An Advanced Decision-Making Model for Evaluating Manufacturing Plant Locations using Fuzzy Inference System

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Abstract

Locating a manufacturing plant is a complex multi-criteria decision-making problem as it involves many tangible and intangible criteria. This paper contributes to the existing theory by integrating a qualitative Delphi and a quantitative fuzzy inference system (FIS) for developing an advanced and intelligent decision-making framework for evaluating manufacturing plant locations. The Delphi method is used to identify the most significant manufacturing plant location selection criteria. The identified major criteria are used to develop an advanced FIS framework to evaluate potential manufacturing plant locations. A real-life case is presented to demonstrate the applicability of the developed decision-making framework. This paper contributes to the literature by developing an advanced decision-making framework for evaluating manufacturing plant locations and by integrating qualitative Delphi and quantitative FIS, which can help industrial managers locate their manufacturing plant locations intelligently and accurately.

Keywords: Manufacturing location; Intelligent decision-making; Fuzzy inference system (FIS); Multi-criteria decision-making.

1. INTRODUCTION

Decisions regarding the selection of a manufacturing plant's location have a significant impact on a firm's competitiveness, survival and market share (Jahr & Borrmann, 2018). The selection of an appropriate manufacturing plant location contributes significantly to achieving the objectives of the company by minimizing operations and facility costs and maximizing the best use of available resources and capabilities (Shafiee-Gol et al., 2021; Devi and Yadav, 2013). Selecting the best manufacturing plant location is not a straightforward decision; rather, it is very complex in nature because firms need to assess a large volume of data effectively by considering both tangible and intangible criteria in order to evaluate alternative locations (Min & Melachrinoudis, 1996; Mousavi et al., 2013). Further, the impact of some of these criteria on the firm's output may be positive, while the impact of others may be negative (Dogan, 2012; Jimenez Capilla et al., 2016). Therefore, manufacturing plant location selection has long been considered a complex, long-term and multi-criteria decision-making (MCDM) problem (Cebi & Otay, 2015; Yoon & Hwang, 1985).

Plant location problems can be broadly classified into two categories of approaches: factor assessment and mathematical approach (Huang et al., 2019). The factor assessment approach mostly focuses on evaluating the strategic factors involved in decision-making to identify the most suitable sites from a number of alternatives. These factors or selection criteria might be both tangible and intangible, and may include the availability of raw materials, land price, the availability of power supply, the security of location, investment cost, the business environment and climate (Yang & Hung 2007; Mousavi et al., 2013). Under a mathematical approach, the most common objectives are cost minimization or profit maximization through the selection of appropriate plant location (Melo et al., 2009).

Although historically firms focus more on the economic dimensions of site selection for their manufacturing plant, several recent studies have indicated that nowadays it is becoming increasingly necessary for manufacturing firms to consider other crucial factors – technical, social and environmental – during plant location selection (Alam et al., 2015; Beskese et al., 2015; Cebi & Otay, 2015; Chang, 2015; Jimenez Capilla et al., 2016). For example, a study conducted by Dey & Ramcharan (2008) considered technical, economic, environmental, socio-cultural and national planning factors to select a site for the extension of limestone quarry operations to support cement production in Barbados. In another study, Capilla et al. (2016) considered terrain, distance, climate and risk factors to select a site for upper reservoirs in pump-back systems. Dou and Sarkis (2010) summarized selection factors for plant location decisions in terms of strategy, accessibility, community, business climate, labor, utility, risk, and financial and special factors. In order to analyze the facility selection process of manufacturing firms, Dogan (2012) considered 36 criteria (variables) under 12 tangible and intangible categories such as quality of life, quality of supplier, financial efficiency and regulation. In a recent study via a systematic literature review, Chen et al. (2014) stated that, in manufacturing facility location studies, focusing on industry and country factors is a new trend. The criteria for selecting locations vary across the types of facilities, origins of firms and cities in which the firms are looking for locations (Cebi & Otay, 2015). Moreover, the relative importance of such criteria on decision-making also differs with respect to the objectives of the firm and the country of its operation (Beskese et al., 2015; Ertugrul & Karakasoglu, 2009). It appears that there may be different strategic reasons for location decisions for different manufacturing facilities. Considering all the factors that impact location selection, it is evident that determining the best possible location for manufacturing facilities has become increasingly difficult (Chen et al., 2014).

As plant location selection is critical for the survival of firms, practitioners recognize the importance of analyzing this multi-criteria problem (Cebi & Otay 2015). In order to solve plant location problems, researchers have identified MCDM approaches as effective and powerful tools (Mousavi et al., 2013). Moreover, MCDM approaches can address both the subjective and objective factors of decision-making and can also involve practitioners in decision-making processes. The analytic hierarchy process (AHP) is the most widely used MCDM plant location method that simultaneously integrates qualitative and quantitative information to prioritize alternatives when multiple criteria must be considered. AHP is used to resolve different location decision problems such as: site-selection for limestone quarry expansion; manufacturing plant location selection; site selection for upper reservoirs; restaurant location selection; and facility location selection (Dey & Ramcharan, 2008; Jimenez Capilla et al., 2016; Mousavi et al., 2013; Tzeng et al., 2002). Among other MCDM tools, the technique for order preference by similarity to ideal solution (TOPSIS) is used to select the plant location within a linguistic environment (Adhikary et al., 2015; Ertugrul & Karakasoglu, 2009; Farahani & Asgari, 2007; Yang & Hung, 2007). Previous research (Mousavi et al., 2013) has also utilized outranking methods such as the preference ranking organization method for enrichment of evaluations (PROMETHEE). For manufacturing facility location selection, researchers (Tuzkaya et al. 2008; Partovi 2006) also utilized the VIKOR method – a term originating from the Serbian name '*vlse kriterijumska optimizacija kompromisno resenje*', which means 'multi-criteria optimization and compromise solution' (Adhikary et al., 2015). The VIKOR method is used to determine the compromise ranking list and compromise solution from a list of alternatives in the existence of conflicting and non-commensurable (attributes with different weights) criteria (Opricovic & Tzeng 2004). Some researchers have also used multiple MCDM approaches to solve the location problem. For example, Adhikary et al. (2015) and Opricovic & Tzeng (2004) have used TOPSIS and VIKOR and Mousavi et al. (2013) have combined AHP and PROMETHEE approaches.

These MCDM approaches are criticized in the literature as they do not consider the ambiguity and vagueness inherent in real-world plant location selection problems (Cebi & Otay, 2015; Devi & Yadav, 2013). To overcome this issue, various studies have utilized fuzzy set theory (J. R. Chou, 2018; Song et al., 2019) using different fuzzy MCDM approaches including fuzzy TOPSIS, fuzzy AHP, fuzzy simple additive weighting system (SAWS) and fuzzy Elimination and Choice Expressing Reality (ELECTRE). For example, Beskese et al. (2015) have used fuzzy AHP with fuzzy TOPSIS for a landfill site selection.

However, these fuzzy MCDM methods are time-consuming in formulating real-life problems, particularly when firms need to consider a large number of locations and criteria, and final solutions of ranking carry insignificant differences (Amindoust et al., 2012). Furthermore, because of the need to consider several qualitative and quantitative criteria, plant location selection using the above approaches is very complex and challenging (Devi & Yadav, 2013). In addition, none of the above approaches is intelligent in solving complex real-world problems. Considering their complexity and user unfriendliness, most decision-makers are reluctant to apply these traditional techniques to solve plant location problems. Hence, it is important to develop an intelligent and user-friendly decision-making tool to select a manufacturing plant location (Xu et al., 2018). However, to our knowledge, none of the previous studies developed such an intelligent tool for the plant location selection problem. Hence, our objective is to develop an intelligent framework by integrating the Delphi method and rule-based fuzzy inference system (FIS) to evaluate the manufacturing plant locations. To the best of our knowledge, this study is effective in terms of developing a new MCDM framework that can evaluate location alternatives intelligently with no additional inputs from decision-makers. The proposed framework is easy to use as it has some internal artificial intelligence capacity within the system, and it is user friendly because it requires fewer complex mathematical calculations.

We use the Delphi method to identify key location selection criteria and their respective weights, as determined from experts' opinions, to use in the proposed intelligent framework. Such an integration adds to the current literature on the plant location selection problem. While this integration has been recognized as useful for strategic decisions and was used in other areas, such as supplier selection (Tahriri et al., 2014) and third-party logistics selection (Liu & Wang, 2009), none of the previous studies on location selection used this integration. We validate the results of the framework by comparing these with the results obtained from TOPSIS. Finally, to validate the applicability of our developed tool we use it in a real-world example of manufacturing plant location selection for an apparel manufacturing company in Bangladesh.

The present study serves as a new study that uses an integration of the qualitative Delphi method and quantitative FIS in the area of manufacturing plant location to provide managers with a decision-modeling framework. The main contributions of the present study can be summarized as follows.

i. Identification of the key selection criteria thorough literature review and Delphi method for selecting manufacturing plant location. This study contributes to the literature by identifying and categorizing manufacturing plant location selection criteria based on both negative and positive influences.
ii. Integration of qualitative Delphi method and quantitative FIS approach to developing an advanced decision-making framework.
iii. Comparison of results obtained from another standard method namely TOPSIS.
iv. Confirm the applicability of the developed decision-making framework via a real-life application.

The rest of the paper is organized as follows. In Section 2, we discuss and summarize the literature review. The research methods of this study are described in Section 3. Results and a real-world case study are presented in Section 4. Finally, Section 5 provides the conclusion and managerial implications.

2. LITERATURE REVIEW

In this section, we discuss the different processes involved in manufacturing plant location selection. Firstly, we discuss the criteria used for selecting manufacturing plant locations and then discuss the most recent tools and techniques applied to prioritize locations.

2.1 Manufacturing Location Selection Criteria

Since location problems are different across different industries and contexts, prior studies have already considered numerous problems in the different contexts, such as plant location problems (Mousavi et al., 2013), facility location problems, (S. Y. Chou et al., 2008), battery charging location problems (Guo et al., 2018), add-on retail products location problems (Huang et al., 2019), grain-silo location-allocation problems (Mogale et al., 2018), temporary medical service location problems (Y. Liu et al., 2019), and travel facility location problems (Amiri-Aref et al., 2019). These studies have analyzed location selection criteria under different categories and with respect to different factors (Current & Weber, 1994). For instance, Dogan (2012) categorized location decision criteria as dependent on tangible and intangible factors. Chen et al. (2014) categorized manufacturing location decision factors as economic, environmental and related to social sustainability. In another study, through a systematic literature review, Farahani et al. (2010) categorized location selection criteria into twelve groups: cost, values and benefits, environmental risks, resource accessibility, public facility, political and regulatory, competition, economic, population, capacity, distance, and suitability.

From the nature of these groupings, it is apparent that economic factors are dominant in manufacturing location selection. In the economic category, selection criteria are related to different types of costs and expenses, such as the cost of site development, production, materials, labor, maintenance, utilities, and transportation, as well as, land prices and taxation (Beskese et al., 2015; T.-Y. Chou et al., 2008; Dogan, 2012; Kabir & Sumi, 2012; Mousavi et al., 2013; Partovi, 2006). However, nowadays, besides economic factors, firms are increasingly attaching importance to environmental, social and infrastructure-related factors (Adhikary et al., 2015; Alam et al., 2015; Beskese et al., 2015; Cebi and Otay, 2015; Chang, 2015; Capilla et al., 2016; Mousavi et al., 2013).

Environmental factors including waste disposal and treatment opportunity, the availability of renewable resources, energy consumption, and biological and ecological factors such as temperature, humidity, and rain and sunshine, are also associated with the smooth production processes of manufacturing plants (Adhikary et al., 2015; Beskese et al., 2015; Cebi & Otay, 2015; S. Y. Chou et al., 2008; T.-Y. Chou et al., 2008; Dey & Ramcharan, 2008; Farahani & Asgari, 2007; Kabir & Sumi, 2014; Partovi, 2006). These factors become more crucial when the location problems involve multinational options (Min & Melachrinoudis, 1996). In the social category, the dominant factors for selecting a location include corruption (Bai & Sarkis, 2010; Chowdhury & Paul, 2020; Jørgensen & Knudsen, 2006), political stability, general education levels, human rights, safety, population, job creation, local support, contribution to society, and maintaining culture and heritage (Adhikary et al., 2015; Cebi & Otay, 2015; Kabir & Sumi, 2012). Further, decision-makers considered strategic infrastructure factors during site selection for the manufacturing plant (Beskese et al., 2015; Dey and Ramcharan, 2008; Farahani et al., 2010; Kabir and Sumi, 2014; Mousavi et al., 2013). Diverse factors related to site characteristics, such as land suitability, drainage capability, site capacity, expansion capacity, and distance from water zones, are considered in selecting the best plant location (Chang, 2015; Chu, 2002b; Mousavi et al., 2013; Yoon & Hwang, 1985). In addition, the authors of these studies have considered several other infrastructural factors, such as the availability of transportation facilities, local labor, raw materials, fuel, water, and power in selecting the appropriate plant location (Chu, 2002b; Devi & Yadav, 2013; Mousavi et al., 2013; Yoon & Hwang, 1985).

From the literature, it is evident that decision-makers consider numerous factors when selecting a suitable site for a manufacturing plant. The relative importance of these factors varies from country to country and industry to industry (Chen et al., 2014). For example, in apparel manufacturing, it is beneficial to consider the availability of labor, labor productivity, minimum wages, facilities available to transport goods to and from the factory, the availability of raw materials, cost, the availability of infrastructures such as electricity and water, and proximity to the nearest port. Hence, it is important to determine plant location selection criteria for specific industries and countries that are applicable in a local context.

Plant location selection criteria have either a positive or negative influence on location selection decisions (Jimenez Capilla et al., 2016). We group the location decision factors as positive and negative criteria (shown in Table 1). Positive are those that might have a positive influence on location selection decisions. For example, a water supply facility is a positive criterion as the high availability of water supply in a location will favor that location in ranking. On the other hand, some criteria have a negative impact on the ultimate location selection decision. For example, the high production costs of a location will unfavorably impact that location in ranking.

Table 1: Criteria for selecting plant location

Criteria	References	Influence
Fuel/gas supply facility	Cebi & Otay (2015); Farahani et al. (2010)	Positive
Water supply facility	Cebi & Otay (2015); Farahani & Asgari (2007)	Positive
Power supply facility	Cebi & Otay (2015); Farahani & Asgari (2007)	Positive
Raw material availability	Cebi & Otay (2015); Mousavi et al. (2013)	Positive
Labor availability	Chou et al. (2008); Chen (2001)	Positive
Health care facility for employees	Current et al. (1990); Yoon & Hwang (1985)	Positive
Convenience of garbage disposal	Tuzkaya et al. (2008); Tzeng et al. (2002)	Positive
Labor skills and competence	Devi & Yadav (2013); Yoon & Hwang (1985)	Positive
Transportation system facility	Beskese et al. (2015); Chou et al. (2008)	Positive
Alternative transportation facility	Dogan (2012); Kabir & Sumi (2012)	Positive
Proximity to supplier	Dogan (2012); Ertugrul & Karakasoglu (2008)	Positive
Proximity to market	Ertugrul & Karakasoglu (2008); Chen (2001)	Positive
Proximity to public facilities	Chou et al. (2008); Tzeng et al. (2002)	Positive
Investment cost/Development cost	Devi & Yadav (2013); Mousavi et al. (2013); Kabir & Sumi (2012)	Negative
Production cost	Kabir & Sumi (2014); Partovi (2006)	Negative
Land price/Rent	Beskese et al. (2015); Nazari et al. (2012)	Negative
Raw material cost	Partovi (2006); Chu (2002b)	Negative
Transportation cost	Kabir & Sumi (2012); Nazari et al. (2012)	Negative
Maintenance cost	Yoon & Hwang (1985)	Negative
Utility cost	Partovi (2006); Chu (2002b)	Negative
Distance from central warehouse	Beskese et al. (2015); Cebi & Otay (2015)	Negative

2.2 Evaluation of Fuzzy Multi-Criteria Techniques for Location Selection

Earlier studies used different types of mathematical models such as the network location model, the continuous location model (Current et al., 1990; Klose & Drexl, 2005; Wang et al., 2019), the mixed integer programming model (Amiri-Aref et al., 2019), integrated multi-objective, multi-modal and multi-period mathematical model (Mogale et al., 2018; Tsao & Thanh, 2019), and the non-monolithic model (Cao & Chen, 2006) for location problems. Fewer recent studies (Aktaş et al., 2013; Anvari & Turkay, 2017; Chang, 2015; Dogan, 2012) have also used mathematical models to analyze several location problems. The main limitation of these mathematical models is that they do not consider subjective factors in analyzing location alternatives, even though they consider objective factors (Dey & Ramcharan, 2008). MCDM tools (such as AHP, TOPSIS, PROMETHEE and VIKOR) overcome issues in measuring subjective and objective factors; however, they fail to consider ambiguity and vagueness in the model, both of which exist in real-world location problems (Dotoli & Epicoco, 2018; Wan et al., 2019). The issues of MCDM problems encourage researchers to opt for fuzzy MCDM tools.

Fuzzy MCDM tools are the most recent phenomena used to solve different facility location problems including manufacturing plant location selection. In Table 2, we summarize the literature on fuzzy-MCDM approaches according to their specific application areas. Among the fuzzy-MCDM tools, some notable methods are fuzzy AHP, fuzzy TOPSIS, fuzzy simple additive weighting system (SAWS), and fuzzy ELECTRE.

Table 2: Fuzzy-MCDM approaches used to solve the location problem

Fuzzy-MCDM approaches	**References**	**Application in facility location problems**
Fuzzy AHP	Beskese et al. (2015); Nazari et al. (2012); Ertugrul & Karakasoglu (2009); Ertugrul & Karakasoglu (2008); Chou et al. (2008); Kahraman et al. (2003); Kuo et al. (2002)	Landfill site selection; manufacturing plant location selection; tourist hotel location selection; facility location selection; and convenience store location selection.
Fuzzy TOPSIS	Beskese et al. (2015); Cebi and Otay (2015); Chen (2001); Chen and Lee (2010); Chu (2002b, 2002a); Ertugrul and Karakasoglu (2008); Yang and Hung (2007); Yong (2006)	Landfill site selection; manufacturing plant location selection; plant layout design selection; distribution and other facility site selection; and airport site selection.
Fuzzy SAWS	Chou et al. (2008)	Facility location selection.
Fuzzy ELECTRE	Devi & Yadav (2013)	Manufacturing plant location selection.
Fuzzy additive ratio assessment	Karagöz et al. (2021)	Recycling location selection
Fuzzy MCDM-based combinative distance-based assessment	Karagoz et al. (2020)	Dismantling center location

2.3 Fuzzy Inference System (FIS)

In the literature, several studies applied the concept of a fuzzy decision support system such as fuzzy climate decision (Habib et al., 2017), bipolar fuzzy digraphs (Akram et al., 2016), decision support system for fertilizer and CPU scheduling algorithm (Ashraf et al., 2014; Butt & Akram, 2016), and risk analysis (Ali et al., 2021; Habib & Akram, 2018). However, the FIS is a rule-based decision-making technique that considers different inputs and relates inputs to output according to rules (Paul & Azeem, 2010). Output is determined based on these relationships and the final output is obtained from the aggregated optimized result of individual rules. The fuzzy set theory was originally presented by Zadeh (1965), and fuzzy logic was developed from it later, primarily to handle uncertain and vague information, and secondarily to represent knowledge in an operationally powerful form (Frantti & Mahomen, 2001). Fuzzy inference is the process of formulating mapping from a given input to an output using fuzzy logic, which then provides a basis from which decisions can be made and/or patterns discerned (Ahmed et al., 2013). After examining linguistic variables, membership functions are determined. The general working principle of FIS for the input and output variables is shown in Figure 1.

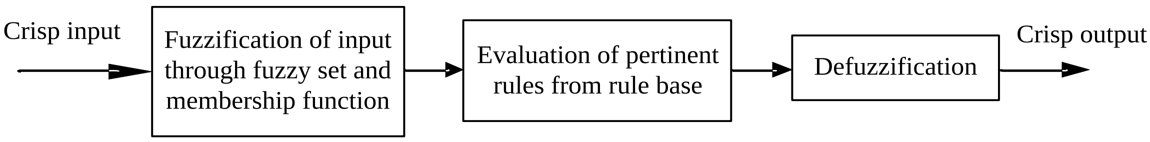


Figure 1: Working principle of FIS (Ahmed et al., 2013)

Because of its multidisciplinary nature, FIS appears under a number of different names, including: fuzzy rule-based system, fuzzy expert system, fuzzy modelling, fuzzy associative memory, fuzzy logic controller, or simply (and ambiguously) a fuzzy system. Mamdani's FIS is the most commonly used fuzzy methodology and was among the first control systems built using fuzzy set theory (Hasan, Shohag, Azeem, & Paul, 2015; Kothamasu & Huang, 2007).

In the fuzzy logic toolbox, the fuzzy inference process has five parts: fuzzification of the input variables; application of the fuzzy operator (AND or OR) in the antecedents; implication from the antecedents to consequents; aggregation of the consequents across the rules, and defuzzification. The general components of a FIS are presented in Figure 2 (Paul, 2015; Paul et al., 2017). A brief description of these components is as follows:

i. **FIS Editor:** In this editor, input and output variables are designed. The number of input and output variables can be edited.

ii. **Membership Function Editor:** In this editor, membership functions are designed for input and output variables. There are a few types of membership functions such as Triangular, Gaussian and Trapezoidal. The types and number of membership functions can be edited.

iii. **Rule Editor:** In this editor, pertinent rules are designed to relate input variables to output. The number of rules is dependent on the specific problem and the number of inputs and outputs. These rules can be edited in this editor.

iv. **Rule Viewer:** In this viewer, the decision-maker inputs the value of multiple input variables and obtains the value of the output of the corresponding input.

v. **Surface Viewer:** In this viewer, the graphical relationship between input and output variables can be perceived. These relationships are obtained from developed membership functions and pertinent rules.

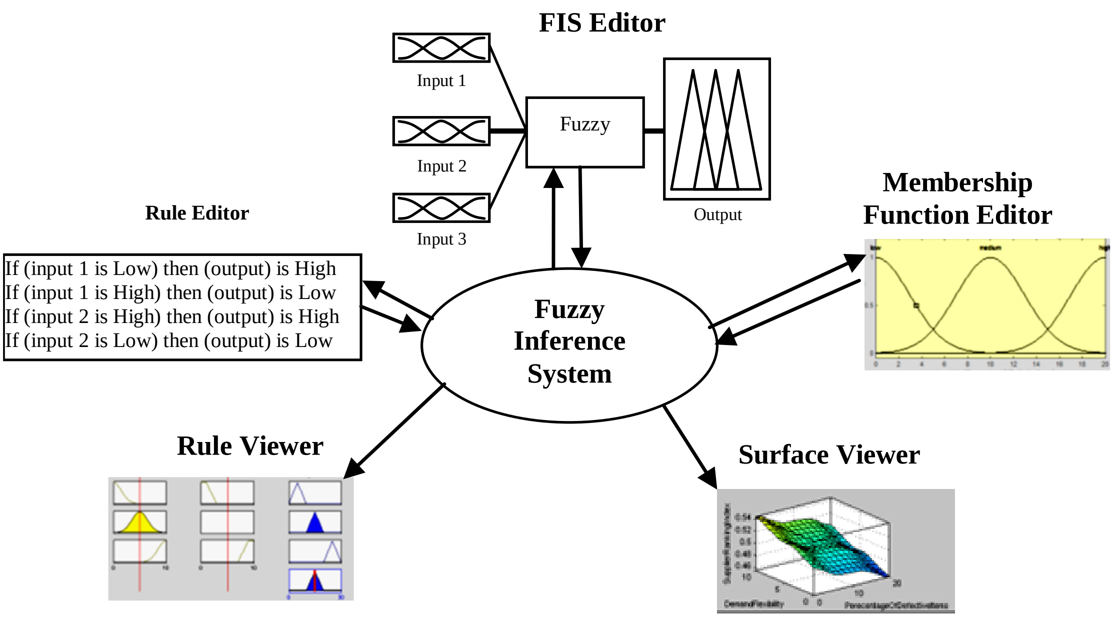


Figure 2: General components of a FIS (Paul, 2015; Paul et al., 2017)

All fuzzy MCDM approaches are very complex in nature, and hence challenging to implement in real-world situations (Devi & Yadav, 2013). Moreover, none of the above approaches is intelligent in terms of user-friendliness and ease of application to real-world problems. In the literature, to our knowledge, a few studies have integrated qualitative survey and quantitative MCDM techniques to evaluate and assess plant location. As a result, these fuzzy-MCDM approaches have gained limited acceptance from practitioners. In this paper, to assist decision-makers, we develop a decision-making framework by integrating both the qualitative Delphi method and quantitative FIS to develop an intelligent and user-friendly

MCDM tool for manufacturing plant location selection. The proposed tool is easy to use and less time-consuming in determining the ranking of the location once the criteria and respective weight of the criteria are given or decided. To fulfill the objectives, we utilize the Delphi method to gather both positive and negative influential criteria and their respective weights to use in the proposed intelligent FIS framework. In this study, we also implement our proposed FIS framework to the real-world case of a garment manufacturing company in Bangladesh by selecting a plant location problem for the firm.

3. RESEARCH METHODS

We have used the Delphi technique to determine the weights of plant selection criteria and the FIS to solve a manufacturing plant location selection problem. The framework is tested by using a manufacturing plant location problem in the context of an emerging economy.

The integrated decision-making framework is illustrated as shown in Figure 3. Our research employs several steps in making a decision in regard to the best location for manufacturing plants. Initially, we identify the most important criteria for selecting manufacturing plant locations and their respective weights based on experts' opinions, according to the qualitative Delphi method. Next, by utilizing the quantitative FIS tool, we calculate and normalize the ranking index for each alternative location. Finally, by utilizing the ranking index we select the best location out of all alternatives for the manufacturing plant. In brief, the research steps are as follows:

Step 1: Identification of major location selection criteria (in positive and negative categories) from experts' opinions using the Delphi method.

Step 2: Development of FIS framework using Mamdani-type fuzzy inference system.

Step 3: Use of FIS to select the best location.

Step 4: Application of the developed FIS framework.

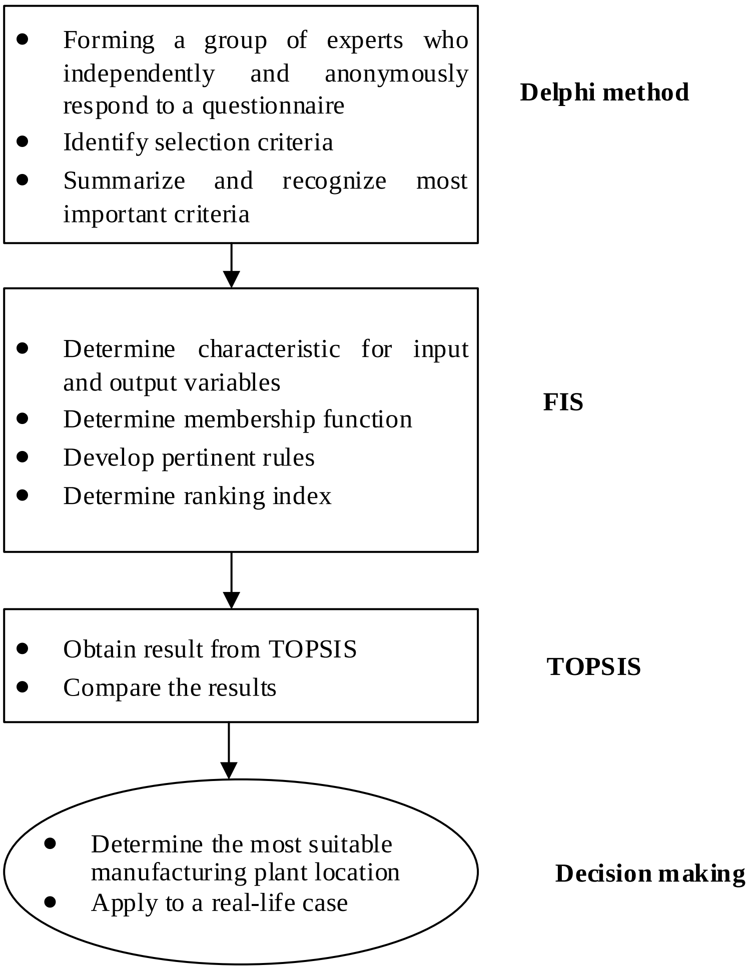


Figure 3: Integrated decision-making framework for evaluating manufacturing plant locations

We select the ready-made garment (RMG) industry in Bangladesh as the context of the application. At present, there are around 3500 ready-made garment manufacturing companies in Bangladesh. The total export industry of Bangladesh comprised USD 31.2 billion in the year 2014-15, 81.69% of which was made up of ready-made garments (Latifee, 2016). In Bangladesh, most garment manufacturing companies are located in two big cities (Dhaka and Chittagong). Because of the increasing demand of RMG products at national and international levels, it is becoming increasingly important to build new plants. Many factory owners are expanding their factories and some of them are relocating to sites where there are good infrastructure facilities and supply links. Hence, we consider the garment manufacturing plant as a case study.

3.1 Location Selection Criteria-Identification using the Delphi Method

The Delphi method originated in 1950 from a series of studies by the RAND corporation, and is one of the most effective techniques to identify and prioritize issues related to managerial decision-making (Devadasan et al., 2005; Okoli and Pawlowski, 2004). This method utilizes the opinions of a group of experts or decision-makers to obtain the most reliable and accurate agreement about an issue. This group shares their views, expertise and judgment without direct confrontation until consensus is reached (Adler & Ziglio, 1996; Sung, 2001). This method has been extensively used in previous research to reveal criteria related to a particular country or sector (Mousavi et al., 2013). Therefore, our research identifies the manufacturing plant location selection criteria and their respective weights from the opinion of experts in the garment manufacturing industry in Bangladesh.

Consultation with a group of 10-18 experts is recommended by Okoli & Pawlowski (2004) to maintain the group dynamics for reaching a consensus among experts; this number may vary depending on the objective of the study and purpose of using the Delphi method (Keeney et al., 2001). In this study, a group of 15 experts (managing directors and owners) of 15 different garment manufacturing firms in Bangladesh participated in the Delphi study to identify appropriate criteria for manufacturing plant location selection and to specify their respective weights. As managing directors/owners hold the knowledge and experience regarding plant location selection issues, we consider them as experts for this study. These experts have extensive experience (15-25 years) in strategic company decision-making, such as site selection for the garment industry, site selection of warehouses, or decision-making on the extension or expansion of the current facilities.

In using the Delphi method to identify plant location selection criteria and their respective weights, we follow a two-stage process. At the first stage (rounds 1–4), we attempt to obtain important plant location selection criteria, while in the second stage (round 5) we explore the weight of each criterion.

In the first round, we sent the questionnaire to individual experts and asked them to send a list of as many criteria as possible that they considered important in apparel/garment manufacturing plant location selection. After obtaining responses from all the experts we prepared a consolidated list by removing exact duplicates and unifying terminology. In the second round, we sent the consolidated list of criteria to the participants and asked them to clarify or comment on the list of criteria and to provide additional criteria to select the plant location. Based on their responses, we refined the questionnaire and found a total of 15 criteria for plant location selection. In the third round, we sent out the list of these 15 criteria and asked the experts to rank them in such a way that the most important criteria would be assigned a first rank (hereafter rank 1). Based on the experts' opinions we found two criteria to be less important than the other thirteen. Therefore, we remove these two criteria from the list and created a new list containing the 13 most important criteria related to garment manufacturing plant location in the Bangladeshi context. In the fourth round, we sent the list of 13 criteria to the experts for final validation. All the experts agreed that the 13 criteria were important to consider in the context of the garment manufacturing sector of Bangladesh. Subsequently, we prepared the final list of 13 plant location selection criteria, which is shown in the second column of Table 3. In the fifth round, we requested the experts to rate these criteria on a scale of 0-1 based on importance, where 1 is vitally important and 0 is not important at all. From that rating, we calculated the mean of the weight of each criterion, which is included in the third column of Table 3.

Table 3: Plant location selection criteria and their respective weights

Serial number	Plant location selection criteria	Weight
1	Distance from central warehouse	1
2	Production cost	1
3	Land price/Rent	1
4	Transportation system facility	1
5	Labor availability	0.8
6	Security	0.7
7	Power supply facility	1
8	Raw material availability	0.8
9	Raw material cost	0.5
10	Water supply facility	1
11	Environmental impact	0.6
12	Suitability of climate and land	0.6
13	Fuel/gas supply facility	0.7

3.2 Proposed FIS Tool for Manufacturing Plant Location Selection

In this study, a FIS tool is developed to evaluate manufacturing plant locations. The algorithm for the developed FIS tool has the following steps:

Step 1: Determination of the characteristic for each input selection criteria.

Step 2: Determination of the characteristic of output variable (Ranking Index).
Step 3: Definition of the range of input and output variables and determination of the membership function for each input and output variable.
Step 4: Evaluation of pertinent rules.
Step 5: Determination of the location ranking index from surface viewer.
Step 6: Determination of the ranking index for all alternative locations using Step 5.
Step 7: Normalization of the ranking index value for all locations.
Step 8: Selection of the best location from the highest normalized value.

Using the Delphi method, we obtained 13 different categories of manufacturing plant location criteria and their weights as provided by the experts. The criteria are categorized into positive and negative criteria, some of which had a positive impact and some of which had a negative impact on ranking index value. The input criteria and output value are scaled using the Likert scale (Boone & Boone, 2012), as this is very important to quantify the data. The input criteria are scaled between 0 and 10, where for positive criteria 0 is least favorable and 10 most favorable, and for negative criteria 0 means most favorable and 10 the least.

During the generation of the FIS's linguistic variables, 13 major manufacturing plant location selection criteria are identified, for each of which three linguistic variables are developed and used to evaluate the ranking index. In designing the linguistic variables of input and output a triangular membership function is considered.

For all these inputs to the tool, the linguistic variables are 'Low', 'Medium' and 'High', and for the output, the 'Ranking Index' are 'Very Low', 'Low', 'Medium', 'High' and 'Very High'. After examining the linguistic variables, membership functions are designed.

The developed FIS tool for manufacturing plant location selection is shown in Figure 4, in which the input variables are shown on the left and the output variable on the right. The parameters for the developed FIS are presented in Table 4. We have used a Mamdani-Type FIS because it is the most commonly used fuzzy methodology. We have also used 'min' for 'and method', 'max' for 'or method', 'min' for 'implication method', 'max' for 'aggregation method', and 'centroid' for 'defuzzification method'. There are 13 inputs (selection criteria) and one output (ranking index).

Table 4: FIS parameters for location selection

Aspects	**Selected parameter**
Type	'Mamdani'
And method	'min'
Or method	'max'
Implication method	'min'
Aggregation method	'max'
Defuzzification method	'centroid'
Input	13 (1x3 struct)
Output	1 (1x5 struct)
Input membership function	'triangular'
Output membership function	'triangular'

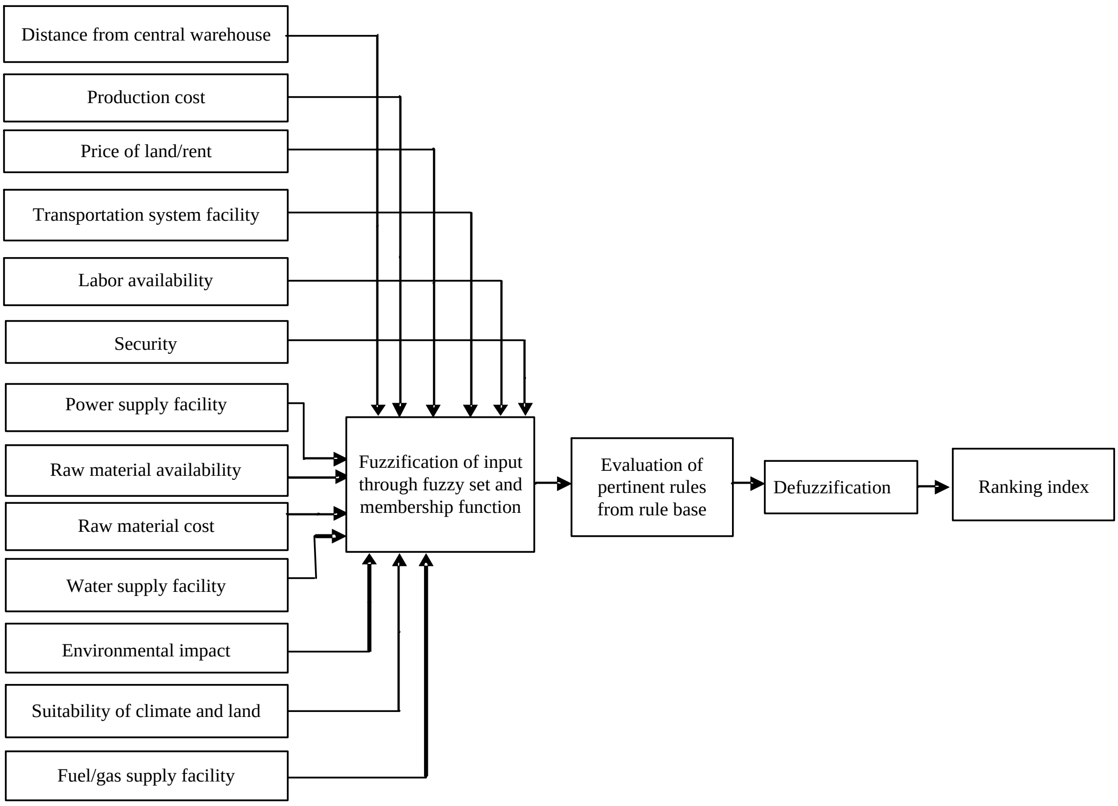


Figure 4: FIS framework for manufacturing plant location selection

3.2.1 Triangular membership function (TMF)

The triangular curve is a function of a vector, x, and depends on three scalar parameters: a, b, and c, shown in Figure 5. The parameters a, b and c respectively specify the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event. The degree of membership of a triangular fuzzy number can be defined using equation (1).

$$f(x;a,b,c)=\begin{cases}0, & x\leq a\\ \dfrac{x-a}{b-a}, & a\leq x\leq b\\ \dfrac{c-x}{c-b}, & b\leq x\leq c\\ 0, & c\leq x\end{cases} \tag{1}$$

3.2.2 Using TMF to define input and output variables

A range of value is defined for each variable. Then the range is divided into several linguistic variables based on characteristics and requirements, including 'Very Low', 'Low', 'Medium', 'High' and 'Very High'. For each linguistic variable, a triangular curve is designed.

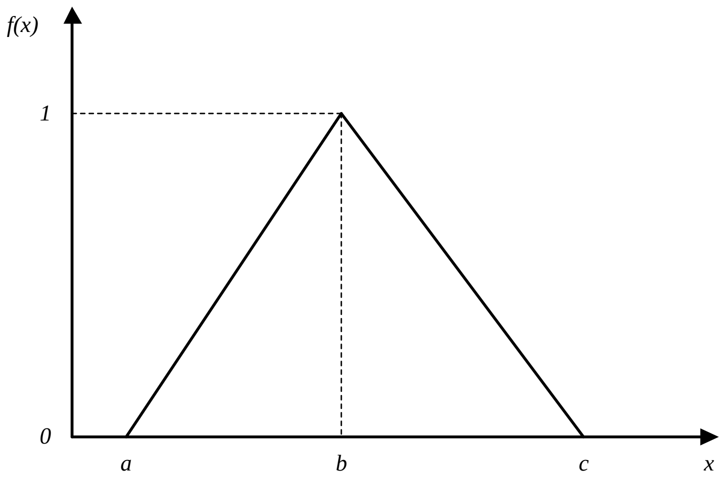
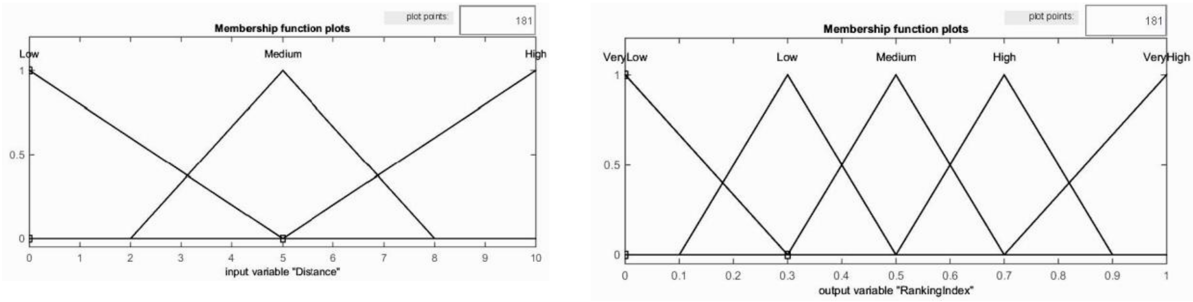


Figure 5: A triangular membership functions and linguistic variables

3.2.3 Designing parameters for input and output variables

In this section, the parameters for input and output variables are designed. The values of the input criteria like production cost, price of land/rent can vary significantly based on the size and location of the plant, type of manufacturing products, demographic area, currency, and other causes. As the main objective of this study is to develop a general rule-based fuzzy inference system (FIS) framework for the best manufacturing plant location selection, we consider all the input variables between 0 and 10. Any quantitative criteria value can convert easily within the scale of 0-10. As input variables are comparative among alternative manufacturing plant locations, we consider triangular membership function for designing the FIS, and the linguistic variables for input selection criteria are 'Low', 'Medium', and 'High' with values of [0 0 5], [2 5 8] and [5 10 10] respectively. Figure 6(a) shows the membership functions with linguistic variables for the input criteria ‘distance from the central warehouse’. Similarly, membership functions and linguistic variables are designed for other input criteria. Table 5 presents the designed parameters for input criteria. The linguistic variables for the output ‘Ranking Index’ are ‘Very Low’, ‘Low’, ‘Medium’, ‘High’ and ‘Very High’ with values of [0 0 0.3], [0.1 0.3 0.5], [0.3 0.5 0.7], [0.5 0.7 0.9] and [0.7 1 1] respectively. Figure 6(b) shows the membership functions with linguistic variables for ‘ranking index’. Table 6 presents the designed parameters for the output.



a) Membership Function for input criteria “Distance from central warehouse”

b) Membership function for output variable “Location Ranking Index”

Figure 6: Membership functions for input criteria and output variable

Table 5: Designed parameters of input criteria

Input number	Input Criteria	Range	Linguistic variables [Low], [Medium], [High]	Membership Function Structure	Impact* on output
1	Distance	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Negative
2	Production Cost	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Negative
3	Price of Land/Rent	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Negative
4	Transportation System Facility	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
5	Labor Availability	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
6	Security	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
7	Power Supply Facility	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
8	Raw Material Availability	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
9	Raw Material Cost	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Negative
10	Water Supply Facility	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
11	Environmental Impact	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Negative
12	Suitability of Climate and Land	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
13	Fuel/Gas Supply Facility	[0,10]	[0 0 5], [2 5 8], [5 10 10]	1x3 struct	Positive
***Negative means higher the **input value, lower the output; and positive means higher the input value, higher the output.**					

Table 6: Designed parameter for the output

Output	Range	Linguistic variables [Very Low], [Low], [Medium], [High], [Very High]	Membership Function Structure
Ranking Index	[0,1]	[0 0 0.3], [0.1 0.3 0.5], [0.3 0.5 0.7], [0.5 0.7 0.9], [0.7 1 1]	1x5 struct

3.2.4 Rules with weight

Rules are used to define the relationship between input criteria and output variables. In total 50 rules are designed. Each rule has a weight value based on the weight value for each input criteria. A few examples of developed rules are as follows:

i. If (Distance is Low) and (Production Cost is Low) and (Land Price/Rent is Low) and (Transport Facility is High) then (Ranking Index is Very High) (1)

ii. If (Distance is High) and (Production Cost is High) and (Land Price/Rent is High) and (Transport Facility is Low) then (Ranking Index is Very Low) (1)
iii. If (Distance is Medium) and (Production Cost is Medium) and (Land Price/Rent is Medium) and (Transport Facility is Medium) then (Ranking Index is Medium) (1)
iv. If (Labor Availability is Low) and (Security is Low) and (Power Supply is Low) and (Raw Material Availability is Low) then (Ranking Index is Very Low) (0.8)
v. If (Labor Availability is High) and (Security is High) and (Power Supply is High) and (Raw Material Availability is High) then (Ranking Index is High) (0.8)
vi. If (Labor Availability is Medium) and (Security is Medium) and (Power Supply is Medium) and (Raw Material Availability is medium) then (Ranking Index is Medium) (0.8)

The reminder rules are presented in Appendix A.

4. NUMERICAL EXPERIMENTS

4.1 Random Experimentation

A numerical example considering random data for eight different locations (L1, L2, L3, L4, L5, L6, L7 and L8) is presented. Each location has different values for the input criteria, as shown in the second column of Table 7.

Table 7: Random input data for eight different locations

Location	Input value [input1, input2…input13]	FIS			TOPSIS	
		Ranking Index	Normalized Value	Rank	Ratio, R	Rank
L1	[9, 10, 8, 4, 2, 4, 5, 6, 8, 8, 4, 6, 1]	0.465	0.114	7	0.080	7
L2	[7, 4, 3, 7, 10, 6, 6, 10, 5, 1, 3, 6, 2]	0.500	0.123	4	0.134	4
L3	[4, 6, 2, 7, 8, 8, 1, 8, 6, 3, 3, 1, 6]	0.489	0.120	6	0.124	6
L4	[8, 10, 9, 2, 5, 2, 3, 1, 8, 7, 5, 4, 4]	0.397	0.098	8	0.061	8
L5	[7, 10, 5, 3, 9, 4, 9, 9, 9, 9, 1, 2, 4]	0.497	0.122	5	0.124	5
L6	[4, 1, 8, 6, 4, 5, 4, 6, 4, 10, 3, 10, 8]	0.528	0.130	2	0.141	2
L7	[2, 3, 1, 9, 10, 8, 7, 8, 3, 10, 4, 9, 9]	0.678	0.167	1	0.198	1
L8	[6, 1, 7, 9, 1, 5, 6, 5, 2, 8, 3, 9, 5]	0.508	0.125	3	0.138	3

A ranking index for each location is determined by using the rule viewer of the developed FIS. The data for input criteria is given here and the ranking index is determined based on the pertinent developed rules. The ranking index is determined for all the alternative locations by providing the value of input criteria of all locations, which is shown in the last column of Table 8. Figure 7 shows the rule viewer from the developed FIS for location L1 as a sample representation

We generated 200 random test problems by varying the values for input criteria. Then we used our developed FIS framework to evaluate the ranking index. We found that our tool can deal with all random cases efficiently and of determining the ranking index value.

4.2 Results Comparison

To judge the validity of the developed tool, we compared the FIS results with those obtained from the TOPSIS technique. We used the same data and weight as used in the FIS framework. We obtained the same location ranking from both the FIS framework and the TOPSIS technique. Then, we also generated 30 location selection problems by varying the input data and weight randomly. We used uniform random distribution to generate the test problems and the results are presented in Table 7. We observed that the ranking and selection from both techniques were the same for all random problems. However, the developed intelligent framework offers several advantages over the TOPSIS method such as,

- It mirrors the logical response of a rational human being.
- It can integrate ambiguity and uncertainty of human decision-making into the assessment process.
- The causal relationship between the inputs and output for different scenarios can be resented effectively.
- It can provide more reliable results with a small amount of data considering the expert's judgment and experience.
- The framework development steps remain the same regardless of the number of criteria added or removed.
- It allows decision-making with estimated values using incomplete or uncertain information.

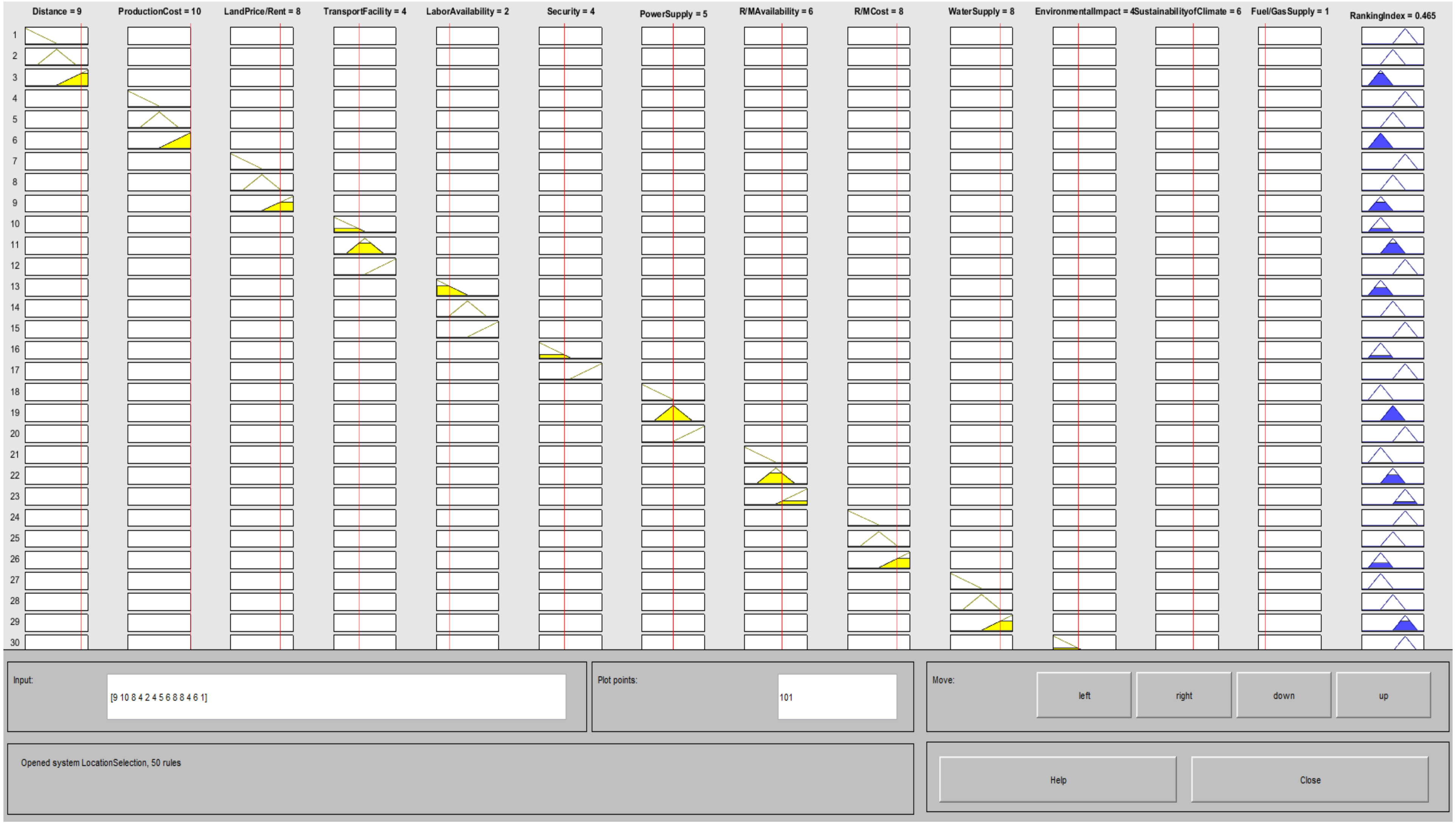


Figure 7: Rule viewer for determining ranking index of L1

4.3 Sensitivity Analysis

This analysis is designed by increasing the positive criteria by 0.5 starting at 1 and decreasing the negative criteria by 0.5 starting at 10. Then we found 19 possible cases; among them, case number 1 is the least favorable and case number 19 is the most favorable for location selection. Then we observed how the ranking index changes with the case number. The changes of ranking index value are presented in Table 8 for 19 possible cases, and the most desirable is highlighted in bold. We observed that the ranking index value increases with the most favorable input criteria values and that this correlated increase is desirable. The relationship between individual input and output is also analyzed, as presented in Appendix B under supplementary materials.

Table 8: Changes of ranking index values with input criteria values

Case number	Input													Ranking index
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	
1	10	10	10	1	1	1	1	1	10	1	10	1	1	0.218
2	9.5	9.5	9.5	1.5	1.5	1.5	1.5	1.5	9.5	1.5	9.5	1.5	1.5	0.222
3	9	9	9	2	2	2	2	2	9	2	9	2	2	0.227
4	8.5	8.5	8.5	2.5	2.5	2.5	2.5	2.5	8.5	2.5	8.5	2.5	2.5	0.274
5	8	8	8	3	3	3	3	3	8	3	8	3	3	0.315
6	7.5	7.5	7.5	3.5	3.5	3.5	3.5	3.5	7.5	3.5	7.5	3.5	3.5	0.353
7	7	7	7	4	4	4	4	4	7	4	7	4	4	0.387
8	6.5	6.5	6.5	4.5	4.5	4.5	4.5	4.5	6.5	4.5	6.5	4.5	4.5	0.420
9	6	6	6	5	5	5	5	5	6	5	6	5	5	0.453
10	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	0.500
11	5	5	5	6	6	6	6	6	5	6	5	6	6	0.547
12	4.5	4.5	4.5	6.5	6.5	6.5	6.5	6.5	4.5	6.5	4.5	6.5	6.5	0.580
13	4	4	4	7	7	7	7	7	4	7	4	7	7	0.613
14	3.5	3.5	3.5	7.5	7.5	7.5	7.5	7.5	3.5	7.5	3.5	7.5	7.5	0.647
15	3	3	3	8	8	8	8	8	3	8	3	8	8	0.685
16	2.5	2.5	2.5	8.5	8.5	8.5	8.5	8.5	2.5	8.5	2.5	8.5	8.5	0.726
17	2	2	2	9	9	9	9	9	2	9	2	9	9	0.773
18	1.5	1.5	1.5	9.5	9.5	9.5	9.5	9.5	1.5	9.5	1.5	9.5	9.5	0.778
19	**1**	**1**	**1**	**10**	**10**	**10**	**10**	**10**	**1**	**10**	**1**	**10**	**10**	**0.782**

4.4 A Real-Life Application

We implemented the proposed FIS framework to select an appropriate location for a real-world manufacturing plant location decision case. During the Delphi method studies, one of the experts from an apparel manufacturing company (termed Company-X in this discussion for privacy reasons) invited us to solve their plant location problem. The company owner explained that they were looking for a new site as part of the expansion of their current businesses.

The head office of Company-X is located in Dhaka, Bangladesh. The current manufacturing plant is located in Gazipur, Bangladesh and produces knitwear, exporting to several countries including Australia, the USA and some within the EU. Recently, the firm decided to expand its business to woven wear. In order to establish a woven-wear unit, Company-X was looking for the best location from four options – Gazipur, Narayanganj, Savar, and Chittagong. Excluding Chittagong, all locations are close to Dhaka, where the central warehouse is located. While the company wanted to reduce the distance from the central warehouse to ensure better synchronization of material and prompt delivery of material from the warehouse to the plant, it also had to consider other plant location selection factors as listed in Table 3 for selecting the best location. When the company considered all the selection criteria of all four locations, it is found that the selection of one location is not a straightforward decision as each location is preferred from others for some criteria but not for all. As a result, the company had to analyze the score of all 13 criteria of the four locations using an appropriate MCDM tool to ensure that the company selected the best location. However, the firm faced difficulties analyzing different variables and criteria to select the best location using the current MCDM tools due to their complexity and user unfriendliness. After developing the FIS framework, we took the opportunity to contact Company-X to apply the designed tool to select the most appropriate plant location for woven wear.

Initially, we contacted the company owner about the nature of the data we needed for the input variables of the FIS. Since we needed quantitative (weight and input value for each criterion) data for each of the 13 choice criteria, the owner could not immediately provide this. He discussed the issue with company management and later provided us with the required data to solve the firm’s location selection problem. For some criteria, we were provided actual or approximate data, while, for other criteria, a judgmental score on a scale from 0 to 10 was provided for each of the four locations (Table 9).

Table 9: Nature of data provided by Company X for each criterion

Criteria	Nature of data provided
Distance from central warehouse	Actual distance in kilometer
Production cost	Approximate production cost per unit in Bangladeshi taka (BDT)
Land price/Rent	Approximate cost per square feet in BDT
Transportation system facility	Judgmental score
Labor availability	Judgmental score
Security	Judgmental score
Power supply facility	Judgmental score
Raw material availability	Judgmental score
Raw material cost	Approximate raw material cost per unit in BDT
Water supply facility	Judgmental score
Environmental impact	Judgmental score
Suitability of climate and land	Judgmental score
Fuel/gas supply facility	Judgmental score

Because of the confidentiality and data-sharing agreement, the actual or approximate values of the criteria like distance from central warehouse, production cost, raw material cost, and price of land/rent were not disclosed. Therefore, the actual values of the criteria were converted on a scale from 0 to 10. This conversion also provided uniformity in the scale across all 13 criteria as the values of other criteria were provided on a scale from 0 to 10. The final input values of all 13 criteria are presented in Table 10.

Table 10: Input data (for location criteria score) from Company-X

Location	Input value [input1, input2…input13]
Gazipur	[4, 6, 7, 8, 7.5, 8.5, 8.5, 7, 6.5, 8, 8, 7, 8.5]
Narayanganj	[6, 6, 7.5, 4.5, 6, 7, 7.5, 5, 6, 6, 7, 6.5, 7.5]
Savar	[1, 4, 6, 9, 9.5, 8, 9, 9, 7, 9, 8, 7, 9.5]
Chittagong	[4, 7, 7, 5.5, 5, 6, 5, 6, 7, 5, 6, 7, 6]

Afterwards, we utilized the collected data to determine the rank of the four locations. The ranking index of each location is calculated based on the rule viewer of the developed FIS as discussed in 3.3.3 and 3.3.4. The ranking index was then normalized to determine the rank of the four locations as shown in Table 11.

Table 11: Ranking of four alternative locations

Location	Ranking Index	Normalized value	Rank
Gazipur	0.527	0.2599	2
Narayanganj	0.487	0.2401	3
Savar	0.537	0.2648	1
Chittagong	0.477	0.2352	4

Analysis showed that out of four location choices, Savar is the best location with the normalized ranking index value of 0.2648 for Company-X to establish a new plant, even though Gazipur receives a very similar value of 0.2599. However, the other two locations - Chittagong and Narayanganj – received much lower normalized ranking index values of 0.2352 and 0.2401 respectively, and thus are not the right places for the firm to establish its new manufacturing plant.

The owner of the company also said that management was very confused regarding Savar and Gazipur:

> "*Even though we have considered four locations to establish our new plant, we knew ultimately we would be establishing our new plant either at Savar or Gazipur. However, we were so confused in regards to which one of Savar and Gazipur would be our best choice. We discussed the issue multiple times in our board meeting but we could not make any final decision*".

5. CONCLUSIONS AND MANAGERIAL IMPLICATIONS

The main objective of this paper is to develop an intelligent FIS-based decision-making framework for evaluating the manufacturing plant locations. In our developed framework, we use the Delphi technique to identify important criteria for garment manufacturing location selection decisions. We found that experts' inputs can reduce the unnecessary effort in searching for suitable location selection criteria. Managers and their input are critical to this evaluation process, but too many factors and relationships between the factors can easily cause fatigue in decision-making. Therefore, in order to make effective location selection decisions, a focus on the specific uses of industry and country-specific location selection criteria, as determined by experts, is necessary. Using the Delphi method, we identify 13 critical criteria for garment manufacturing site selection and determine that these are essential to address in order to select the most suitable manufacturing location. The most important criteria are related to categories such as cost; the availability of utilities (electricity supply, water supply, gas or fuel supply) and security; convenience in using logistics facilities such as labor and raw materials. It appears that when organizations look for new manufacturing locations they look at cost, resources available in the new location, service facilities, and safety and security issues. Comparing the criteria obtained by Capilla et al. (2016) and Dou and Sarkis (2010), it appears that our results are focusing more on the cost of production and access to utilities and facilities, and not much on community and business climate.

Based on the collected information from Delphi, we developed a rule-based FIS framework to assist in plant location decision-making. The tool is capable of giving a ranking index value for each alternative location based on the input value of the 13 criteria. The best location was selected based on the highest normalized value of the ranking index. To further analyse the validity and applicability of the proposed FIS framework, a real-world application from an apparel manufacturing company in Bangladesh is analyzed. The proposed FIS framework is innovative in solving MCDM problems as it integrates both qualitative Delphi and quantitative FIS and considered both positive and negative influences of the selection criteria. The framework is developed based on a user-friendly graphical interface, which is easy to use by decision-makers, and for which the user doesn't need knowledge of the FIS. Moreover, the proposed FIS framework can easily be implemented in any similar type of MCDM problem with no/minor adjustment. Once the input criteria and their respective weights and values are given, this tool can provide the ranking index for each option. Therefore, the practitioner can implement this tool to solve the multi-criteria problem, particularly for the location selection problem, without any difficulty. However, managers should focus on determining the key criteria and their respective weights and values accurately before using this tool because the ranking index (output value) fully depends on the input value. Also, the manager needs to scale the input criteria and output value using the Likert scale. Hence, we suggest using the proposed tool with care as the location selection problem is complex and determining qualitative and quantitative input values is challenging.

In future, our approach can be extended to develop decision-making tools for other MCDM problems, such as distribution and other facility site selection, convenience store location selection, supplier selection, service location selection, and project site selection. Also, researchers should consider the impacts of large-scale disruptions, such as the recent COVID-19 pandemic, while finalizing the criteria for manufacturing plant locations (Chowdhury et al., 2021). In a methodological context, it also would be worthwhile to consider different types of membership functions such as trapezoidal and Gaussian membership functions for input and output variables in the FIS and compare the results for these.

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Appendix A: The rules with corresponding weight

i. If (Distance is Low) then (Ranking Index is High) (1)
ii. If (Distance is Medium) then (Ranking Index is Medium) (1)
iii. If (Distance is High) then (Ranking Index is Low) (1)
iv. If (Production Cost is Low) then (Ranking Index is High) (1)
v. If (Production Cost is Medium) then (Ranking Index is Medium) (1)
vi. If (Production Cost is High) then (Ranking Index is Low) (1)
vii. If (Land Price/Rent is Low) then (Ranking Index is High) (1)
viii. If (Land Price/Rent is Medium) then (Ranking Index is Medium) (1)
ix. If (Land Price/Rent is High) then (Ranking Index is Low) (1)
x. If (Transport Facility is Low) then (Ranking Index is Low) (1)
xi. If (Transport Facility is Medium) then (Ranking Index is Medium) (1)
xii. If (Transport Facility is High) then (Ranking Index is High) (1)
xiii. If (Labor Availability is Low) then (Ranking Index is Low) (0.8)
xiv. If (Labor Availability is Medium) then (Ranking Index is Medium) (0.8)
xv. If (Labor Availability is High) then (Ranking Index is High) (0.8)
xvi. If (Security is Low) then (Ranking Index is Low) (0.7)
xvii. If (Security is High) then (Ranking Index is High) (0.7)
xviii. If (Power Supply is Low) then (Ranking Index is Low) (1)
xix. If (Power Supply is Medium) then (Ranking Index is Medium) (1)
xx. If (Power Supply is High) then (Ranking Index is High) (1)
xxi. If (Raw Material Availability is Low) then (Ranking Index is Low) (0.8)
xxii. If (Raw Material Availability is Medium) then (Ranking Index is Medium) (0.8)
xxiii. If (Raw Material Availability is High) then (Ranking Index is High) (0.8)
xxiv. If (Raw Material Cost is Low) then (Ranking Index is High) (0.5)
xxv. If (Raw Material Cost is Medium) then (Ranking Index is Medium) (0.5)
xxvi. If (Raw Material Cost is High) then (Ranking Index is Low) (0.5)
xxvii. If (Water Supply is Low) then (Ranking Index is Low) (1)
xxviii. If (Water Supply is Medium) then (Ranking Index is Medium) (1)
xxix. If (Water Supply is High) then (Ranking Index is High) (1)
xxx. If (Environmental Impact is Low) then (Ranking Index is High) (0.6)
xxxi. If (Environmental Impact is Medium) then (Ranking Index is Medium) (0.6)
xxxii. If (Environmental Impact is High) then (Ranking Index is Low) (0.6)

xxxiii. If (Suitability of Climate and Land is Low) then (Ranking Index is Low) (0.6)

xxxiv. If (Suitability of Climate and Land is Medium) then (Ranking Index is Medium) (0.6)

xxxv. If (Suitability of Climate and Land is High) then (Ranking Index is High) (0.6)

xxxvi. If (Fuel/Gas Supply facility is Low) then (Ranking Index is Low) (0.7)

xxxvii. If (Fuel/Gas Supply facility is Medium) then (Ranking Index is Medium) (0.7)

xxxviii. If (Fuel/Gas Supply facility is High) then (Ranking Index is High) (0.7)

xxxix. If (Distance is Low) and (Production Cost is Low) and (Land Price/Rent is Low) and (Transport Facility is High) and (Labor Availability is High) and (Security is High) and (Power Supply is High) and (Raw Material Availability is High) and (Raw Material Cost is Low) and (Water Supply is High) and (Environmental Impact is Low) and (Suitability of Climate and Land is High) and (Fuel/Gas Supply facility is High) then (Ranking Index is Very High) (1)

xl. If (Distance is High) and (Production Cost is High) and (Land Price/Rent is High) and (Transport Facility is Low) and (Labor Availability is Low) and (Security is Low) and (Power Supply is Low) and (Raw Material Availability is Low) and (Raw Material Cost is High) and (Water Supply is Low) and (Environmental Impact is High) and (Suitability of Climate and Land is Low) and (Fuel/Gas Supply facility is Low) then (Ranking Index is Very Low) (1)

xli. If (Distance is Medium) and (Production Cost is Medium) and (Land Price/Rent is Medium) and (Transport Facility is Medium) and (Labor Availability is Medium) and (Security is Medium) and (Power Supply is Medium) and (Raw Material Availability is Medium) and (Raw Material Cost is Medium) and (Water Supply is Medium) and (Environmental Impact is Medium) and (Suitability of Climate and Land is Medium) and (Fuel/Gas Supply facility is Medium) then (Ranking Index is Medium) (1)

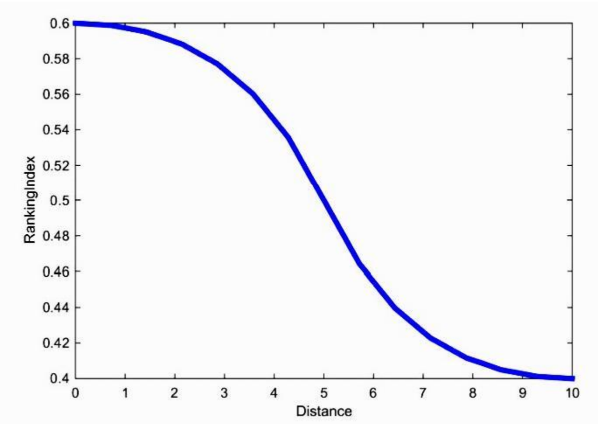
xlii. If (Raw Material Cost is Low) and (Water Supply is High) and (Environmental Impact is Low) and (Suitability of Climate and Land is High) and (Fuel/Gas Supply facility is High) then (Ranking Index is Very High) (0.6)

xliii. If (Raw Material Cost is High) and (Water Supply is Low) and (Environmental Impact is High) and (Suitability of Climate and Land is Low) and (Fuel/Gas Supply facility is Low) then (Ranking Index is Very Low) (0.6)

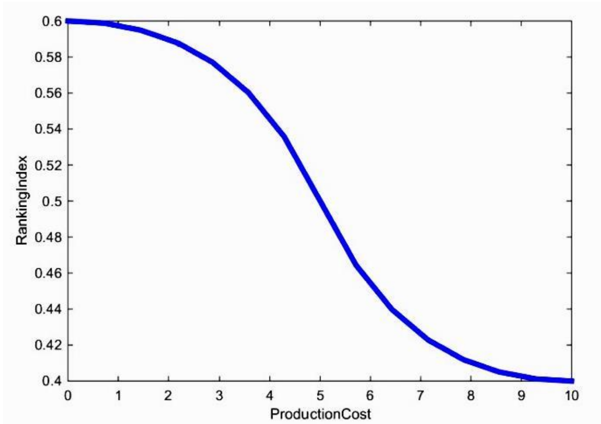
xliv. If (Raw Material Cost is Medium) and (Water Supply is Medium) and (Environmental Impact is Medium) and (Suitability of Climate and Land is Medium) and (Fuel/Gas Supply facility is Medium) then (Ranking Index is Medium) (0.6)

Appendix B: Relationship between input and output variables

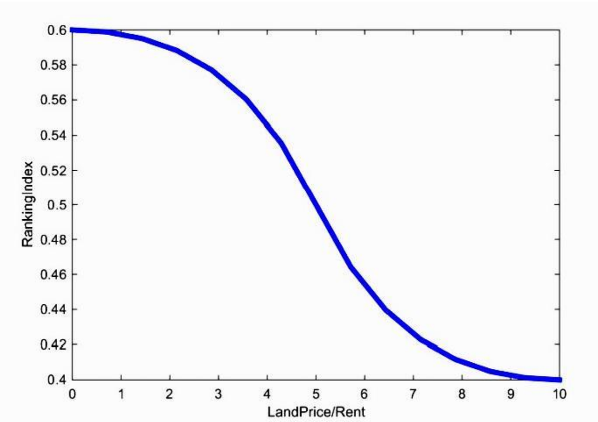
There is a relationship (either positive or negative) between input and output variables. This study shows how the ranking index changes with changing input criteria. In each study, one input criteria has changed and reminders are kept constant at a default value of 5. We have observed that the ranking index value increases with the increment of value of positive criteria and the ranking index value decreases with the increment of value of negative criteria.



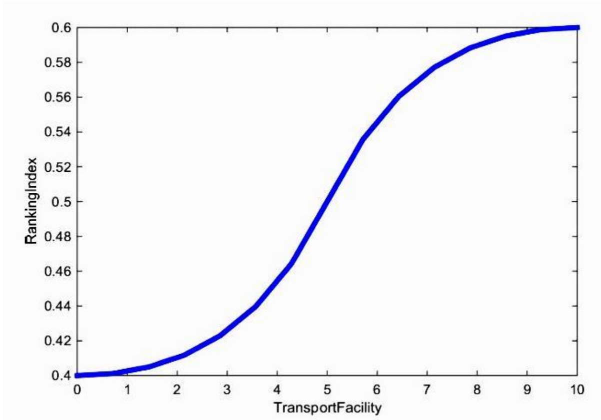
(a) Ranking Index vs Distance



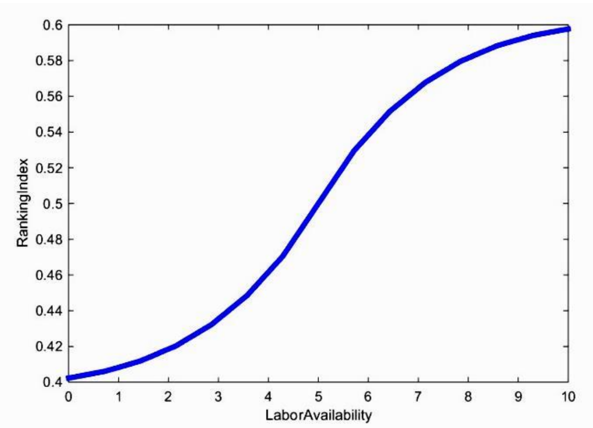
(b) Ranking Index vs Production Cost



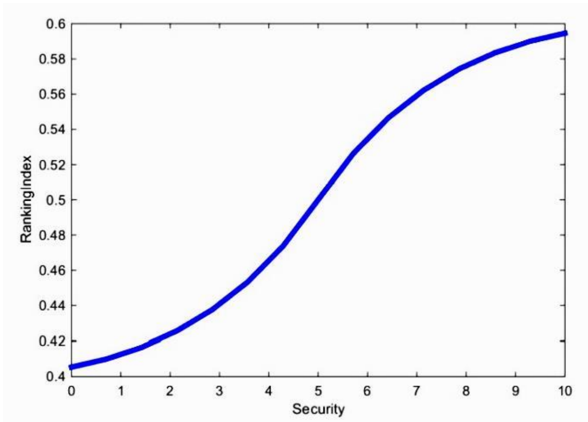
(c) Ranking Index vs Land Price/Rent



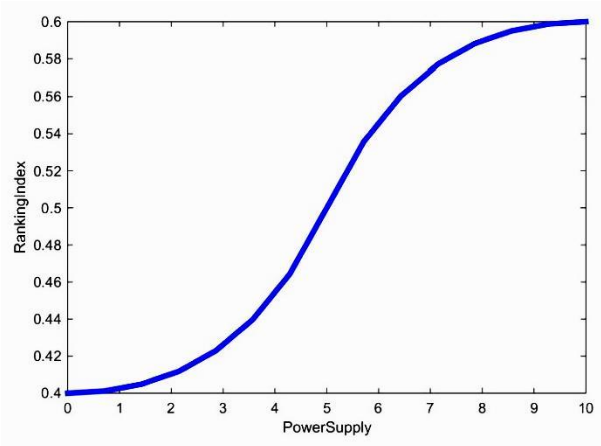
(d) Ranking Index vs Transport Facility



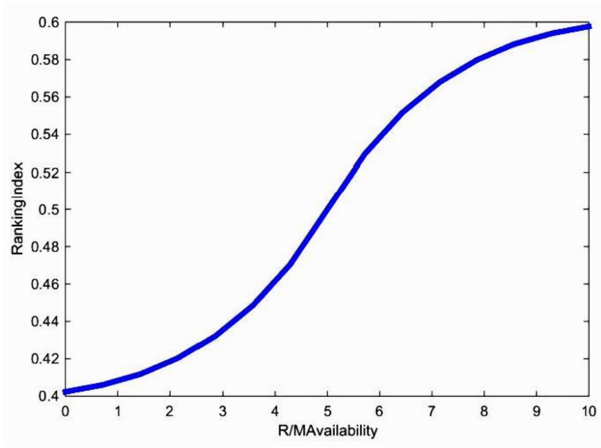
(e) Ranking Index vs Labor Availability



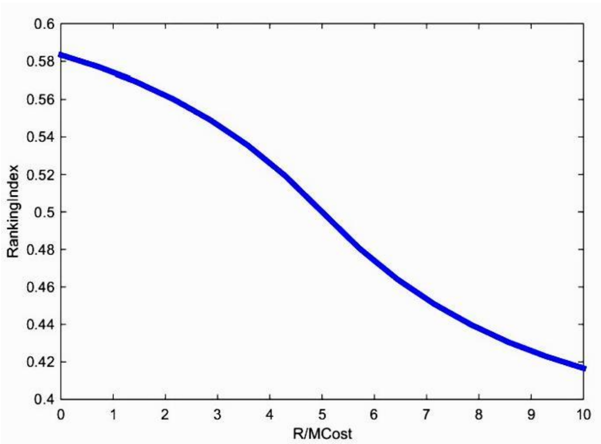
(f) Ranking Index vs Security



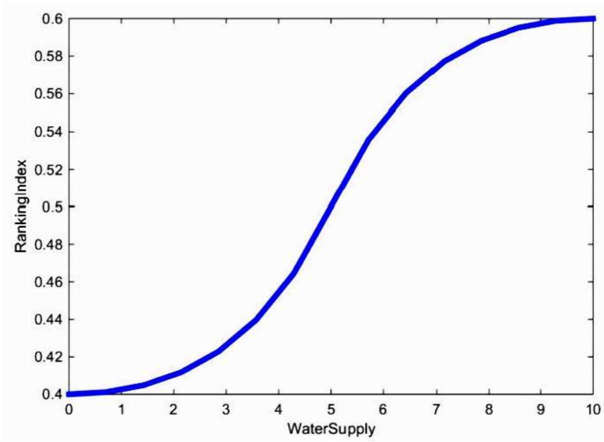
(g) Ranking Index vs Power Supply Facility



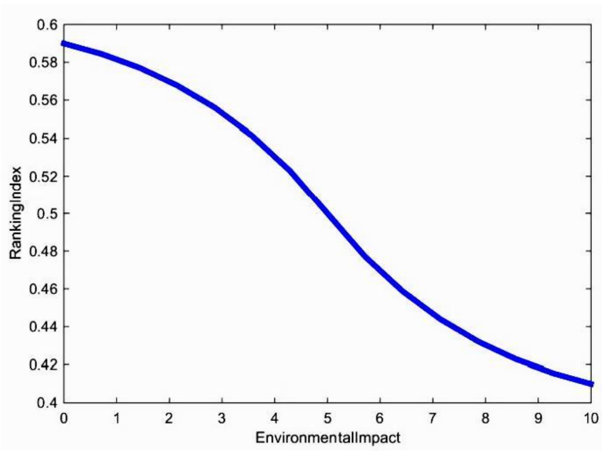
(h) Ranking Index vs Raw Material Availability



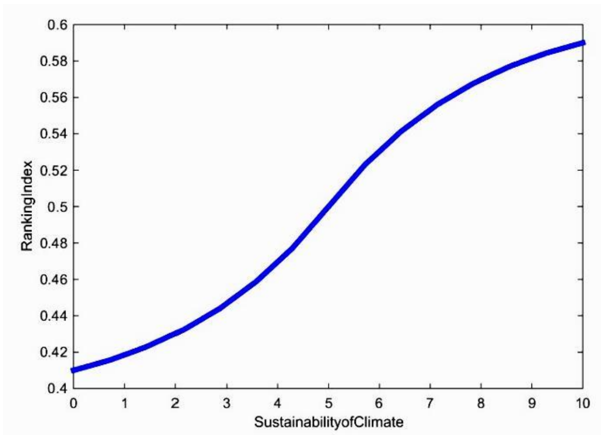
(i) Ranking Index vs Raw Material Cost



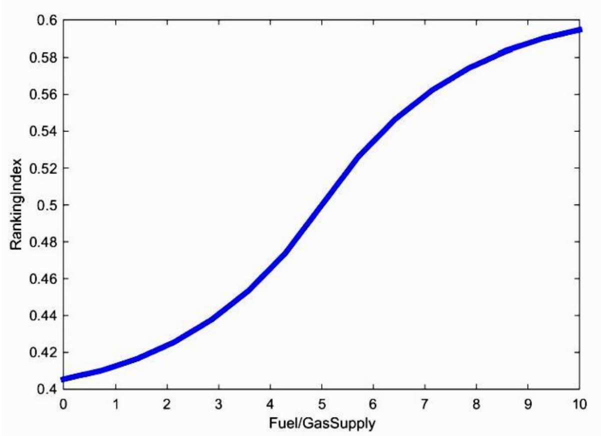
(j) Ranking Index vs Water Supply Facility



(k) Ranking Index vs Environmental Impact



(l) Ranking Index vs Suitability of Climate and Land



(m) Ranking Index vs Fuel/Gas Supply Facility

Fig. B1: Relationship between different criteria and ranking index value