ideas.

These ideas (alternatives) were:
Alternative 1 (A1)
Alternative 2 (A2)
Alternative 3 (A3)

The criteria's which affected the decision making were:
Design (C1)
Manufacturing (C2)
Cost (C3)
Ergonomics (C4)
Handling (C5).

The decision-making process involved three decision makers namely:
Design manager (DM1)
Manufacturing manager (DM2)
Marketing manager (DM3).
The structure of the problem is ideal for solving using multi attribute decision making approach.

5.5 Calculation using proposed ranking method

Step 1: There are three alternatives (A1, A2, A3), five criteria's (C1, C2, C3, C4, C5) and three decision makers (DM1, DM2, DM3). Criteria C1, C2, C4 and C5 are benefit type whereas criteria C3 is cost type.

Step 2: The three decision makers gave the weightages for each criterion as well as assigned the linguistic variable for each alternative against criteria (Tables 5.2 - 5.3). Standard fuzzy scale shown in Table 5.1 was used to convert the linguistic data to triangular fuzzy number.

Table 5.2: Linguistic rating for weightages.

Criteria weightages			
Criteria	DMI	DM2	DM3
C1	VH	H	H
C2	H	H	H
C3	M	L	VH
C4	H	M	M
C5	H	M	VH

Table 5.3: Linguistic rating for alternatives against each criterion.

Alternative ratings									
Criteria	A1			A2			A3		
	DMI	DM2	DM3	DMI	DM2	DM3	DMI	DM2	DM3
C1	G	G	G	G	VG	F	G	G	F
C2	F	G	G	G	VG	G	F	F	G
C3	VG	G	G	VG	G	F	G	G	G
C4	G	G	F	G	G	G	G	F	G
C5	VG	G	P	G	G	F	G	F	P

Step 3: Get the average weights of criteria and ratings of alternatives given by the "k" decision makers using Equation 5.1 and 5.2. Refer Table 5.4. This step helps in aggregating the decision of all the decision makers for criteria weightages and alternative ratings.

Table 5.4 Aggregated values for proposed method

Alternative rating aggregation										Aggregated criteria weights		
Criteria	A1			A2			A3					
C1	5	7	9	5	7	8.333	4.333	6.333	8.333	5.667	7.667	9
C2	4.333	6.333	8.333	5.667	7.667	9	3.667	5.667	7.667	5	7	9
C3	5.667	7.667	9	5	7	8.333	5	7	9	3.667	5.667	7
C4	4.333	6.333	8.333	5	7	9	4.333	6.333	8.333	3.667	5.667	7.667
C5	4.333	6.333	7.667	4.333	6.333	8.333	3	5	7	5	7	8.333

Step 4 & 5: Construct normalized fuzzy decision matrix as shown in Table 5.5 using Equations 5.4 and 5.5 and normalized fuzzy criteria weight matrix as shown in Table 5.6. Normalization helps in unbiasedness and easy interpretation of fuzzy data.

Table 5.5: Normalized fuzzy decision matrix for proposed method.

Normalized fuzzy alternative rating									
Criteria	A1			A2			A3		
C1	0.556	0.778	1	0.556	0.778	0.926	0.481	0.704	0.926
C2	0.481	0.704	0.926	0.63	0.852	1	0.407	0.63	0.852
C3	0.882	0.652	0.556	1	0.714	0.6	1	0.714	0.556
C4	0.481	0.704	0.926	0.556	0.778	1	0.481	0.704	0.926
C5	0.52	0.76	0.92	0.52	0.76	1	0.36	0.6	0.84

Table 5.6: Normalized fuzzy criteria weight matrix for proposed method.

Normalized fuzzy criteria weight			
C1	0.630	0.852	1
C2	0.556	0.778	1
C3	1	0.649	0.525
C4	0.478	0.739	1
C5	0.600	0.840	1

Step 6: The ideal solution consists of all of best values attainable of criteria. The FPIS is taken as: $\breve{v}_j^+$ = (1.000, 1.000, 1.000). Calculate the separation measures using Equation 5.6 and 5.7. Refer Table 5.7 and 5.8. Finding the separation measures allows us to convert the fuzzy number to crisp number in form of distance from the positive ideal solution. The distances are reflective of the weightages and relative importance among the criteria and alternative ratings. Lesser the distance, better is the criteria weightage and the alternative rating.

Table 5.7: Separation measures for criteria weights for proposed method.

Criteria	Weightages
C1	0.230
C2	0.287
C3	0.341
C4	0.337
C5	0.249

Table 5.8: Separation measures for alternative ratings for proposed method.

Criteria	A1	A2	A3
C1	0.287	0.29	0.347
C2	0.347	0.23	0.412
C3	0.333	0.284	0.305
C4	0.347	0.287	0.347
C5	0.313	0.31	0.445

Step 7: Convert the alternative rating matrix to maximization alternative rating matrix (l_{ij}^{M}) by using Equation 5.9 and 5.10 and criteria weightage matrix to maximum criteria weightage vector (u_j^M) using Equation 5.11 and 5.12. Refer Table 5.9 and 5.10. Converting to maximization matrix allows us to take higher value in the final solution as the better alternative.

Table 5.9: Maximization alternative rating matrix for proposed method.

Criteria	A1	A2	A3
C1	0.713	0.710	0.653
C2	0.653	0.770	0.588
C3	0.333	0.284	0.305
C4	0.653	0.713	0.653
C5	0.687	0.690	0.555

Table 5.10: Maximization criteria weightage vector for proposed method.

Criteria	Weightage
C1	0.770
C2	0.713
C3	0.659
C4	0.663
C5	0.751

Step 8: Normalize the alternative rating maximization matrix and criteria weightages maximization vector to remove the biasness and for easy understanding of the data as shown in Table 5.11.

Table 5.11: Normalized maximization alternative rating matrix and maximization criteria weightage vector for proposed method.

Criteria	A1	A2	A3	Normalized weightages
C1	0.344	0.342	0.314	0.216
C2	0.325	0.383	0.292	0.210
C3	0.361	0.308	0.331	0.185
C4	0.323	0.353	0.323	0.186
C5	0.356	0.357	0.287	0.211

Step 9 & 10: Convert the first level factors and second level factors in to a hierarchical structure. Consider the elements of the criteria weightage's maximization vector as first level factors and the elements of the alternative rating maximization matrix as second level factors. Structure the first level factor and the second level factor in such a way so as to get a hierarchical order. This is done by placing the second level factors for particular criteria under the first level factor for that criterion as shown in Table 5.12. To get the globalized weight for each alternative rating the denominator consists of summation of second level factors of all criteria except for the criteria under consideration. The global weights are then normalized so that they add up to 1.

Table 5.12: Hierarchical structure for getting global weights for proposed method

Weights of first level factors	Weights of second level factors	Global weights	Normalized weights
0.216	0.344	0.019	0.074
	0.342	0.019	0.074
	0.314	0.017	0.068
0.201	0.325	0.016	0.065
	0.383	0.019	0.077
	0.292	0.015	0.059
0.185	0.361	0.017	0.067
	0.308	0.014	0.057
	0.331	0.015	0.061
0.186	0.323	0.015	0.060
	0.353	0.016	0.066
	0.323	0.015	0.060
0.211	0.356	0.019	0.075
	0.357	0.019	0.075
	0.287	0.015	0.061

Step 11 & 12: The ranking of the alternative (Ai) is obtained by summing up all the global weightages for that alternative i.e., the values associated with a particular alternative against each criterion is summed up to gets its score, which in turn is used for evaluating the best alternative. The alternative A2 with the highest sum is the best alternative. Table 5.13 shows the raking of the alternatives. Figure 5.2 shows the graph plotted for the alternative ranking.

Table 5.13: Ranking of alternatives for proposed method.

Alternative	Ai	Ui	Rank
A1	0.342	97.86	2
A2	0.349	100.00	1
A3	0.309	88.46	3

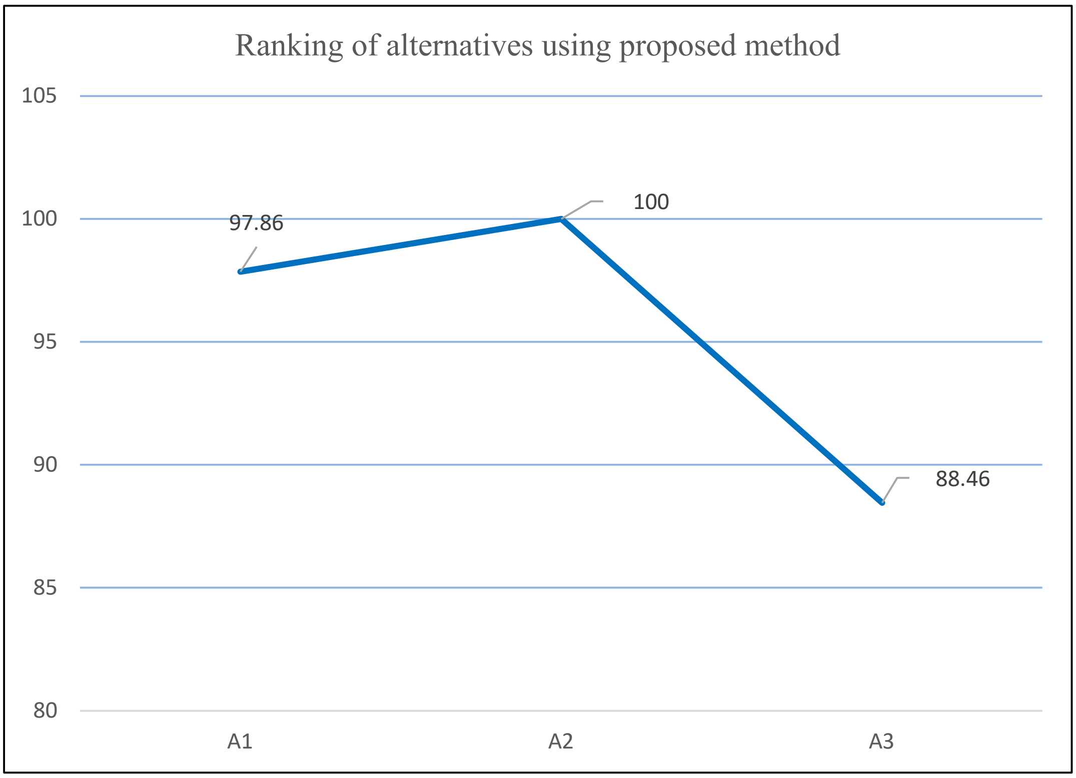

Figure 5.2: Graph for alternative ranking using proposed method.

5.6 Calculation using COPRAS-G method

For the application of the COPRAS method apply the initial steps of the proposed method till we get the aggregated Table for criteria weightage matrix and alternative rating matrix and follow the below steps.

Step 1: Normalized the data to get the normalized decision matrix as shown in Table 5.14.

Table 5.14: Normalized decision matrix for COPRAS-G method.

Weights	C1		C2		C3		C4		C5	
	0.231		0.215		0.169		0.174		0.210	
Alternative	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2
A1	0.149	0.198	0.137	0.188	0.156	0.195	0.136	0.186	0.152	0.200
A2	0.149	0.190	0.171	0.214	0.141	0.180	0.153	0.203	0.152	0.209
A3	0.132	0.182	0.120	0.171	0.141	0.187	0.136	0.186	0.114	0.171

Step 2: Obtain the weighted normalized decision matrix (D) from the normalized decision matrix as shown in Table 5.15.

Table 5.15: Weighted normalized decision matrix for COPRAS-G method.

Weights	C1		C2		C3		C4		C5	
	0.231		0.215		0.169		0.174		0.210	
Alternative	X1	X2	X1	X2	X1	X2	X1	X2	X1	X2
A1	0.034	0.046	0.029	0.040	0.026	0.033	0.024	0.033	0.032	0.042
A2	0.034	0.044	0.037	0.046	0.024	0.030	0.027	0.035	0.032	0.044
A3	0.030	0.042	0.026	0.037	0.024	0.032	0.024	0.033	0.024	0.036

Step 3: Sum up the beneficial and non-beneficial criteria for the weighted normalized matrix shown in Table 5.16.

Table 5.16: Beneficial and non-beneficial values for COPRAS-G method.

Alternatives	S_i+	S_i-
A1	0.14	0.03
A2	0.15	0.027
A3	0.13	0.028

Step 4 & 5: Determine the relative significances or priorities of each alternative (Q_i) and the quantitative utility for all alternatives (U_i). Table 5.17 provides the ranking of alternatives. Figure 5.3 shows the graph for alternative ranking using COPRAS-G method.

Table 5.17: Ranking of alternatives for COPRAS-G method.

Alternatives	Q_i	U_i	Rank
A1	0.167	93.25	2
A2	0.179	100	1
A3	0.154	86.22	3

It is observed that alternative 2 is the best alternative followed by alternative 1 and then alternative 3. The ranking order of alternatives is found to be A2 > A1 > A3.

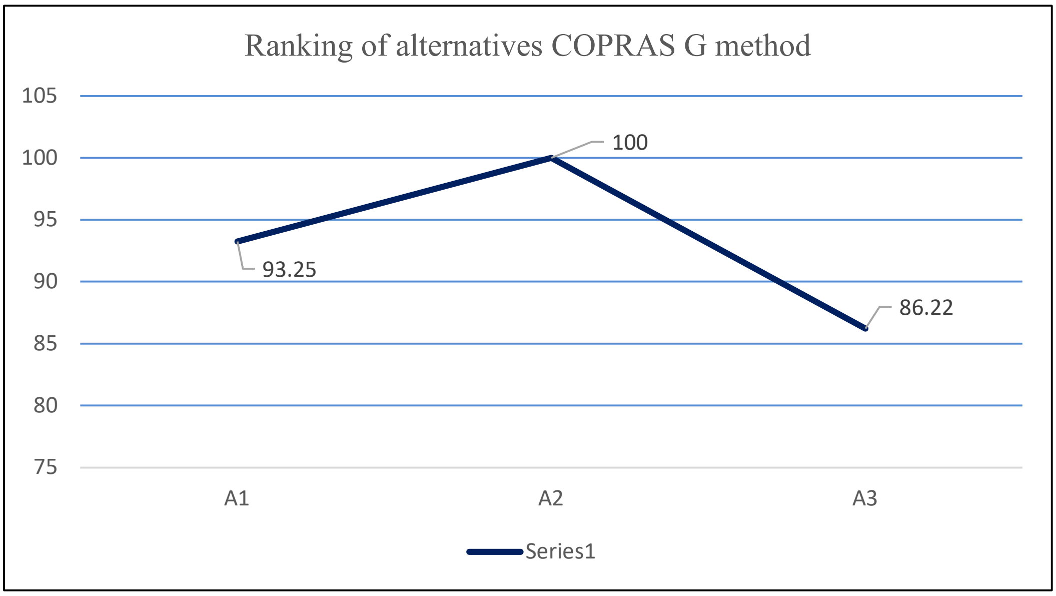

Figure 5.3: Graph for alternative ranking using COPRAS-G method.

5.7 Calculation using Fuzzy TOPSIS method

Step 1: Construct the fuzzy decision matrix as shown in Table 5.18. It involves making a combined table of criteria weightages and alternative ratings against each criterion.

Table 5.18: Aggregated ratings for alternative against criteria for Fuzzy TOPSIS method.

Criteria			Alternatives								
			A1			A2			A3		
5.67	7.67	9	5	7	9	5	7	8.33	4.33	6.33	8.33
5	7	9	4.33	6.33	8.33	5.67	7.67	9	3.67	5.67	7.67
3.67	5.67	7	5.67	7.67	9	5	7	8.33	5	7	9
3.67	5.67	7.67	4.33	6.33	8.33	5	7	9	4.33	6.33	8.33
5	7	8.33	4.33	6.33	7.67	4.33	6.33	8.33	3	5	7

Step 2: Construct normalized fuzzy decision matrix as shown in Table 5.19.

Table 5.19: Normalized fuzzy decision matrix for Fuzzy TOPSIS method.

Criteria	Alternatives								
	A1			A2			A3		
C1	0.556	0.778	1	0.556	0.778	0.926	0.481	0.704	0.926
C2	0.481	0.704	0.926	0.63	0.852	1	0.407	0.63	0.852
C3	0.648	0.479	0.408	0.734	0.524	0.44	0.734	0.524	0.408
C4	0.481	0.704	0.926	0.556	0.778	1	0.481	0.704	0.926
C5	0.52	0.76	0.92	0.52	0.76	1	0.36	0.6	0.84

Step 3: Calculate the weighted normalized decision matrix as shown in Table 5.20. The weighted normalized decision matric is obtained by multiplying the criteria weightages to the alternating ratings against each criterion.

Table 5.20: Weighted normalized fuzzy decision matrix for Fuzzy TOPSIS method.

Criteria	Alternatives								
	A1			A2			A3		
C1	3.148	5.963	9	3.148	5.963	8.333	2.728	5.395	8.333
C2	2.407	4.926	8.333	3.148	5.963	9	2.037	4.407	7.667
C3	2.375	2.713	2.854	2.691	2.971	3.083	2.691	2.971	2.854
C4	1.765	3.988	7.099	2.037	4.407	7.667	1.765	3.988	7.099
C5	2.601	5.322	7.67	2.601	5.322	8.337	1.801	4.202	7.003

Step 7: The FPIS is taken as: A* = (9.000, 9.000, 9.000) and the FNIS is taken as: A- = (1.000, 1.000, 1.000) as shown in Table 5.21. The distance separation formula is used to calculate the distance of each alternative from the fuzzy positive ideal solution and the fuzzy negative ideal solution.

Table 5.21: Separation measures for each alternative for Fuzzy TOPSIS method.

Criteria	A1		A2		A3	
	FPIS	FNIS	FPIS	FNIS	FPIS	FNIS
C1	3.806	5.575	3.825	5.260	4.194	5.035
C2	4.490	4.870	3.806	5.575	4.876	4.363
C3	6.355	1.659	6.087	1.922	6.162	1.842
C4	5.198	3.945	4.876	4.363	5.198	3.945
C5	4.329	4.680	4.278	5.002	5.126	3.955
$\sum$ d	24.182	20.732	22.875	22.124	25.558	19.143

Step 4: Finally, the closeness coefficient was calculated and the ranking were carried out. It was observed that alternative 2 was the best among the three alternatives as shown in Table 5.22. Figure 5.4 indicates the ranking of the alternatives using the fuzzy TOPSIS method.

Table 5.22: Relative closeness to the ideal solution for Fuzzy TOPSIS method.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.462	93.89	2
A2	0.492	100.000	1
A3	0.428	87.10	3

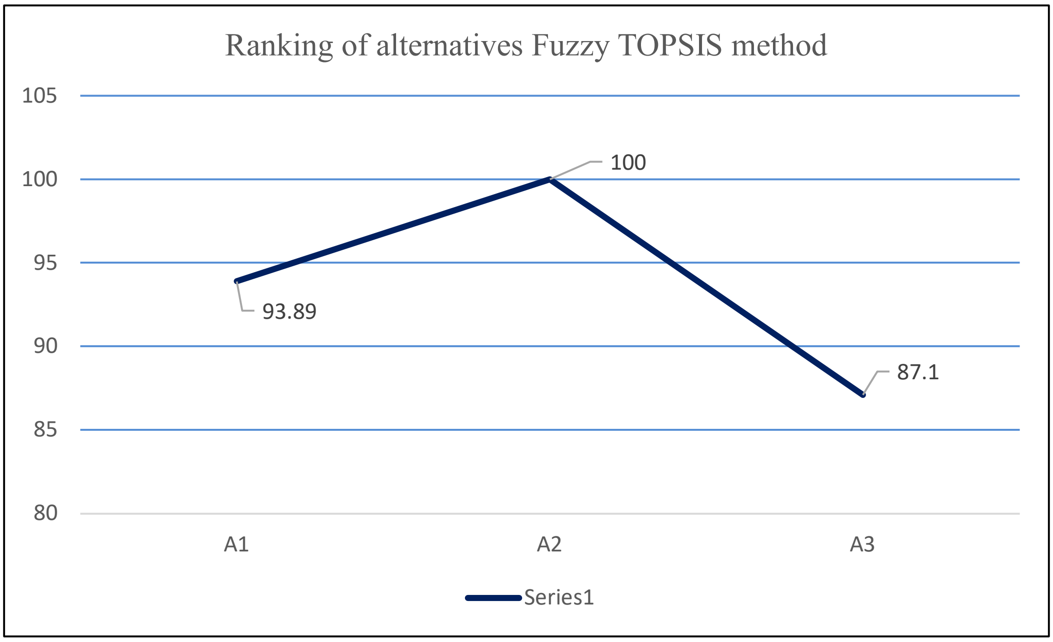

Figure 5.4: Ranking of alternatives Fuzzy TOPSIS method.

The ranking was consistent in all the three methods (refer Table 5.23). Figure 5.5 shows the graphical representation of the ranking achieved using all the three methods.

Table 5.23: Comparison between proposed method, COPRAS-G and Fuzzy TOPSIS.

Alternative	Proposed ranking method	COPRAS-G	Fuzzy TOPSIS	Rank
A1	97.86	93.25	93.89	2
A2	100.00	100	100.000	1
A3	88.46	86.22	87.10	3

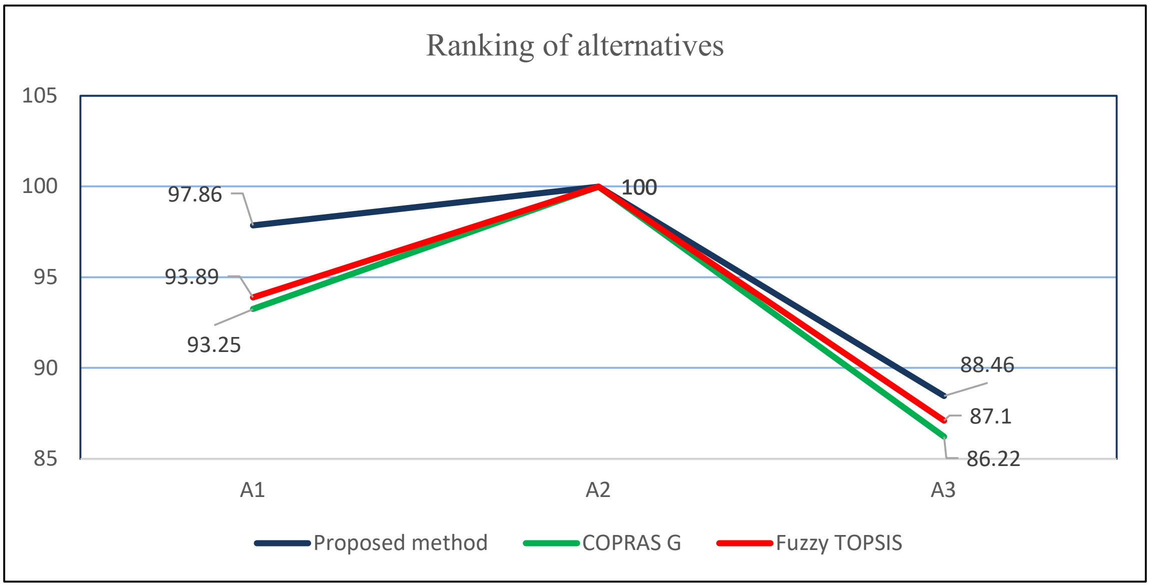

Figure 5.5: Ranking of alternatives by all the three methods.

5.8 Sensitivity Analysis

The last step in the decision-making process is the sensitivity analysis. Vulnerability of the data can be checked using the sensitivity analysis. In the sensitivity analysis procedure, certain criteria are assigned very high number and the other criteria are assigned smaller number and the effect on the final outcome is observed. Further investigation might be needed if there is change in the outcome of the decision-making process. The process is said to be sensitive if there is change in decision making outcome, otherwise it is known as stable if the decision-making outcome does not change much. The criteria which will have the most effect on the outcome can be known from the sensitivity analysis and hence correct MADM methods can be selected. Here we carry out the sensitivity analysis on the proposed method and the methods which are used to validate the proposed methods i.e., COPRAS-G and Fuzzy TOPSIS.

5.8.1 Sensitivity analysis on proposed method

In the proposed method since we use the fuzzy scale, the highest triangular fuzzy number is 7, 7, 9 and the lowest triangular fuzzy number is 1, 1, 3.

Case 1: Maximize criteria 1 of proposed method

In this case criteria 1 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages are assigned fuzzy number 1, 1, 3 as shown Table 5.24.

Table 5.24: Maximize criteria 1 of proposed method.

Criteria	Weightage
C1	7, 7, 9
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.25.

Table 5.25: Ranking of the alternatives of proposed method for case 1.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.231	95.455	2
A2	0.242	100	1
A3	0.221	91.322	3

Case 2: Maximize criteria 2 of proposed method

In this case criteria 2 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1 are assigned fuzzy number 1, 1, 3 as shown Table 5.26.

Table 5.26: Maximize criteria 2 of proposed method.

Criteria	Weightage
C1	1, 1, 3
C2	7, 7, 9
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

`

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.27.

Table 5.27: Ranking of the alternatives of proposed method for case 2.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.227	89.723	2
A2	0.253	100	1
A3	0.211	83.399	3

Case 3: Maximize criteria 3 of proposed method

In this case criteria 3 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1 and 2 are assigned fuzzy number 1, 1, 3 as shown Table 5.28.

Table 5.28: Maximize criteria 3 of proposed method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	7, 7, 9
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.29.

Table 5.29: Ranking of the alternatives of proposed method for case 3.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.186	88.152	1
A2	0.211	100	2
A3	0.184	87.204	3

Case 4: Maximize criteria 4 of proposed method

In this case criteria 4 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 4 are assigned fuzzy number 1, 1, 3 as shown Table 5.30.

Table 5.30: Maximize criteria 4 of proposed method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	7, 7, 9
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.31.

Table 5.31: Ranking of the alternatives of proposed method for case 4.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.217	93.133	2
A2	0.233	100	1
A3	0.211	90.558	3

Case 5: Maximize criteria 5 of proposed method

In this case criteria 5 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 5 are assigned fuzzy number 1, 1, 3 as shown in Table 5.32.

Table 5.32: Maximize criteria 5 of proposed method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	7, 7, 9

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.33.

Table 5.33: Ranking of the alternatives of proposed method for case 5.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.241	94.882	2
A2	0.254	100	1
A3	0.233	91.732	3

We can see from the sensitivity analysis that alternative 2 is the best alternative followed by alternative 1 and the last preference goes to alternative 3. In general, sensitivity analysis has proved that the decision-making process is stable and alternative 2 is the best alternative to go ahead for manufacturing. Table 5.34 shows the utility value in all the cases. Figure 5.6 shows the outcome of the sensitivity analysis for the proposed method. In the Figure the red colour line indicates alternative 2. As seen the red colour line touches 100 % for all the criteria.

Table 5.34: Utility value in all the sensitivity analysis cases of proposed method.

	C1	C2	C3	C4	C5
A1	95.455	89.723	88.152	93.133	94.882
A2	100	100	100	100	100
A3	91.322	83.399	87.204	90.558	91.732

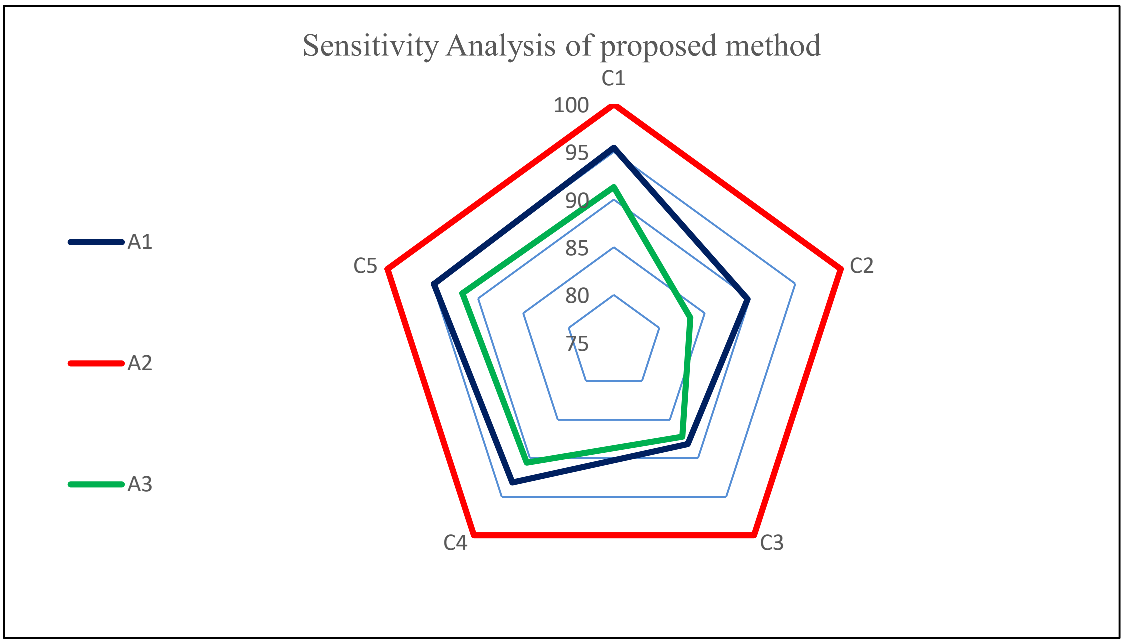

Figure 5.6: Outcome of the sensitivity analysis for proposed method.

5.8.2 Sensitivity analysis on COPRAS-G

In the COPRAS-G method since we use the grey scale, the highest grey number is 8, 9 and the lowest triangular fuzzy number is 1, 2.

Case 1: Maximize criteria 1 of COPRAS-G method

In this case criteria 1 is assigned the fuzzy number 8, 9 and rest all the criteria weightages are assigned fuzzy number 1, 2 as shown Table 5.35.

Table 5.35: Maximize criteria 1 of COPRAS-G method.

Criteria	Weightage
C1	8, 9
C2	1, 2
C3	1, 2
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.36.

Table 5.36: Ranking of the alternatives by COPRAS-G method for case 1.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.169	97.4	2
A2	0.174	100	1
A3	0.156	89.5	3

Case 2: Maximize criteria 2 of COPRAS-G method

In this case criteria 2 is assigned the fuzzy number 8, 9 and rest all the criteria weightages including criteria 1 are assigned fuzzy number 1, 2 as shown Table 5.37.

Table 5.37: Maximize criteria 2 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	8, 9
C3	1, 2
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.38.

Table 5.38: Ranking of the alternatives by COPRAS-G method for case 2.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.164	88.656	2
A2	0.185	100	1
A3	0.15	81.143	3

Case 3: Maximize criteria 3 of COPRAS-G method

In this case criteria 3 is assigned the fuzzy number 8, 9 and rest all the criteria weightages including criteria 1and 2 are assigned fuzzy number 1, 2 as shown Table 5.39.

Table 5.39: Maximize criteria 3 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	8, 9
C4	1, 2
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.40.

Table 5.40: Ranking of the alternatives by COPRAS-G method for case 3.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.162	92.085	2
A2	0.176	100	1
A3	0.162	91.927	3

Case 4: Maximize criteria 4 of COPRAS-G method

In this case criteria 4 is assigned the fuzzy number 8, 9 and rest all the criteria weightages excluding 4 are assigned fuzzy number 1, 2 as shown Table 5.41.

Table 5.41: Maximize criteria 4 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	1, 2
C4	8, 9
C5	1, 2

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.42.

Table 5.42: Ranking of the alternatives by COPRAS-G method for case 4.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.163	91.732	2
A2	0.178	100	1
A3	0.158	88.518	3

Case 5: Maximize criteria 5 of COPRAS-G method

In this case criteria 5 is assigned the fuzzy number 8, 9 and rest all the criteria weightages excluding 5 are assigned fuzzy number 1, 2 as shown Table 5.43.

Table 5.43: Maximize criteria 5 of COPRAS-G method.

Criteria	Weightage
C1	1, 2
C2	1, 2
C3	1, 2
C4	1, 2
C5	8, 9

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.44.

Table 5.44: Ranking of the alternatives by COPRAS-G method for case 5.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.171	95.114	2
A2	0.179	100	1
A3	0.149	82.963	3

The sensitivity analysis points out that alternative 2 is the best alternative followed by alternative 1 and then by alternative 3. But in case 3, wherein criteria 3 is made the best, it is observed that alternative 2 and alternative 3 are very close to each other in terms of utility value. This has happened because criteria 3 is cost type. This same phenomenon was observed in sensitivity analysis of proposed method. In general, sensitivity analysis has proved that the decision-making process is stable process with alternative 2 being the best alternative for manufacturing. Table 5.45 shows the utility value in all the cases. Figure 5.7 shows the outcome of the sensitivity analysis wherein alternative 2 is the best alternative

Table 5.45: Utility value in all the sensitivity analysis cases of COPRAS-G method.

	C1	C2	C3	C4	C5
A1	97.404	88.656	92.085	91.732	95.114
A2	100	100	100	100	100
A3	89.500	81.143	91.927	88.518	82.963

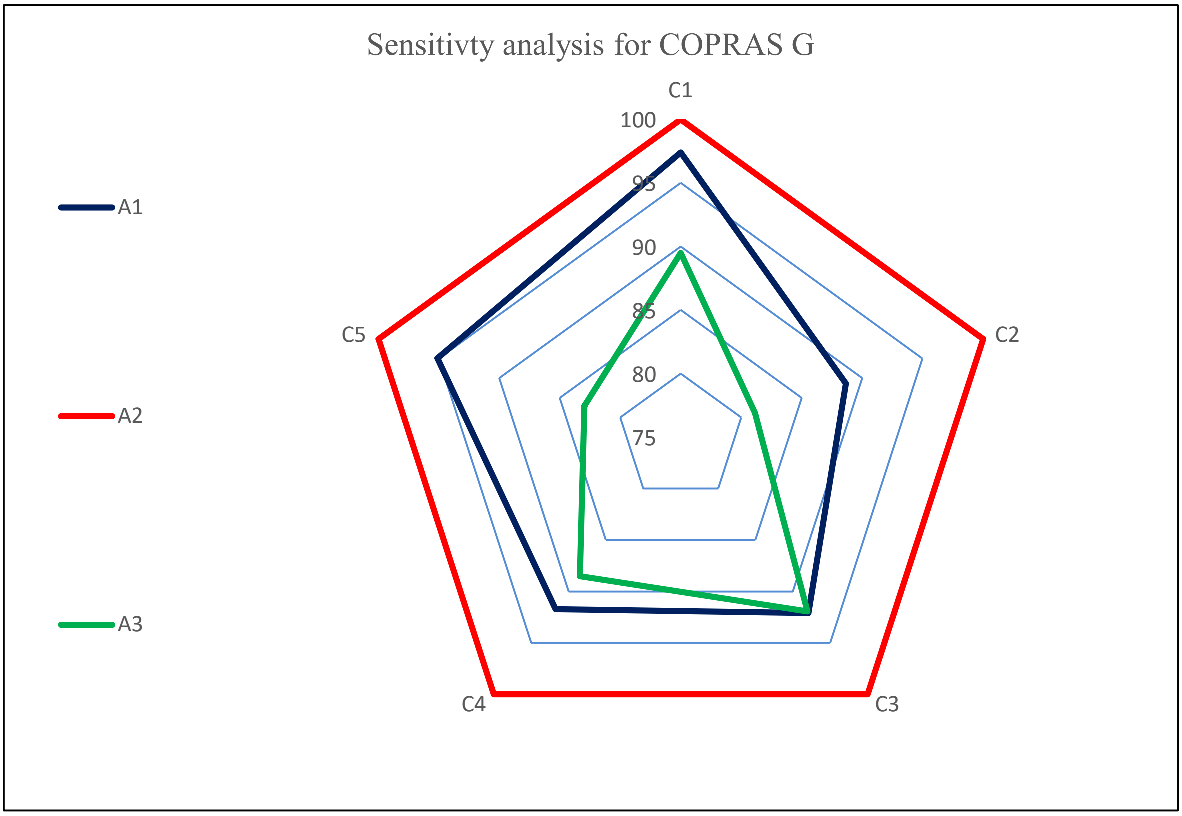

Figure 5.7: Outcome of sensitivity analysis for COPRAS-G method.

5.8.3 Sensitivity analysis on fuzzy TOPSIS

In the fuzzy TOPSIS method since we use the fuzzy scale, the highest triangular fuzzy number is 7, 9, 9 and the lowest triangular fuzzy number is 1, 1, 3.

Case 1: Maximize criteria 1 of Fuzzy TOPSIS method

In this case criteria 1 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages are assigned fuzzy number 1, 1, 3 as shown Table 5.46.

Table 5.46: Maximize criteria 1 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	7, 7, 9
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.47.

Table 5.47: Ranking of the alternatives by Fuzzy TOPSIS method for case 1.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.218	98.912	2
A2	0.220	100	1
A3	0.200	90.697	3

Case 2: Maximize criteria 2

In this case criteria 2 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1 are assigned fuzzy number 1, 1, 3 as shown Table 5.48.

Table 5.48: Maximize criteria 2 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	7, 7, 9
C3	1, 1, 3
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.49.

Table 5.49: Ranking of the alternatives by Fuzzy TOPSIS method for case 2.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.207	89.956	2
A2	0.230	100	1
A3	0.189	81.962	3

Case 3: Maximize criteria 3 of Fuzzy TOPSIS method

In this case criteria 3 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages including criteria 1and 2 are assigned fuzzy number 1, 1, 3 as shown Table 5.50.

Table 5.50: Maximize criteria 3 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	7, 7, 9
C4	1, 1, 3
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.51.

Table 5.51: Ranking of the alternatives by Fuzzy TOPSIS method for case 3.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.176	91.932	3
A2	0.191	100	1
A3	0.177	92.553	2

Case 4: Maximize criteria 4 of Fuzzy TOPSIS method

In this case criteria 4 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 4 are assigned fuzzy number 1, 1, 3 as shown Table 5.52.

Table 5.52: Maximize criteria 4 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	7, 7, 9
C5	1, 1, 3

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.53.

Table 5.53: Ranking of the alternatives by Fuzzy TOPSIS method for case 4.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.207	93.022	2
A2	0.223	100	1
A3	0.200	89.569	3

Case 5: Maximize criteria 5 of Fuzzy TOPSIS method

In this case criteria 5 is assigned the fuzzy number 7, 7, 9 and rest all the criteria weightages excluding 5 are assigned fuzzy number 1, 1, 3 as shown Table 5.54.

Table 5.54: Maximise criteria 5 of Fuzzy TOPSIS method.

Criteria	Weightage
C1	1, 1, 3
C2	1, 1, 3
C3	1, 1, 3
C4	1, 1, 3
C5	7, 7, 9

The closeness coefficient value, utility value and the ranking of the alternatives is shown in Table 5.55.

Table 5.55: Ranking of the alternatives by Fuzzy TOPSIS method for case 5.

Alternative	Closeness Coefficient	Utility Value	Ranking
A1	0.212	96.251	2
A2	0.220	100	1
A3	0.185	83.873	3

We can see from the sensitivity analysis that alternative 2 is the best alternative followed by alternative 1 and the last preference goes to alternative 3. But in case 3, wherein criteria 3 is made the best, it is observed that alternative 2 still remains the best, but it is followed by alternative 3 and then alternative 1. This has happened because criteria 3 is cost type. In general, sensitivity analysis has proved that the decision-making process is stable and alternative 2 is the best alternative to go ahead for manufacturing. Table 5.56 shows the utility value in all the cases. Figure 5.8 shows the outcome of the sensitivity analysis.

Table 5.56: Utility value in all the sensitivity analysis cases of Fuzzy TOPSIS.

	C1	C2	C3	C4	C5
A1	98.912	89.956	91.932	93.022	96.251
A2	100	100	100	100	100
A3	90.697	81.962	92.553	89.569	83.873

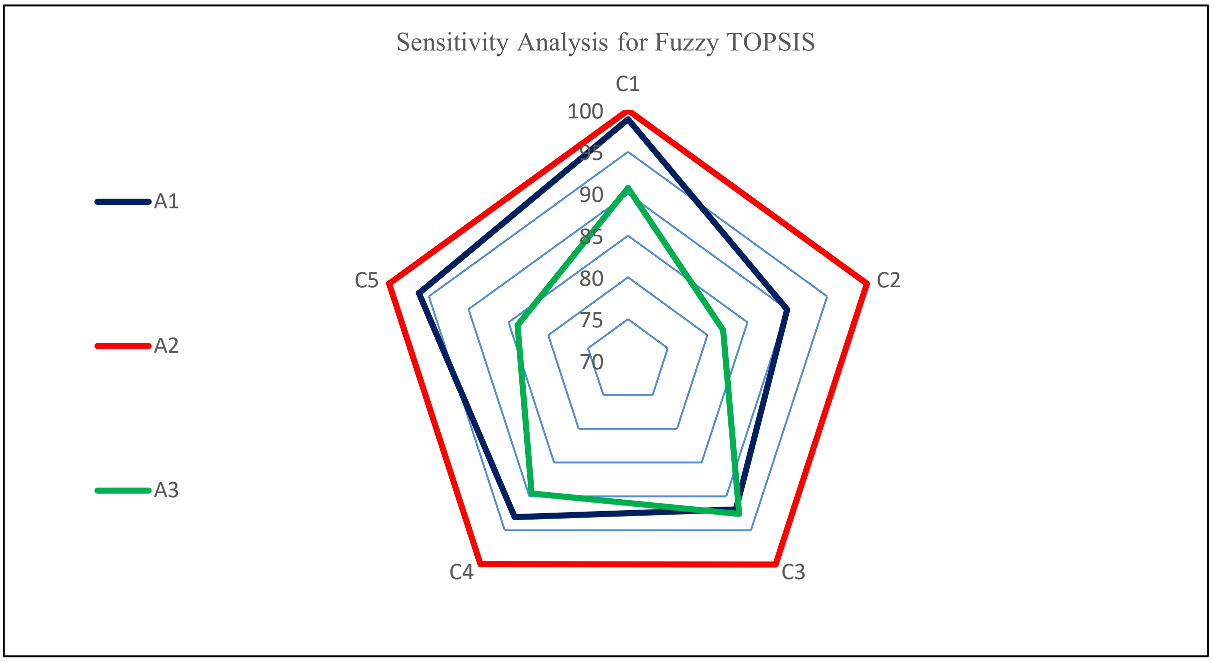

Figure 5.8: Outcome of the sensitivity analysis for Fuzzy TOPSIS method.

5.9 Conclusion

Fuzzy TOPSIS and COPRAS-G are the most commonly used MCDM methods in the evaluation of the best alternative. The literature review pointed out that data from all the alternative rating is not taken in to consideration during the decision-making process. The algorithmics superiority of the proposed method lies in the fact that, to get the global weightage for each alternative rating against criteria, the effect of sum of all the alternative rating is taken except for the one under consideration. The method either undermines or inflates the value of the global weight for that alternative rating based on its overall relationship with respect to the other data points. The proposed method was validated using the standard MCDM methods. The best idea or alternative is the one which has the highest utility value amongst all the other alternatives.

5.10 Summary

In this chapter a unique ranking method was presented for selecting the best new product idea for an X-ray manufacturing industry under fuzzy environment. The idea screening phase of NPD involves listing a number of ideas and shortlisting among them a few which are feasible. The best alternative or idea is the one which has a higher score as compared to the other. The case study approach consisted of three steps. In step 1, the new product ideas (alternatives) and criteria based on which decisions are to be taken were identified. These alternatives were: Concept A (A1), Concept B (A2) and Concept C (A3). The criteria's which affected the decision making were: Design (C1), Manufacturing (C2), Cost (C3), Ergonomics (C4) and Handling (C5). In step 2, decision makers who can contribute meaningfully, provided the linguistic ratings for criteria weightages as well as linguistic ratings for alternatives against each criterion. The decision-making process involved three decision makers namely: Design manager (DM1), Manufacturing manager (DM2) and Marketing manager (DM3). In step 3, proposed ranking method was applied to aggregate the ratings and generate an overall performance score for selecting the best new product idea. The highest score alternative was selected. The data was validated by solving the same case study using COPRAS-G and Fuzzy TOPSIS. It was observed that the ranking was consistent in all the three methods. Alternative 2 turned out to be the best alternative followed by alternative 1 and then alternative 3. Sensitivity analysis was carried out for all the three methods including the proposed method. For the benefit type of criteria, the alternative ranking remained the same i.e. A1 > A2 > A3. But for cost type criteria there was change in the ranking for fuzzy TOPSIS. Alternative 2 still remained the best alternative but there was change in position between alternative 1 and alternative 3. Similarly for cost type criteria under proposed method and COPRAS-G it was observed that alternative 2 was the best followed by alternative 1 and then alternative 2. In the cost type constraint, the ranking remained the same but the utility score was very close for alternative 1 and alternative 3.

The algorithmics superiority of the proposed method lies in the fact that, to get the global weightage for each alternative rating against criteria, the effect of sum of all the alternative rating is taken except for the one under consideration. The method either undermines or inflates the value of the global weight for that alternative rating based on its overall relationship with respect to the other data points. To check the superiority of proposed method with respect to other MADM methods, two most commonly used methods i.e., Fuzzy TOPSIS and COPRAS-G were used for comparison. A program was written with number of alternatives ranging from 2 to 10, number of criteria ranging from 2 to 10 and number of decision makers between 2 to 5. Random data sets were generated in linguistic form using the code and some data was taken from published papers. More than 100 numerical were solved using all the three methods i.e., Fuzzy TOPSIS, COPRAS-G and the proposed hierarchal method and alternative ranking was obtained for each of the method. Spearmen co-relation formula was used to get the co-relation coefficient. It was observed that the co-relation coefficient ranged from 0.88 to 0.91 when applied between proposed method and Fuzzy TOPSIS and proposed method and COPRAS-G. This method provides an improved solution not only in selecting best idea during idea screening phase of NPD, but also can be applied to rank alternatives in various other MADM applications. The short coming of this method is that, it involves more mathematical steps in getting the best alternative, hence the computational time is slightly more as compared to the conventional MADM method. Also, further work has to be carried out to validate the proposed method against higher number of alternatives and criteria.

Chapter 6

Modified SVNS TOPSIS and Score Function based SVNS TOPSIS method

6.1 General

New product are basically innovative products based on technological development and provides a totally different experience to the customers. A common example of this are smart phones, tablets, vaccines etc. In majority of new product development cases, historical data might not be available to go about in the decision-making process or the data available might be incomplete in nature. Hence there is always uncertainty which creeps in the decision-making process. Also, a fact about new product development is that data collection, consumer survey, sales person opinions are very critical for the success of NPD. But the collected information is mostly dependent on human judgement and opinion which can be inconsistent or misleading or incomplete in majority of the cases. Another common problem associated with new product development is the group decision making process. Since the product has to be developed from the conceptual stage, a lot many personnel are involved in the decision-making process, be it the design manager or the manufacturing manager or the production manager or even the finance or marketing manager. All of them will have a say during the conceptualisation stage although their relative importance might vary. The input they give will vary based on differences in technical backgrounds, departmental goals and constraints etc. Finally at the end all the individual preferences have to be collected and reduced to a single collective preference. Uncertainty, inconsistency are the common things which are observed during group decision making process. Even if we consider developing the new product based on competitors' data, then also there are lot of uncertainties regarding, which customer group the competitor company is targeting, what price band are they going to release their product, within what time frame are they going to release their product and so on. Although there are number of MADM methods available for new product development, not all of them are able to take care of the uncertainty, incompleteness, impreciseness and inconsistency of the data.

The problem with fuzzy system is that, they are defined with respect to membership function only and hence don't deal with the non-membership and indeterminacy function. A step ahead is the intuitionistic fuzzy set. Here the connectors are defined with respect to membership and non-membership, but nothing is talked about the indeterminacy. Neutrosophic logic can take care of the uncertainty, incompleteness, impreciseness and inconsistency in the data as it is very close to stimulating human thinking and is an extension of classic set, fuzzy set, intuitionistic fuzzy set and interval valued intuitionistic fuzzy set. The three basic components of neutrosophic sets are truth membership function, indeterminacy membership function and the falsity membership function. In new product development in particular, the decision makers are not able to have conviction in their statement in terms of degree of truth or falsity when there is lack of knowledge, lack of time, pressure. Neutrosophic logic has been compared with other well-known logical tools and stands out if there is uncertainty and vagueness in the data [183]. The most common method employing the neutrosophic logic is the SVNS TOPSIS method. The step-by-step procedure involve in the SVNS TOPSIS method involves lot of calculation and hence the computation time required is more. Also, the procedure involved in application of neutrosophic set theory is not easy to understand. Hence an attempt has been made in this chapter to provide simpler means of applying the SVNS TOPSIS method while still retaining the advantages of the method to deal with uncertainty, incompleteness, impreciseness and inconsistency of the data. Two methods have been proposed which are:

(i) Modified SVNS TOPSIS method

(ii) Score Function based SVNS TOPSIS method

These methods have the advantage of simplicity in understanding, fewer and simpler calculation and faster computational speed. An added advantage is that during the decision-making process of ranking the alternatives, all the alternative rating values of the criteria, except for the one for which the decision is being made, are taken into consideration. Both the methods are validated against the standard methods to check for their consistency.

6.2 Steps in Proposed Modified SVNS – TOPSIS

As stated earlier the modified method allows the advantage of simplicity, less computational requirement and faster speed of processing. The procedure for modified SVNS TOPSIS method is shown below:

Step 1: Identify the decision makers required for the decision-making process. Let the decision makers be represented by ‘k’. List down the attributes in form of criteria based on which decisions will be made. Let the attribute or criteria be represented by ‘n’. Define the probable alternatives. Let the alternatives be represented by ‘m’.

Step 2: Let the decision makers assign linguistic variables for each of the attribute based on their knowledge and perception. criteria weightages denoted by $\tilde{\omega}_j$. Similarly assign linguistic variables for alternative ratings with respect to each criterion and let them be represented by $\check{x}_j$. Use SVNS scale to covert linguistic variable to neutrosophic numbers.

Step 3: Get the relative weights for each of the decision makers.

Based on the linguistic data on the decision maker, get the relative weights for the decision makers. If there are 'k' decision makers and the SVN number is given by $A_t = (a_t, b_t, c_t)$, where the subscript 't' indicated the t^{th} decision maker, the relative weights for the t^{th} decision maker is given by:

$$\delta_t = \frac{a_t + b_t\left(\frac{a_t}{a_t + c_t}\right)}{\sum_{t=1}^{k} a_t + b_t\left(\frac{a_t}{a_t + c_t}\right)} \tag{6.1}$$

where $\delta t \geq 0$ and $\sum_{t=1}^{k} \delta_t = 1$

Step 4: Calculate the aggregated weightage matrix

Let $W = (w_1, w_2, \ldots, w_n)$ indicate the weights of the criteria where w_j indicates the relative importance of criterion β_j where $j=1, 2, \ldots, n$. For criteria β_j the SVN number for the t^{th} decision maker will be $wj^{(t)}=(aj^{(t)}, bj^{(t)}, cj^{(t)})$. Therefore, the final criteria weights are given by Equation 6.2.

$$w_j = \delta_1 w_j^{(1)}, \delta_2 w_j^{(2)}, \ldots\ldots, \delta_k w_j^{(k)}$$

$$= \langle\left(1 - \prod_{t=1}^{k}\left(1 - a_j^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(b_j^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(c_j^{(t)}\right)^{\delta t}\right)\rangle \tag{6.2}$$

Step 5: Calculate the aggregated alternative rating for each criterion matrix.

Let the aggregated alternative ratings against each criterion matrix be represented by D.

D is given by $D = \sum_{t=1}^{k} \delta_t D^t$

where $D = d_{ij} = (u_{ij}, r_{ij}, v_{ij})$

$$\text{and } d_{ij} = \left(1 - \prod_{t=1}^{k}\left(1 - u_{ij}^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(r_{ij}^{(t)}\right)^{\delta t}, \prod_{t=1}^{k}\left(v_{ij}^{(t)}\right)^{\delta t}\right) \tag{6.3}$$

Hence D can be expressed as,

$$D = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{12} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2n} \\ \vdots & & & \vdots \\ \rho_{m1} & \rho_{m2} & \cdots & \rho_{mn} \end{pmatrix} \tag{6.4}$$

where ρij (i=1, 2, …, m; j=1, 2, …, n) denotes a single value neutrosophic number.

Step 6: Identify the SVNS Positive Ideal Solution ($\check{v}_j^+$). Calculate the separation measures for each alternative rating from the SVN positive ideal solution using Equation 6.5 and form the alternative rating matrix (l_{ij}). Similarly calculate separation measure for criterion weightages from the SVN positive ideal solution using Equation 6.6 to get the criteria weightage vector (u_j).

$$l_{ij} = \sum_{j=1}^{n} d_v\left(dij, \check{v}_j^+\right) \tag{6.5}$$

$$u_j = \sum_{j=1}^{n} d_v\left(w_j, \check{v}_j^+\right) \tag{6.6}$$

Here d_v(.,.) represents the distance between two SVNS numbers using the vertex method. According to the vertex method, the distance between SVNS numbers D_1 (a_1, a_2, a_3) and D_2 (b_1, b_2, b_3) is calculated using Equation 6.7.

$$(D_1, D_2) = \sqrt{\frac{1}{3}\left[(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2\right]} \tag{6.7}$$

Step 7: Carry out the normalisation of the criteria weights.

$$u_j^M = \frac{w_j}{\sum_{j=i}^{n} w_j} \tag{6.8}$$

Step 8: For the benefit type criteria, the alternative rating value l_{ij}^M will remain the same as per Equation 6.9, whereas for the cost type criteria the alternative rating value l_{ij}^M is given by Equation 6.10.

$$l_{ij}^M = d_{ij} \text{ (Benefit criteria)} \tag{6.9}$$

$$l_{ij}^M = 1 - d_{ij} \text{ (Cost criteria)} \tag{6.10}$$

Step 9: Let the elements of the criteria weightage be first level factors (u_j^M) and the elements of the alternative rating second level factors (l_{ij}^M). For each criterion (first level factor), arrange under it the alternative rating values against that criterion itself. Do this for all criteria so as to get a hierarchical structure.

Step 10: Transform the relative value associated with each alternative rating in to the final value (W_{ij}) by using Equation 6.11.

$$W_{ij} = \frac{u_j^M * l_{ij}^M}{\sum l_{ij}^M} \qquad (6.11)$$

i = 1, 2, 3 ………….. m
j = 1, 2, 3……………n
k = 1, 2, 3……………m and k ≠ j

Step 11: The alternative ranking (Ai) is done by adding up all the final values for alternative as shown in Equation 6.12. The highest value of Ai is the best alternative.

$$\mathrm{A_i} = \sum_{i=}^{n} W_{ij}^N \text{ for j= 1, 2,……..n} \qquad (6.12)$$

Step 12: Calculate the quantitative utility for all alternatives (Ui) using equation 6.13. The alternative with the highest value is the best alternative.

$$\mathrm{U_i} = \left[\frac{\mathrm{A_i}}{\mathrm{A_{imax}}}\right] * 100\% \qquad (6.13)$$

where A_{imax} is maximum value of A_i.

6.3 Validation of Proposed Method using a Case Study

The case study which was considered in Section 5.4 is taken again for validation of the modified SVNS TOPSIS method. The problem consists of three decision makers, five criteria and three alternatives. Here all the decision makers are having equal say in the decision-making process and hence each of them has equal weightage. The weightage for each decision maker is 0.333.

Step 1: The problem consists of three decision makers, five criteria and three alternatives. Here all the decision makers are having equal say in the decision-making process and hence each of them has equal weightage. The weightage for each decision maker is 0.333.

Step 2: Table 5.2 provides the linguistic variables assigned by the decision makers to each criterion. Similarly, Table 5.3 provides the linguistic variables for alternative ratings against each criterion. SVNS scale is used to covert linguistic variable to neutrosophic numbers. Table 6.1 shows the SVNS Table for alternative ratings. Table 6. 2 shows the SVNS Table for criteria weights.

Table 6.1: SVNS Table for alternative ratings.

	A1								
C1	0.75	0.25	0.20	0.75	0.25	0.20	0.75	0.25	0.20
C2	0.50	0.50	0.50	0.75	0.25	0.20	0.75	0.25	0.20
C3	0.90	0.10	0.10	0.75	0.25	0.20	0.75	0.25	0.20
C4	0.75	0.25	0.20	0.75	0.25	0.20	0.50	0.50	0.50
C5	0.90	0.10	0.10	0.75	0.25	0.20	0.35	0.75	0.80

	A2								
C1	0.75	0.25	0.20	0.90	0.10	0.10	0.50	0.50	0.50
C2	0.75	0.25	0.20	0.90	0.10	0.10	0.75	0.25	0.20
C3	0.90	0.10	0.10	0.75	0.25	0.20	0.50	0.50	0.50
C4	0.75	0.25	0.20	0.75	0.25	0.20	0.75	0.25	0.20
C5	0.75	0.25	0.20	0.75	0.25	0.20	0.50	0.50	0.50

	A3								
C1	0.75	0.25	0.20	0.75	0.25	0.20	0.50	0.50	0.50
C2	0.50	0.50	0.50	0.50	0.50	0.50	0.75	0.25	0.20
C3	0.75	0.25	0.20	0.75	0.25	0.20	0.75	0.25	0.20
C4	0.75	0.25	0.20	0.50	0.50	0.50	0.75	0.25	0.20
C5	0.75	0.25	0.20	0.50	0.50	0.50	0.35	0.75	0.80

Table 6.2: SVNS Table for criteria weights.

Criteria	DM1		0.333	DM2		0.333	DM3		0.333
C1	0.9	0.1	0.1	0.75	0.25	0.2	0.75	0.25	0.2
C2	0.75	0.25	0.2	0.75	0.25	0.2	0.75	0.25	0.2
C3	0.5	0.5	0.5	0.35	0.75	0.8	0.9	0.1	0.1
C4	0.75	0.25	0.2	0.5	0.5	0.5	0.5	0.5	0.5
C5	0.75	0.25	0.2	0.5	0.5	0.5	0.9	0.1	0.1

Step 3: Since all the decision makers have equal say in the decision-making process, the relative weights among the decision makers will remain the same i.e., $\delta_t = 0.33$.

Step 4: The aggregated weightage matrix is obtained using Equation 6.2. The values of the aggregated weightage matrix are shown in Table 6.3.

Table 6.3: Aggregated weightage SVNS matrix.

Criteria	Weightage		
C1	0.815	0.185	0.159
C2	0.750	0.250	0.200
C3	0.681	0.335	0.342
C4	0.603	0.397	0.369
C5	0.768	0.232	0.216

Step 5 The aggregated alternative rating is obtained using Equation 6.3. The values of the aggregated weightage matrix are shown in Table 6.4.

Table 6.4: Aggregated alternative rating SVNS matrix.

	A1			A2			A3		
C1	0.750	0.250	0.200	0.768	0.232	0.216	0.685	0.315	0.272
C2	0.685	0.315	0.272	0.815	0.185	0.159	0.603	0.397	0.369
C3	0.815	0.185	0.159	0.768	0.232	0.216	0.750	0.250	0.200
C4	0.685	0.315	0.272	0.750	0.250	0.200	0.685	0.315	0.272
C5	0.746	0.266	0.252	0.685	0.315	0.272	0.567	0.455	0.431

Step 6: The SVN PIS consists of all of best values attainable for the criteria. In this case the truth membership function will be 1, the indeterminacy function will be 1 and the falsity function will be 1. The SVN PIS is taken as: $\breve{v}_j^+$ = (1.000, 1.000, 1.000). Calculate the separation measures for criterion weightages from the SVN positive ideal solution using Equation 6.7 as shown in Table 6.5 and calculate the separation measures for each alternative rating from the SVN positive ideal solution using Equation 6.7 as shown in Table 6.6.

Table 6.5: Separation measures for criterion weightages from the SVN PIS.

Criteria weightages	
C1	0.685
C2	0.649
C3	0.571
C4	0.554
C5	0.648

Table 6.6: Separation measures for each alternative rating from the SVN PIS.

	A1	A2	A3
C1	0.649	0.648	0.605
C2	0.605	0.685	0.554
C3	0.685	0.648	0.649
C4	0.605	0.649	0.605
C5	0.622	0.605	0.519

Step 7: The normalised criteria weight matrix for SVNS is shown in Table 6.7 so that sum of all the weightages add up to 1.

Table 6.7: Normalised criteria weight matrix for SVNS.

Criteria weightages	
C1	0.220
C2	0.209

C3	0.184
C4	0.178
C5	0.209

Step 8: Since criteria C1, C2, C4 and C5 are beneficial type criteria their values will remain the same, whereas for the non-beneficial criteria C3 the values are a calculated as per Equation 6.10. The final alternative rating matrix is shown by Table 6.8.

Table 6.8: Final alternative rating matrix.

	A1	A2	A3
C1	0.649	0.648	0.605
C2	0.605	0.685	0.554
C3	0.315	0.352	0.351
C4	0.605	0.649	0.605
C5	0.622	0.605	0.519

Steps 9 and 10: Arrange the data in a hierarchical manner as explained in step 9 and find the final values for the alternative ratings against each criterion using Equation 6.11.

Table 6.9: Final values for the alternative ratings against each criterion.

Criteria weightage		Alternative values	Final alternative rating values	Normalised values	Alternative
C1	0.220	0.649	0.022	0.087	A1
		0.648	0.022	0.086	A2
		0.605	0.021	0.081	A3
C2	0.209	0.605	0.019	0.076	A1
		0.685	0.022	0.086	A2
		0.554	0.018	0.069	A3
C3	0.184	0.315	0.008	0.031	A1
		0.352	0.009	0.035	A2

		0.351	0.009	0.034	A3
C4	0.178	0.605	0.017	0.065	A1
		0.649	0.018	0.070	A2
		0.605	0.017	0.065	A3
C5	0.209	0.622	0.020	0.077	A1
		0.605	0.019	0.075	A2
		0.519	0.016	0.064	A3
		8.370	0.255	1.000	

Steps 11 and 12: Equation 6.12 is used to get the alternative ranking (Ai) based on the score available in Table 6.9. The values of the respective alternatives are added up for making the decision. Table 6.10 represents the alternative scores. The utility values are calculate using equation 6.13 and are reflected in Table 6.10.

Table 6.10: Alternative scores and utility values.

Alternatives	Alternative values	Utility values	Ranking
A1	0.335	95.444	2
A2	0.351	100	1
A3	0.314	89.299	3

The alternative 2 turns out to be the best alternative, followed by alternative 1 and then alternative 3. The same result was obtained when this case study was solved in chapter 5 using proposed hierarchical method, Fuzzy TOPSIS and COPRAS-G. It was also observed that utility values were lying in the same range. Figure 6.1 shows the alternative ranking using Modified SVNS TOPSIS.

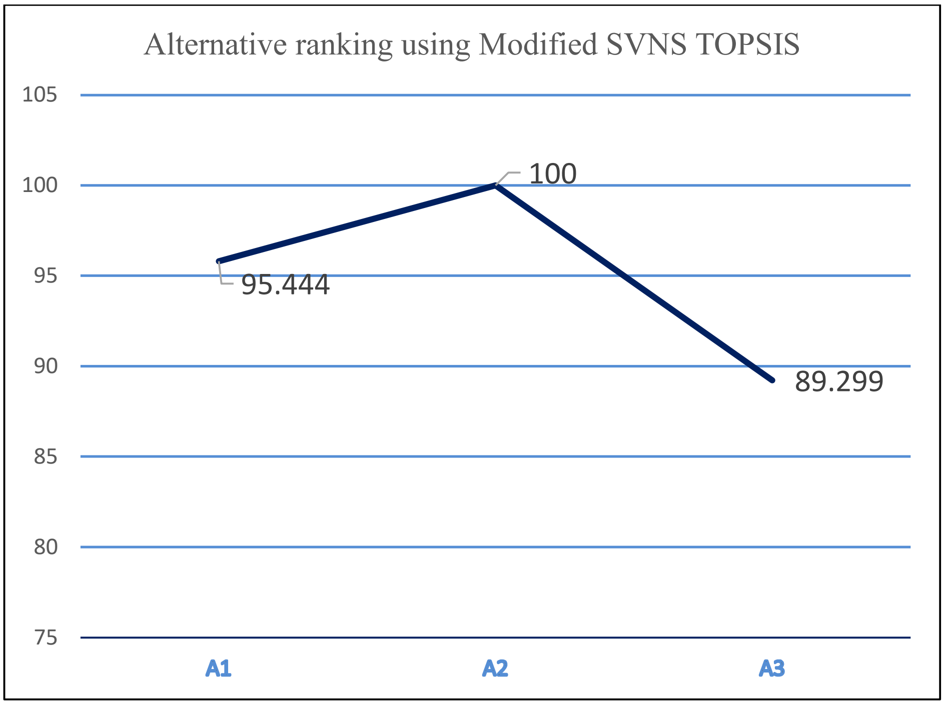

Figure 6.1: Alternative ranking using Modified SVNS TOPSIS.

6.4 Sensitivity Analysis on Modified SVNS TOPSIS Method

In the proposed method since we use the neutrosophic scale, the highest single value neutrosophic number is (0.9, 0.1, 0.1) i.e., truth function equal to 0.9, indeterminacy function equal to 0.1 and falsity function equal to 0.1 and the lowest single value neutrosophic number is (0.1, 0.9, 0.9) i.e., truth function equal to 0.1, indeterminacy function equal to 0.9 and falsity function equal to 0.9.

Case 1: Maximize criteria 1 of proposed modified SVNS TOPSIS method. In this case, criteria 1 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.11.

Table 6.11: Ranking of the alternatives by modified SVNS TOPSIS case 1.

Alternatives	Alternative values	Utility values	Ranking
A1	0.335	95.652	2
A2	0.350	100	1
A3	0.315	89.835	3

Case 2: Maximize criteria 2 of proposed modified SVNS TOPSIS method. In this case, criteria 2 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.12.

Table 6.12: Ranking of the alternatives by modified SVNS TOPSIS case 2.

Alternatives	Alternative values	Utility values	Ranking
A1	0.334	94.644	2
A2	0.353	100	1
A3	0.313	88.761	3

Case 3: Maximize criteria 3 of proposed modified SVNS TOPSIS method. In this case, criteria 3 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.13.

Table 6.13: Ranking of the alternatives by modified SVNS TOPSIS case 3.

Alternatives	Alternative values	Utility values	Ranking
A1	0.333	94.999	2
A2	0.351	100	1
A3	0.316	89.927	3

Case 4: Maximize criteria 4 of proposed modified SVNS TOPSIS method. In this case, criteria 4 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.13.

Table 6.14: Ranking of the alternatives by modified SVNS TOPSIS case 4.

Alternatives	Alternative values	Utility values	Ranking
A1	0.334	95.070	2
A2	0.351	100	1
A3	0.315	89.816	3

Case 5: Maximize criteria 5 of proposed modified SVNS TOPSIS method. In this case, criteria 5 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.15.

Table 6.15: Ranking of the alternatives by modified SVNS TOPSIS case 5.

Alternatives	Alternative values	Utility values	Ranking
A1	0.336	95.818	2
A2	0.351	100	1
A3	0.313	89.227	3

The sensitivity analysis indicates that alternative 2 is the best in all the cases followed by alternative 1 and the last preference goes to alternative 3. In case 3, where the criteria is of cost type, the final alternative ranking remains the same. The results are in line with the earlier results obtained in chapter 5. Figure 6.2 shows the outcome of the sensitivity analysis wherein alternative 2 is the best alternative. In the Figure the red colour line indicates alternative 2. Table 6.16 shows the utility values for all the 5 cases.

Table 6.16: Utility value for sensitivity analysis of modified SVNS TOPSIS method.

	C1	C2	C3	C4	C5
A1	95.65	94.64	95.00	95.07	95.82
A2	100	100	100	100	100
A3	89.84	88.76	89.93	89.82	89.23

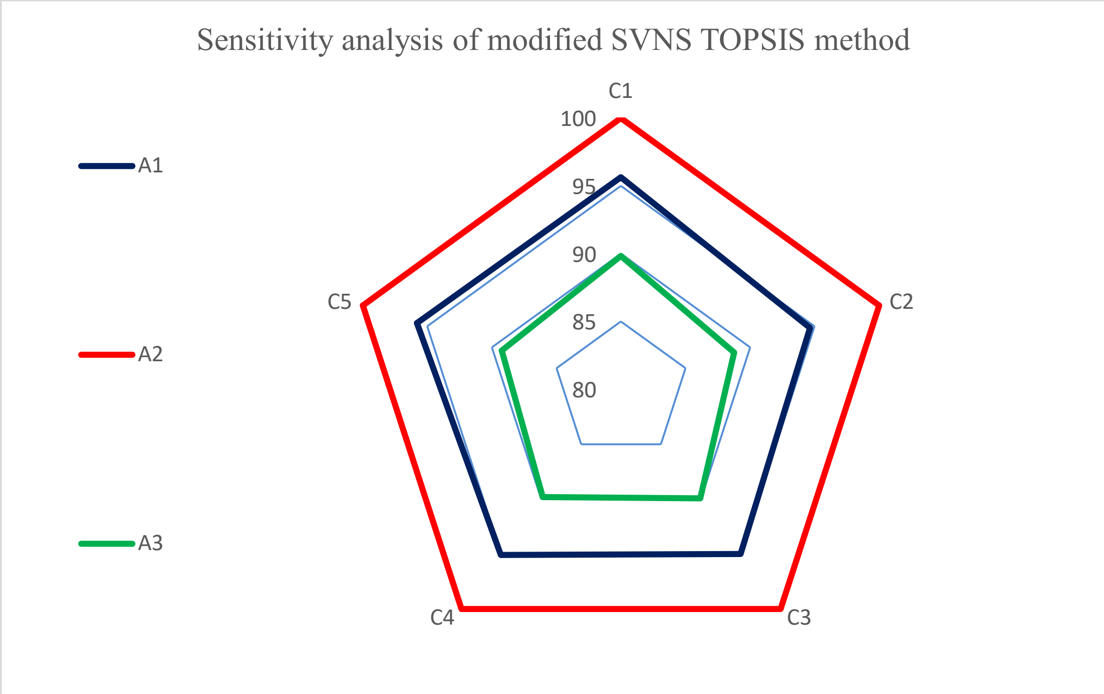

Figure 6.2: Outcome of the sensitivity analysis for modified SVNS TOPSIS method.

6.5 Score Function based SVNS TOPSIS method

The score function converts a SVN number having the truth membership, indeterminacy membership and falsity membership in to a single number which is representative of that SVN number. This single value can therefore be used in the decision-making process. If P = (p1, p2, p3) is a SVN number, then the score function S which is based on all the three-membership degree i.e., truth, indeterminacy and falsity is given by,

$$S(\mathrm{P}) = (1 + p_1 - 2\,p_2 - p_3) / 2 \tag{6.14}$$

Let any two SVN number be represented by P1 = (0.6,0.2,0.5) and P2 = (0.7,0.3,0.2). Let these two SVN number represent two alternatives on which decision has to be made. Applying formula from Equation 6.14:

$$S(\mathrm{P}_1) = \frac{1+0.6-2\times0.2-0.5}{2} = 0.35$$

$$S(\mathrm{P}_2) = \frac{1+0.7-2\times0.3-0.2}{2} = 0.50$$

In this case, we can say that alternative P2 is better than P1. As seen with the example, the score function is a representative of the original SVN number has been used in decision making process of selecting the best alternative. The score function can be either positive or negative. If we take a higher neutrosophic number then the score function will be positive whereas if we take a lower neutrosophic number the score function will be negative. Irrespective of whether it is positive or negative it still is representative of the neutrosophic number. Based on this concept of score function a method has been proposed to rank a given set of alternatives influenced by various attributes. The method involves the use of SVNS number and provides a ranking method with fewer amount of calculation as compared to the original SVNS TOPSIS method. Also as shown in the earlier method, it arranges the data in a hierarchical manner which results in a better decision-making process. Below a detained step by step procedure is given on how to use the score function for decision making process.
The procedure for Score Function based SVNS TOPSIS method is shown below:

Repeat Step 1 to Step 5 of the original SVNS TOPSIS method.

Step 6: Calculate the SVNS score function S for each d_{ij} and w_j using Equation 6.14.
Let u_j^M represent the score function for the individual criterion. Based on the number of criteria, we will get those many score function representing each criterion.
Let l_{ij}^M represent the score function for the alternative rating against each criterion.

Step 7: For the benefit type criteria, the score function for the alternative rating against each criterion l_{ij}^M will remain the same as per equation 6.5, whereas for the cost type criteria the score function for the alternative rating against each criterion l_{ij}^M is given by Equation 6.15.

$$l_{ij}^M = 1 - S(P) \qquad \text{(Cost criteria)} \tag{6.15}$$

Step 8: Let the elements of the criteria weightage be first level factors (u_j^M) and the elements of the alternative rating second level factors (l_{ij}^M). For each criterion (first level factor), arrange under it the alternative rating values against that criterion itself. Carry out this procedure for all criteria so as to get a hierarchical structure.

Step 9: Transform the relative value associated with each alternative rating in to the final value (W_{ij}) by using Equation 6.16.

$$W_{ij} = \frac{u_j^M * l_{ij}^M}{\sum l_{ij}^M} \quad (6.16)$$

i = 1, 2, 3 …………... m
j = 1, 2, 3……………n
k = 1, 2, 3……………m and k ≠ j

Step 10: The alternative ranking (Ai) is done by adding up all the final values for alternative as shown in Equation 6.17. The highest value of Ai is the best alternative.

$$\mathrm{A_i} = \sum_{i=}^{n} W_{ij}^{N} \text{ for j= 1, 2,……..n} \quad (6.17)$$

Step 11: Calculate the quantitative utility for all alternatives (Ui) using Equation 6.18. The alternative with the highest value is the best alternative.

$$\mathrm{U_i} = \left[\frac{\mathrm{A_i}}{\mathrm{A_{imax}}}\right] * 100\% \quad (6.18)$$

where A_{imax} is maximum value of A_i.

6.6 Validation of Score Function based SVNS TOPSIS Method

The case study discussed in Section 5.4 is again taken for validation of the score function based SVNS TOPSIS method. Steps 1 to 5 of the SVNS TOPSIS method are repeated to get the aggregated criteria weightage matrix and the aggregated alternative ratings against each criterion matrix. Here all the decision makers are having equal say in the decision-making process.

Step 6: The SVNS score function S for each d_{ij} and w_j is found out using equation 6.14. Table 6.17 shows the score function value for criteria weightages. Table 6.18shows the score function value for alternative rating against each criterion.

Table 6.17: Score function value for criteria weightages.

Criteria	Weightage			Score Function
C1	0.815	0.185	0.159	0.644
C2	0.750	0.250	0.200	0.524
C3	0.681	0.335	0.342	0.334
C4	0.603	0.397	0.369	0.220
C5	0.768	0.232	0.216	0.543

Table 6.18: Score function value for alternative rating against each criteria.

	Alternative 1			Score Function
C1	0.750	0.250	0.200	0.524
C2	0.685	0.315	0.272	0.391
C3	0.815	0.185	0.159	0.644
C4	0.685	0.315	0.272	0.391
C5	0.746	0.266	0.252	0.481

	Alternative 2			Score Function
C1	0.768	0.232	0.216	0.543
C2	0.815	0.185	0.159	0.644
C3	0.768	0.232	0.216	0.543
C4	0.750	0.250	0.200	0.524
C5	0.685	0.315	0.272	0.391

	Alternative 3			Score Function
C1	0.685	0.315	0.272	0.391
C2	0.603	0.397	0.369	0.220
C3	0.750	0.250	0.200	0.524
C4	0.685	0.315	0.272	0.391
C5	0.567	0.455	0.431	0.113

Step 7: For the benefit type criteria, the score function for the alternative rating against each criterion remains the same, whereas for the cost type criteria the score function for the alternative rating against each criterion l_{ij}^{M} is given by Equation 6.15. Hence the final score function for the alternative rating is given by Table 6.19.

Table 6.19: Final score function for the alternative rating.

Criteria	Alternative 1 Score function	Alternative 2 Score function	Alternative 3 Score function
C1	0.524	0.543	0.391
C2	0.391	0.644	0.220
C3	0.356	0.457	0.476
C4	0.391	0.524	0.391
C5	0.481	0.391	0.113

Steps 8 and 9: Arrange the data in a hierarchical manner as explained in step 8 and find the final values for the alternative ratings against each criterion using Equation 6.16. Refer Table 6.20.

Table 6.20: Final values for the alternative ratings against each criterion.

<table>
<tr><th colspan="2">Criteria weightage</th><th>Alternative values</th><th>Final alternative rating values</th><th>Normalised values</th><th>Alternative</th></tr>
<tr><td rowspan="3">C1</td><td rowspan="3">0.644</td><td>0.524</td><td>0.070</td><td>0.123</td><td>A1</td></tr>
<tr><td>0.543</td><td>0.072</td><td>0.127</td><td>A2</td></tr>
<tr><td>0.391</td><td>0.052</td><td>0.091</td><td>A3</td></tr>
<tr><td rowspan="3">C2</td><td rowspan="3">0.524</td><td>0.391</td><td>0.041</td><td>0.071</td><td>A1</td></tr>
<tr><td>0.644</td><td>0.067</td><td>0.118</td><td>A2</td></tr>
<tr><td>0.220</td><td>0.023</td><td>0.040</td><td>A3</td></tr>
<tr><td rowspan="3">C3</td><td rowspan="3">0.334</td><td>0.356</td><td>0.024</td><td>0.042</td><td>A1</td></tr>
<tr><td>0.457</td><td>0.030</td><td>0.054</td><td>A2</td></tr>
<tr><td>0.476</td><td>0.032</td><td>0.056</td><td>A3</td></tr>
<tr><td rowspan="2">C4</td><td rowspan="2">0.220</td><td>0.391</td><td>0.017</td><td>0.030</td><td>A1</td></tr>
<tr><td>0.524</td><td>0.023</td><td>0.041</td><td>A2</td></tr>
</table>

		0.391	0.017	0.030	A3
C5	0.543	0.481	0.049	0.087	A1
		0.391	0.040	0.070	A2
		0.113	0.012	0.020	A3
		6.293	0.569	1.000	

Steps 10 and 11: Equation 6.17 is used to get the alternative ranking (Ai) based on the score available in Table 6.20 The values of the respective alternatives are added up for making the decision. Table 6.21 represents the alternative scores. The utility values are calculate using Equation 6.18 and are reflected in Table 6.21.

Table 6.21: Alternative scores and utility values for score function-based method.

Alternatives	Alternative values	Utility values	Ranking
A1	0.383	93.511	2
A2	0.409	100	1
A3	0.358	87.482	3

Again, it is observed that the alternative 2 is the best alternative. Second best alternative is A1 and the last choice should be alternative 3. The result of this method and the other methods have remained the same. Figure 6.3 shoes the alternative ranking with the score function-based method.

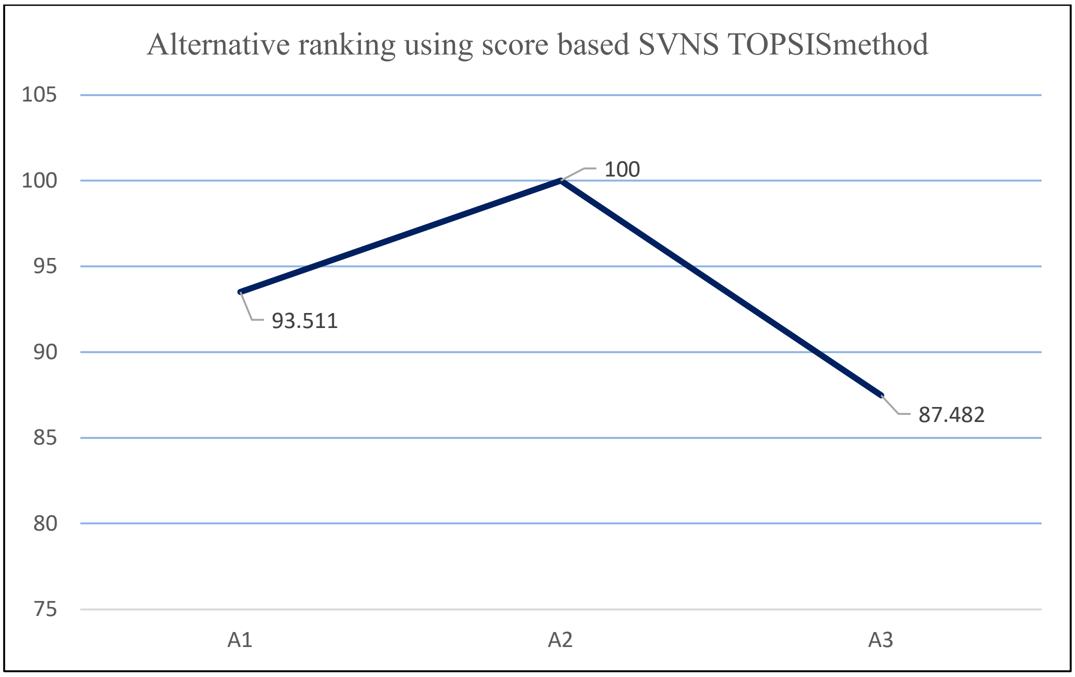

Figure 6.3: Alternative ranking using score based SVNS TOPSIS method.

6.7 Sensitivity Analysis on Score Function based SVNS TOPSIS Method

In the proposed Score Function based SVNS TOPSIS method the highest single value neutrosophic number is (0.9, 0.1, 0.1) and the lowest single value neutrosophic number is (0.1, 0.9, 0.9).

Case 1: Maximize criteria 1 of score function based SVNS TOPSIS method. In this case, criteria 1 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.22.

Table 6.22: Ranking of the alternatives by score function-based method case 1.

Alternatives	Alternative values	Utility values	Ranking
A1	0.383	86.619	2
A2	0.442	100	1
A3	0.364	82.375	3

Case 2: Maximize criteria 2 of score function based SVNS TOPSIS method. In this case, criteria 2 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.23.

Table 6.23: Ranking of the alternatives by score function-based case 2.

Alternatives	Alternative values	Utility values	Ranking
A1	0.337	94.271	2
A2	0.357	100	1
A3	0.306	85.722	3

Case 3: Maximize criteria 3 of score function based SVNS TOPSIS method. In this case, criteria 3 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.24.

Table 6.24: Ranking of the alternatives by score function-based case 3.

Alternatives	Alternative values	Utility values	Ranking
A1	0.361	82.525	2
A2	0.437	100	1
A3	0.341	78.048	3

Case 4: Maximize criteria 4 of score function based SVNS TOPSIS method. In this case, criteria 4 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.25.

Table 6.25: Ranking of the alternatives by score function-based case 4.

Alternatives	Alternative values	Utility values	Ranking
A1	0.388	94.715	2
A2	0.410	100	1
A3	0.352	85.880	3

Case 5: Maximize criteria 5 of score function based SVNS TOPSIS method. In this case, criteria 5 is assigned the neutrosophic number (0.9, 0.1, 0.1) and rest all the other criteria weightages are assigned neutrosophic number (0.1, 0.9, 0.9). The alternative coefficient value, utility coefficient value and the ranking of the alternatives is shown in Table 6.26.

Table 6.26: Ranking of the alternatives by score function-based case 5.

Alternatives	Alternative values	Utility values	Ranking
A1	0.377	91.928	2
A2	0.410	100	1
A3	0.343	83.562	3

The sensitivity analysis indicates that alternative 2 is the best in all the cases followed by alternative 1 and the last preference goes to alternative 3. In case 3, where the criteria is of cost type, the final alternative ranking remains the same. The results are in line with the earlier results obtained in chapter 5. Figure 6.4 shows the outcome of the sensitivity analysis wherein alternative 2 is the best alternative. In the Figure the red colour line indicates alternative 2. Table 6.27 shows the utility values for all the 5 cases.

Table 6.27: Utility value for sensitivity analysis of score function based SVNS TOPSIS method.

	C1	C2	C3	C4	C5
A1	86.619	94.271	82.525	94.715	91.928
A2	100	100	1	100	100
A3	82.375	85.722	78.048	85.880	83.562

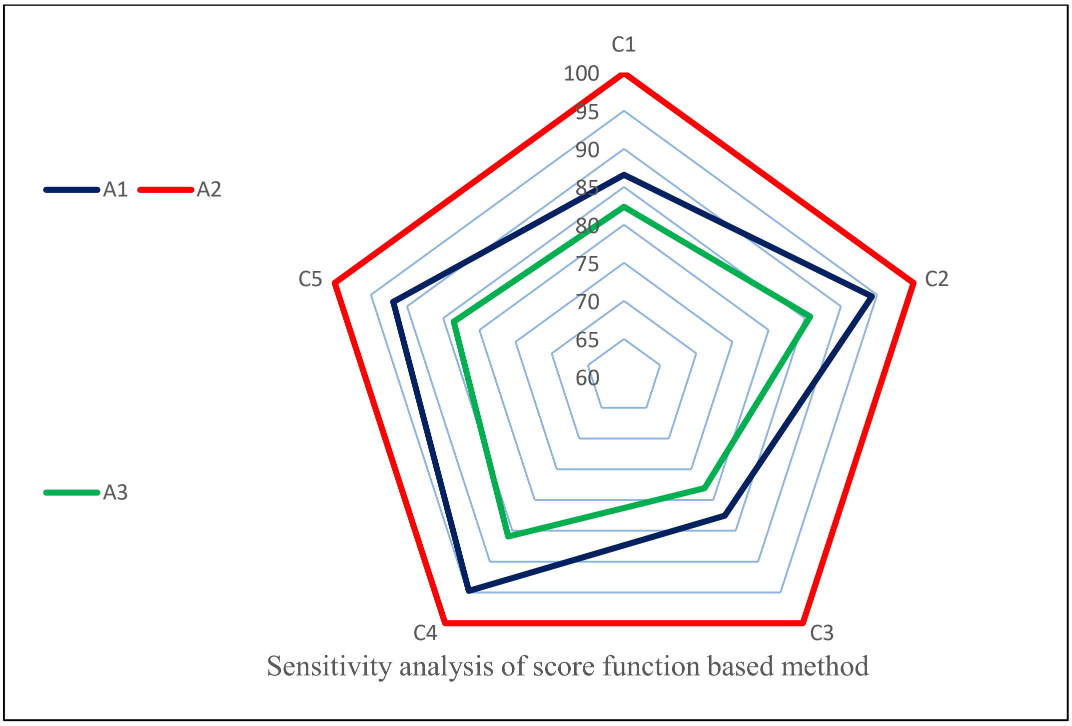

Figure 6.4: Outcome of the sensitivity analysis for score function based SVNS TOPSIS method.

6.7 Summary

Real life data, particularly data required for new product development is imprecise, incomplete, uncertain and inconsistent in nature. Neutrosophic logic with its truth, indeterminacy and falsity membership function comes very close to replicating human thinking and hence is best suited for new product development. The most commonly used method i.e., SVNS TOPSIS involves lot of computational steps. In this chapter two new methods have been proposed, which retains the advantage of the original neutrosophic logic, but at the same time results in ease of understanding and less computational speed and requirement. The first method is Modified SVNS TOPSIS method, which is based on fining the separation distance between all the neutrosophic numbers and the best positive neutrosophic number. This data is then arranged in hierarchical manner to take advantage of the structure which leads to ranking of the alternatives. The method was validated by solving an industrial example form Section 5.4. It was observed that the ranking remained the same as obtained using the proposed method, Fuzzy TOPSIS method and COPRAS-G method. Sensitivity analysis was performed to check for consistency of the data and rule out any biasness. It was observed that in all the cases the ranking remained the same. To check the superiority of proposed method with respect to other MADM methods, two most commonly used methods i.e., Fuzzy TOPSIS and COPRAS-G were used for comparison. A program was written with number of alternatives ranging from 2 to 10, number of criteria ranging from 2 to 10 and number of decision makers between 2 to 5. Random data sets were generated in linguistic form using the code and some data was taken from published papers. More than 100 numerical were solved using all the three methods i.e., Fuzzy TOPSIS, COPRAS-G and the modified SVNS TOPSIS and alternative ranking was obtained for each of the method. Spearmen co-relation formula was used to get the co-relation coefficient. It was observed that the co-relation coefficient ranged from 0.85 to 0.90 when applied between proposed modified SVNS TOPSIS and Fuzzy TOPSIS and proposed modified SVNS TOPSIS and COPRAS-G. This shows that the correlation coefficient is very high and the proposed modified SVNS TOPSIS method is consistent when compared to standard methods. This method provides an improved solution, not only in selecting best idea during idea screening phase of NPD, but also can be applied to rank alternatives in various other MADM applications. The second method was based on the score function of any neutrosophic number. A given neutrosophic number can be expressed as a single number by finding its score function. This score function is representative of that neutrosophic number. The aggregated criteria weightages and the aggregated alternative rating against each criterion were converted to a single number using the score function and the data was arranged in hierarchical form to take advantage of the hierarchical structure which provided the required ranking of the alternatives. The method was validated by solving the same problem from Section 5.4 and it was observed that the ranking remained the same. Sensitivity analysis was carried out and it was observed that the ranking remained the same and hence the results obtained using the score function-based method was stable and consistent. In both the methods alternative 2 was found to be the best alternative to go ahead for new product development. Apart from NPD, both the methods can be applied to other MADM applications. Further work has to be carried out to validate both the proposed method against higher number of alternatives and criteria.

Chapter 7

Self-Assessment Model for NPD Performance in SMEs

7.1 General

SMEs are the backbone engine for socio-economic development of a state as well the country. There are 6.5 lakhs SME units based in India contributing to the 30% of gross domestic product (GDP). These SMEs roughly employ around 46 crores people. After the agriculture sector, SMEs stand second in terms of employment of men power. As per the ministry of Micro, Small and Medium Enterprises, small enterprises are the one which can invest up to 10 crores in plant and machinery and having an annual turnover of not more than 50 crores whereas medium enterprises are the one which can invest up to 50 crores in plant and machinery and having an annual turnover of not more than 250 crores. Although the SMEs have a major contribution towards the GDP, the growth of SME's is hampered due to ineffective conventional methods of doing business, lower technological growth, lack of experienced personnel either at the technical or managerial level and restricted capital allocation for carrying out research. Inability of the government to provide innovation support system for SMEs result in a formidable challenge for developing the economy of the country. It is paradoxical to see that, although the SMEs are important for the socio-economic development of the country, there is neglect towards them and the research carried out on new product development is more towards the larger units. The SMEs have to remain competitive at both local and global level. Older study done in empirical manner by Booz [31] also does not discuss or stress on the situation in SMEs and are biased towards large units. On the other hand, 34% of the India's output in manufacturing is through SMEs. SMEs involved in manufacturing contribute towards 90% of all the industrial unit in India. The highly sophisticated and rapidly changing market demands product life cycle to be reduced to satisfy the ever-changing customer demand. For SME's the survival in the global world requires, having a knowledge intensive relation inside and outside their borders [52]. Particularly in the area of new product development, their lack of technical knowhow and other resources have to be tackled by cooperation with the external resources in and around [53]. Selecting the best possible alternative at the idea generation phase of the NPD is very critical for survival and success of the SMEs [32]. As part of manufacturing, design for manufacturability talks about actively designing of products to optimize the manufacturing process. Consideration of DFM factors during product design shorten the product life cycle minimizing production and manufacturing time, ensuring smooth flow of product, minimizing cost etc. Quality issues resulting from part interaction can be reduced by selecting better parts and proper matching of parts. The literature review points out that substantial benefits have been realized by firms, using design for manufacturability during product design or using existing product database and applying it to new product. Identifying the critical design for manufacturability factors can substantially bring improvement in the success of new product development for small and medium enterprises involved in manufacturing. The research work proposes a model for ranking critical factors affecting new product development from design for manufacturability consideration and validating the model using multi attribute decision making (MADM) methods.

7.2 Model for Critical DFM Factors

It was observed that significantly less amount of research was carried out in the area of critical design for manufacturing factors affecting NPD in SME's. Identifying the critical design for manufacturability factors can substantially bring improvement in the success of new product development for small and medium enterprises involved in manufacturing. The research work proposes a model which can take care of the literature gap identified. The model involves identifying critical global and local factors affecting NPD decision from design for manufacturability point of view. The identification of factors was done by using survey forms filled by technical top brass and academia scholar. All the global and local factors listed were then ranked using analytic hierarchical process. Cronbach alpha value was calculated to check for consistency of the data. A ranking method is proposed which allows all the local factors to be ranked on a common scale. To validate the ranking method, it was compared using standard method available. Spearmen coefficient and Karl Pearson coefficient was then calculated to validate the ranking method. The model proposes various scenario's which can help the SMEs to go ahead with the new product development. The model is illustrated with a case study of SME in the state of Goa and was validated using COPRAS-G and hybrid method involving genetic algorithm and artificial neural network. The flow chart for the proposed model is shown in Figure 7.1.

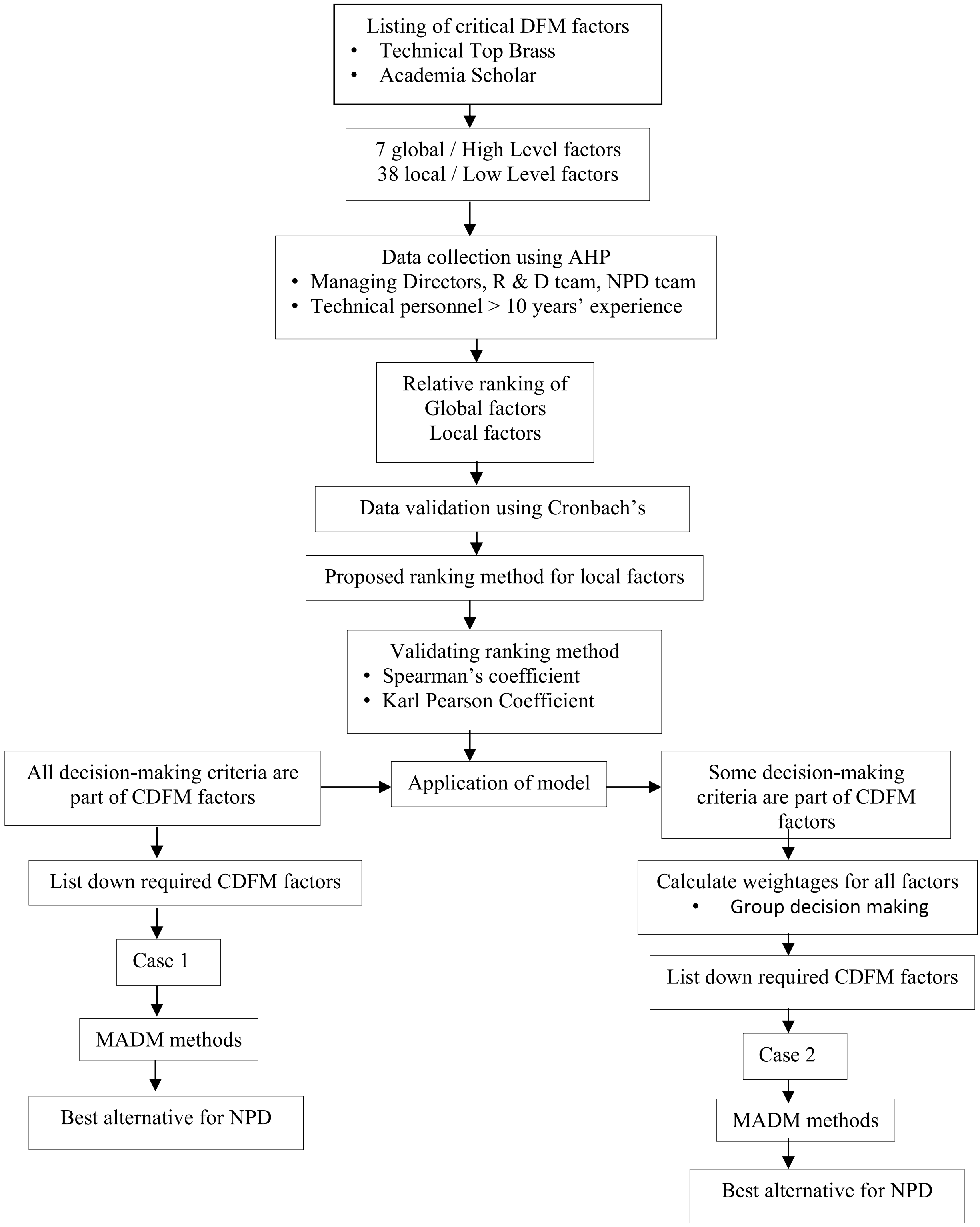

Figure 7.1: Model for critical DFM factors.

7.3 Data Collection

A gathering of technical top brass and academia scholars resulted in listing out all the factors that would affect new product development decision from design for manufacturability point of view. After a lot of deliberations all the critical factors were listed down. There were seven global or high-level factors and each high-level factor had its own list of low level or local level factors. Some of the factors are discussed below:

7.3.1 Product complexity

If the design of the product is complex, then it results in bottlenecks on the assembly line which in turn effects the time frame of the product getting launched or delivered. Also servicing of the product might not be easy.

7.3.2 Product variants

The product variants should be as minimum as possible as keeping track of suppliers, materials tools and equipment becomes challenging. To have agile manufacturing, product variants should be minimal. But on the other hand, to cater to multiple customer requirement, it is sometimes advisable to have high numbers of product variants. The trade-off between having high variants or a smaller number of variants will depend on the situation prevailing in that particular enterprise.

7.3.3 Component availability and price

The component available should have their end of life either greater than or equal to the life cycle of the product. More the number of components, difficult it becomes in keeping the track. Price of the component directly affects the product cost which in turn affects the profitability.

7.3.4 Reusable design

The concept of modular design is very important in design for manufacturability so that any changes required in the future can be made with minimal effort. Reusable design reduces design time or production time if changes are there and provides a high return of investment.

7.3.5 Managing design costs

Design cost directly corelates to the final product cost, hence effort should be made to minimize design cost by keeping rework to minimum if there are sudden design related changes. Design re-spins should be avoided as it increases the development cost, hence affecting the profit.

7.3.6 Incorporating last stage design changes

During prototype testing a lot of difficulties might come which requires changes in the original design. Design for manufacturability has to take these factors in to account so that there is no delay in the product launch schedule.

7.3.7 Production friendly design

Product design has to take in to account the available manufacturing processes, the assembly layout, so that manufacturing and assembly time can be reduced. Proper placement of mating components, better routing of components and providing enough space for placing components are some of the factors which affects the production time of the product.

7.3.8 Product quality and regulatory requirements

Product quality and regulatory requirements are very important factors for any new product development and they are specific to the industry and they should be strictly complied with. The design has to be done as per the designated frame work so that every certification requirement is satisfied.

7.3.9 Quality standard framework

The success of any product is determined by the quality of that product. DFM should ensure that any changes made in the design should not affect the quality and performance of the end product.

Once the list of factors was made ready, a list of 252 personnel from the state of Goa mainly consisting of managing directors, research and development people, new product development team members, technical people related to design, manufacturing and production having more than 15 year of experience was created. Face to face interviews using paper-based questionnaires was carried out for 20 to 30 minutes with each individual. The process took six months to complete.

7.4 Data Validation of Design and Manufacturing Personnel

It was seen during literature review, that design people were given more consideration, when it comes to new product development. But in this model, since new product development process involved design for manufacturability factors for decision making, it was decided to take people from both group in decision making. Design people tend to be more biased towards the design factors, similarly manufacturing people are more biased towards the manufacturing factors. Hence to check for the consistency of the opinion between the design and manufacturing personnel, an equal group of 100 design personnel and 100 manufacturing personnel was created and the ranking for each of the higher and lower-level factors was carried out using the AHP method for both the groups. At the global level the spearmen coefficient turned out to be 0.607 which showed a moderate relation as seen in Table 7.1. It was observed that there was difference in ranking for the local factors under the following global factors: production friendly design, product complexity, product variants/ add-ons, managing cost and reusable design as seen in Table 7.2, Table 7.3, Table 7.4, Table 7.6, Table 7.7, whereas for local factors under the quality standard framework and component availability and price the ranking remained the same as seen in Table 7.5 and Table 7.8. It was found that for production friendly design the spearmen coefficient was 0.714, for product complexity the spearmen coefficient was 0.6 showing a moderate corelation, for product variants/ add-ons the spearmen coefficient was 0.8, for managing cost the spearmen coefficient was 0.78, for reusable design the spearmen coefficient was 0.3 showing a very weak corelation, for component availability and price and quality standard frame work the spearmen coefficient was 1 indicating a very high corelation. One thing to be noted was that both design and manufacturing personnel gave equal importance to quality as was evident from the high value of corelation. Using the ranking method proposed by Gaonkar [215], all the 38 factors were than ranked on a common platform for both the groups. Table 7.9 shows the ranking obtained for the local factors on a common platform with respect to data taken from design people. Similarly, Table 7.10 shows the ranking obtained for the local factors on a common platform with respect to data taken from manufacturing people. The Spearmen corelation formula was applied to get the corelation coefficient for data in Table 7.11. The corelation coefficient turned out to be 0.593 which was a moderate corelation. Taking opinion of only design personnel or only manufacturing personnel in getting the weightages for the 37 factors would not serve the purpose. Hence it is required that the study to get the ranking and weightages of all the global and local factors have to be done in combined manner.

Table 7.1: Ranking of global factors based on design and manufacturing data.

	Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Production friendly design	0.097	6	0.154	4	2	4	0.607
Product complexity	0.132	3	0.119	5	-2	4	
Product variants / add-ons	0.092	7	0.088	6	1	1	
Component availability and price	0.108	5	0.085	7	-2	4	
Managing cost	0.124	4	0.168	2	2	4	
Reusable design	0.213	2	0.221	1	1	1	
Quality standard framework	0.235	1	0.164	3	-2	4	

Table 7.2: Ranking of production friendly design factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Production friendly design	Production feasibility	0.142	4	0.226	2	2	4	0.714
	Product launch schedules	0.130	5	0.116	5	0	0	
	Prototype testing	0.073	6	0.046	6	0	0	
	Placement and routing of cables	0.243	1	0.206	3	-2	4	
	Incorporate last minute design changes	0.170	3	0.143	4	-1	1	
	Minimum production assembly time	0.242	2	0.263	1	1	1	

Table 7.3: Ranking of product complexity factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Product complexity	Ease of manufacturing	0.159	4	0.212	2	2	4	0.6
	Ease of assembly	0.269	1	0.273	1	0	0	

	Assembly bottlenecks	0.140	5	0.152	4	1	1	
	Manufacturing life cycle	0.206	2	0.148	5	-3	9	
	Assembly life cycle	0.187	3	0.169	3	0	0	
	Material handling	0.039	6	0.045	6	0	0	

Table 7.4: Ranking of Product variants / add-ons factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Product variants / add-ons	Conforming to various international standards	0.201	3	0.204	3	0	0	0.8
	Functional add-ons	0.153	4	0.141	4	0	0	
	Aesthetics / styling	0.291	2	0.329	1	1	1	
	Product pride	0.355	1	0.326	2	-1	1	

Table 7.5: Ranking of Component availability and price factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficien t
Component availability and price	In-house capability	0.209	2	0.253	2	0	0	1
	FERA	0.038	6	0.029	6	0	0	
	Vendor support and flexibility	0.277	1	0.284	1	0	0	
	Lead time	0.208	3	0.191	3	0	0	
	Number of 'A' class items	0.087	5	0.079	5	0	0	
	Vendor component monopoly	0.182	4	0.164	4	0	0	

Table 7.6: Ranking of Managing cost factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Managing cost	Equipment development cost	0.099	7	0.084	7	0	0	0.785
	Tooling development cost	0.139	3	0.102	6	-3	9	
	Manpower training cost	0.111	6	0.109	5	1	1	
	Raw material cost	0.136	4	0.139	3	1	1	
	Material handling cost	0.119	5	0.117	4	1	1	
	Minimum rejects	0.192	2	0.222	2	0	0	
	Minimum rework	0.202	1	0.227	1	0	0	

Table 7.7: Ranking of Reusable design factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Reusable design	Modular product design	0.236	3	0.149	4	-1	1	0.3
	Standardisation	0.242	1	0.181	3	-2	4	
	Interchangeability	0.240	2	0.258	2	0	0	
	Modification of existing product	0.073	5	0.115	5	0	0	
	Add on to existing product	0.209	4	0.297	1	3	9	

Table 7.8: Ranking of Quality standard framework factors based on design and manufacturing data.

		Design ranking		Manufacturing ranking		d	d^2	Spearmen coefficient
Quality standard framework	Industry regulatory requirement	0.220	3	0.192	3	0	0	1
	Design as per designated framework	0.178	4	0.160	4	0	0	
	Quality in design	0.380	1	0.414	1	0	0	
	Production performance impact due to change	0.222	2	0.234	2	0	0	

Table 7.9: Ranking of all local factors based on data from design personnel.

Lower-Level Factors	Weights of lower-level factors	Global Weights	Normalised Weights	Ranking (Design)
Production feasibility	0.142	0.0893	0.0155	30
Product launch schedules	0.130	0.0817	0.0142	31
Prototype testing	0.073	0.0461	0.0080	36
Placement and routing of cables	0.243	0.1530	0.0265	17
Incorporate last minute design changes	0.170	0.1071	0.0185	26
Minimum production assembly time	0.242	0.1523	0.0264	18
Ease of manufacturing	0.159	0.1463	0.0253	19
Ease of assembly	0.269	0.2478	0.0429	5
Assembly bottlenecks	0.140	0.1295	0.0224	23
Manufacturing life cycle	0.206	0.1902	0.0330	10
Assembly life cycle	0.187	0.1726	0.0299	12
Material handling	0.039	0.0355	0.0062	37
Conforming to various international standards	0.201	0.0776	0.0134	32
Functional addons	0.153	0.0590	0.0102	35
Aesthetics / styling	0.291	0.1123	0.0194	25
Product pride	0.355	0.1371	0.0237	21
In house capability	0.209	0.1627	0.0282	14
FERA	0.038	0.0295	0.0051	38
Vendor support and flexibility	0.277	0.2156	0.0373	9
Lead time	0.208	0.1623	0.0281	15
Number of 'A' class items	0.087	0.0679	0.0118	34
Vendor component monopoly	0.182	0.1416	0.0245	20
Equipment development cost	0.112	0.0975	0.0169	29
Tooling development cost	0.152	0.1325	0.0229	22
Manpower training cost	0.113	0.0984	0.0170	28
Raw material cost	0.135	0.1179	0.0204	24
Material handling cost	0.119	0.1042	0.0180	27
Minimum rejects	0.179	0.1561	0.0270	16
Minimum rework	0.190	0.1658	0.0287	13
Modular product design	0.260	0.3121	0.0541	3
Standardisation	0.263	0.3168	0.0549	2
Interchangeability	0.234	0.2816	0.0488	4
Modification of existing product	0.059	0.0705	0.0122	33
Add on to existing product	0.184	0.2215	0.0384	6
Industry regulatory requirement	0.220	0.2158	0.0374	8
Design as per designated framework	0.178	0.1751	0.0303	11
Quality in design	0.380	0.3726	0.0645	1
Production performance impact due to change	0.222	0.2181	0.0378	7

Table 7.10: Ranking of all local factors based on data from manufacturing personnel.

Lower-Level Factors	Weights of lower-level factors	Global Weights	Normalised Weights	Ranking (Manufacturing)
Production feasibility	0.226	0.2415	0.0401	7
Product launch schedules	0.116	0.1235	0.0205	26
Prototype testing	0.046	0.0491	0.0082	36
Placement and routing of cables	0.206	0.2198	0.0365	9
Incorporate last minute design changes	0.143	0.1530	0.0254	17
Minimum production assembly time	0.263	0.2814	0.0467	5
Ease of manufacturing	0.212	0.1726	0.0286	13
Ease of assembly	0.273	0.2226	0.0369	8
Assembly bottlenecks	0.152	0.1239	0.0206	25
Manufacturing life cycle	0.148	0.1210	0.0201	29
Assembly life cycle	0.169	0.1378	0.0229	19
Material handling	0.045	0.0370	0.0061	37
Conforming to various international standards	0.204	0.0762	0.0126	33
Functional addons	0.141	0.0528	0.0088	34
Aesthetics / styling	0.329	0.1230	0.0204	27
Product pride	0.326	0.1217	0.0202	28
In house capability	0.253	0.1649	0.0274	15
FERA	0.029	0.0186	0.0031	38
Vendor support and flexibility	0.284	0.1851	0.0307	11
Lead time	0.191	0.1241	0.0206	24
Number of 'A' class items	0.079	0.0517	0.0086	35
Vendor component monopoly	0.164	0.1067	0.0177	31
Equipment development cost	0.084	0.1048	0.0174	32
Tooling development cost	0.102	0.1268	0.0210	23
Manpower training cost	0.109	0.1354	0.0225	20
Raw material cost	0.139	0.1723	0.0286	14
Material handling cost	0.117	0.1460	0.0242	18
Minimum rejects	0.222	0.2761	0.0458	6
Minimum rework	0.227	0.2820	0.0468	4
Modular product design	0.149	0.1754	0.0291	12
Standardisation	0.181	0.2122	0.0352	10
Interchangeability	0.258	0.3027	0.0502	2
Modification of existing product	0.115	0.1353	0.0224	21
Add on to existing product	0.297	0.3484	0.0578	1
Industry regulatory requirement	0.192	0.1346	0.0223	22
Design as per designated framework	0.160	0.1117	0.0185	30
Quality in design	0.414	0.2901	0.0481	3
Production performance impact due to change	0.234	0.1641	0.0272	16

Table 7.11: Difference in ranking based on data from design and manufacturing personnel.

Lower-Level Factors	Design ranking	Manufacturing ranking	Difference in ranking
Production feasibility	30	7	23
Product launch schedules	31	26	5
Prototype testing	36	36	0
Placement and routing of cables	17	9	8
Incorporate last minute design changes	26	17	9
Minimum production assembly time	18	5	13
Ease of manufacturing	19	13	6
Ease of assembly	5	8	-3
Assembly bottlenecks	23	25	-2
Manufacturing life cycle	10	29	-19
Assembly life cycle	12	19	-7
Material handling	37	37	0
Conforming to various international standards	32	33	-1
Functional addons	35	34	1
Aesthetics / styling	25	27	-2
Product pride	21	28	-7
In house capability	14	15	-1
FERA	38	38	0
Vendor support and flexibility	9	11	-2
Lead time	15	24	-9
Number of 'A' class items	34	35	-1
Vendor component monopoly	20	31	-11
Equipment development cost	29	32	-3
Tooling development cost	22	23	-1
Manpower training cost	28	20	8
Raw material cost	24	14	10
Material handling cost	27	18	9
Minimum rejects	16	6	10
Minimum rework	13	4	9
Modular product design	3	12	-9
Standardisation	2	10	-8
Interchangeability	4	2	2
Modification of existing product	33	21	12
Add on to existing product	6	1	5
Industry regulatory requirement	8	22	-14
Design as per designated framework	11	30	-19
Quality in design	1	3	-2
Production performance impact due to change	7	16	-9

7.5 Ranking of Global and Local Factors using AHP

Once it is established that data had to be taken collectively from design and manufacturing personnel, each individual was told to rate the global and the local factors from 1 to 9 using the pair wise comparison method of AHP. Table 7.12 represents the list of global or high-level factor and local or low-level factors. Table 7.13 shows the relative ranking of the global or high-level factors. Table 7.14 shows the relative ranking of the low-level factor under production friendly design. Table 7.15 shows the relative ranking of the low-level factor under product complexity. Table 7.16 shows the relative ranking of the low-level factor under product variants / add-ons. Table 7.17 shows the relative ranking of the low-level factor under component availability and price. Table 7.18 shows the relative ranking of the low-level factor under managing design cost. Table 7.19 shows the relative ranking of the low-level factor under reusable design. Table 7.20 shows the relative ranking of the low-level factor under quality standard framework. From Table 7.14 it is observed that reusable design had the highest ranking among the global factors followed by quality standard framework. Ease of assembly and ease of manufacturing were the top contenders under product complexity. The make in India concept propagated by the Prime Minister of India is well reflected in Table 7.17, with product pride having the highest ranking. Since most of the SME's do not deal with import of raw material, Foreign Exchange Regulation Act (FERA) has taken a back seat in the ranking as seen in Table 7.18. In Table 7.20, add-on to existing product has better ratings since it is a core factors in decision making from DFM consideration.

Table 7.12: List of global or high-level factor and local or low-level factors.

Production friendly design (C1)	Product complexity (C2)	Product variants / add-ons (C3)	Component availability and price (C4)
C11- Production feasibility	C21 - Ease of manufacture	C31 - Conforming to various international standards	C41 – In-house capability
C12- Product launch schedules	C22 - Ease of assembly	C32 - Functional add-ons	C42 – FERA (Foreign exchange regulation act)
C13- Prototype testing	C23 - Assembly bottlenecks	C33 - Aesthetic/ styling	C43 - Vendor support and flexibility
C14- Placement and routing	C24 - Manufacturing life cycle	C34 - Product pride	C44 - Lead time
C15 - Last minute design change	C25 - Assembly life cycle		C45 - Number of 'A' class items

C16 - Min. production assembly time	C26 - Material handling		C46 - Vendor component monopoly

Managing design cost (C5)	Reusable design (C6)	Quality standard framework (C7)
C51 - Equipment development cost	C61 - Modular product design	C71 - Industry regulatory requirements
C52 - Tooling development cost	C62 - Standardization	C72 - Design as per designated framework
C53 - Manpower training cost	C63 - Interchangeability	C73 - Quality in design
C54 - Raw material cost	C64 - Modification of existing product	C74 - Production performance impact due to design change
C55 - Material handling cost	C65 - Add on to existing product	
C56 - Minimum rejects		
C57 - Minimum rework		

Table 7.13: Relative ranking of the global or high-level factors>

	Production friendly design	Product complexity	Product variants / add-ons	Component availability and price	Managing cost	Reusable design	Quality standard framework	Weights	Rank
Production friendly design	1.00	3.64	3.36	2.75	1.72	1.95	2.84	0.139	3
Product complexity	3.19	1.00	3.21	2.15	2.32	2.81	2.06	0.139	4
Product variants / add-ons	1.99	1.81	1.00	2.52	1.72	0.45	2.02	0.089	7
Component availability and price	2.96	3.76	2.74	1.00	1.24	0.20	1.54	0.097	6
Managing cost	5.44	3.64	2.67	3.69	1.00	0.70	1.85	0.137	5
Reusable design	4.23	3.24	5.40	6.13	4.67	1.00	2.66	0.203	1

Quality standard framework	3.56	3.95	3.89	3.44	4.35	3.96	1.00	0.195	2
	22.37	21.03	22.27	21.69	17.02	11.08	13.97	1.000	

Table 7.14: Relative ranking of the local factors under production friendly design.

	Production feasibility	Product launch schedules	Prototype testing	Placement and routing	Last minute design change	Minimum production assembly time	Weights	Rank
Production feasibility	1.00	3.90	4.48	2.19	3.28	2.60	0.200	3
Product launch schedules	1.90	1.00	3.43	0.97	1.81	0.98	0.110	5
Prototype testing	1.45	1.42	1.00	0.46	0.59	1.68	0.083	6
Placement and routing	3.42	4.62	6.14	1.00	3.99	2.48	0.229	1
Last minute design change	2.86	2.81	5.38	1.27	1.00	0.23	0.136	4
Minimum production assembly time	3.02	5.02	3.61	2.70	6.64	1.00	0.241	2
	13.66	18.76	24.04	8.59	17.31	8.97	1.000	

Table 7.15: Relative ranking of the local factors under product complexity.

	Ease of manufacturing	Ease of assembly	Assembly bottlenecks	Manufacturing life cycle	Assembly life cycle	Material handling	Weights	Rank
Ease of manufacturing	1.00	1.24	2.37	2.05	3.51	4.90	0.181	2
Ease of assembly	3.80	1.00	4.90	4.70	2.99	4.59	0.266	1
Assembly bottlenecks	2.31	0.83	1.00	3.21	0.73	4.60	0.152	5
Manufacturing life cycle	3.21	0.24	1.73	1.00	4.43	5.57	0.174	4
Assembly life cycle	1.15	1.55	5.54	0.56	1.00	5.51	0.176	3
Material handling	0.84	0.42	0.93	0.23	0.64	1.00	0.052	6
	12.32	5.28	16.47	11.74	13.30	26.16	1.000	

Table 7.16: Relative ranking of the local factors under product variants / add-ons.

	Conforming to various international standards	Functional add-ons	Aesthetics / styling	Product pride	Weights	Rank
Conforming to various international standards	1.00	2.15	2.21	2.33	0.226	3
Functional add-ons	3.08	1.00	0.27	1.25	0.140	4
Aesthetics / styling	3.89	4.04	1.00	2.74	0.299	2
Product pride	3.73	4.42	3.57	1.00	0.336	1
	11.70	11.62	7.05	7.32	1.000	

Table 7.17: Relative ranking of the local factors under component availability and price.

	In house capability	FERA	Vendor support and flexibility	Lead time	Number of 'A' class items	Vendor component monopoly	Weights	Rank
In house capability	1.00	4.13	2.04	2.96	4.56	3.15	0.222	2
FERA	0.72	1.00	0.39	0.22	0.27	0.18	0.036	6
Vendor support and flexibility	4.32	5.29	1.00	4.51	4.50	5.84	0.295	1
Lead time	2.34	5.57	0.58	1.00	4.91	5.95	0.200	3
Number of 'A' class items	1.37	4.09	0.67	0.22	1.00	0.18	0.078	5
Vendor component monopoly	2.87	6.43	0.71	0.49	6.70	1.00	0.170	4
	12.62	26.51	5.38	9.40	21.94	16.30	1.000	

Table 7.18 Relative ranking of the local factors under managing cost

	Equipment development cost	Tooling developmen t cost	Manpower training cost	Raw material cost	Material handling cost	Minimum rejects	Minimum rework	Weights	Rank
Equipment development cost	1.00	3.04	0.45	1.70	0.77	0.18	0.30	0.051	7

Tooling development cost	2.81	1.00	2.55	2.05	1.84	0.43	0.18	0.074	6
Manpower training cost	4.40	3.11	1.00	2.04	3.81	0.54	0.26	0.100	4
Raw material cost	5.28	3.43	3.49	1.04	2.53	1.09	1.27	0.143	3
Material handling cost	6.22	3.41	2.16	2.13	1.00	0.70	0.69	0.113	5
Minimum rejects	6.04	5.79	5.82	5.75	5.87	1.00	2.63	0.255	2
Minimum rework	5.71	7.04	6.59	6.39	6.65	2.06	1.00	0.263	1
	31.46	26.82	22.07	21.09	22.48	5.99	6.33	1.000	

Table 7.19: Relative ranking of the local factors under reusable design.

	Modular product design	Standard ization	Interchange -ability	Modification of existing product	Add-on to existing product	Weights	Rank
Modular product design	1.00	2.73	2.47	3.08	2.05	0.198	3
Standardization	3.38	1.00	3.83	4.40	1.50	0.217	2
Interchangeability	3.21	1.22	1.00	4.53	1.79	0.182	4
Modification of existing product	3.49	1.24	1.20	1.00	0.20	0.105	5
Add-on to existing product	4.10	4.81	3.76	6.30	1.00	0.299	1
	15.17	11.00	12.26	19.31	6.54	1.000	

Table 7.20: Relative ranking of the local factors under quality standard framework.

	Industry regulatory requirement	Design as per designated framework	Quality in design	Production performance impact due to change	Weights	Rank
Industry regulatory requirement	1.00	2.63	2.35	2.80	0.247	2
Design as per designated framework	3.40	1.00	0.15	3.04	0.164	4
Quality in design	4.06	7.13	1.00	5.32	0.384	1
Production performance impact due to change	2.84	2.46	1.52	1.00	0.206	3
	11.30	13.22	5.01	12.16	1.000	

7.6 Cronbach's Alpha for checking Data Consistency

It is of the upmost importance that the data collected from the survey is checked for biasness and consistency and not used directly for analysis purpose. One such method available for checking data consistency is Cronbach's alpha [216]. A modified Cronbach's alpha method was used using spread sheets to cater to the 252 respondents and consistency for data for local and global factor was carried out. For the local factors the Cronbach's alpha value came out to be 0.887 which proved that the data was consistent in nature. Table 7.21 shows the calculation for alpha value.

Table 7.21: Calculation for alpha value.

K	38
SIG VAR	1019.276
VAR	7518.066
ALPHA	0.887

7.7 Ranking of Local Factors

All the local factors were grouped against their global factors in a hierarchical form. The first step involves converting the local weights in to normalized global weights. The ranking of all the local factors is brought about using the normalized global weights. The uniqueness of the formula lies in the fact that the denominator is made up of sum of all the other factors except for the ones under the global factor for which decision is being made. The denominator value will be more if the other factors have higher local weights, which will significantly reduce the ranking of those local factors for which ranking is carried out. On the other hand, if the denominator value is less, it will significantly increase the ranking of those local factors for which ranking is carried out. The following steps are carried out for ranking of all the local factors:

Step 1: Get the relative weights for all the global or higher-level factors using AHP

Step 2: Get the relative weights of all the low-level factors under each global factor using AHP.

Step 3: Transform the local weights in to final global weights using the lower and higher-level weights.

Step 4: Carry out normalization of the global weights.

Step 5: Use the proposed formula and find the ranking for the local weights.

Table 7.22 shows the weightage calculation done using AHP. Table 7.23 shows the relative ranking of all the local factors on a common scale using the proposed method.

$$W_{ij} = \frac{C_i * C_{ij}}{\sum C_{kj}} \tag{7.2}$$

Ci = weight of 'n' upper-level actor

Cij = weight of 'm' low level factor

Wij = global weight of each low-level criteria

i = 1, 2, 3 …………... n

j = 1, 2, 3……………m

k = 1, 2,3……………m and k ≠ i

$$W_{ij}^{N} = \frac{W_{ij}}{\sum W_{ij}} \tag{7.3}$$

W_{ij}^{N} = Normalized global weights

i = 1, 2, 3 …………... n

j = 1, 2, 3……………m

Table 7.22: Weightage calculation done using AHP.

Upper-level factors	Weights of upper-level factors	Lower-level factors	Weights of lower-level factors
Production friendly design	0.139	Production feasibility	0.200
		Product launch schedules	0.110
		Prototype testing	0.083
		Placement and routing	0.229
		Last minute design change	0.136
		Minimum production assembly time	0.241
Product complexity	0.139	Ease of manufacturing	0.181
		Ease of assembly	0.266
		Assembly bottlenecks	0.152

		Manufacturing life cycle	0.174
		Assembly life cycle	0.176
		Material handling	0.052
Product variants	0.089	Conforming to various international standards	0.226
		Functional add-ons	0.140
		Aesthetics / styling	0.299
		Product pride	0.336
Component availability and price	0.097	In-house capability	0.222
		FERA	0.036
		Vendor support and flexibility	0.295
		Lead time	0.200
		Number of 'A' class items	0.078
		Vendor component monopoly	0.170
Managing cost	0.137	Equipment development cost	0.051
		Tooling development cost	0.074
		Manpower training cost	0.100
		Raw material cost	0.143
		Material handling cost	0.113
		Minimum rejects	0.255
		Minimum rework	0.263
Reusable design	0.203	Modular product design	0.198
		Standardization	0.217
		Interchangeability	0.182
		Modification of existing product	0.105
		Add-on to existing product	0.299
Quality standard framework	0.195	Industry regulatory requirement	0.247
		Design as per designated framework	0.164
		Quality in design	0.384
		Production performance impact due to change	0.206

Table 7.23: Relative ranking of all the local factors on a common scale using the proposed method.

Upper-level factors	Weights of upper-level factors	Lower-level factors	Weights of lower-level factors	Global Weights	Normalized Weights	Rank
Production friendly design	0.139	Production feasibility	0.200	0.0046	0.0280	16
		Product launch schedules	0.110	0.0026	0.0155	30
		Prototype testing	0.083	0.0019	0.0117	33
		Placement and routing	0.229	0.0053	0.0321	13
		Last minute design change	0.136	0.0032	0.0190	27
		Minimum production assembly time	0.241	0.0056	0.0338	11
Product complexity	0.139	Ease of manufacturing	0.181	0.0042	0.0252	18
		Ease of assembly	0.266	0.0062	0.0371	7
		Assembly bottlenecks	0.152	0.0036	0.0215	22
		Manufacturing life cycle	0.174	0.0040	0.0242	20
		Assembly life cycle	0.176	0.0041	0.0246	19
		Material handling	0.052	0.0012	0.0072	36
Product variants	0.089	Conforming to various international standards	0.226	0.0033	0.0201	24
		Functional add-ons	0.140	0.0021	0.0125	32
		Aesthetics / styling	0.299	0.0044	0.0267	17
		Product pride	0.336	0.0050	0.0300	14
Component availability and price	0.097	In-house capability	0.222	0.0036	0.0217	21
		FERA	0.036	0.0006	0.0035	38
		Vendor support and flexibility	0.295	0.0048	0.0289	15
		Lead time	0.200	0.0032	0.0195	26
		Number of 'A' class items	0.078	0.0013	0.0076	35
		Vendor component monopoly	0.170	0.0028	0.0166	28
Managing cost	0.137	Equipment development cost	0.051	0.0012	0.0071	37
		Tooling development cost	0.074	0.0017	0.0103	34
		Manpower training cost	0.100	0.0023	0.0137	31
		Raw material cost	0.143	0.0033	0.0197	25

		Material handling cost	0.113	0.0026	0.0156	29
		Minimum rejects	0.255	0.0058	0.0352	10
		Minimum rework	0.263	0.0060	0.0363	8
Reusable design	0.203	Modular product design	0.198	0.0067	0.0403	5
		Standardization	0.217	0.0072	0.0434	4
		Interchangeability	0.182	0.0059	0.0357	9
		Modification of existing product	0.105	0.0034	0.0206	23
		Add-on to existing product	0.299	0.0099	0.0594	2
Quality standard framework	0.195	Industry regulatory requirement	0.247	0.0080	0.0483	3
		Design as per designated framework	0.164	0.0053	0.0321	12
		Quality in design	0.384	0.0125	0.0752	1
		Production performance impact due to change	0.206	0.0067	0.0402	6

Factors such as quality in design, add-on to existing product were among the top factors in terms of ranking, whereas FERA, equipment development cost, tooling development cost took a backseat which was as expected. The final ranking was shown to pool of technical people and their opinion was taken. The experts were convinced by the relative positions of the various factors and their rankings. A similar ranking method was proposed to find the traffic safety index of vessel by Gaonkar [215]. To check the validity of the proposed formula, the ranking using both the methods were compared using Spearman rank correlation coefficient and Pearson correlation coefficient. Spearmen rank corelation and Pearson corelation gives degree of association between any two variable and are non-parametric test. The corelation coefficient should lie between -1 and +1. If it is +1, it indicates a very high level of corelation, but if it -1, it indicates a high level of corelation but in opposite direction. The value of the coefficient after calculation turned out to be 0.9067 which showed a high degree of association between the ranks in both the methods. Hence the proposed ranking method is quite capable of carrying out the ranking of any variables. Table 7.24 shows the difference in ranking using both the methods. It was observed that add-on to existing product and quality in design were among the top 2 factors in both the ranking methods while material handling and FERA were listed at the bottom of the ranking Table in both the methods. The largest difference in ranking was for aesthetic or styling followed by product pride. It was heartening to see that product pride was ranked very highly using the proposed method as compared to the available method.

Table 7.24: Ranking comparison.

Upper-level factors	Weights of upper-level factors	Lower-level factors	Ranking using proposed method	Ranking using index method	Difference in ranking
Production friendly design	0.139	Production feasibility	16	13	3
		Product launch schedules	30	30	0
		Prototype testing	33	33	0
		Placement and routing	13	10	3
		Last minute design change	27	26	1
		Minimum production assembly time	11	7	4
Product complexity	0.139	Ease of manufacturing	18	15	3
		Ease of assembly	7	5	2
		Assembly bottlenecks	22	21	1
		Manufacturing life cycle	20	17	3
		Assembly life cycle	19	16	3
		Material handling	36	37	-1
Product variants	0.089	Conforming to various international standards	24	31	-7
		Functional add-ons	32	36	-4
		Aesthetics / styling	17	28	-11
		Product pride	14	23	-9
Component availability and price	0.097	In-house capability	21	18	3
		FERA	38	38	0
		Vendor support and flexibility	15	8	7
		Lead time	26	20	6
		Number of 'A' class items	35	35	0
		Vendor component monopoly	28	25	3
Managing cost	0.137	Equipment development cost	37	34	3
		Tooling development cost	34	32	2
		Manpower training cost	31	29	2
		Raw material cost	25	19	6
		Material handling cost	29	24	5
		Minimum rejects	10	4	6
		Minimum rework	8	3	5
Reusable design	0.203	Modular product design	5	9	-4
		Standardization	4	6	-2
		Interchangeability	9	12	-3
		Modification of existing product	23	27	-4
		Add-on to existing product	2	1	1
Quality standard framework	0.195	Industry regulatory requirement	3	11	-8
		Design as per designated framework	12	22	-10
		Quality in design	1	2	-1
		Production performance impact due to change	6	14	-8

7.8 Application of the Self-Assessment Model

Weights for the critical DFM factors were generated from a gathering of large pool personnel having wide variety of technical knowledge from the state of Goa. This data will help in tackling one of the most important constraints a SME faces in decision making i.e., lack of technical know-how. If any of the SME's involved in manufacturing wants to go for developing a new product, then the standard weights obtained, will help them in choosing the best alternative among a given set of alternatives irrespective of the technical experience of the personnel involved in that SME. Table 7.25 shows how to go about asking questions to the respondents to get alternative ratings against criteria data. Different situation can arise while using the standardized weights. They are (i) The standardized DFM criteria with their weights are all that is required for decision making in NPD (ii) Apart from some of the standardized DFM criteria there are other criteria which are part of the decision making. The model provides means to tackle each of these cases as follows:

Case 1: All decision-making criteria are part of the standard critical DFM factors listed.

Step 1: List down all those factors from the 38 local factors along with their weightages which are required for decision making.
Step 2: Change the weights of the factors as per the formula given below:

$$W_{ij}^{new} = \frac{W_{ij}^{old}}{\sum W_{ij}^{old}} \tag{7.4}$$

where W_{ij}^{new} = New weight for the criteria
W_{ij}^{old} = Old weigh of the criteria
$i = 1, 2, 3 \ldots\ldots n$
$j = 1, 2, 3 \ldots\ldots m$

Step 3: Using any MADM method carry out the analysis and find out the best alternative.

Case 2: Only few critical DFM factors are part of the decision-making criteria along with other factors.
Step 1: List down those critical DFM factors along with their weightages which are required for decision making. Group all of them as one criterion.

Step 2: Using group decision or individual decision from the concerned SME, calculate the weights of all the criteria which are required for decision making.

Step 3: Once the weights assigned to the grouped DFM criteria is known, calculate the weights of all the listed criteria in the group using the below formula and then use them in decision making using the other factors.

$$W_{ij}^{new} = \frac{W_{ij}^{old} * \sum W_{ij}^{old}}{W^N} \tag{7.5}$$

where W_{ij}^{new} = New weight for the criteria

W_{ij}^{old} = Old weigh of the criteria

W^N = New value of weight for the DFM group

$i = 1, 2, 3 \ldots\ldots n$

$j = 1, 2, 3 \ldots\ldots m$

Step 4: Using any MAADM method carry out the analysis and find out the best alternative.

Table 7.25: Questions to be asked to the respondents.

Factors	Sub factors	SCENARIO: There are four ideas/ alternatives to be screened using the below listed factors to the get the best idea/ alternative.
Production friendly design	Production feasibility	Are the ideas feasible for production?
	Product launch schedules	Is it possible to launch/ develop a particular idea in the given schedule
	Prototype testing	Is prototype testing possible for the ideas.
	Placement and routing of components	Is placement/ assembly/ routing of components easier in any of the ideas?
	Incorporate last stage design changes	Does any of the idea support last stage design change?
	Minimum production assembly time	Which idea will have minimum production assembly time?
Product complexity	Ease of manufacture	Which idea is easier to manufacture?
	Ease of assembly	Which idea is easier to assemble?
	Assembly bottlenecks	Which idea will have less assembly bottlenecks?
	Manufacturing life cycle	Which idea will have less manufacturing life cycle?
	Assembly life cycle	Which idea will have less assembly life cycle?

	Material handling	Which idea will have less material handling time?

Product variants / add-ons	Conforming to various international standards	Which idea confirms to all International Standards
	Functional add-ons	Which idea has more functional add-ons?
	Aesthetic/ styling	Which idea has better aesthetic /styling?
	Product pride	Which Idea can be made totally inhouse? (MAKE IN INDIA)

Component availability and price	Inhouse capability	Which idea can be made inhouse?
	FERA	Which idea will be affected by FERA?
	Vendor support and flexibility	Which idea will have better vendor support and flexibility?
	Lead time	Which idea will have less lead time?
	Number of 'A' class items	Which idea has more 'A' class item (w.r.t inventory holding)
	Vendor component monopoly	Which idea will require component from vendor who has monopoly with respect to that component?

Managing cost	Equipment Development Cost	Which idea will have more equipment development cost?
	Tooling development cost	Which idea will have more tooling development cost?
	Manpower training cost	Which idea will have more manpower training cost?
	Raw material cost	Which idea will have more raw material cost?
	Material handling cost	Which idea will have more material Handling cost?
	Minimum rejects	Which idea will have minimum rejects?
	Minimum rework	Which idea will have more minimum rework?

Reusable design	Modular product Design	Which idea has modular product design?
	Standardization	Which idea has standard parts?
	Interchangeability	Which idea will provide better interchangeability of parts?
	Modification of existing product	Which idea can be developed by modifying existing product?
	Add-on to existing product	Which idea can be developed by adding to the existing product?

Quality standard framework	Industry regulatory requirements	To what extent each idea confirms to industry regulatory requirements? Quality restrictions can be maintained?
	Design as per designated framework	To what extent each idea confirms to designated industrial codes?
	Quality in design	Which idea offers better quality?
	Production performance impact due to design change	Which idea will have less production performance impact on quality due to change in design?

7.9 Case Study

A case study was carried out in a motor manufacturing unit located in Goa, India to validate the proposed model. The unit is involved in manufacturing of various types of motors used in fans, air conditioners, washing machines, coolers and running of various pumps. Any new motor to be manufactured was done by working on one or more than one previous model. In this paper a case study was taken wherein a new motor had to be manufactured. The company shortlisted four previous designs on which they could work with. There were 17 criteria which were part of the decision-making process. All the 17 criteria were part of the standard 38 design to manufacturing factors. To validate the model the weightages for the criteria were taken from two sources (i) standard weights found out for the DFM factors (ii) using technical personnel from the company itself in finding out the weightages for the criteria. For the second case there were four decision makers who were told to rank the criteria using linguistic scale shown in Table 7.26. Table 7.27 shows the weight of the criteria after normalizing from the set of standard DFM factors. Table 7.28 shows the weight of the criteria obtained from the four decision makers. Table 7.29 shows the linguistic rating for alternatives against each criterion given by decision makers

Table 7.26: Grey rating for linguistic variable.

Criteria		Alternative		Grey number
Very low	VL	Very poor	VP	1 - 2
Low	L	Poor	P	2 - 4
Medium	M	Fair	F	4 - 6
High	H	Good	G	6 - 8
Very high	VH	Very good	VG	8 - 9

Table 7.27: Weight of the criteria from the set of standard DFM factors.

Criteria	Low level factors	Weights	Normalized weights
C1	Production feasibility	0.031	0.058
C2	Production launch schedules	0.017	0.032
C3	Placement and routing	0.035	0.067
C4	Minimum production assembly time	0.037	0.070
C5	Ease of manufacturing	0.028	0.054
C6	Ease of assembly	0.042	0.079
C7	Conforming to various international standards	0.014	0.027
C8	Aesthetics / styling	0.019	0.036
C9	In-house capability	0.027	0.052
C10	Vendor component monopoly	0.021	0.040
C11	Raw material cost	0.027	0.051
C12	Minimum rejects	0.048	0.091
C13	Minimum rework	0.049	0.094
C14	Add-on to existing product	0.054	0.103
C15	Quality in design	0.053	0.101
C16	Equipment development cost	0.010	0.018
C17	Tooling development cost	0.014	0.027
	Sum	0.524	1.0

Table 7.28: Weight of the criteria obtained from the four decision makers.

Criteria	Low level factors	DM1	DM2	DM3	DM4	Average	Weights
C1	Production feasibility	M	M	H	M	5	0.0498
C2	Production launch schedules	L	M	M	M	4.5	0.0448
C3	Placement and routing	M	L	M	L	4	0.0398
C4	Minimum production assembly time	H	H	VH	VH	8	0.0796
C5	Ease of manufacturing	H	VH	H	VH	8	0.0796
C6	Ease of assembly	M	H	M	H	6	0.0597
C7	Conforming to various international standards	L	VL	VL	L	2	0.0199
C8	Aesthetics / styling	L	L	VL	VL	2.5	0.0249
C9	In-house capability	M	H	H	VH	7	0.0697
C10	Vendor component monopoly	M	H	H	VH	7	0.0697
C11	Raw material cost	VH	H	H	L	6.5	0.0647
C12	Minimum rejects	M	M	M	M	5	0.0498

C13	Minimum rework	M	M	M	M	5	0.0498
C14	Add-on to existing product	H	M	H	H	6.5	0.0647
C15	Quality in design	VH	H	VH	H	8	0.0796
C16	Equipment development cost	VH	H	VH	VH	8.5	0.0846
C17	Tooling development cost	H	M	H	VH	7	0.0697
						100.5	1

Table 7.29: Linguistic rating for alternatives against each criterion given by decision makers.

Alternative 1						Alternative 2					
Criteria	DM 1	DM 2	DM 3	DM 4	Average	Criteria	DM 1	DM 2	DM 3	DM 4	Average
C1	VG	VG	VG	VG	9	C1	VG	VG	G	VG	8.5
C2	G	VG	G	G	7.5	C2	G	VG	VG	G	8
C3	G	G	G	G	7	C3	G	G	G	VG	7.5
C4	F	F	F	F	5	C4	F	G	F	F	6
C5	G	F	G	G	6.5	C5	G	F	VG	VG	7.5
C6	F	G	VG	F	6.5	C6	G	F	VG	F	6.5
C7	G	G	F	F	6	C7	VG	G	G	F	7
C8	F	VG	G	G	7	C8	G	VG	G	G	7.5
C9	G	F	F	F	5.5	C9	G	G	F	G	6.5
C10	F	F	G	P	5	C10	F	G	G	F	6
C11	G	F	F	G	6	C11	G	F	F	F	5.5
C12	G	F	G	G	6.5	C12	VG	F	G	F	6.5
C13	G	G	G	F	7	C13	G	G	G	G	7
C14	VG	G	G	G	7.5	C14	VG	G	F	VG	7.5
C15	VG	VG	VG	F	8	C15	VG	VG	VG	G	8.5
C16	VG	VG	G	G	8	C16	VG	VG	G	G	8
C17	G	G	VG	G	7.5	C17	G	G	VG	F	7

Alternative 3						Alternative 4					
Criteria	DM 1	DM 2	DM 3	DM 4	Average	Criteria	DM 1	DM 2	DM 3	DM 4	Average
C1	VG	VG	G	G	8	C1	G	VG	G	VG	8
C2	G	G	G	G	7	C2	G	G	G	G	7
C3	F	G	F	G	6	C3	F	G	P	VG	6
C4	P	F	F	G	5	C4	P	F	F	G	5
C5	F	F	F	G	5.5	C5	F	F	F	G	5.5
C6	F	G	G	F	6	C6	F	F	F	G	5.5
C7	G	G	F	G	6.5	C7	VG	G	G	G	7.5
C8	F	G	F	F	5.5	C8	G	G	F	G	6.5
C9	G	F	G	F	6	C9	F	G	G	G	6.5
C10	G	F	G	G	6.5	C10	G	G	F	G	6.5
C11	G	G	F	G	6.5	C11	G	G	G	F	6.5
C12	G	F	G	G	6.5	C12	G	F	F	P	5
C13	F	G	VG	F	6.5	C13	F	F	VG	G	6.5
C14	VG	P	VG	G	7	C14	G	P	VG	G	6.5
C15	VG	VG	G	F	7.5	C15	VG	G	F	G	7
C16	VG	G	VG	G	8	C16	VG	VG	G	G	8
C17	F	VG	G	G	7	C17	G	G	G	F	6.5

7.9.1 Validation using COPRAS-G method

Case (i): Standard DF1 and 2: Construct aggregated alternative rating and criteria weightages Table and normalized weighted Table. The weighted normalized data is shown in Table 7.30.

Table 7.30: Weighted normalized data.

Criteria	A1	A2	A3	A4	Weights	Criteria	A1	A2	A3	A4
C1	0.269	0.254	0.239	0.239	0.058	C1	0.016	0.015	0.014	0.014
C2	0.254	0.271	0.237	0.237	0.032	C2	0.008	0.009	0.008	0.008
C3	0.264	0.283	0.226	0.226	0.067	C3	0.018	0.019	0.015	0.015
C4	0.238	0.286	0.238	0.238	0.070	C4	0.017	0.020	0.017	0.017
C5	0.260	0.300	0.220	0.220	0.054	C5	0.014	0.016	0.012	0.012

C6	0.265	0.265	0.245	0.224	0.079	C6	0.021	0.021	0.019	0.018
C7	0.222	0.259	0.241	0.278	0.027	C7	0.006	0.007	0.007	0.008
C8	0.264	0.283	0.208	0.245	0.036	C8	0.010	0.010	0.007	0.009
C9	0.224	0.265	0.245	0.265	0.052	C9	0.012	0.014	0.013	0.014
C10	0.208	0.250	0.271	0.271	0.040	C10	0.008	0.010	0.011	0.011
C11	0.245	0.224	0.265	0.265	0.051	C11	0.012	0.011	0.013	0.013
C12	0.265	0.265	0.265	0.204	0.091	C12	0.024	0.024	0.024	0.019
C13	0.259	0.259	0.241	0.241	0.094	C13	0.024	0.024	0.023	0.023
C14	0.263	0.263	0.246	0.228	0.103	C14	0.027	0.027	0.025	0.024
C15	0.258	0.274	0.242	0.226	0.101	C15	0.026	0.028	0.025	0.023
C16	0.250	0.250	0.250	0.250	0.018	C16	0.005	0.005	0.005	0.005
C17	0.268	0.250	0.250	0.232	0.027	C17	0.007	0.007	0.007	0.006

Step 3, 4 and 5: The weighted normalized values are summed for both beneficial and non-beneficial criteria. Table 7.31 shows the relative significances or priorities of each alternative Qi and Ui.

Table 7.31: Relative significances or priorities of each alternative.

Alternatives	Qi	Ui	Rank
A1	0.250	94.349	2
A2	0.264	100	1
A3	0.241	90.973	4
A4	0.245	92.754	3

Case (ii): Weightages obtained from four decision makers.

Step 1 and 2: Construct aggregated alternative rating and criteria weightages Table and normalized weighted Table. The weighted normalized data is shown in Table 7.32.

Table 7.32: Weighted normalized data.

Criteria	A1	A2	A3	A4	Weights	Criteria	A1	A2	A3	A4
C1	0.269	0.254	0.239	0.239	0.050	C1	0.013	0.013	0.012	0.012
C2	0.254	0.271	0.237	0.237	0.045	C2	0.011	0.012	0.011	0.011
C3	0.264	0.283	0.226	0.226	0.040	C3	0.011	0.011	0.009	0.009
C4	0.238	0.286	0.238	0.238	0.080	C4	0.019	0.023	0.019	0.019
C5	0.260	0.300	0.220	0.220	0.080	C5	0.021	0.024	0.018	0.018
C6	0.265	0.265	0.245	0.224	0.060	C6	0.016	0.016	0.015	0.013
C7	0.222	0.259	0.241	0.278	0.020	C7	0.004	0.005	0.005	0.006
C8	0.264	0.283	0.208	0.245	0.025	C8	0.007	0.007	0.005	0.006
C9	0.224	0.265	0.245	0.265	0.070	C9	0.016	0.018	0.017	0.018
C10	0.208	0.250	0.271	0.271	0.070	C10	0.015	0.017	0.019	0.019
C11	0.245	0.224	0.265	0.265	0.065	C11	0.016	0.015	0.017	0.017
C12	0.265	0.265	0.265	0.204	0.050	C12	0.013	0.013	0.013	0.010
C13	0.259	0.259	0.241	0.241	0.050	C13	0.013	0.013	0.012	0.012
C14	0.263	0.263	0.246	0.228	0.065	C14	0.017	0.017	0.016	0.015
C15	0.258	0.274	0.242	0.226	0.080	C15	0.021	0.022	0.019	0.018
C16	0.250	0.250	0.250	0.250	0.085	C16	0.021	0.021	0.021	0.021
C17	0.268	0.250	0.250	0.232	0.070	C17	0.019	0.017	0.017	0.016

Step 3, 4 and 5: The weighted normalized values are summed for both beneficial and non-beneficial criteria. Table 7.33 shows the relative significances or priorities of each alternative Qi)and Ui.

Table 7.33: Relative significances or priorities of each alternative.

Alternatives	Qi	Ui	Rank
A1	0.247	93.035	2
A2	0.265	100	1
A3	0.242	91.143	4
A4	0.246	92.591	3

It is observed that both the solutions gave the same ranking. Hence the weightages used from the standard DFM model are validated.

7.9.2 Validation using integrated GA-ANN method

Case (i): Standard DFM weightages.

After obtaining the criteria weights in Table 7.27, we calculate the weight matrix of the alternatives with respect to all criteria. This weight matrix is shown in Table 7.34.

Table 7.34: Weight matrix of alternatives with respect to all criteria.

Criteria	Low level factors	A1	A2	A3	A4
C1	Production feasibility	0.500	0.250	0.125	0.125
C2	Production launch schedules	0.250	0.500	0.125	0.125
C3	Placement and routing	0.306	0.529	0.082	0.082
C4	Minimum production assembly time	0.143	0.571	0.143	0.143
C5	Ease of manufacturing	0.230	0.634	0.068	0.068
C6	Ease of assembly	0.364	0.364	0.182	0.091
C7	Conforming to various international standards	0.074	0.275	0.138	0.512
C8	Aesthetics / styling	0.283	0.513	0.050	0.155
C9	In-house capability	0.091	0.364	0.182	0.364
C10	Vendor component monopoly	0.058	0.200	0.371	0.371
C11	Raw material cost	0.182	0.091	0.364	0.364
C12	Minimum rejects	0.316	0.316	0.316	0.053
C13	Minimum rework	0.333	0.333	0.167	0.167
C14	Add-on to existing product	0.364	0.364	0.182	0.091
C15	Quality in design	0.275	0.512	0.138	0.074
C16	Equipment development cost	0.250	0.250	0.250	0.250
C17	Tooling development cost	0.444	0.222	0.222	0.111

Step 3: Using optimization toolbox of MATLAB, we find out the optimal function value for all the criteria for each alternative. The parameters settings are as follows:

Population size = 20; Scaling function = rank; Selection = roulette wheel; Crossover fraction = 0.8;

Mutation = adaptive feasible; Crossover fraction = scattered; Stopping criteria = 100.

After solving using the optimization toolbox, the function values for the criteria are shown in Table 7.35.

Table 7.35: Optimum function values for the criteria.

Criteria	Low level factors	Optimum function value
C1	Production feasibility	8.988
C2	Production launch schedules	8.612
C3	Placement and routing	7.902
C4	Minimum production assembly time	8.896
C5	Ease of manufacturing	7.840
C6	Ease of assembly	7.923
C7	Conforming to various international standards	7.961
C8	Aesthetics / styling	7.492
C9	In-house capability	5.609
C10	Vendor component monopoly	8.706
C11	Raw material cost	0.003
C12	Minimum rejects	0.010
C13	Minimum rework	0.020
C14	Add-on to existing product	7.192
C15	Quality in design	7.904
C16	Equipment development cost	0.010
C17	Tooling development cost	0.012

Step4: The data obtained in the previous step becomes the input to the input layer of the feed forward network leading to calculation of the output of the input layer. The input layer calculation is shown in Table 7.36.

Table 7.36: Input layer calculation.

Criteria	Low level factors	Function value from GA	Criteria weightages	Bias	Sigmoidal value	Input to the output layer
C1	Production feasibility	8.988	0.058	0.3	0.823	0.695
C2	Production launch schedules	8.612	0.032	0.3	0.577	0.640
C3	Placement and routing	7.902	0.067	0.3	0.827	0.696
C4	Minimum production assembly time	8.896	0.070	0.3	0.925	0.716
C5	Ease of manufacturing	7.840	0.054	0.3	0.723	0.673
C6	Ease of assembly	7.923	0.079	0.3	0.929	0.717

C7	Conforming to various international standards	7.961	0.027	0.3	0.517	0.626
C8	Aesthetics / styling	7.492	0.036	0.3	0.570	0.639
C9	In-house capability	5.609	0.052	0.3	0.589	0.643
C10	Vendor component monopoly	8.706	0.040	0.3	0.644	0.656
C11	Raw material cost	0.003	0.051	0.3	0.300	0.574
C12	Minimum rejects	0.010	0.091	0.3	0.301	0.575
C13	Minimum rework	0.020	0.094	0.3	0.302	0.575
C14	Add-on to existing product	7.192	0.103	0.3	1.042	0.739
C15	Quality in design	7.904	0.101	0.3	1.102	0.751
C16	Equipment development cost	0.010	0.018	0.3	0.300	0.574
C17	Tooling development cost	0.012	0.027	0.3	0.300	0.575

Step 5: The output value of the input layer becomes the input value for the output layer of the feed forward network. The output of this output layer gives the ranking of the alternatives. Table 7.37 shows the relative rankings of the alternative based on the input feed to the output layer. Table 7.38 sows the final ranking in terms of output of the output layer.

Table 7.37: Relative rankings of the alternative based on the input feed to the output layer.

Criteria	Low level factors	Weight	A1	A2	A3	A4
C1	Production feasibility	0.695	0.500	0.250	0.125	0.125
C2	Production launch schedules	0.640	0.250	0.500	0.125	0.125
C3	Placement and routing	0.696	0.306	0.529	0.082	0.082
C4	Minimum production assembly time	0.716	0.143	0.571	0.143	0.143
C5	Ease of manufacturing	0.673	0.230	0.634	0.068	0.068
C6	Ease of assembly	0.717	0.364	0.364	0.182	0.091
C7	Conforming to various international standards	0.626	0.074	0.275	0.138	0.512
C8	Aesthetics / styling	0.639	0.283	0.513	0.050	0.155
C9	In-house capability	0.643	0.091	0.364	0.182	0.364
C10	Vendor component monopoly	0.656	0.058	0.200	0.371	0.371
C11	Raw material cost	0.574	0.182	0.091	0.364	0.364
C12	Minimum rejects	0.575	0.316	0.316	0.316	0.053
C13	Minimum rework	0.575	0.333	0.333	0.167	0.167
C14	Add-on to existing product	0.739	0.364	0.364	0.182	0.091
C15	Quality in design	0.751	0.275	0.512	0.138	0.074
C16	Equipment development cost	0.574	0.250	0.250	0.250	0.250
C17	Tooling development cost	0.575	0.444	0.222	0.222	0.111

Table 7.38: Final ranking in terms of output of the output layer.

Alternatives	Criteria v/s alternative weightages	Bias	Sigmoidal value	Output of the output Layer	Ranking
A1	2.914	0.300	3.214	0.961	2
A2	4.174	0.300	4.474	0.989	1
A3	1.976	0.300	2.276	0.907	4
A4	2.000	0.300	2.300	0.909	3

Case (ii): Weightages obtained from four decision makers.

After obtaining the criteria weights in Table 7.27, we calculate the weight matrix of the alternatives with respect to all criteria. This weight matrix is shown in Table 7.39.

Table 7.39: Weight matrix of alternatives with respect to all criteria.

Criteria	Low level factors	A1	A2	A3	A4
C1	Production feasibility	0.500	0.250	0.125	0.125
C2	Production launch schedules	0.250	0.500	0.125	0.125
C3	Placement and routing	0.306	0.529	0.082	0.082
C4	Minimum production assembly time	0.143	0.571	0.143	0.143
C5	Ease of manufacturing	0.230	0.634	0.068	0.068
C6	Ease of assembly	0.364	0.364	0.182	0.091
C7	Conforming to various international standards	0.074	0.275	0.138	0.512
C8	Aesthetics / styling	0.283	0.513	0.050	0.155
C9	In-house capability	0.091	0.364	0.182	0.364
C10	Vendor component monopoly	0.058	0.200	0.371	0.371
C11	Raw material cost	0.182	0.091	0.364	0.364
C12	Minimum rejects	0.316	0.316	0.316	0.053
C13	Minimum rework	0.333	0.333	0.167	0.167
C14	Add-on to existing product	0.364	0.364	0.182	0.091
C15	Quality in design	0.275	0.512	0.138	0.074
C16	Equipment development cost	0.250	0.250	0.250	0.250
C17	Tooling development cost	0.444	0.222	0.222	0.111

Step 3: Using optimization toolbox of MATLAB, we find out the optimal function value for all the criteria for each alternative. After solving using the optimization toolbox, the function values for the criteria are shown in Table 7.40.

Table 7.40: Optimum function values for the criteria.

Criteria	Low level factors	Optimum function value
C1	Production feasibility	8.988
C2	Production launch schedules	8.612
C3	Placement and routing	7.902
C4	Minimum production assembly time	8.896
C5	Ease of manufacturing	7.840
C6	Ease of assembly	7.923
C7	Conforming to various international standards	7.961
C8	Aesthetics / styling	7.492
C9	In-house capability	5.609
C10	Vendor component monopoly	8.706
C11	Raw material cost	0.003
C12	Minimum rejects	0.010
C13	Minimum rework	0.020
C14	Add-on to existing product	7.192
C15	Quality in design	7.904
C16	Equipment development cost	0.010
C17	Tooling development cost	0.012

Step 4: The data obtained in the previous step becomes the input to the input layer of the feed forward network leading to calculation of the output of the input layer. The input layer calculation is shown in Table 7.41.

Table 7.41: Input layer calculation.

Criteria	Low level factors	Function Value From GA	Criteria weightages	Bias	Sigmoidal Value	Input to the Output Layer
C1	Production feasibility	8.988	0.050	0.3	0.747	0.679
C2	Production launch schedules	8.612	0.045	0.3	0.686	0.665
C3	Placement and routing	7.902	0.040	0.3	0.614	0.649
C4	Minimum production assembly time	8.896	0.080	0.3	1.008	0.733
C5	Ease of manufacturing	7.840	0.080	0.3	0.924	0.716

C6	Ease of assembly	7.923	0.060	0.3	0.773	0.684
C7	Conforming to various international standards	7.961	0.020	0.3	0.458	0.613
C8	Aesthetics / styling	7.492	0.025	0.3	0.486	0.619
C9	In-house capability	5.609	0.070	0.3	0.691	0.666
C10	Vendor component monopoly	8.706	0.070	0.3	0.906	0.712
C11	Raw material cost	0.003	0.065	0.3	0.300	0.574
C12	Minimum rejects	0.010	0.050	0.3	0.301	0.575
C13	Minimum rework	0.020	0.050	0.3	0.301	0.575
C14	Add-on to existing product	7.192	0.065	0.3	0.765	0.682
C15	Quality in design	7.904	0.080	0.3	0.929	0.717
C16	Equipment development cost	0.010	0.085	0.3	0.301	0.575
C17	Tooling development cost	0.012	0.070	0.3	0.301	0.575

Step 5: The output value of the input layer becomes the input value for the output layer of the feed forward network. The output of this output layer gives the ranking of the alternatives. Table 7.42 shows the relative rankings of the alternative based on the input feed to the output layer. Table 7.43 sows the final ranking.

Table 7.42: Relative rankings of the alternative based on the input feed to the output layer.

Criteria	Low level factors	Weight	A1	A2	A3	A4
C1	Production feasibility	0.679	0.500	0.250	0.125	0.125
C2	Production launch schedules	0.665	0.250	0.500	0.125	0.125
C3	Placement and routing	0.649	0.306	0.529	0.082	0.082
C4	Minimum production assembly time	0.733	0.143	0.571	0.143	0.143
C5	Ease of manufacturing	0.716	0.230	0.634	0.068	0.068
C6	Ease of assembly	0.684	0.364	0.364	0.182	0.091
C7	Conforming to various international standards	0.613	0.074	0.275	0.138	0.512
C8	Aesthetics / styling	0.619	0.283	0.513	0.050	0.155
C9	In-house capability	0.666	0.091	0.364	0.182	0.364
C10	Vendor component monopoly	0.712	0.058	0.200	0.371	0.371
C11	Raw material cost	0.574	0.182	0.091	0.364	0.364
C12	Minimum rejects	0.575	0.316	0.316	0.316	0.053
C13	Minimum rework	0.575	0.333	0.333	0.167	0.167
C14	Add-on to existing product	0.682	0.364	0.364	0.182	0.091
C15	Quality in design	0.717	0.275	0.512	0.138	0.074
C16	Equipment development cost	0.575	0.250	0.250	0.250	0.250
C17	Tooling development cost	0.575	0.444	0.222	0.222	0.111

Table 7.43: Final ranking in terms of output of the output layer.

Alternatives	Criteria v/s alternative weightages	Bias	Sigmoidal value	Output of the output Layer	Ranking
A1	2.867	0.3	3.167	0.960	2
A2	4.150	0.3	4.450	0.988	1
A3	1.980	0.3	2.280	0.907	4
A4	2.011	0.3	2.311	0.910	3

It is again observed that both the solutions gave the same ranking. Hence the weightages used from the standard DFM model are validated.

7.10 Summary

In this chapter, a model was proposed wherein the critical factors affecting new product development in SMEs from design for manufacturing consideration were listed and their weights were found out using the AHP method. The data was then checked for consistency using Cronbach's alpha method and a ranking method was developed to rank all the local factors on a common scale and get their relative weights. The ranking obtained using the proposed method was then checked with the ranking obtained by another standard method. Spearmen rank coefficient and Pearson coefficient was found out. Both the coefficient showed a high level of corelation. The uniqueness of the ranking formula lied in the fact that, the denominator is made up of sum of all the other factors except for the ones under the global factor, for which decision is being made. The denominator value will be more if the other factors have higher local weights, which will significantly reduce the raking of those local factors for which ranking is carried out. On the other hand, if the denominator value is less, it will significantly increase the raking of those local factors for which ranking is carried out. The later part of the model provided solution to tackle any NPD application encountered by the SME's. To validate the model a case study in the motor industry located in Goa, India was taken up. COPRAS-Grey and hybrid method involving ANN-GA was used to solve the MADM problem. The input was taken from two sources i) standard weights obtained for the DFM factors (ii) weights given by four decision makers from the company. It was observed that the final solution using both the methods was same irrespective of the input data. In both the case irrespective of the methods used, alternative 2 came up to be the best followed by alternative 1. In both cases alternative 3 was the last. This model will allow the SMEs to overcome their biggest constraint of technical know-how by using the standardised weights calculated for the design for manufacturing factors. A further step would be tackling a scenario wherein all the decision-making criteria are all not part of the standard critical DFM factors. Limitation to the study is that case study was taken for the state of Goa. Using the self-assessment model for SMEs in other parts India and comparing the data has to be carried out.

Chapter 8

Summary and Conclusions

8.1 Discussions

In an increasingly competitive global market, companies must be better at developing new products. The trend of the industry is to move towards the design and manufacture of more sophisticated products because of the global competition involved. The sophistication involves products with better and safer performance, more environmental friendliness, higher quality and reliability, and shorter time. Particularly for the companies with short product life cycle, development of new products fulfilling reasonable quality demands, performance and cost is of prime importance. The rate of NPD project failure is around one-third or even higher, although it varies from industry to industry. NPD is made up of structured phases and translates a new concept in to a physical product. Decisions are required to be taken, at various phases by the management, to take the project further and then finally it gets culminated in to a finish product. The most critical decisions are the ones which are taken during the idea screening phase. There are usually numerous new product ideas during the early stage of project development. Some of the ideas have high probability of success, while majority of them could be unfeasible. Project screening helps to eliminate the ideas that have high probability of failure. Thus, it is imperative to conduct project screening, as selecting a right project for commercialization is the first step to the success of NPD.

NPD project screening helps to eliminate projects that have high potential of failure and allocate the development resources to the projects that have the highest potential of success. As a result, the growth of companies can be sustained and the overall NPD failure rate can be reduced. The process of NPD is multidisciplinary in nature. It requires the participation of a group of people from different departments in making decisions. A problem of judgment synthesis arises because of this group approach. Each group members may present different judgments about project screening decisions because of differences in technical backgrounds, departmental goals and constraints etc. The reliability of the decisions may depend on the way the diverse judgments are synthesized. The group discussion involves focusing on what actions and criteria to be considered, what weights and other necessary parameters will be appropriate. Group decision involves reduction of different individual preferences on a given set to a single collective preference. The most important characteristic of group decision is that all individuals involved in decision making belong to the same organization. Also, the parameters or criteria on which the decision is to be made quantitative in nature or subjective/ qualitative in nature. The impreciseness, vagueness, incompleteness and uncertainty further add to the complexity of the decision-making process. A wrong judgement might result in tremendous loss to the company. A structured approach is hence required to take care of this uncertainty in the data. Multi attribute decision making techniques can take care about these problems as it involves structured approach.

8.2 Conclusions

The literature review pointed out that most of the known MADM methods used in NPD have a drawback i.e., the effect of alternative rating variables of all alternatives taken together are not incorporated in selecting the best idea during the idea screening. Since the failure rate of in NPD is high and at the same time the cost of failure is high, importance of methods used for idea selection cannot be undermined. The gap identification led to proposal of three novel methods wherein all the data involved i.e., criteria weightages data and alternative rating data are arranged in a hierarchical form and a unique ranking method is proposed which takes in to account effect of alternatives with respect to criteria variables of other alternatives to make decision for a particular alternative.

The first proposed method takes the criteria weightages and alternative rating in linguistic form from the decision-makers so as to retain maximum original information. This linguistic data is then converted to fuzzy number to tackle the uncertainty in the data. The criteria weightage data and the alternative rating data are then aggregated and normalised. The separation measure of both the data from the fuzzy positive ideal solution is obtained. The separation measure is than converted to maximisation value so that higher value will result in a better solution. Both the maximisation matrix is then normalised. The elements of both the matrix are arranged in hierarchical structure by placing the alternative rating values for a given criteria under that particular criteria weight. The uniqueness of the method lies in the fact that, to get the global weightage for each alternative rating against criteria, the effect of sum of all the alternative rating is taken except for the one under consideration. A case study was then carried out in an automotive industry for finding the best alternative using the proposed method and COPRAS-G and Fuzzy TOPSIS method were used to validate the result. It was observed that both the methods resulted in the same ranking of the alternatives.

The second method known as Modified SVNS TOPSIS method involves converting the linguistic value in to SVNS value to take care of the inconsistency, impreciseness, uncertainty, incompleteness in the data normally associated with the new product development. After aggregating the criteria weightage and the alternative rating data, the distance of each data point from the positive ideal SVNS number is found out. The data is then arranged in a hierarchical manner by considering the criteria weightage data as upper-level data and alternative rating data as lower-level data. The alternative ranking is found out using the formula proposed. The same case study used in the validating the first method was used to validate the second method. The alternative ranking was found to be consistent. This method provides a simpler means of applying the SVNS TOPSIS method while still retaining the advantages of the primary method to deal with uncertainty, incompleteness, impreciseness and inconsistency of the data. The method is easier to understand and apply and requires less computational steps. The algorithmics superiority of both these methods lies in the fact that, to get the global weightage for each alternative rating against criteria, the effect of sum of all the alternative rating is taken except for the one under consideration. These methods either undermines or inflates the value of the global weight for that alternative rating based on its overall relationship with respect to the other data points. To check the superiority of both the proposed methods with respect to other MADM methods, two most commonly used methods i.e., fuzzy TOPSIS and COPRAS-G were used for comparison. A program was written with number of alternatives ranging from 2 to 10, number of criteria ranging from 2 to 10 and number of decision-makers between 2 to 5. Random data sets were generated in linguistic form using the code and some data was taken from published papers. More than 100 numerical were solved using all the four methods, i.e., (i) proposed hierarchal method (ii) modified SVNS TOPSIS (iii) Fuzzy TOPSIS method and (iv) COPRAS-G method and alternative ranking was obtained for each of the method. Spearmen co-relation formula was used to get the co-relation coefficient. It was observed that the co-relation coefficient ranged from 0.88 to 0.91 when applied between proposed method and Fuzzy TOPSIS method and proposed method and COPRAS-G method. Similarly, it was observed that the co-relation coefficient ranged from 0.85 to 0.90 when applied between modified SVNS TOPSIS and Fuzzy TOPSIS method and modified SVNS TOPSIS and COPRAS-G method. The correlation coefficient in both the cases indicates that there is higher degree of correlation between all the four methods.

The third method is based on converting the SVN number in to a single crisp number using the score function. This score function is representative of that neutrosophic number. The aggregated criteria weightages and the aggregated alternative rating against each criterion were converted to a single number using the score function and the data was arranged in hierarchical form to take advantage of the hierarchical structure which provided the required ranking of the alternatives. The method was validated by solving the same problem solved for the other two proposed methods and it was observed that the ranking remained the same. Sensitivity analysis was carried out and it was observed that the ranking remained the same and hence the results obtained using the score function-based method was stable and consistent. All these three methods provide an improved solution not only in selecting best idea during idea screening phase of NPD, but also can be applied to rank alternatives in various other MADM applications.

It is very difficult to get historical data for new product development. Hence mostly subjective data in qualitative form is considered. Incorporating this subjective data as input for traditionally superior MADM method is a very important requirement. At the same time, the NPD process is multidisciplinary in nature. Groups of people from different departments take part in decision making process. Judgment synthesis becomes synonymous with this group approach. Accuracy of the decisions and synthetization are directly proportional to the final decision-making outcome. Use of fuzzy scale or grey scale helps to convert the linguistic variables to either fuzzy numbers or grey numbers while still retaining the maximum original information, thus leading to reliable final decision solution. Evidential reasoning method finds its use in wide number of application due to its ability in handling uncertainties. Two hybrid methods have been proposed to bring together the effectiveness of fuzzy scale and grey scale along with the evidential reasoning algorithm. In both the methods the input data is taken in linguistic form to take in to account the advantage associated with it and evidential reasoning method was then applied to get the final decision. A manufacturing case study data was considered to get the best alternative assessment. It was observed that in both the methods i.e., Hybrid Grey ER and Hybrid Fuzzy ER, the alternative ranking turned out to be the same as the one obtained with Fuzzy TOPSIS and COPRAS G methods. The validation proved that the proposed method can be used to combine linguistic data with the evidential reasoning method using either grey scale or fuzzy scale.

SMEs are the backbone engine for socio-economic development of a state as well the country. Presently India ranks ahead among the fastest growing economic countries. In India, SMEs provide a large number of job opportunities and act as a source of employment for lakhs of people living in villages and semi urban towns. The growth of SME’s is hampered due to lack of experienced personnel either at the technical or managerial level and restricted capital allocation for carrying out research. NPD is an important part of any industry. NPD helps SMEs to cater to customer satisfaction and remain competitive in the market. It was observed that significantly less amount of research was carried out in the area of critical design for manufacturing factors affecting NPD in SME’s.

Design for manufacturability talks about actively designing of products to optimize the manufacturing process. Consideration of DFM factors during product design shorten the product life cycle minimizing production and manufacturing time, ensuring smooth flow of product, minimize cost etc... The literature review points out that substantial benefits have been realized by firms using design for manufacturability during product design or using existing product database and applying it to new product. Identifying the critical design for manufacturability factors can substantially bring improvement in the success of new product development for small and medium enterprises involved in manufacturing. It was decided to list down the key performance criteria for SMEs, based on design for manufacturability factors, which would help them in the new product development process and also to propose a self-assessment model for checking the NPD performance of SMEs. A gathering of technical top brass and academia scholars resulted in listing out all the factors that would affect new product development decision from design for manufacturability point of view. After lot of deliberations all the critical factors were listed down. There were 38 factors in total covering wide range of areas such as production friendly design, product complexity, products variants or add-ons, component availability and price, managing design cost, reusable design and the last but not the least quality standard framework.

The broader classification was considered as high-level factors and the 38 factors known as low level factors were listed under each of these high-level factors. Once the factors were made ready, a list of 252 personnel from design and manufacturing field from the state of Goa mainly consisting of managing directors, research and development people, new product development team members, technical people related to design, manufacturing and production having more than 15 year of experience was created. Face to face interviews using paper-based questionnaires was carried out for 20 to 30 minutes with each individual. Each individual was told to rate the global and the local factors from 1 to 9 using the pair wise comparison method of AHP. To check for the consistency of the opinion between the design and manufacturing personnel, an equal group of 100 design personnel and 100 manufacturing personnel was created and the ranking for each of the higher and lower-level factors was carried out using the AHP method for both the groups. It was observed that there was difference in ranking for the local factors under the following global factors: production friendly design, product complexity, product variants or add-ons, managing cost and reusable design, whereas for local factors under the quality standard framework and component availability and price the ranking remained the same. Using the ranking method available, all the 38 factors were than ranked on a common platform for both the groups. The Spearmen corelation formula was applied to get the corelation coefficient. The corelation coefficient turned out to be 0.593 which was a moderate corelation. Taking opinion of only design personnel or only manufacturing personnel in getting the weightages for the 37 factors would not serve the purpose. Hence it is required that the study to get the ranking and weightages of all the global and local factors have to be done in combined manner. After the combined study was carried out, the data was checked for consistency using a modified Cronbach alpha method. The alpha value turned out to be 0.887 which showed that the data collected from the 252 personnel using AHP method was consistent. A ranking method was proposed for the hierarchical structure.

The uniqueness of the method lies in the fact that the denominator is made up of sum of all the other factors except for the ones under the global factor for which decision is being made. The method was checked for consistency with the available ranking method and the spearmen coefficient was found to be 0.9067 which showed a high degree of corelation. The model further proposed ways to tackle various situation which SMEs could face during the decision-making process based on the decision-making criteria. To validate the model a case study in the motor industry located in Goa, India was taken up. COPRAS-Grey and hybrid method involving ANN-GA was used to solve the MADM problem. The input was taken from two sources i) standard weights obtained for the DFM factors (ii) weights given by decision makers from the company. It was observed that the final solution in terms of ranking using both the methods was same irrespective of the input data. This model provides an advantage which will allow the SMEs to overcome their biggest constraint of technical knowhow by using the standard weights calculated for the design for manufacturing factors.

8.3 Contributions

MADM methods used in NPD have a drawback i.e., the effect of alternative rating variables of all alternatives taken together are not incorporated in selecting the best idea during the idea screening. The gap identification led to proposal of three novel methods for ranking wherein all the data involved i.e., criteria weightages data and alternative rating data are arranged in a hierarchical form and a unique ranking method is proposed which takes in to account effect of alternatives with respect to criteria variables of other alternatives to make decision for a particular alternative. The methods takes care of the uncertainty associated with product development process, by incorporating fuzzy data sets or neutrosophic data sets. The superiority of the algorithm in terms of giving better ranking as compared to the traditional MADM methods is one of the highlights of the research work. Two hybrid methods involving grey scale and fuzzy scale along with evidential reasoning method were also proposed to take advantages associated with linguistic data. Listing of critical design for manufacturability factors affecting new product development of small and medium enterprises, a ranking method for the hierarchical structure of the factors and a self-assessment model to check for the NPD performance of SMEs are the other major contribution to the research work.

8.4 Limitations

The critical design for manufacturability factors affecting new product development of small and medium enterprises and the ranking of these factors on a common scale was done using data collected from design and manufacturing expert from the state of Goa and the states surrounding it. The case study for validating the self-assessment model was also carried out in one of the SMEs located in the state of Goa. Since the research proposes a generic model for SMEs located in any part of the world, be it developed or developing or under developed, the data needs to be collected from wider sources and then the weightages and relative ranking of the factors will have to be calibrated. This is one of the major drawbacks of the research work.

8.5 Overview of objectives, research outcomes with benefits and limitation.

The overview of the objectives and the research outcome along with the benefits and limitations are listed in Table 8.1.

Table 8.1: Overview of objectives, research outcomes with benefits and limitation.

Sr No	Objectives	Research Outcomes	Benefit	Limitation
1	Investigate the commonly used MADM approaches in NPD	Fuzzy TOPSIS and COPRAS-G method were applied to a case study and the results were validated	Traditional Methods, Easy to understand	Alternative rating data for all alternatives was not taken in to consideration while making the decision on the best alternative
2	Check the Effectiveness of Group/ Hybrid based MADM Approach	Two hybrid methods namely hybrid Grey ER and hybrid Fuzzy ER were proposed and validated with case study. Three new methods were proposed for finding the best alternative. These methods were validated with a case study	In the proposed methods to get the global weightage for each alternative rating against criteria, the effect of sum of all the alternative rating is taken except for the one under consideration	It involves more mathematical steps in getting the best alternative as compared to the conventional MADM method
3	Consider Design and Development in the process of New Product	Survey was conducted with the help of top-level design, manufacturing, R & D, academic people. A study was carried out to	Design people tend to be more biased towards the design factors, similarly manufacturing people are more biased towards the	One to one physically collecting data involves lot of time and patience

	Development	check the influence of only design personnel and only manufacturing personnel in the development of new product	manufacturing factors. In this model, since new product development process involved design for manufacturability factors for decision making, it was decided to take people from both group in decision making	
4	Understand the key DFM Criteria of NPD for SMEs	The survey resulted in 7 high level factors and 37 low level factors being listed. The data was checked for consistency and a unique ranking method was proposed to rank the low-level factors on a common scale	These factors are critical for success of NPD in SMEs from design for manufacturability point of view. The critical design for manufacturability factors affecting new product development of small and medium enterprises and the ranking of these factors on a common scale was done using data collected from design and manufacturing expert from the state of Goa and the states surrounding it	The data needs to be collected from wider sources and then the weightages and relative ranking of the factors will have to be calibrated
5	Devise a Self-Assessment Model for NPD Performance for SMEs	A self-assessment model was developed to select the best alternative among a given set of alternatives and the model was validated with a case study	The model provides an advantage which allows the SMEs to overcome their biggest constraint of technical knowhow by using the standard weights calculated for the design for manufacturing factors	The case study for validating the self-assessment model was carried out in one of the SMEs located in the state of Goa. Since the research proposes a generic model for SMEs located in any part of the world, be it developed or developing or under developed, more case studies have to be carried out in various places and validated

8.6 Future scope

There is lot of scope for the present research work. The areas identified for future research work can be listed as follows:

1. The critical DFM factors can be generalised for all SMEs, be it in developed or developing or under developed country.

2. The self-assessment model was validated by taking a case study in the state of Goa. Similar case study could be carried out for SMEs in other developing or under developed countries and compared with the existing result.

3. A case study wherein the decision-making criteria for selecting the best alternative in the idea screening phase of NPD, are all not part of the standard critical DFM factors can be taken up and validated by other methods shown in the research work.

4. Further study of group based or hybrid MADM methods should be carried out to check their superiority over the conventional MADM methods.

5. The proposed novel hierarchical method has a short coming in that it involves more mathematical steps in getting the best alternative, hence the computational time is slightly more as compared to the conventional MADM method. Also, further work has to be carried out to validate the proposed method against higher number of alternatives and criteria.

7. The proposed two methods under neutrosophic logic has to be validated against higher number of alternatives and criteria problem.

6. The proposed three methods can be used to get ranking of alternatives in other MADM application apart from new product development.

Appendix 1

Sample AHP form from Senior Design Manager for global and local factors

	Production Friendly Design	Product Complexity	Product Variants / Addons	Component Availablity and Price	Managing Cost	Reusable Design	Quality Standard Framework
Production Friendly Design	1.00	9.00	9.00	5.00	7.00	5.00	5.00
Product Complexity	0.11	1.00	7.00	0.14	7.00	0.14	7.00
Product Variants / Addons	0.11	0.14	1.00	0.14	0.33	0.14	0.33
Component Availablity and Price	0.20	7.00	7.00	1.00	3.00	0.20	3.00
Managing Cost	0.14	0.14	3.00	0.33	1.00	0.14	0.14
Reusable Design	0.20	7.00	7.00	5.00	7.00	1.00	5.00
Quality Standard Framework	0.20	0.14	3.00	0.33	0.14	0.20	1.00

Production Friendly Design	Production Feasibility	Product Launch Schedules	Prototype Testing	Placement And Routing of Cables	Incorporate Last Minute Design Changes	Minimum Production Assembly Time	
Production Feasibility	1.00	7.00	7.00	3.00	3.00	7.00	
Product Launch Schedules	0.14	1.00	3.00	0.14	0.33	0.14	
Prototype Testing	0.14	0.33	1.00	0.14	0.33	0.14	
Placement And Routing of Cables	0.33	7.00	7.00	1.00	3.00	0.14	
Incorporate Last Minute Design Changes	0.33	3.00	3.00	0.33	1.00	0.14	

Minimum Production Assembly Time	0.14	7.00	7.00	7.00	7.00	1.00	
Product Complexity	Ease of Manufacturing	Ease of Assembly	Assembly Bottlenecks	Manufacturing Life Cycle	Assembly Life Cycle	Material Handling	
Ease of Manufacturing	1.00	0.20	0.20	5.00	5.00	5.00	
Ease of Assembly	5.00	1.00	0.20	7.00	7.00	5.00	
Assembly Bottlenecks	5.00	5.00	1.00	7.00	7.00	5.00	
Manufacturing Life Cycle	0.20	0.14	0.14	1.00	1.00	5.00	
Assembly Life Cycle	0.20	0.14	0.14	1.00	1.00	5.00	
Material Handling	0.20	0.20	0.20	0.20	0.20	1.00	
Product Variants / Addons	Conforming To Various International Standards	Functional Addons	Aesthetics / Styling	Product Pride			
Conforming To Various International Standards	1.00	9.00	9.00	9.00			
Functional Addons	0.11	1.00	0.33	0.20			
Aesthetics / Styling	0.11	3.00	1.00	3.00			
Product Pride	0.11	5.00	0.33	1.00			

Component Availability and Price	In House Capability	FERA	Vendor Support and Flexibility	Lead Time	Number of 'A' Class Items	Vendor Component Monopoly	
In House Capability	1.00	5.00	0.14	0.20	5.00	7.00	
FERA	0.20	1.00	0.20	0.20	0.33	0.14	
Vendor Support and Flexibility	7.00	5.00	1.00	5.00	5.00	9.00	
Lead Time	5.00	5.00	0.20	1.00	5.00	5.00	
Number of 'A' Class Items	0.20	3.00	0.20	0.20	1.00	0.14	
Vendor Component Monopoly	0.14	7.00	0.11	0.20	7.00	1.00	
Managing Cost	Equipment Development Cost	Tooling Development Cost	Manpower Training Cost	Raw Material Cost	Material Handling Cost	Minimum Rejects	Minimum Rework
Equipment Development Cost	1.00	5.00	0.33	9.00	0.20	0.20	0.20
Tooling Development Cost	0.20	1.00	9.00	9.00	5.00	0.20	0.20
Manpower Training Cost	3.00	0.11	1.00	9.00	9.00	0.11	0.20
Raw Material Cost	0.11	0.11	0.11	1.00	0.20	0.11	0.11
Material Handling Cost	5.00	0.20	0.11	5.00	1.00	0.11	0.11
Minimum Rejects	5.00	5.00	9.00	9.00	9.00	1.00	1.00
Minimum Rework	5.00	5.00	5.00	9.00	9.00	1.00	1.00

Reusable Design	Modular Product Design	Standardisation	Interchangeability	Modification of Existing Product	Add on to Existing Product		
Modular Product Design	1.00	5.00	5.00	7.00	0.20		
Standardisation	0.20	1.00	5.00	5.00	0.20		
Interchangeability	0.20	0.20	1.00	7.00	0.20		
Modification of Existing Product	0.14	0.20	0.14	1.00	0.20		
Add on to Existing Product	5.00	5.00	5.00	5.00	1.00		
Quality Standard Framework	Industry Regulatory Requirement	Design As Per Designated Framework	Quality in Design	Production Performance Impact Due to Change			
Industry Regulatory Requirement	1.00	5.00	5.00	5.00			
Design As Per Designated Framework	0.20	1.00	0.20	5.00			
Quality in Design	0.20	5.00	1.00	7.00			
Production Performance Impact Due to Change	0.20	0.20	0.14	1.00			

Appendix 2

Sample AHP form from Senior Project Manager for global and local factors

	Production Friendly Design	Product Complexity	Product Variants / Addons	Component Availability and Price	Managing Cost	Reusable Design	Quality Standard Framework
Production Friendly Design	1.00	9.00	0.14	9.00	0.14	0.14	7.00
Product Complexity	0.11	1.00	0.14	7.00	0.14	0.14	5.00
Product Variants / Addons	7.00	7.00	1.00	7.00	0.14	0.14	7.00
Component Availability and Price	0.11	0.14	0.14	1.00	0.14	0.14	3.00
Managing Cost	7.00	7.00	7.00	7.00	1.00	3.00	7.00
Reusable Design	7.00	7.00	7.00	7.00	0.33	1.00	0.14
Quality Standard Framework	0.14	0.14	0.20	0.33	1.70	7.00	1.00
Production Friendly Design	Production Feasibility	Product Launch Schedules	Prototype Testing	Placement And Routing of Cables	Incorporate Last Minute Design Changes	Minimum Production Assembly Time	
Production Feasibility	1.00	5.00	5.00	5.00	5.00	7.00	
Product Launch Schedules	0.20	1.00	5.00	0.14	0.20	0.14	
Prototype Testing	0.20	0.20	1.00	0.14	0.20	0.11	
Placement And Routing of Cables	0.20	7.00	7.00	1.00	5.00	0.14	

Incorporate Last Minute Design Changes	0.20	5.00	5.00	0.20	1.00	0.14	
Minimum Production Assembly Time	0.14	7.00	7.00	7.00	7.00	1.00	
Product Complexity	Ease of Manufacturing	Ease of Assembly	Assembly Bottlenecks	Manufacturing Life Cycle	Assembly Life Cycle	Material Handling	
Ease of Manufacturing	1.00	0.33	7.00	5.00	3.00	7.00	
Ease of Assembly	3.00	1.00	7.00	3.00	1.00	5.00	
Assembly Bottlenecks	0.14	0.14	1.00	3.00	0.20	9.00	
Manufacturing Life Cycle	0.20	0.33	0.33	1.00	3.00	7.00	
Assembly Life Cycle	0.33	1.00	5.00	0.33	1.00	7.00	
Material Handling	0.14	0.20	0.11	0.14	0.14	1.00	
Product Variants / Addons	Conforming to Various International Standards	Functional Addons	Aesthetics / Styling	Product Pride			
Conforming to Various International Standards	1.00	0.33	0.20	0.20			
Functional Addons	3.00	1.00	0.33	5.00			
Aesthetics / Styling	5.00	3.00	1.00	5.00			
Product Pride	5.00	0.20	0.20	1.00			

Component Availability and Price	In House Capability	FERA	Vendor Support and Flexibility	Lead Time	Number of 'A' Class Items	Vendor Component Monopoly	
In House Capability	1.00	3.00	5.00	5.00	5.00	5.00	
FERA	0.33	1.00	0.20	0.33	0.33	0.14	
Vendor Support and Flexibility	0.20	5.00	1.00	3.00	5.00	9.00	
Lead Time	0.20	3.00	0.33	1.00	5.00	7.00	
Number of 'A' Class Items	0.20	3.00	0.20	0.20	1.00	0.14	
Vendor Component Monopoly	0.20	7.00	0.11	0.14	7.00	1.00	
Managing Cost	Equipment Development Cost	Tooling Development Cost	Manpower Training Cost	Raw Material Cost	Material Handling Cost	Minimum Rejects	Minimum Rework
Equipment Development Cost	1.00	5.00	0.33	0.14	0.11	0.20	0.20
Tooling Development Cost	0.20	1.00	0.20	0.20	0.20	0.14	0.11
Manpower Training Cost	3.00	5.00	1.00	0.20	7.00	0.14	0.11
Raw Material Cost	7.00	5.00	5.00	1.00	3.00	0.14	0.11
Material Handling Cost	9.00	5.00	0.14	0.33	1.00	0.14	0.11
Minimum Rejects	5.00	7.00	7.00	7.00	7.00	1.00	3.00
Minimum Rework	5.00	9.00	9.00	9.00	9.00	0.33	1.00

Reusable Design	Modular Product Design	Standardisation	Interchangeability	Modification of Existing Product	Add On to Existing Product		
Modular Product Design	1.00	0.14	0.20	0.20	0.11		
Standardisation	7.00	1.00	5.00	5.00	0.20		
Interchangeability	5.00	0.20	1.00	5.00	0.20		
Modification of Existing Product	5.00	0.20	0.20	1.00	0.11		
Add On to Existing Product	9.00	5.00	5.00	9.00	1.00		
Quality Standard Framework	Industry Regulatory Requirement	Design As Per Designated Framework	Quality In Design	Production Performance Impact Due To Change			
Industry Regulatory Requirement	1.00	0.33	0.11	5.00			
Design As Per Designated Framework	3.00	1.00	0.14	5.00			
Quality In Design	9.00	7.00	1.00	9.00			
Production Performance Impact Due To Change	0.20	0.20	0.11	1.00			

Appendix 3

Sample AHP form from Project R & D Manager for global and local factors

	Production Friendly Design	Product Complexity	Product Variants / Addons	Component Availability and Price	Managing Cost	Reusable Design	Quality Standard Framework
Production Friendly Design	1.00	9.00	9.00	5.00	3.00	9.00	9.00
Product Complexity	0.11	1.00	5.00	5.00	5.00	3.00	0.33
Product Variants / Addons	0.11	0.20	1.00	0.20	0.20	0.20	0.33
Component Availability and Price	0.20	0.20	5.00	1.00	0.20	0.20	0.33
Managing Cost	0.33	0.20	0.20	5.00	1.00	0.33	0.33
Reusable Design	0.11	0.33	5.00	5.00	3.00	1.00	0.33
Quality Standard Framework	0.11	3.00	3.00	3.00	3.00	3.00	1.00
Production Friendly Design	Production Feasibility	Product Launch Schedules	Prototype Testing	Placement And Routing of Cables	Incorporate Last Minute Design Changes	Minimum Production Assembly Time	
Production Feasibility	1.00	5.00	0.20	0.33	5.00	3.00	
Product Launch Schedules	0.20	1.00	0.20	0.20	3.00	0.33	
Prototype Testing	5.00	5.00	1.00	5.00	5.00	7.00	
Placement And Routing of Cables	3.00	5.00	0.20	1.00	5.00	3.00	
Incorporate Last Minute Design Changes	0.20	0.33	0.20	0.20	1.00	0.33	

Minimum Production Assembly Time	0.33	3.00	0.14	0.33	3.00	1.00	
Product Complexity	Ease of Manufacturing	Ease of Assembly	Assembly Bottlenecks	Manufacturing Life Cycle	Assembly Life Cycle	Material Handling	
Ease of Manufacturing	1.00	0.33	5.00	5.00	5.00	3.00	
Ease of Assembly	3.00	1.00	3.00	5.00	3.00	5.00	
Assembly Bottlenecks	0.20	0.33	1.00	3.00	0.20	5.00	
Manufacturing Life Cycle	0.20	0.20	0.33	1.00	3.00	5.00	
Assembly Life Cycle	0.20	0.33	5.00	0.33	1.00	3.00	
Material Handling	0.33	0.20	0.20	0.33	0.20	1.00	
Product Variants / Addons	Conforming to Various International Standards	Functional Addons	Aesthetics / Styling	Product Pride			
Conforming to Various International Standards	1.00	3.00	3.00	0.20			
Functional Addons	0.33	1.00	0.33	0.20			
Aesthetics / Styling	0.33	3.00	1.00	0.20			
Product Pride	5.00	5.00	5.00	1.00			

Component Availability and Price	In House Capability	FERA	Vendor Support and Flexibility	Lead Time	Number of 'A' Class Items	Vendor Component Monopoly	
In House Capability	1.00	5.00	0.11	0.20	5.00	3.00	
FERA	0.20	1.00	0.20	0.33	0.33	0.33	
Vendor Support and Flexibility	9.00	5.00	1.00	5.00	5.00	9.00	
Lead Time	5.00	3.00	0.20	1.00	5.00	3.00	
Number Of 'A' Class Items	0.20	3.00	0.20	0.20	1.00	0.33	
Vendor Component Monopoly	0.33	3.00	0.11	0.33	3.00	1.00	
Managing Cost	Equipment Development Cost	Tooling Development Cost	Manpower Training Cost	Raw Material Cost	Material Handling Cost	Minimum Rejects	Minimum Rework
Equipment Development Cost	1.00	5.00	0.33	0.33	0.11	0.20	0.20
Tooling Development Cost	0.20	1.00	0.20	0.20	0.20	0.33	0.33
Manpower Training Cost	3.00	5.00	1.00	0.20	3.00	0.33	0.33
Raw Material Cost	3.00	5.00	5.00	1.00	3.00	0.33	0.33
Material Handling Cost	9.00	5.00	0.33	0.33	1.00	0.33	0.33
Minimum Rejects	5.00	3.00	3.00	3.00	3.00	1.00	3.00
Minimum Rework	5.00	3.00	3.00	3.00	3.00	0.33	1.00
Reusable Design	Modular Product Design	Standardisation	Interchangeability	Modification of Existing Product	Add On to Existing Product		

Modular Product Design	1.00	5.00	5.00	3.00	5.00		
Standardisation	0.20	1.00	5.00	3.00	5.00		
Interchangeability	0.20	0.20	1.00	3.00	5.00		
Modification of Existing Product	0.33	0.20	0.33	1.00	0.33		
Add ON to Existing Product	0.20	5.00	0.20	3.00	1.00		
Quality Standard Framework	Industry Regulatory Requirement	Design As Per Designated Framework	Quality In Design	Production Performance Impact Due to Change			
Industry Regulatory Requirement	1.00	3.00	3.00	5.00			
Design As Per Designated Framework	0.33	1.00	0.20	5.00			
Quality In Design	0.33	5.00	1.00	3.00			
Production Performance Impact Due to Change	0.20	0.20	0.33	1.00			

Appendix 4

Output of the program code written for Proposed Hierarchical method

	A1			A2			A3		
	D1	**D2**	**D3**	**D1**	**D2**	**D3**	**D1**	**D2**	**D3**
C1	G	G	G	G	VG	F	G	G	F
C2	F	G	G	G	VG	G	F	F	G
C3	VG	G	G	VG	G	F	G	G	G
C4	G	G	F	G	G	G	G	F	G
C5	VG	G	P	G	G	F	G	F	P

Alternative ratings

	D1	D2	D3
C1	VH	H	H
C2	H	H	H
C3	M	L	VH
C4	H	M	M
C5	H	M	VH

Criteria ratings

	A1			A2			A3		
	D1	**D2**	**D3**	**D1**	**D2**	**D3**	**D1**	**D2**	**D3**
C1	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
C2	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)	(5, 7, 9)
C3	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
C4	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
C5	(7, 9, 9)	(5, 7, 9)	(1, 3, 5)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)

Alternative table

	D1	D2	D3
C1	(7, 9, 9)	(5, 7, 9)	(5, 7, 9)
C2	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
C3	(3, 5, 7)	(1, 3, 5)	(7, 9, 9)
C4	(5, 7, 9)	(3, 5, 7)	(3, 5, 7)
C5	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)

Criteria table

	A1			A2			A3		
	a	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**
C1	5.000	7.000	9.000	5.000	7.000	8.333	4.333	6.333	8.333
C2	4.333	6.333	8.333	5.667	7.667	9.000	3.667	5.667	7.667
C3	5.667	7.667	9.000	5.000	7.000	8.333	5.000	7.000	9.000
C4	4.333	6.333	8.333	5.000	7.000	9.000	4.333	6.333	8.333
C5	4.333	6.333	7.667	4.333	6.333	8.333	3.000	5.000	7.000

Alternative aggregate table

	a	b	c
C1	5.667	7.667	9.000
C2	5.000	7.000	9.000
C3	3.667	5.667	7.000
C4	3.667	5.667	7.667
C5	5.000	7.000	8.333

Criteria aggregate table

	0	1	2	3	4
Alternative coefficients	9.000	9.000	5.000	9.000	8.333
Criteria Coefficients	9.000	9.000	3.667	7.667	8.333

Normalizing coefficient

	A1			A2			A3		
	a	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**
C1	0.556	0.778	1.000	0.556	0.778	0.926	0.481	0.704	0.926
C2	0.481	0.704	0.926	0.630	0.852	1.000	0.407	0.630	0.852
C3	0.882	0.652	0.556	1.000	0.714	0.600	1.000	0.714	0.556
C4	0.481	0.704	0.926	0.556	0.778	1.000	0.481	0.704	0.926
C5	0.520	0.760	0.920	0.520	0.760	1.000	0.360	0.600	0.840

Normalized Alternative aggregate table

	a	b	c
C1	0.630	0.852	1.000
C2	0.556	0.778	1.000
C3	1.000	0.647	0.524

	a	b	c
C4	0.478	0.739	1.000
C5	0.600	0.840	1.000

Normalized Criteria aggregate table

	A1	A2	A3
	0	**0**	**0**
C1	0.287	0.290	0.347
C2	0.347	0.230	0.412
C3	0.333	0.284	0.305
C4	0.347	0.287	0.347
C5	0.313	0.310	0.445

Alternative Separation Measure

	0
C1	0.230
C2	0.287
C3	0.342
C4	0.337
C5	0.249

Criteria Separation Measure

	0
C1	0.238
C2	0.220
C3	0.106
C4	0.205
C5	0.232

Normalized Criteria Maximum / 1st level factor

		2nd Lvl factor	Global Weights	Normalized weights
C1	**A1**	0.344	0.020	0.082
	A2	0.342	0.020	0.081
	A3	0.314	0.019	0.075
C2	**A1**	0.325	0.018	0.071
	A2	0.383	0.021	0.084

		2nd Lvl factor	Global Weights	Normalized weights
	A3	0.292	0.016	0.064
C3	**A1**	0.361	0.010	0.038
	A2	0.308	0.008	0.033
	A3	0.331	0.009	0.035
C4	**A1**	0.323	0.017	0.066
	A2	0.353	0.018	0.072
	A3	0.323	0.017	0.066
C5	**A1**	0.356	0.021	0.082
	A2	0.357	0.021	0.083
	A3	0.287	0.017	0.067

H Structure

	Closeness Coefficient	Scaled	Ranks
A1	0.340	96.207	2
A2	0.353	100.000	1
A3	0.307	86.838	3

Results

	Closeness Coefficient	Scaled	Ranks
A1	0.341	97.899	2
A2	0.349	100.000	1
A3	0.310	88.833	3

Criteria 1 is best

	Closeness Coefficient	Scaled	Ranks
A1	0.338	95.268	2
A2	0.355	100.000	1
A3	0.306	86.227	3

Criteria 2 is best

	Closeness Coefficient	Scaled	Ranks
A1	0.339	95.679	2
A2	0.354	100.000	1
A3	0.307	86.570	3

Criteria 3 is best

	Closeness Coefficient	Scaled	Ranks
A1	0.338	96.484	2
A2	0.351	100.000	1
A3	0.311	88.784	3

Criteria 4 is best

	Closeness Coefficient	Scaled	Ranks
A1	0.343	97.764	2
A2	0.351	100.000	1
A3	0.305	86.989	3

Criteria 5 is best

	Closeness Coefficient	Scaled	Ranks
A1	0.339	95.862	2
A2	0.354	100.000	1
A3	0.307	86.747	3

All benefit type are best

	Closeness Coefficient	Scaled	Ranks
A1	0.339	95.679	2
A2	0.354	100.000	1
A3	0.307	86.570	3

All cost type are best

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LIST OF PUBLICATIONS

International Journals

[1] "A novel hierarchical ranking method for idea screening in new product development", *International Journal of Business Excellence, Inder-Science* (Accepted and under publication)

[2] "Model for ranking critical factors affecting new product development from design for manufacturability consideration for small and medium enterprises" (Under Review)

[3] "Application of Standardised Weights for SMEs in NPD based on DFM Factors" (To be Communicated)

[4] "Modified SVNS TOPSIS method for idea screening in new product development" (To be Communicated)

National Journals

[1] "Uncertainty Identification in New product Development", Industrial Engineering Journal, Volume X & Issue no.12, December 2017, pp., 41-45.

International Conferences

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