# A FUZZY CREDIBILITY BASED CHANCE CONSTRAINED OPTIMIZATION MODEL FOR MULTIPLE OBJECTIVE AGGREGATE PRODUCTION PLANNING PROBLEM IN A SUPPLY CHAIN UNDER UNCERTAIN ENVIRONMENT

**BY**

**MR. DOAN HOANG TUAN**

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ENGINEERING (LOGISTICS AND SUPPLY CHAIN SYSTEMS ENGINEERING)**

**SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY**
**THAMMASAT UNIVERSITY**

**ACADEMIC YEAR 2020**

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THESIS

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ENTITLED

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# ABSTRACT

This study focuses on developing a mathematical model for an Aggregate Production Planning (APP) problem in a Supply Chain (SC) including multiple suppliers, a production plant, and multiple customers under uncertain environments. The uncertain conditions including uncertainties of customer demand, operation costs (purchasing cost, production cost, transportation cost, and so on), production plant's allowable defective rate of raw material, and supplier's service level. The proposed model considers simultaneously four conflicting different objective functions, which are (1) minimizing the total cost of Supply Chain (SC), (2) the minimizing of total product shortages to enhance the customer's satisfaction, (3) minimizing the variation in changing workforce level and (4) maximizing total of purchasing cost. To solve the proposed Fuzzy Multiple objective Mixed Integer Linear Programming (FMOMILP) model, a hybrid approach has been developed by combining the Fuzzy Chance-constrained Programming (FCCP) and the Fuzzy Multiple Objective Programming

(FMOP). Firstly, the proposed fuzzy multiple objectives model is transformed into the equivalent crisp multiple objectives model by using chance-constrained programming based on the credibility measure of a fuzzy event. Secondly, the Fuzzy Multiple Objective Linear Programming (FMOLP) integrating the concept of the weight-consistent solution is applied to find the optimal efficient solutions. Then, a sensitivity analysis is carried out to explore the impact of the uncertainty and generate a set of optimal solutions (both the balance and unbalance compromise solution among four conflicting objective functions and decision variables). The obtained outcomes can assist to satisfy the decision-maker's aspiration, as well as provide more alternative strategy selections based on their preferences. Finally, a case experiment is given to demonstrate the validity and effectiveness of the proposed formulation model.

**Keywords:** Aggregate production planning, Supply chain, Credibility, Chance-constrained modelling, Fuzzy Multiple Objective Optimization, Weight-consistent solution.

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# LIST OF SYMBOLS/ABBREVIATIONS

| Symbols/Abbreviations Terms | Terms |
| --- | --- |
| DMs | Decision Makers |
| SCM | Supply Chain Management |
| APP | Aggregate Production Planning |
| MILP | Mixed-Integer Linear Programming |
| MOMILP | Multiple Objective Mixed Integer Linear Programming |
| FMP | Fuzzy Mathematical Programming |
| FLP | Fuzzy Linear Programming |
| FCCP | Fuzzy Chance Constraint Programming |
| CFCCP | Credibility-based Fuzzy Chance-constrained Programming |
| FMOP | Fuzzy Multiple Objective Programming |
| FGP | Fuzzy Goal Programming |
| LH | Lai and Huang |
| LZL | Li, Zhang, and Li |
| SO | Selim and Ozkarahan |
| TH | Torabi and Hassini |

# CHAPTER 1
# INTRODUCTION

Nowadays, the globalization of markets and international trade is rapid development. Besides, the customer's expectation is increasingly higher and higher in many different aspects. Therefore, satisfying customer's requirement in a competitive and uncertain market like that pose a significant challenge for companies and enterprises. To exist in this harsh environment, it requires the companies and enterprises to plan and control efficiently the production and operational activities through Supply Chain Management (SCM). A Supply Chain (SC) is defined as a set of activities that are coordinated among suppliers, manufacturers, distribution centers, and customers so that the final products are manufactured and distributed to customers with the right quantities at the right time. Based on this definition, Supply Chain Management (SCM) has become the core value of operations management in production planning for the entire supply chain. Its impacts have an important role in the performance of an organization for competitiveness based on sales price, commodity quality, customer reliability, quick responsiveness, and flexibility in the market.

Without Aggregate Production Planning (APP), procurement, production, transportation, and distribution activities will be implemented independently and separately, causing conflicts in operations and with the given goals. Hence, APP is one of the most crucial issues that should be addressed in supply chain management. APP is acknowledged as an essential stage in production systems because of its links with business strategies. It makes a significant contribution to the planning for enterprise resources and organizational integration. APP is a process by which a company identifies the planned levels of production, capacity, inventory, subcontracting, stockouts, and even pricing in an intermediate time frame (3 to 12 or even 18 months). Most organizations attempt to create an effective aggregate production plan that meets customer requirements and has a minimum total cost (Chiadamrong & Sutthibutr, 2020).

In the presence of such a competitive environment, Decision-Makers (DMs) have to cope with two important problems that can affect the performance of the entire supply chain. The first problem is the conflicting objectives from the properties of operations and the configuration of an SC when adjusting the targets of the different partners in the SC. Each partner in the SC, it has its own goals or interests (e.g. minimizing the total cost of the supply chain, maximizing the satisfaction of customers, or maximizing the value of purchasing). The second problem is the uncertainty of data. The uncertainty of data could arise from two sources: (1) Environmental uncertainty due to the performance of suppliers and the behavior of customers in terms of supply and demand, and (2) System uncertainty due to the unreliability of operations and processes inside an organization (Cha-ume & Chiadamrong, 2012). Therefore, it is necessary to address these two problems when designing and operating a supply chain.

From the abovementioned problems, the purposes of this thesis involving two intentions, Firstly, propose a multiple objectives model for APP in a SC including multiple suppliers, a production plant and multi-customers which integrate the plan of procurement, production, and distribution considering imprecise parameters such as operation costs, customer demands, acceptable failure ratio, and average service level. Secondly, introduce a hybrid approach that helps decision-makers to deal with the fuzziness of data and multiple objective decision-making.

## 1.1 Problem statement

Nowadays, two of the most difficult problems in planning that the decision-makers always meet are to handle with the ambiguity of data and satisfy many goals at the same time. In this thesis, to cope with two main abovementioned issues, a hybrid approach which is a coordination of the defuzzification method (Credibility-based Fuzzy Chance-constrained Programming – CFCCP) and Fuzzy Multiple Objective Programming (FMOP) is proposed. CFCCP can support the Decision-Makers (DMs) to handle the vagueness of data while FMOP is utilized to satisfy simultaneously many goals. Fuzzy Chance-constrained Programming (FCCP) using the credibility measure currently is known as a defuzzification method that can be used to substitute for the traditional fuzzy programming. It is based on the measurement of possibility or the necessity for a fuzzy event. The capability of CFCCP not only deals with non-deterministic parameters that are denoted as fuzzy sets, but also provides a credibility level that indicates the confidence level of the created (efficient) management strategies. With FMOP, many approaches have been researched and applied, but one of the common approaches is fuzzy programming with several objective functions that was proposed by Zimmermann (1978). This model is known as the symmetric model because there is no priority for any fuzzy objective functions (All of the fuzzy objective functions are considered to have the same importance). Therefore, the symmetric model cannot be suitable for making decisions for multiple objectives in a practical environment. Being aware of a deficiency in the above problem, Tiwari, Dharmahr, and Rao (1978) proposed an improved approach, called the weighted additive method. By assigning a specific weight to represent the importance of each fuzzy objective function, this method can provide an efficient compromise solution that can satisfy the aspiration level of each objective function according to the preferences of the DMs. Subsequently, some extended approaches (e.g. the LH method, LZL method, SO method, and TH method) were introduced by Lai and Huang (1994), Li, Zhang, and Li (2006), Selim and Ozkarahan (2006), and Torabi and Hassini (2008), respectively. However, these approaches still did not consider the weight-consistent solution (the homogeneity of ranking objective function weights and their satisfaction levels). As a result, these approaches do not satisfy the aspiration level of the DMs in some cases. Taking into consideration of this matter, a weight-consistent constraint is further proposed to add to FMOP. This ensures that the obtained solutions can be more consistent with DM expectations.

## 1.2 Objective of the research

The research objectives of this thesis including:

1. To develop a multi-objective Mixed-Integer Linear Programming (MILP) model for the Aggregate Production Planning (APP) problem in a Supply Chain (SC).
2. To embed the fuzziness of data into the model.
3. To propose a hybrid resolution for solving the multiple objective Aggregate Production Planning (APP) problem in a Supply Chain (SC) under uncertain environment.

**1.3 Organization of the thesis**

This thesis is divided into 7 Chapters that are arranged as follows: Chapter 1 includes introduction, problem statement, objectives and overview of the thesis. Chapter 2 provides a literature review that contains a synopsis about characteristics, contributions of the previous related studies, which help to identify the research gap that this study attempts to fill. Next, Chapter 3 gives the description, assumption, notation, and mathematical formulation of the APP problem in an SC. Chapter 4 presents the proposed methodology for solving the multiple-objective APP model in an SC under uncertainty. Then, Chapter 5 gives an illustration of a case experiment. Subsequently, Chapter 6 shows the obtained results of the proposed mathematical model and discussions. Finally, Chapter 7 draws the conclusions, gives the limitation, and recommends directions for further work.

# CHAPTER 2
# LITERATURE REVIEWS

The literature review can be divided into two parts. The first part focus on the relevant studies which define the structure of APP model. Several important issues (e.g multiple product items, product characteristics, labor characteristics, and supply chain concept) are embedded in the proposed APP model. The second part reviews previous approaches that are related to the application of modeling optimization under uncertainty.

## 2.1 Aggregate Production Planning (APP)

Aggregate production planning is the intermediate-time capacity plan that identifies the cost minimization of production plan and human resources to fulfill market needs in the most effective way. Its purpose is to identify a suitable quantity of production and inventory level in a term of aggregation. The time period ranging of aggregate production planning is from 2 to 12, or even 18 months (Techawiboonwong & Yenradee, 2003). APP brings a connection between strategic and operations management. In addition, APP operating strategies play a significant role in organizational integration and enterprise resource planning. The target of making APP in manufacturing enterprise is to acquire minimum cost and the maximum profit by determining the quantity of produced product, the quantity of subcontracting product, the levels of labor, and so forth., to fulfill the market demand (Iris & Cevikcan, 2014).

Based on the uncertainty level in the APP model, the APP model can be categorized into two different groups. The input data is used in the APP models that could change from deterministic value to fuzzy value, or stochastic value. There is another significant criterion that can also impact the structure of the APP model is the consideration of the number of objective functions in the model. By combining these two above mentioned criteria, the APP model can be separated into six major structural groups. These six main structural groups are shown more detail in Figure 1.1.

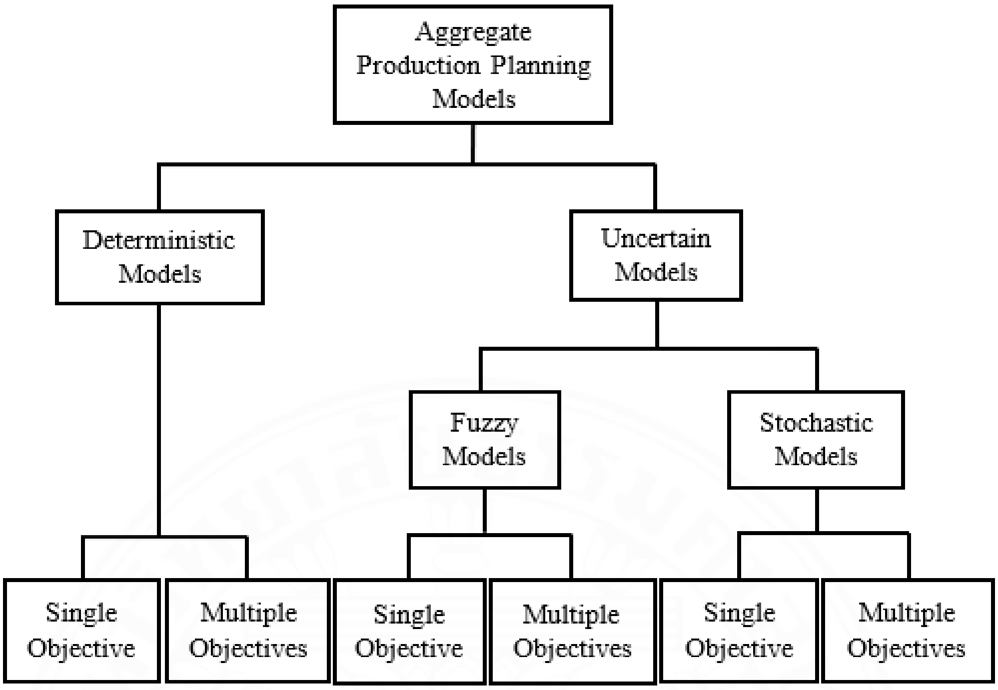


**Figure 2.1** Schemes for APP models.

### 2.1.1 Single objective function

With a single-objective function model, the most optimal solution is related to the value of minimizing or maximizing of a single objective function. The integration of all different objectives is then found. It is valuable as a model that gives DMs an insight into the properties of the problem. However, it is often impossible to give alternative solutions (compromise solutions), which is a trade-off among the different conflicting objectives. Sillekens, Koberstein, and Suhl (2011) introduced a new modeling approach in Mixed-Integer Linear Programming (MILP) for APP problems in the automobile industry. Their single- objective function is the total cost minimization including production cost, holding cost, fixed cost, and cost of changing the production capacity. Zhang, Zhang, Xiao, and Kaku (2012) presented a MILP model for APP problems in a production system with capacity extension and many activity centers. In the model formulation, the objective function minimizes the total costs of the APP plan that consists of production cost, holding cost, and investment cost in the whole planning horizon. Wang and Yeh (2014) studied Particle Swarm Optimization (PSO) for the APP problem. They presented an APP model for a manufacturing company specializing in garden equipment. Their APP model is formulated as a Mixed Integer Linear Programming (MILP) model in which the main objective function minimizes the total relevant cost. The total cost consists of production cost (regular time and overtime production cost, inventory cost, backorder cost, and subcontracting cost), and labor cost (hiring cost and firing cost). Erfanian and Pirayesh (2016) studied the integration of APP with the maintenance activity using the MILP model. They proposed a model, which is limited by workforce resources and equipment. The formulated objective function of the model minimizes the total cost, including production and maintenance costs.

### 2.1.2 Multiple objective function

For a multiple-objective function model, the objective functions in the model can conflict with each other. Thus, its solution is an interaction among different objective functions. The multiple-objective model can provide a set of different efficient solutions (compromise solutions) that are widely known as non-dominated or Pareto-optimal solutions. The consideration of many objective functions (simultaneously) in the model can help to determine a larger scope of these different options, to makes the model of a problem more realistic. Silva and Marins. (2014) presented a multiple-objective model for APP in sugar and ethanol milling companies. In their study, a Fuzzy Goal Programming (FGP) model is used to cope with the multiple objective APP problem in vague conditions. The outcome of the proposed model brings an efficient analysis of the problem, providing more dependable and more accurate outcomes from the perspectives of technology and the economy. Entezaminia, Heydari, and Rahmani (2016) developed a multiple-objective APP model in a Green Supply Chain (GSC) considering a reverse logistic network. The main goal of their study is to generate compromise solutions among costs and green criteria. The objective functions simultaneously minimize the total Supply Chain (SC) cost and maximize the total environmental commodity scores. The obtained outcome of their model is a set of Pareto-optimal solutions that show the trade-off among the conflicting objective functions. Mehdizadeh, Niaki, and Hemati (2018) presented a bi-objective optimization model for APP considering labor skills and machine degradation. The first objective function of the model maximizes the total profit, and the second objective function improves customer satisfaction.

### 2.1.3 Deterministic model

In APP, the input data in the APP model can be deterministic, fuzzy, or stochastic values. Thus, the approaches or methodologies that are applied can be categorized according to the different types of input data that are used in the model. In the deterministic model for APP problems, parameters such as production cost, inventory cost, labor cost, subcontracting cost, backorder cost, machine capacity, market demand, sale price, etc. are assumed to be exactly known before planning and to be deterministic. The first model of APP problem was proposed by Holt, Modigliani, and Simon (1955) along with its linear decision rules. Since then, a lot of researchers have evolved many models to tackle APP problems. Based on the complications of an APP problem, it is often modeled by the MILP model. MILP is well-known for solving APP problems with inputs of data that are deterministic or crisp values (Paiva & Morabito 2009; Chaturvedi & Bandyopadhyay, 2015; Chakrabortty & Hasin, 2013).

### 2.1.4 Uncertain model

In contrast, fuzzy data are imprecise data. Their boundaries are not defined explicitly. This is often encountered in the field of human judgment, where assessment and decisions are crucial, such as reasoning, learning, decision-making, etc. (Bellman & Zadeh, 1970). The fuzzy data can be described and analyzed based on the fuzzy set theory. The fuzzy set theory can be applied with an APP models in unclear situations. Some uncertain data in the APP model such as production time, production capacity, customer demand, etc. are not suitable for the probability distribution. Therefore, an APP model needs to be formulated based on the principle of fuzzy set theory and fuzzy optimization approaches so that the APP models can handle and be optimized with uncertainty (Zadeh, 1965; Zimmerman, 1976).

Stochastic data is a type of uncertain data that can be described by the theory of randomness and probability. Stochastic model and its method are restricted to tackling uncertainties with probability distributions (Tang, Fung, & Yung, 2003). Besides, its method requires a great amount of collected historical data which is hard to obtain in case of APP problem. In addition, Lai and Hwang (1992) argued that the application of stochastic models can be lack of computational efficiency and the theory of probability could not be able to provide the right meaning to solve some decision-making problems in practice. Therefore, stochastic model and its method will be not mentioned in the next section of the literature review.

### 2.1.5 Important issues in the APP models

The complexity of APP problems is largely caused by the requirement of coordinating interactive variables so that the company can meet the market demand most efficiently (Kumar & Suresh, 2009). Some primary problems that are mostly used in any APP model such as production capacity, inventory, backorder, warehouse space, market demand, costs of production, subcontracting, labor level, hiring and firing cost, and product price. In addition, there have been some supplementary problems (or new assumptions) considered as “crucial problems” that are also integrated into the APP model (e.g. multiple product items, product characteristics, labor characteristics, degree of DM satisfaction for a solution, set up decisions, multiple production plants, time value of money, machine utilization, financial concepts, supply chain concepts, and multiple product markets). These supplementary problems were discussed and explained in detail by Cheraghalikhani, Khoshalhan, and Mokhtari (2019). Based on these crucial problems, APP problems can be developed and modeled more effectively, which helps to enhance their capacities as well as their compatibility in a real-life environment.

## 2.2 Mathematical approaches

In practice, the input data of APP problems are regularly imprecise due to some information that is incomplete or cannot be accurately obtained. In these circumstances, fuzzy logic can provide a form of reasoning that allows approximate human inference skills to be used as knowledge-based systems. Zadeh (1965) first introduced the theory of fuzzy logic, and a mathematical framework was provided to incorporate the uncertainty related to human operations, such as reasoning and thinking. The theory of fuzzy sets has been extensively adopted in many fields (e.g. management science, operations research, artificial intelligence, and control theory). By applying the theory of fuzzy sets, Fuzzy Mathematical Programming (FMP) has become a well-known method for decision-making. Zimmermann (1976) first proposed the fuzzy set theory in a typical Linear Programming (LP) model that has fuzzy objectives and fuzzy constraints. An equivalent single-goal linear programming model is obtained by combining a linear membership function and the fuzzy decision-making method of Bellman and Zadeh (1970) that is introduced in this study. Subsequently, some fuzzy optimization methods for handling APP problems in ambiguous conditions have been developed based on FMP. Moreover, Zadeh (1978) introduced the possibility theory, which is related to the fuzzy set theory. The possibility distribution concept is defined as a vague limitation, which can work as a flexible constraint on the values that may be allocated to a variable. The research also shows the significance of the possibility theory because most of the information about human decisions is understood to be possibilistic instead of being probabilistic (as in nature). The uncertainties of these types of data cannot be completely depicted by frequency-based probability distributions. Therefore, it is necessary to use the fuzzy set theory and fuzzy optimization approaches in formulating and optimizing the APP model.

### 2.2.1 Fuzzy programming

Fuzzy Linear Programming (FLP) is an approach that can be used to associate fuzzy input data that should be modeled by subjective preference-based membership functions. Tang, Wang, and Fung (2000) developed a fuzzy optimization method to deal with multiple product APP problems. This was the first time an APP problem with fuzzy demands and fuzzy capacities was formulated by utilizing the concept of fuzzy equation in terms of a degree of accuracy. They also explained the satisfaction levels in making production and inventory plans to meet the market demand. The fuzzy solution of this approach can offer Decision-Makers (DMs) more options in constructing an aggregate production plan, in order to guarantee the feasibility of the family disaggregation plan, especially in an uncertain environment. Wang and Fang (2001) studied an APP problem with some fuzzy parameters that consist of the product price, subcontracted cost, production quantity, workforce level, market demand, and the fuzzy satisfaction levels of objective functions. Their proposed approach provided a systematic framework to interactively support DMs until satisfactory results were achieved. An aggregation operator was deployed at the final step to acquire the compromise solution of the proposed system. Iris and Cevikcan (2014) provided a mathematical programming framework for aggregate production planning problem under imprecise data environment. After providing background information about fuzzy linear programming and APP problem, the fuzzy linear programming model of APP was solved on an illustrative example for different α-cut values. Chen and Huang (2014) proposed a novel methodology for solving the APP problem in uncertain conditions. After constructing the membership function by applying Zadeh's extension principle and fuzzy solutions, an equivalent mathematical parametric programming is formed to identify the lower and upper bound of the total cost with the different levels of α. The objective value is represented based on a membership function. Thus, the achieved solutions can have more information with more accuracy, which provides more opportunities to gain the optimal solution on the disaggregate plan. That is also beneficial to DMs in practical applications.

### 2.2.2 Credibility-based Fuzzy Chance-constrained Programming (CFCP)

Credibility-based Fuzzy Chance-constrained Programming (CFCP) is known as a fuzzy optimization approach based on the concept of credibility measure of fuzzy numbers in the theory of fuzzy sets (as the average of possibility and necessity measure). This method is used in order to ensure that the satisfaction of both fuzzy objectives and fuzzy constraints can be solved at a minimum allowed of a confident level (Liu & Liu, 2002). Currently, the CFCP has been applied to solve some uncertain problems in a practical environment. Zhu and Zhang (2009) investigated a model for an APP problem under uncertainty. By applying credibility-based fuzzy chance-constrained programming, the fuzzy APP model is converted into an equivalent crisp model and then solved with different confidence levels. Zhang, Zhu, and Hua (2010) studied an APP model with uncertain information in the realistic condition of a manufacturing company. To solve the proposed fuzzy APP model, a fuzzy chance-constrained programming was formulated based on the theory of credibility. Throughout the results of this model, it was found that the theory of credibility is capable of decreasing the influence of uncertainty. Pishvaee, Torabi, and Razmi (2012) studied a mathematical model to design the configuration of green logistics in an ambiguous environment. They proposed a credibility-based fuzzy mathematical optimization model that integrates the expected value of fuzzy numbers and chance-constrained programming in which the expected value of fuzzy numbers are applied to handle fuzzy parameters in the objective function while the chance-constrained programming is used to manipulate the confident levels for the satisfaction of fuzzy constraints. Zhang, Huang, Lu, and He (2015) presented a comprehensive credibility-based chance-constrained programming approach by applying the concept of credibility theory into the fuzzy mathematical optimization model. The proposed approach not only assists to cope with the imprecise parameters in both the right-hand side as well as the left-hand-side of fuzzy constraints but also yields a level of credibility that represents how much confidence the DMs are able to trust on the obtained solution.

### 2.2.3 Goal Programming (GP)

To simultaneously satisfy many conflicting objectives in an APP problem, Goal Programming (GP) is an optimization method that is used to solve an APP problem with multiple objectives by order of priority. The lower- priority goal is solved later without decreasing the relative importance of a higher-priority goal. Leung, Wu, and Lai (2003) proposed a GP approach for a multiple site APP model with multiple objectives that maximizes the total profit, minimizes the variation of the workforce level, and maximizes the utilization of import quotas. By changing the hierarchy of the priority that corresponds to each objective, DMs can realize the flexibility and robustness of the proposed model.  Leung and Ng (2007) formulated a pre-emptive GP model to optimize the APP problem for perishable products in ambiguous conditions. The model of their study considered three objective functions which minimize the operational cost, minimize the inventory cost, and minimize the labor cost. Leung and Chan (2009) presented a multi-objective model for the APP problem with constraints on resource utilization. Maximizing the profit, minimizing the repairing cost, and maximizing the utilization of machine are the three main objective functions, with goal values that are optimized hierarchically. To cope with multiple goals in the APP problem, a goal programming model was applied. The flexibility and robustness of the model were illustrated by different scenarios.

### 2.2.4 Fuzzy Goal Programming (FGP)

FGP is an extension of traditional GP, in which the satisfaction level of each objective is taken as unity. FGP is concerned with the achievement of the highest degree of fuzzy goals based on the linear membership function. Jamalnia and Soukhakian (2009) presented a Hybrid Fuzzy Multi-Objective Nonlinear Programming (H-FMONLP) model with different goal priorities for a multiple-product multiple-period APP problem under an uncertain environment. Liang and Cheng (2011) designed a fuzzy multiple-objective LP model for the APP problem that simultaneously minimizes the total costs, total carrying and back-ordering levels, and total changing rates of labor levels. These parameters are related to the machine capacity, inventory holding levels, labor levels, warehouse storage space, and budget availability. A two-phase FGP approach for handling multiple-objective APP decision problems with multiple products and multiple periods was developed. Madadi and Wong (2014) studied a multiple-objective APP model in a fuzzy environment. Based on the fuzzy membership function, FGP was used for solving the APP decision problem by minimizing the total costs while maximizing the quality of products and customer service levels. Mosadegh, Khakbazan, Salmasnia, and Mokhtari (2017) presented a multiple objective APP problem. In their study, the FGP model is applied for solving the APP problem with four objectives (goals): (1) lost sales and inventory, (2) idle time and overtime, (3) labor level, and (4) exchange savings. Chauhan, Aggarwal, and Kumar (2017) studied fuzzy multiple-objective MILP for the APP decision problem in an uncertain environment. In their study, FGP was introduced to optimize APP problems for multiple products and multiple periods.

### 2.2.5 Weight-consistent solution

Taking into the consideration of the achieved solutions of the Fuzzy Goal Programming (FGP) approach, the weight-consistent solution implies that the satisfaction level of each fuzzy goal must be compatible with the expected relative important weight of its goal. In other words, the ranking of achieved satisfaction levels for fuzzy goals must be the same as the ranking of the goal's weight. For instance, it is assumed that the goal's weights $(\theta_h)$ are ranked as follows: $\theta_1 \geq \theta_2 \geq \theta_3 \geq \theta_4$. Where $h$ represents the index of a goal. As a result, the weight-consistent solution will have the ranking of achieved satisfaction level of goals $\mu_h$ as follows: $\mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$ (Amid, Ghodsypour, & O'Brien, 2011). Generally, if a goal is assigned with a high important weight, that means the expectation of the DMs will be able to obtain a high satisfaction level for that goal, and otherwise.

## 2.3 Summary of literature review

**Table 2.1** A summary of the literature on APP problem.

| Articles | No. objectives | Type of data | Chance constraint | Important issues in APP | | | | | | Consistent solution | Mathematical Modelling | Solution approaches |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Multiple Product | Product characteristics | Labor characteristics | Supply Chain concept | Multiple period planning | Satisfaction of solution | | | |
| Techawiboonwong and Yenradee (2003) | S | D | – | ✓ | – | – | – | ✓ | – | – | MILP | LDR |
| Iris and Cevikcan (2014) | S | F | – | ✓ | – | – | – | ✓ | – | – | FMILP | ParP |
| Sillekens, Koberstein, and Suhl (2011) | S | D | – | ✓ | – | ✓ | – | ✓ | – | – | MILP | H |
| Zhang, Zhang, Xiao, and Kaku (2012) | S | D | – | ✓ | – | ✓ | – | ✓ | – | – | MILP | H |
| Wang and Yeh (2014) | S | D | – | – | – | ✓ | – | ✓ | – | – | MILP | PSO |
| Erfanian and Pirayesh (2016) | S | D | – | ✓ | – | – | – | ✓ | – | – | MILP | SS |
| Da Silva and Marins (2014) | M | D | – | ✓ | ✓ | – | S-P | ✓ | – | – | MOMILP | SS |
| Entezaminia, Heydari, and Rahmani (2016) | M | D | – | ✓ | – | – | S-P-C-Co-R | ✓ | – | – | MOMILP | SS |
| Mehdizadeh, Niaki, and Hemati (2018) | M | D | – | ✓ | – | – | – | ✓ | – | – | MOMILP | GA |
| Paiva and Morabito (2009) | S | D | – | ✓ | ✓ | – | S-P | ✓ | – | – | MILP | SS |
| Chakrabortty and Hasin (2013) | M | D | – | ✓ | – | – | – | ✓ | – | – | MILP | GA |
| Chaturvedi and Bandyopadhyay (2015) | S | D | – | – | – | – | – | – | – | – | MILP | H |
| Tang et al. (2000) | S | F | – | ✓ | – | – | – | ✓ | ✓ | – | FMILP | FLP |
| Wang and Fang (2001) | M | F | – | ✓ | – | – | – | ✓ | ✓ | – | FMOMILP | FLP |
| Chen and Huang (2014) | S | F | – | ✓ | – | – | – | ✓ | – | – | FMILP | ParP |
| Zhu and Zhang (2009) | S | F | ✓ | ✓ | – | – | – | ✓ | – | – | FMILP | FCCP |
| Zhang, Zhu, and Hua (2010) | S | F | ✓ | ✓ | – | – | – | ✓ | – | – | FMILP | FCCP |
| Leung, Wu, and Lai (2003) | M | D | – | ✓ | – | – | – | ✓ | ✓ | – | MOMILP | GP |
| Leung and Ng (2007) | M | D | – | ✓ | ✓ | – | – | ✓ | – | – | MOMILP | GP |
| Leung and Chan (2009) | M | D | – | ✓ | – | – | – | ✓ | – | – | MOMILP | GP |
| Jamalnia and Soukhakian (2009) | M | F | – | ✓ | – | – | – | ✓ | ✓ | – | FMONILP | FLP+GA |
| Liang and Cheng (2011) | M | F | – | ✓ | – | – | – | ✓ | ✓ | – | FMOMILP | FGP |
| Madadi and Wong (2014) | M | F | – | ✓ | ✓ | – | – | ✓ | ✓ | – | FMOMILP | FLP |
| Mosadegh, Khakbazan, Salmasnia, and Mokhtari (2017) | M | F | – | ✓ | – | – | – | ✓ | ✓ | – | FMOMILP | FGP |
| Chauhan, Aggarwal, and Kumar (2017) | M | F | – | ✓ | ✓ | – | S-P-C | ✓ | ✓ | – | FMOMILP | FLP |
| This study | M | F | ✓ | ✓ | ✓ | ✓ | S-P-C | ✓ | ✓ | ✓ | FMOMILP | FCCP+FGP |

Notes: S: Single, M; Multiple, D: Deterministic, F: Fuzzy, MP: Multiple products, LC: Labor characteristic, PC: Product characteristic, SCc: Supply chain concept. S: Supplier, P: Production Plant, C: Customer, Co: Collection center, R: Recycling center, MILP:

Mix-integer linear programming, FMILP: Fuzzy mix-integer linear programming, MOMILP: Multiple objective mix-integer linear programming, FMOMILP: Fuzzy multiple objective mix-integer linear programming, FMONILP: Fuzzy multiple objective mix-integer non-linear programming, LDR: Linear decision rules, ParP: Parametric Programming, PSO: Particle Swarm Optimization, SS: Solver software (i.e. Lingo, Gam, Cplex), H: Heuristic, GA: Genetic algorithm, FLP: Fuzzy linear programming , GP: goal programming, FGP: Fuzzy goal programming, FCCP: Fuzzy chance constraint programming.

Based on a literature review, some research gaps related to APP models were identified, such as the integration of new concepts (important issues) into APP models, the consideration of uncertain data, and optimization approaches under uncertainty. Therefore, to fill the research gaps, this study focuses on developing a mathematical model for an Aggregate Production Planning (APP) problem in an uncertain environment. To make the APP problem more effective, informative, and more compatible with a real-life environment, the APP problem is considered with multiple objectives and integrated into a Supply Chain (SC) including a production plant, multiple suppliers, and multiple customers. In addition, several important problems such as multiple products, product characteristics, and labor characteristics are embedded in the model. Then, a hybrid approach that integrates Fuzzy Chance-constrained Programming (FCCP) and Fuzzy Multiple Objective Programming (FMOP) is proposed for solving the proposed model. FCCP is utilized to deal with fuzzy parameters in the proposed model while FMOP is applied to deal with multiple objective functions. For FMOLP, by applying an aggregation function and integrating the concept of weight-consistent solution. The proposed approach can achieve the optimal solutions under the balanced and unbalanced compromise solutions among conflicting objective functions. It can also achieve weight-consistent solutions that can satisfy the decision-maker's aspirations and provide more alternative strategy selections based on their preferences. A summary of the literature on APP problems is presented in Table 2.1.

# CHAPTER 3
# DEVELOPMENT OF AGGREGATE PRODUCTION PLANNING (APP) MODEL IN A SUPPLY CHAIN UNDER UNCERTAINTIES

This chapter focus on developing a Fuzzy Multi-Objective Mixed-Integer Linear Programming (FOMILP) to express a comprehensive multi-site, multi-product and multi-period Aggregate Production Planning (APP) problem in Supply Chain (SC) under uncertain environment.

There are three main stages in the model development. The first stage concentrates on the characterization of the problem. This is an important step to understand a detail description of the problem. The second stage is to present a list of notations of parameters and decision variables used in the model. In addition, some assumptions are also outlined and justified at this stage. These assumptions express the restrictions of the developed model to make sure that the model is controllable to be solved. Finally, the third stage shows the formulating mathematical model procedure representing the relations between parameters and decision variables. At this stage, the objective functions and constraints are constructed.

## 3.1 Model Formulation

### 3.1.1 Problem Description

In this study, the proposed fuzzy multiple-objective, multi-product, multi-period APP problem in a supply chain (SC) can be described as follows:

An Aggregate Production Planning (APP) problem is built for the type of raw material $R$ that is provided from supplier $S$ to assemble and produce the type of product $N$ in the production plant, and finally transfer to customer $J$ so that the customer demand can be fulfilled in planning time period $T$. Each product is manufactured by determining the rate of raw materials. The structure of the supply chain network is depicted in Figure 3.1. In fact, this problem aggregates three sub-problems of planning including the (1) procurement plan for purchasing raw materials from suppliers, (2) production plan for producing finished products, and (3) distribution plan for delivering each finished product to each customer in each period. This study concentrates on developing a Fuzzy

Multiple-Objective Mixed Integer Linear Programming (FMOMILP) model to optimize the APP plan in a supply chain (SC) under an uncertain environment. Therefore, customer demand, operating costs (e.g. regular time production cost, overtime production cost, subcontracting cost, purchasing cost, salary, hiring cost, firing cost, transportation cost, and penalty cost) and some other influential parameters are considered as imprecise parameters over each planning period. The fuzzy numbers are considered to represent uncertain parameters. Four conflicting objective functions are formulated simultaneously in the mathematical model. The first objective is to minimize the total Supply Chain (SC) cost. The second objective is to minimize the total maximum product shortages. The third objective is to minimize the rate of changes in human resources, and the fourth objective is to maximize the total value of purchasing.

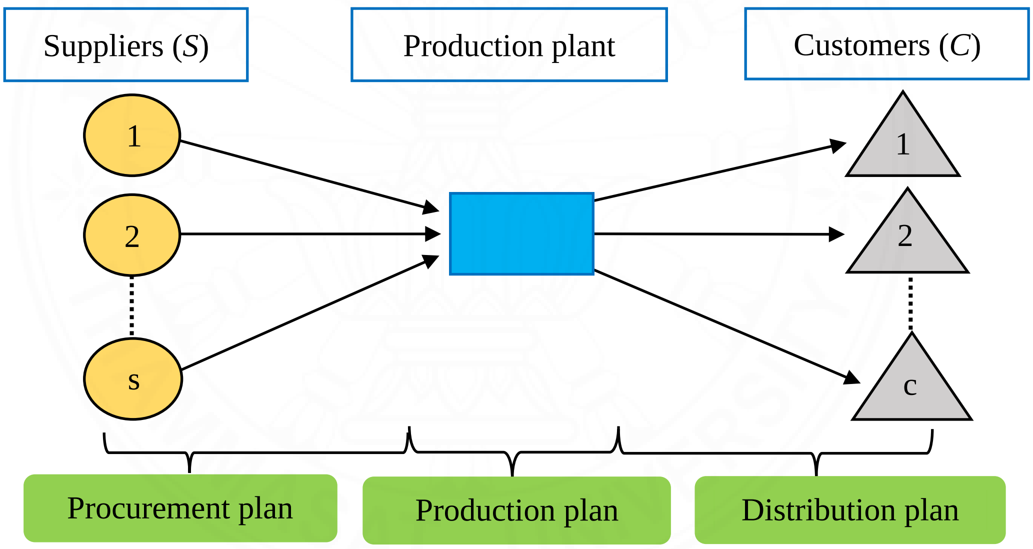


**Figure 3.1** Structure of supply chain network

### 3.1.2 Problem Assumption

The basic assumptions of the fuzzy multiple objectives mathematical programming model are as follows.

- Only the demand for the final product is known but it is imprecise.
- The capacities of the machines and storage are limited by the maximum level at the production plant.
- A set of qualified suppliers is given.

- A production plant produces many types of products to meet customer demand during the planning horizon.
- Before the beginning of the planning period, there is no demand for the finished products.
- The initial labor level is known at the beginning of the planning period.
- The production capacities of suppliers and plant are estimated by taking into consideration of various contingent situations (setups, machine break down, etc.) and achievable capacity supplements (overtime or/and subcontracting production).
- A shortage of products is allowed in the supply chain. However, it will be charged as a penalty cost for compensation if a shortage occurs.
- The acceptable defect rate and service level of suppliers at the production plant are imprecise. They are determined based on the manufacturer's preferences.
- Lead-time is considered as zero.
- The pattern of a triangular fuzzy number is utilized to represent uncertain parameters.
- The membership function of objective functions is expressed in a linear form for all fuzzy sets.

**3.1.3 Problem Notation**

The notations that are used to formulate the mathematical model of the APP problem in a supply chain are expressed as follows:

To formulate the mathematical model, the tilde symbol (˜) refers to ambiguous data that are used in this numerical case study.

- Set of Indices

| | |
|---|---|
| $R$ | Index of raw materials ($r = 1, \ldots, R$) |
| $S$ | Index of suppliers ($s = 1, \ldots, S$) |
| $J$ | Index of customers, ($j = 1, \ldots, J$) |
| $N$ | Index of products ($n = 1, \ldots, N$) |
| $K$ | Index of worker levels ($k = 1, \ldots, K$) |
| $T$ | Index of periods in planning horizon ($t = 1, \ldots, T$) |

- Fuzzy Parameters

***Production cost***

| | |
|---|---|
| $\widetilde{RTPC}_t$ | Fuzzy regular-time production unit cost at the production plant in period *t* ($/min) |
| $\widetilde{OTPC}_t$ | Fuzzy overtime production unit cost at the production plant in period *t* ($/min) |
| $\widetilde{STPC}_{it}$ | Fuzzy subcontracting production unit cost at the production plant in period *t* ($/min) |

***Purchasing cost***

| | |
|---|---|
| $\widetilde{RMSC}_{srt}$ | Fuzzy purchasing unit cost of supplier *s* for raw material *r* in period *t* ($/unit) |

***Labor cost***

| | |
|---|---|
| $\widetilde{SC}_{kt}$ | Fuzzy salary of a worker at level *k* in period *t* ($/person) |
| $\widetilde{HC}_{kt}$ | Fuzzy hiring cost of a worker at level *k* in period *t* ($/person) |
| $\widetilde{FC}_{kt}$ | Fuzzy firing cost of a worker at level *k* in period *t* ($/person) |

***Inventory cost***

| | |
|---|---|
| $\widetilde{IRMC}_{rt}$ | Fuzzy inventory unit cost of raw material *r* at the production plant in period *t* ($/unit) |
| $\widetilde{IPC}_{nt}$ | Fuzzy inventory unit cost of product *n* at the production plant in period *t* ($/unit) |

***Transportation cost***

| | |
|---|---|
| $\widetilde{TRMC}_{st}$ | Fuzzy shipping unit cost of raw material from supplier *s* to the production plant in period *t* ($/unit) |
| $\widetilde{TPC}_{jt}$ | Fuzzy transportation unit cost of finished product from the production plant to customer *j* in period *t* ($/unit) |

***Penalty cost***

| | |
|---|---|
| $\widetilde{PSC}_{njt}$ | Fuzzy penalty unit cost of shortage of product *n* for customer *j* in period *t* ($/unit) |

***Others***

| | |
|---|---|
| $\widetilde{AFRS}_{sr}$ | Fuzzy average failure rate of raw material *r* supplied from supplier *s* to the production plant (%) |

| | |
|---|---|
| $\widetilde{AFRP}_r$ | Fuzzy acceptable failure rate of the production plant for raw material *r* (%) |
| $\widetilde{ASL}_s$ | Fuzzy average service level of supplier *s* (%) |
| $\widetilde{ASLP}$ | Fuzzy acceptable service level of the production plant (%) |
| $\widetilde{D}_{njt}$ | Fuzzy demand of customer *j* for final product *n* in period *t* (units) |

- Deterministic Parameters

| | |
|---|---|
| $MaxPS_{nt}$ | Maximum capacity allowed for subcontracting product *n* in period *t* (units) |
| $MaxMA_{nt}$ | Maximum machine capacity available for product *n* at the production plant in period *t* (machine-hours) |
| $MaxWSA_t$ | Maximum warehouse space available at the production plant in period *t* ($m^2$) |
| $MaxRS_{sr}$ | Maximum capacity of raw material *r* provided by supplier *s* (units) |
| $MHU_{nt}$ | Machine hourly usage for a unit of product *n* at the production plant in period *t* (machine-hours/unit) |
| $WSP_{nt}$ | Warehouse space for a unit of product *n* at the production plant in period *t* ($m^2$/unit) |
| $WSRM_{rt}$ | Warehouse space for a unit of raw material *r* at the production plant in period *t* ($m^2$/unit) |
| $NoRM_{rn}$ | Number of raw material *r* needed to produce for a unit of product *n* (units) |
| $NoL_k^0$ | Number of initial workers at level *k* at the production plant (persons) |
| $RTPA_t$ | Available regular time at the production plant in period *t* (hours) |
| $OTPA_t$ | Available over-time at the production plant in period *t* (hours) |
| $STPA_t$ | Available subcontracting time at the production plant in period *t* (hours) |
| $PTP_n$ | Production time required for producing product *n* at the production plant (min) |
| $SCRM$ | Storage capacity of raw material at the production plant (units) |
| $SCP$ | Storage capacity of final product at the production plant (units) |
| $Prod_k$ | Productivity of workers at level *k* ($0 < Prod_k < 1$) |
| $FWV$ | Acceptable fraction of workforce variation in period *t* (%) |
| $TSSQ_s$ | Total score of supplier *s* by considering quality of raw material (%) |

- *Decision variables*

$QRTP_{nt}$ Quantity of product *n* produced in regular time at the production plant in period *t* (units)

$QOTP_{nt}$ Quantity of product *n* produced in overtime at the production plant in period *t* (units)

$QSTP_{nt}$ Subcontracting quantity of product *n* produced at the production plant in period *t* (units)

$QRMS_{srt}$ Quantity of raw material *r* provided by supplier *s* to the production plant in period *t* (units)

$QPSC_{njt}$ Quantity of final product *n* from the production plant to customer *j* in period *t* (units)

$QW_{kt}$ Number of workers at level *k* at the production plant in period *t* (persons)

$QWH_{kt}$ Number of hired workers at level *k* at the production plant in period *t* (persons)

$QWF_{kt}$ Number of fired workers at level *k* at the production plant in period *t* (persons)

$IP_{nt}$ Inventory of final product *n* at the production plant at the end of period *t* (units)

$IRM_{rt}$ Inventory of raw material *r* at the production plant in period *t* (units)

$QSP_{njt}$ Shortage of product *n* for customer *j* in period *t* (unit)

**3.1.4 Mathematical Model**

The FMOMINLP model for supply chain (SC) production planning is formulated below:

**3.1.4.1 Objective functions**

The current global market of competition forces companies to consider multiple objectives for effective aggregation of procurement, production and distribution planning at the same time. By considering important decisions of the practical APP problem in a supply chain, it is found that objective functions related to the minimization of the overall cost, minimization of product shortages, minimization of changes in workforce levels, and maximization of the total value of purchasing are considered as multiple conflicting objective functions.

1. Minimizing the total supply chain costs ($Z_1$):

Minimizing the total overall cost is the most popular objective that is used in supply chain planning models. The total overall costs of the model in this study comprise the production costs, purchasing cost, labor costs, inventory costs, transportation costs, and shortage costs. The mathematical formulations and explanations of these components are presented as follows:

Total supply chain costs (TC) = Production costs (C1) + Purchasing cost (C2) + Labor costs (C3) + Inventory costs (C4) + Transportation costs (C5) + Shortage cost (C6)

Production costs (C1) include the cost of regular time production, overtime production, and subcontracting production. They are described as follows:

$$C1 = \sum_{n=1}^{N} \sum_{i=1}^{T} PTP_n \times \widetilde{RTPC}_t \times QRTP_{nt}$$
$$+ \sum_{n=1}^{N} \sum_{i=1}^{T} PTP_n \times \widetilde{OTPC}_t \times QOTP_{nt}$$
$$+ \sum_{n=1}^{N} \sum_{i=1}^{T} PTP_n \times \widetilde{STPC}_t \times QSTP_{nt}$$

Purchasing cost (C2) of raw materials from suppliers can be defined as follows:

$$C2 = \sum_{s=1}^{S} \sum_{r=1}^{R} \sum_{i=1}^{T} \widetilde{RMSC}_{srt} \times QRMS_{srt}$$

Labor costs (C3) are the costs that the manufacturer pays for a worker including salary, hiring cost, and firing cost, which are presented as follows:

$$C3 = \sum_{k=1}^{K} \sum_{t=1}^{T} \widetilde{SC}_{kt} \times QW_{kt}$$
$$+ \sum_{k=1}^{K} \sum_{t=1}^{T} \widetilde{HC}_{kt} \times QWH_{kt}$$
$$+ \sum_{k=1}^{K} \sum_{t=1}^{T} \widetilde{FC}_{kt} \times QWF_{kt}$$

Inventory costs (C4) are the summation of the holding cost of raw materials and final product at the production plant. This is expressed as:

$$C4 = \sum_{r=1}^{R} \sum_{t=1}^{T} \widetilde{IRMC}_{rt} \times IRM_{rt}$$
$$+ \sum_{n=1}^{N} \sum_{t=1}^{T} \widetilde{IPC}_{nt} \times IP_{nt}$$

Transportation costs (C5) from suppliers to the production plant and from the production plant to customers for different kinds of raw materials and the final product are defined as follows:

$$C5 = \sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{t=1}^{T}\widetilde{TRMC}_{st}QRMS_{srt} + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\widetilde{TPC}_{jt}QPSC_{njt}$$

The shortage cost (C6) is the cost of shortages for not being able to fulfill the customer demand which is defined as follows:

$$C6 = \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\widetilde{PSC}_{njt}QSP_{njt}$$

Generally, the first objective function for minimizing the total supply chain costs can be summarized as follows:

$$\begin{aligned} Min\ \widetilde{TC} = & \sum_{n=1}^{N}\sum_{i=1}^{T}PTP_n \times \widetilde{RTPC}_t \times QRTP_{nt} \\ & + \sum_{n=1}^{N}\sum_{i=1}^{T}PTP_n \times \widetilde{OTPC}_t \times QRTP_{nt} \\ & + \sum_{n=1}^{N}\sum_{i=1}^{T}PTP_n \times \widetilde{RTPC} \times QRTP_{nt} \\ & + \sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{i=1}^{T}\widetilde{RMSC}_{srt} \times QRMS_{srt} \\ & + \sum_{k}^{K}\sum_{t=1}^{T}\widetilde{SC}_{kt} \times QW_{kt} \\ & + \sum_{k}^{K}\sum_{t=1}^{T}\widetilde{HC}_{kt} \times QWH_{kt} \\ & + \sum_{k}^{K}\sum_{t=1}^{T}\widetilde{FC}_{kt} \times QWF_{kt} \\ & + \sum_{r=1}^{R}\sum_{t=1}^{T}\widetilde{IRMC}_{rt} \times IRM_{rt} \\ & + \sum_{n=1}^{N}\sum_{t=1}^{T}\widetilde{IPC}_{nt} \times IP_{nt} \\ & + \sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{t=1}^{T}\widetilde{TRMC}_{st}QRMS_{srt} \\ & + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\widetilde{TPC}_{jt}QPSC_{njt} \\ & + \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\widetilde{PSC}_{njt}QSP_{njt} \end{aligned} \qquad (3.1)$$

Equation (3.1) shows the first objective function that tries to minimize total cost of supply chain (SC) including production costs, purchasing cost, labor wage, hiring cost, firing cost, inventory cost, transportation cost, and shortage cost.

2. Minimizing the shortages of product to improve the customer satisfaction ($Z_2$):

Customer satisfaction makes a significant contribution in business APP problems. It is the indicator that is used to recognize the dissatisfied customers, measure the loyalty of customers, and enhance revenue. It also is an important point of differentiation that can help companies to attract new customers in competitive business environments. In this study, the customer's satisfaction is assessed through product shortages as follows:

$$Min\ CS = \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{t=1}^{T} QSP_{njt} \qquad (3.2)$$

This second objective function aims to improve the customer's satisfaction by minimizing the summation of shortage product *n* among customer *j* in all periods, as is presented in Equation (3.2)

3. Minimizing the rate of changes in the workforce level ($Z_3$):

In an actual situation of APP, through aggregating the forecast demand in advance, companies are able to estimate the workforce requirements. However, it is difficult to have a varying workforce plan because of worker skills, employment law, and other factors related to the benefits of the workforce. Thus, the workforce levels are required to be stable, to easily manage workforce, and can be presented as follows:

$$Min\ RCW = \sum_{t}^{K} \sum_{t=1}^{T} (QWH_{kt} + QWF_{kt}) \qquad (3.3)$$

Equation (3.3) shows the third objective function that considers the rate of changes in workforce levels by minimizing the variation between the number of fired and hired workers.

4. Maximizing the total value of purchasing ($Z_4$):

The fourth objective function shown in Equation (4) maximizes the total value of purchasing. The total value of purchasing can be described as purchasing criteria (such as sale price, quality of provided raw material, and service level) that influence the selection of the best supplier in procurement planning. It can be calculated by multiplying the overall assessed score of supplier *s* with the purchased quantity of raw materials from that supplier, and presented as follows:

$$Max\ TVP = \sum_{s=1}^{S} TSSQ_s \times \sum_{r=1}^{R} \sum_{t=1}^{T} QRMS_{srt} \qquad (3.4)$$

Note that: $TSSQ_s$ denotes the supplier's overall score (weight). Based upon the knowledge and experience of DMs, the supplier's overall score (weight) can be determined in an efficient way. For example, the Technique for Order Preference by Similarities to Ideal Solution (TOPSIS) is an efficient approach that can help the DMs to calculate the appropriate score (weight) of each supplier.

**3.1.4.2 Constraints**

- Constraint on finished product inventory.

$$IP_{nt} = IP_{n(t-1)} + QRTP_{nt} + QOTP_{nt} + QSTP_{nt} - \sum_{j=1}^{J} QPSC_{njt} \ ; \ \forall\, n, t \qquad (3.5)$$

Equation (3.5) is related to the finished product inventory balance at the production plant. The inventory quantity of finished products at the end of period *t* should be equal to the inventory quantities in the previous period (*t* – 1) plus the number of products manufactured at the production plant minus the sum of the quantity of the finished products transferred to the customers.

- Constraint on raw materials inventory.

$$IRM_{rt} = IRM_{r(t-1)} + \sum_{s=1}^{S} QRMS_{srt} - \sum_{n=1}^{N} (QRTP_{nt} + QOTP_{nt} + QSTP_{nt}) \times NoRM_{rn}; \ \forall\, r, t \qquad (3.6)$$

Equation (3.6) presents the balance of raw material inventory constraint at production plants. This constraint shows that the inventory quantity of raw materials in period *t* is equal to the inventory quantities in the prior period (*t* – *1*) plus the sum of the quantity of provided raw materials from all suppliers minus the quantity of needed raw materials at the production plant.

- Constraint on assigning the initial workforce level.

$$QW_{kt} = NoL^{0}{}_{k}; \ \forall\, k, t < 2 \qquad (3.7)$$

Equation (3.7) corresponds to one of the assumptions that assigns the initial workforce level to the first period of planning ($t < 2$).

- Constraint on balancing for the workforce level.

$$QW_{kt} = QW_{k(t-1)} + QWH_{kt} - QWF_{kt}; \quad \forall\, k, t > 1 \tag{3.8}$$

Equation (3.8) is the balancing constraint of the workforce level. This constraint guarantees that the number of workers at level $k$ in period $t$ must equal the change in workforce in the current period plus the number of workers in the previous period ($t - 1$).

- Constraint on limiting available production time owing to the limited workforce.

$$\sum_{k=1}^{K} QW_{kt} \times Prod_k \times (RTPA_t + OTPA_t) \geq \sum_{n=1}^{N} (QRTP_{nt} + QOTP_{nt}) \times PTP_n; \quad \forall\, t \tag{3.9}$$

Constraint (3.9) shows that the available production time is limited by the available regular-time and overtime workers along with their productivity. This implies that the available production time is determined by the number of workers in regular production and overtime production.

- Constraint on limiting the available production time of the subcontractor.

$$\sum_{n=1}^{N} QSTP_{nt} \times PTP_n \leq STPA_t; \quad \forall\, t \tag{3.10}$$

Equation (3.10) shows that the available subcontracting time is limited by the allowed subcontracting time at each production plant.

- Constraint on limiting the maximum quantity of produced products from the subcontractor.

$$QSTP_{nt} \leq MaxPS_{nt}; \quad \forall\, n, t \tag{3.11}$$

Equation (3.11) means that the quantity of produced products from a subcontractor of production plant must not exceed the allowable maximum quantity of products of the subcontractor.

- Constraint on the machine capacity.

$$MHU_{nt} \times (QRTP_{nt} + QOTP_{nt}) \leq MaxMA_{nt}; \;\; \forall\, n, t \qquad (3.12)$$

Equation (3.12) presents the limitation of machine capacity, where the machine hour usage for producing all the products at the production plant in each period should not surpass the maximum available machine capacity.

- Constraint on the shortages of customer demand.

$$QSP_{njt} = QSP_{nj(t-1)} + \widetilde{D}_{njt} - QPSC_{njt}; \;\; \forall\, n, j, t \qquad (3.13)$$

Equation (3.13) computes the shortage of products in supplying customer $j$ in each period *t*. This constraint is one of the fuzzy constraints used in the model because it contains a fuzzy parameter, which is customer demand $\widetilde{D}_{njt}$.

- Constraint on limiting the warehouse space.

$$\sum_{n=1}^{N}(WSP_{nt} \times IP_{nt}) + \sum_{r=1}^{R}(WSRM_{rt} \times IRM_{rt}) \leq MaxWSA_{t}; \;\; \forall\, t \qquad (3.14)$$

Equation (3.14) shows that the total inventory quantities of the finished products and raw materials at the production plant is limited by the maximum warehouse space.

- Constraint on limiting the storage capacity for raw materials.

$$\sum_{r=1}^{R} IRM_{rt} \leq SCRM; \;\; \forall\, t \qquad (3.15)$$

- Constraint on limiting the storage capacity for the finished products.

$$\sum_{n=1}^{N} IP_{nt} \leq SCP; \;\; \forall\, t \qquad (3.16)$$

Equations (3.15) and (3.16) show that the inventory quantities of finished products and raw materials are limited by the storage allowable capacities at each production plant.

- Constraint on the proportion of workforces in each period.

$$\sum_{k=1}^{K}(QWH_{kt} + QWF_{kt}) \leq FWV \times \sum_{k=1}^{K} QW_{k(t-1)}; \quad \forall\, t \qquad (3.17)$$

Equation (3.17) guarantees that the change in the workforce level in period *t* cannot surpass the fraction of variation allowed in the previous period.

- Constraint on supplier capacity.

$$QRMS_{srt} \leq MaxRS_{srt}; \quad \forall\, s, r, t \qquad (3.18)$$

Equation (3.18) shows that the purchased quantity of raw material *r* is limited by the capacity of supplier *s*.

- Constraint on balancing flow among the suppliers and production plants.

$$\sum_{n=1}^{N} NoRM_{rn} \times (QRTP_{nt} + QOTP_{nt} + QSTP_{nt}) \leq \sum_{s=1}^{S} QRMS_{srt}\,; \quad \forall\, r, t \qquad (3.19)$$

Equation (3.19) displays the flow balances of raw materials from the suppliers to the production plant.

- Constraint on the quality of raw materials.

$$\sum_{s=1}^{S} \widetilde{AFRS}_{sr} \times QRMS_{srt} \leq \widetilde{AFRP}_{r} \times \sum_{s=1}^{S} QRMS_{srt}\,; \quad \forall\, r, t \qquad (3.20)$$

- Constraint on service level (on-time delivery).

$$\sum_{r=1}^{R}\sum_{s=1}^{S} \widetilde{ASL}_{s} \times QRMS_{srt} \geq \widetilde{ASLP} \times \sum_{r=1}^{R}\sum_{s=1}^{S} QRMS_{srt}\,; \quad \forall\, t \qquad (3.21)$$

The quality of raw materials and the service level (on-time delivery) are crucial quantitative criteria that are used to evaluate the performance of each supplier. These requirements are presented in Equations (3.20) and (3.21).

- Constraints on non-negativity of decision variables.

$$QW_{kt}, QWH_{kt}, QWF_{kt} \geq 0 \,\&\, interger;\ \forall k,t$$
$$QRTP_{nt}, QOTP_{nt}, QSTP_{nt} \geq 0;\ \ \forall n,t$$
$$QRMS_{srt} \geq 0;\ \ \forall s,r,t$$
$$QPSC_{njt} \geq 0;\ \ \forall n,j,t \qquad (3.22)$$
$$IRM_{rt} \ \geq 0;\ \ \forall r,t\text{:}\ IP_{nt} \geq 0;\ \ \forall n,t$$
$$QSP_{njt} \ \geq 0;\ \ \forall n,j,t$$

Equation (3.22) shows that most of the decision variables are non-negative, and some of them are non-negative and integer.

# CHAPTER 4
# SOLUTION APPROACH

Transforming the fuzzy mathematical model into an analogous crisp model is a widely used approach to deal with the uncertainty in the fuzzy mathematical model. The transformation of the fuzzy model can be completed based on the measurement of possibility, necessity, or the integration of the possibility and necessity (credibility) (Liu, 2002). In this study, the theory of credibility measure is applied for transforming the fuzzy model into a crisp model. To cope with the multiple-objective function problem, a fuzzy multiple-objective programming approach with the weight-consistent solution is introduced to solve the crisp multiple-objective model.

In this chapter, an appropriate hybrid solution approach for solving the Fuzzy Multi-Objective Mixed-Integer Linear Programming (FMOMILP) model (as explained in Chapter 3) is developed. To solve the FMOMILP model, a proposed approach with two-phased solution is implemented. In the first phase of the solution, the FMOMILP model is transformed into an analogous crisp model by using the credibility measure (credibility theory). In the second phase, fuzzy multiple-objective programming, integrating a weight-consistent constraint and an aggregation function, is used for finding compromise efficient solutions. The consistency of solutions will be ensured by the weight-consistent constraint, while the aggregation function can generate the balanced and unbalanced compromise efficient solutions for the different conflicting objectives.

## 4.1 First phase: transforming the fuzzy MOMILP model into the equivalent crisp model based on FCCP with credibility measure

### 4.1.1 Credibility-Based Fuzzy Chance-constrained Programming (CFCCP)

CFCCP is an efficient fuzzy mathematical programming approach based on the credibility measure of fuzzy numbers (Azadeha, Kokabia, & Hallaj, 2017; Rastaghi, Barzinpour, & Pishvaee, 2018). This method assists DMs in solving some chance constraints at a minimum confidence level. It can also be applied for uncertain parameters with different membership functions such as the triangular, trapezoidal, and nonlinear membership functions, in symmetric and asymmetric forms (Liu & Liu, 2002). For a good understanding of credibility-based fuzzy chance-constrained programming, some basic knowledge of credibility theory and fuzzy chance-constrained programming is introduced in the next sub-sections.

**4.1.1.1 Credibility fundamentals**

The theory of fuzzy sets was introduced by Zadeh in 1965. Since then, it has been developed and applied in various practical situations. In the fuzzy world, there are three main types of measures for dealing with ambiguous parametric information: possibility, necessity, and credibility. In opposition to the possibility and necessity measures that have no self-dual nature, the credibility measure is a self-dual measure (Li & Liu, 2006). Therefore, if the credibility value of a fuzzy event attains 1, the fuzzy event will surely occur. However, when the possibility value of a fuzzy event attains 1, the fuzzy event may fail to occur. In other words, if the possibility value of a fuzzy event achieves 1, that event may fail to occur, and if the necessity value of a fuzzy event is 0, that fuzzy event may occur. If the credibility value of a fuzzy event attains 1, the fuzzy event will occur and if the credibility value of a fuzzy event attains 0, the fuzzy event will not occur (Huang, 2007).

Let $\xi$ be a fuzzy variable with membership function $\mu$ and let $u$ and $R$ be real numbers. The possibility of a fuzzy event, characterized by $R$, is defined by:

$$Pos\{\xi \leq R\} = \sup_{u \leq R} \mu(u) \tag{4.1}$$

The necessity degree of occurrence of this fuzzy event can be specified as follows:

$$Nec\{\xi \leq R\} = 1 - Pos\{\xi \leq R\} = 1 - \sup_{u > R} \mu(u) \tag{4.2}$$

The credibility measure (Cr) can be determined as an average of the possibility and necessity measures as follows:

$$Cr\{\xi \leq R\} = \frac{1}{2}(Pos\{\xi \leq R\} = 1 + Nec\{\xi \leq R\}) \tag{4.3}$$

Let the fuzzy variable $\xi$ be fully determined by the triplet $(\underline{a},\ a,\ \overline{a})$ of crisp numbers with $(\underline{a} \leq a \leq\ \overline{a})$ (Figure 4.1), whose membership function is presented as follows:

$$\mu(R) = \begin{cases} \dfrac{R-\underline{a}}{a-\underline{a}} & \text{if } \underline{a} \le R < a \\ \dfrac{R-\overline{a}}{a-\overline{a}} & \text{if } a \le R \le \overline{a} \\ 0 & \text{otherwise.} \end{cases} \tag{4.4}$$

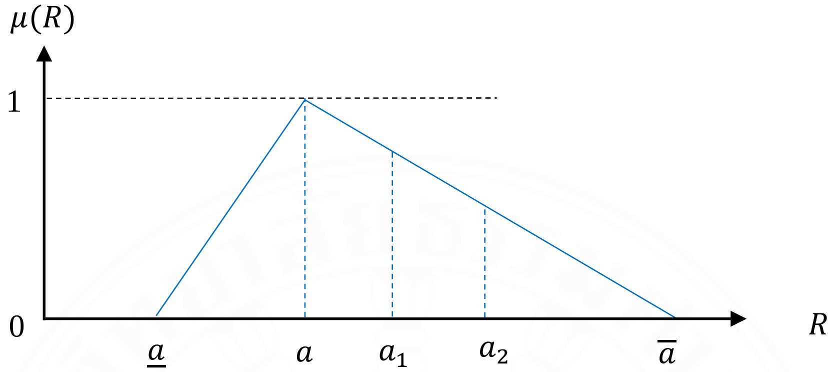


**Figure 4.1** A triangular fuzzy variable $\xi = (\underline{a},\ a,\ \overline{a})$

According to Equations (4.1) – (4.3), the possibility, necessity, and credibility of $\xi \le R$ and $\xi \ge R$ are as follows:

$$Pos\{\xi \le R\} = \begin{cases} 0, & R \le \underline{a} \\ \dfrac{R-\underline{a}}{a-\underline{a}}, & \underline{a} \le R \le a\,; \\ 1, & R \ge \mathrm{a} \end{cases}$$

$$Nec\{\xi \le R\} = \begin{cases} 0, & R \le a \\ \dfrac{R-\underline{a}}{\overline{a}-a}, & a \le R \le \overline{a}\,; \\ 1, & R \ge \overline{a} \end{cases} \tag{4.5}$$

$$Pos\{\xi \ge R\} = \begin{cases} 0, & R \ge \overline{a} \\ \dfrac{\overline{a}-R}{\overline{a}-a}, & a \le R \le \overline{a}\,; \\ 1, & R \le \mathrm{a} \end{cases}$$

$$Nec\{\xi \ge R\} = \begin{cases} 0, & R \ge a \\ \dfrac{a-R}{a-\underline{a}}, & \underline{a} \le R \le a \\ 1, & R \le \underline{a} \end{cases} \tag{4.6}$$

Credibility is the quality of being believable or worthy of trust. An event will definitely occur when the credibility value is 1. The credibility of $\{\xi \le R\}$ and $\{\xi \ge R\}$ are presented by:

$$Cr\{\xi \le R\} = \begin{cases} 0, & R \le \underline{a} \\ \dfrac{R - \underline{a}}{2(a - \underline{a})}, & \underline{a} \le R \le a \\ \dfrac{\overline{a} - 2a + R}{2(\overline{a} - a)}, & a \le R \le \overline{a} \\ 1, & R \ge \overline{a} \end{cases}$$

$$Cr\{\xi \ge R\} = \begin{cases} 0, & R \ge \overline{a} \\ \dfrac{\overline{a} - R}{2(\overline{a} - a)}, & a \le R \le \overline{a} \\ \dfrac{2a - \underline{a} - R}{2(a - \underline{a})}, & \underline{a} \le R \le a \\ 1, & R \le \underline{a} \end{cases} \quad (4.7)$$

To illustrate the three types of measurements in the fuzzy world, consider a triangular fuzzy set $\xi = (\underline{a},\ a,\ \overline{a})$, the possibility, necessity, and credibility of $\xi \le R$ are depicted in Figure 4.2.

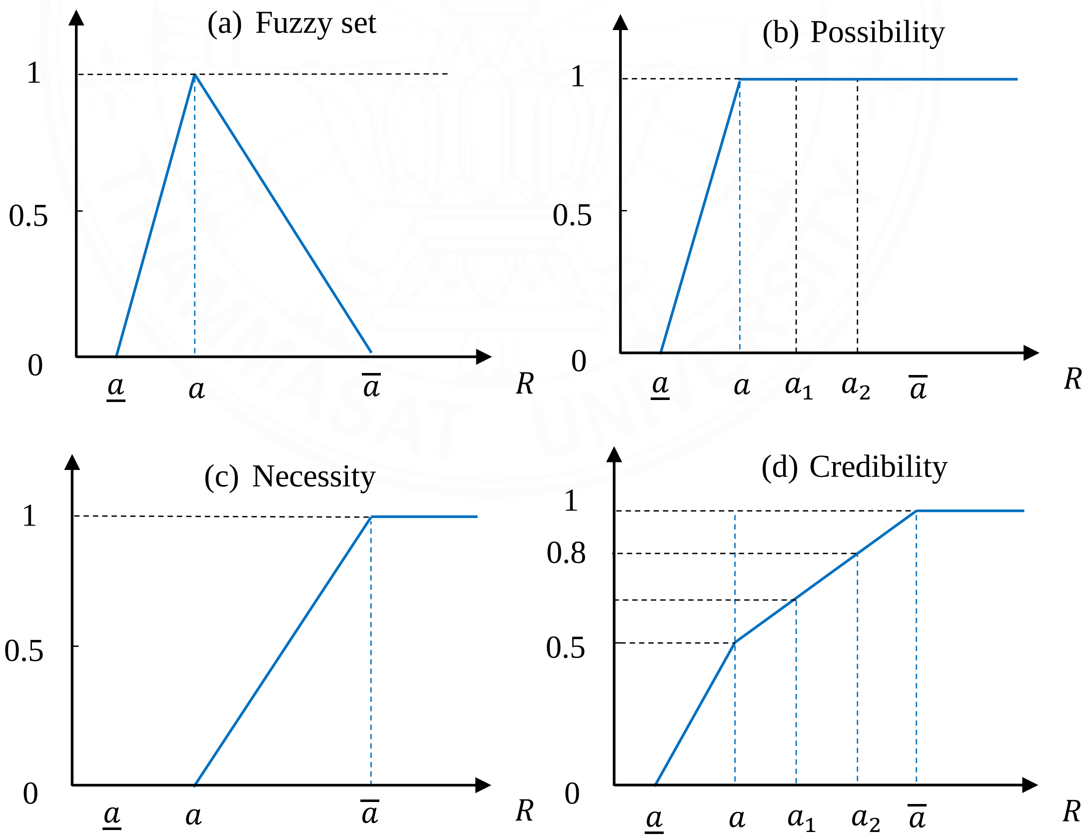


**Figure 4.2** Measures of fuzzy events: (a) fuzzy set, (b) possibility, (c) necessity, and (d) credibility.

Figure 4.2 shows the triangular fuzzy variable $\xi = (\underline{a},\ a,\ \overline{a})$ as a specific case. Let $Pos\{\xi \leq R\} = 1$ when $R \geq a$. Nevertheless, it is obvious that the event $\{\xi \leq R\}$ will not hold when $R = a$ which implies that the desired event will not surely occur even when the confidence level is set as high as “1”. Moreover, for two real number $a_1$ and $a_2$ where $a \leq a_1 \leq a_2 \leq \overline{a}$, clearly, there is no different information about the fuzzy events when the possibility values of the event $\{\xi \leq a_1\}$ and $\{\xi \leq a_2\}$ are 1. However, when applying credibility, $Cr\{\xi \leq a_1\} \leq Cr\{\xi \leq a_2\}$, which means fuzzy event $\{\xi \leq a_2\}$ will have more chance to happen than fuzzy event $\{\xi \leq a_1\}$ does. Once $R \geq \overline{a}$ then $Cr\{\xi \leq R\} = 1$, which implies that when the confidence level is 1, the desired event would certainly occur. Based on the credibility measure, it is obvious that no feature of fuzzy sets is missing. The higher the credibility value is, the more reliable the result is.

Let $\xi = (\underline{a},\ a,\ \overline{a})$ and $\tilde{R} = (\underline{b},\ b,\ \overline{b})$. According to the credibility definition and the rule of fuzzy operations, the credibility of a fuzzy event characterized by$\{\xi \leq \tilde{R}\}$ and $\{\xi \geq \tilde{R}\}$ are as follows:

$$Cr\{\xi \leq \tilde{R}\} = \begin{cases} 1, & \overline{a} \leq \underline{b} \\ \dfrac{\overline{a} - 2a + 2b - \underline{b}}{2(\overline{a} - a + b - \underline{b})}, & a \leq b, \overline{a} > \underline{b} \\ \dfrac{\overline{b} - \underline{a}}{2(\overline{b} - b + a - \underline{a})}, & a > b, \underline{a} < \overline{b} \\ 0, & \underline{a} \geq \overline{b} \end{cases}$$
$$Cr\{\xi \geq \tilde{R}\} = \begin{cases} 1, & \underline{a} \geq \overline{b} \\ \dfrac{\overline{b} - 2b + 2a - \underline{a}}{2(\overline{b} - b + a - \underline{a})}, & a > b, \underline{a} < \overline{b} \\ \dfrac{\overline{a} - \underline{b}}{2(\overline{a} - a + b - \underline{b})}, & a \leq b, \overline{a} > \underline{b} \\ 0, & \overline{a} \leq \underline{b} \end{cases} \quad (4.8)$$

The credibility measure may display the satisfaction degree of an event when parametric information is shown as fuzzy sets. Figure 4.2 demonstrates four credibility situations between two fuzzy sets.

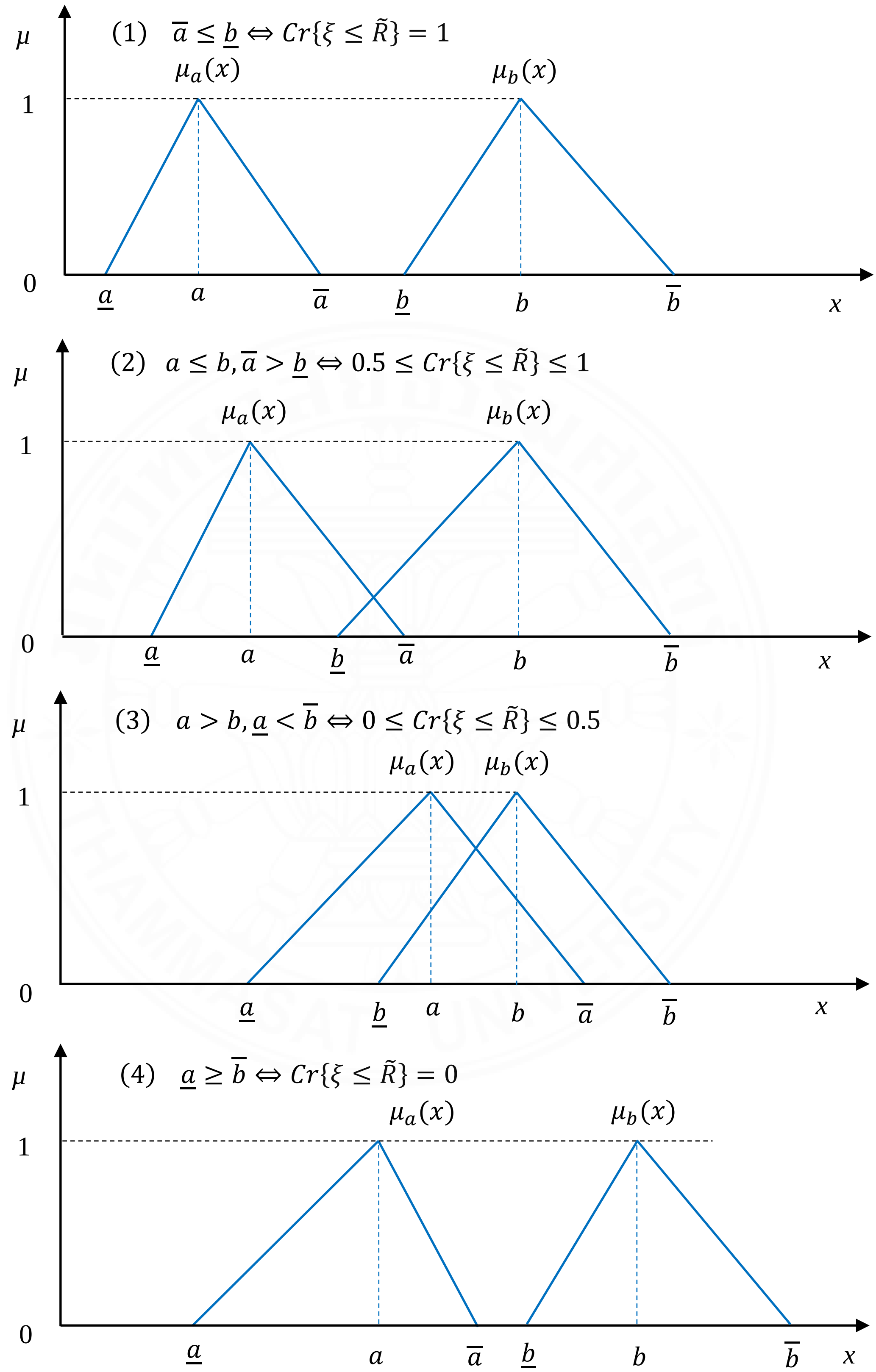


**Figure 4.3** Relative positions of two fuzzy sets are based on credibility measures.

Based on Equations (4.7) and (4.8), it can be shown that for $(0 \leq \alpha \leq 0.5)$:

$$Cr\{\xi \leq R\} \geq \alpha \Leftrightarrow R \geq (1-2\alpha)\underline{a} + (2\alpha)a \tag{4.9}$$

$$Cr\{\xi \geq R\} \geq \alpha \Leftrightarrow R \leq (2\alpha)a + (1-2\alpha)\overline{a} \tag{4.10}$$

$$Cr\{\xi \leq \tilde{R}\} \geq \alpha \Leftrightarrow (1-2\alpha)\underline{a} + (2\alpha)a \leq (2\alpha)b + (1-2\alpha)\overline{b} \tag{4.11}$$

$$Cr\{\xi \geq \tilde{R}\} \geq \alpha \Leftrightarrow (2\alpha)a + (1-2\alpha)\overline{a} \geq (1-2\alpha)\underline{b} + (2\alpha)b \tag{4.12}$$

Similarly, it can be shown that for $(0.5 \leq \alpha \leq 1)$:

$$Cr\{\xi \leq R\} \geq \alpha \Leftrightarrow R \geq (2-2\alpha)a + (2\alpha-1)\overline{a} \tag{4.13}$$

$$Cr\{\xi \geq R\} \geq \alpha \Leftrightarrow R \leq (2\alpha-1)\underline{a} + (2-2\alpha)a \tag{4.14}$$

$$Cr\{\xi \leq \tilde{R}\} \geq \alpha \Leftrightarrow (2-2\alpha)a + (2\alpha-1)\overline{a} \leq (2\alpha-1)\underline{b} + (2-2\alpha)b \tag{4.15}$$

$$Cr\{\xi \geq \tilde{R}\} \geq \alpha \Leftrightarrow (2\alpha-1)\underline{a} + (2-2\alpha)a \geq (2-2\alpha)b + (2\alpha-1)\overline{b} \tag{4.16}$$

**4.1.1.2 Fuzzy chance-constrained programming model**

The Chance-constrained Programming (CCP) model was first introduced by Charnes and Cooper (1959). Then, it was modified and improved in a fuzzy environment (Liu & Iwanmura, 1998, Li & Liu, 2006; Huang, 2007). CCP is used for solving uncertain optimization problems with chance constraints that must be maintained at a specified confidence level, to satisfy DMs.

The general fuzzy chance-constrained programming model can be formulated as follows:

$$\begin{aligned} &\min \bar{f} \\ &s.t. \quad Cr\left\{\textstyle\sum_{j=1}^{n} \tilde{c}_{ij}x_j \leq \bar{f}\right\} \geq \alpha \\ &\qquad Cr\left\{\textstyle\sum_{j=1}^{n} \tilde{a}_{ij}x_j \geq \tilde{b}_i\right\} \geq \alpha \\ &\qquad x_j \geq 0 \end{aligned} \tag{4.17}$$

Applying Equations (4.9) – (4.16), the credibility-based fuzzy chance-constrained programming model is shown in Equation (4.17). They can be converted to the following crisp equivalent equations with confidence levels as follows:

$$min\,\bar{f}$$
$$s.t.$$
$$\sum_{j=1}^{n}\left[(1-2\alpha)\underline{c}_j+(2\alpha)c_j\right]x_j \le \bar{f} \qquad if\ \alpha \le 0.5$$
$$\sum_{j=1}^{n}\left[(2-2\alpha)c_j+(2\alpha-1)\overline{c}_j\right]x_j \le \bar{f} \qquad if\ \alpha \ge 0.5$$
$$\sum_{j=1}^{n}\left[(2\alpha)a_{ij}+(1-2\alpha)\overline{a}_{ij}\right]x_j \qquad (4.18)$$
$$\ge (1-2\alpha)\underline{b}_i+(2\alpha)b_i \qquad if\ \alpha \le 0.5$$
$$\sum_{j=1}^{n}\left[(2\alpha-1)\underline{a}_{ij}+(2-2\alpha)a_{ij}\right]x_j$$
$$\ge (2-2\alpha)b_i+(2\alpha-1)\overline{b}_i \qquad if\ \alpha \ge 0.5$$
$$x_j \ge 0;\ j=1,\dots,n;\ 0\le\alpha\le 1$$

**4.1.2 Equivalent crisp multiple-objective programming model**

In relation to Equations (4.9) – (4.16), it can be used to transform the fuzzy chance-constraints model into equivalent crisp constraints. As aforementioned, the measurement of credibility is an average of the possibility measure and the necessity measure (optimistic and pessimistic viewpoints). Thus, the proposed FMOMILP model, applying the credibility-based chance-constrained modeling can be presented as follows:

$$Min\ Z_1 \qquad (4.19)$$
$$Min\ Z_2=\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}QSP_{njt} \qquad (4.20)$$
$$Min\ Z_3=\sum_{k=1}^{K}\sum_{t=1}^{T}(QWH_{kt}+QWF_{kt}) \qquad (4.21)$$
$$Max\ Z_4=\sum_{s=1}^{S}TSSQ_s\sum_{r=1}^{R}\sum_{t=1}^{T}QRMS_{srt} \qquad (4.22)$$

*Subject to*:

$$Cr\{TC\le Z_1\}\ge\alpha \qquad (4.23)$$
$$Cr\left\{QSP_{njt}=QSP_{nj(t-1)}+\widetilde{D}_{njt}-QPSC_{njt}\right\}\ge\alpha;\ \forall\, n,j,t \qquad (4.24)$$
$$Cr\left\{\sum_{s=1}^{S}\widetilde{AFRS}_{srt}\times QRMS_{srt}\le\widetilde{AFRP}_r\times\sum_{s=1}^{S}QRMS_{srt}\right\}\ge\alpha;\ \forall\, r,t \qquad (4.25)$$
$$Cr\left\{\sum_{r=1}^{R}\sum_{s=1}^{S}\widetilde{ASL}_s\times QRMS_{srt}\ge\widetilde{ASLP}\times\sum_{r=1}^{R}\sum_{s=1}^{S}QRMS_{srt}\right\}\ge\alpha;\ \forall\, r,t \qquad (4.26)$$

Other constraints are the same as the constraints in the FMOMILP model. If (α > 0.5), this means that the chance constraints must be met at a level of confidence that is greater than 0.5. Then, according to Equations (4.17) – (4.18), the fuzzy chance constraints (Equations (4.23) – (4.26)) can be converted into the following crisp equivalents with the confidence level $\alpha$ as follows:

$$(4.23) \Leftrightarrow \sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times RTPC_t^m + (2\alpha-1) \times RTPC_t^p] \times QRTP_{nt}$$
$$+ \sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times OTPC_t^m + (2\alpha-1) \times OTPC_t^p] \times QOTP_{nt}$$
$$+ \sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times STPC_{it}^m + (2\alpha-1) \times STPC_{it}^p] \times QSTP_{nt}$$
$$+ \sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{i=1}^{T} [(2-2\alpha) \times RMSC_{srt}^m + (2\alpha-1) \times RMSC_{srt}^p] \times QRMS_{srt}$$
$$+ \sum_{k}^{K}\sum_{t=1}^{T} [(2-2\alpha) \times SC_{kt}^m + (2\alpha-1) \times SC_{kt}^p] \times QW_{kt}$$
$$+ \sum_{k}^{K}\sum_{t=1}^{T} [(2-2\alpha) \times HC_{kt}^m + (2\alpha-1) \times HC_{kt}^p] \times QWH_{kt} \quad (4.27)$$
$$+ \sum_{k}^{K}\sum_{t=1}^{T} [(2-2\alpha) \times FC_{kt}^m + (2\alpha-1) \times FC_{kt}^p] \times QWF_{kt}$$
$$+ \sum_{r=1}^{R}\sum_{t=1}^{T} [(2-2\alpha) \times IRMC_{rt}^m + (2\alpha-1) \times IRMC_{rt}^p] \times IRM_{rt}$$
$$+ \sum_{n=1}^{N}\sum_{t=1}^{T} [(2-2\alpha) \times IPC_{nt}^m + (2\alpha-1) \times IPC_{nt}^p] \times IP_{nt}$$
$$+ \sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{t=1}^{T} [(2-2\alpha) \times TRMC_{st}^m + (2\alpha-1) \times TRMC_{st}^p] \times QRMS_{srt}$$
$$+ \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} [(2-2\alpha) \times TPC_{jt}^m + (2\alpha-1) \times TPC_{jt}^p] \times QPSC_{njt}$$
$$+ \sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} [(2-2\alpha) \times PSC_{njt}^m + (2\alpha-1) \times PSC_{njt}^p] \times QSP_{njt} \le Z_1$$

$$(4.24) \Leftrightarrow QSP_{njt} = QSP_{nj(t-1)} + [(2-2\alpha) \times D_{njt}^m + (2\alpha-1) \times D_{njt}^p] - QPSC_{njt};\ \forall\, n,t \quad (4.28)$$

$$(4.25) \Leftrightarrow \sum_{s=1}^{S} [(2-2\alpha) \times AFRS_{srt}^m + (2\alpha-1) \times AFRS_{srt}^p] \times QRMS_{srt} \le [(2\alpha-1) \times AFRP_r^o + (2-2\alpha) \times AFRP_r^m] \times \sum_{s=1}^{S} QRMS_{srt}\,;\ \forall\, r,t \quad (4.29)$$

$$(4.26) \Leftrightarrow \sum_{r=1}^{R}\sum_{s=1}^{S} [(2\alpha-1) \times ASL_s^o + (2-2\alpha) \times ASL_s^m] \times QRMS_{srit} \ge (2-2\alpha) \times ASLP^m + (2\alpha-1) \times ASLP^p] \times \sum_{r=1}^{R}\sum_{s=1}^{S} QRMS_{srt}\,;\ \forall\, t \quad (4.30)$$

## 4.2 Second phase: fuzzy multiple-objective linear programming

Fuzzy Multiple Objective Linear Programming (FMOLP) is one of the fuzzy optimization approaches that could be formulated by using subjective preference-based membership functions. It can solve multiple-objective models that contain fuzzy numbers. This approach can be deployed in three steps as follows:

(i). Specify the Positive Ideal Solution (PIS), and the Negative Ideal Solution (NIS) corresponding to each objective function.

(ii). Formulate the membership function for each of the objective functions based on the PIS and the NIS.

(iii). Convert the multiple-objective model into a single-objective model by applying Fuzzy Goal Programming (FGP).

In the FMOLP model, the memberships of each objective function are constructed by classifying every objective function into the maximum objective and the minimum objective. For the minimum objective, the value of the objective function varies from the $Z_h^{PIS}$ value to the $Z_h^{NIS}$ value. In contrast, the value of the objective function varies from the $Z_h^{NIS}$ value to the $Z_h^{PIS}$ value for the maximum objective. A graphical interpretation is presented in Figure 4.4:

(a) Minimization of the objective function (b) Maximization of the objective function

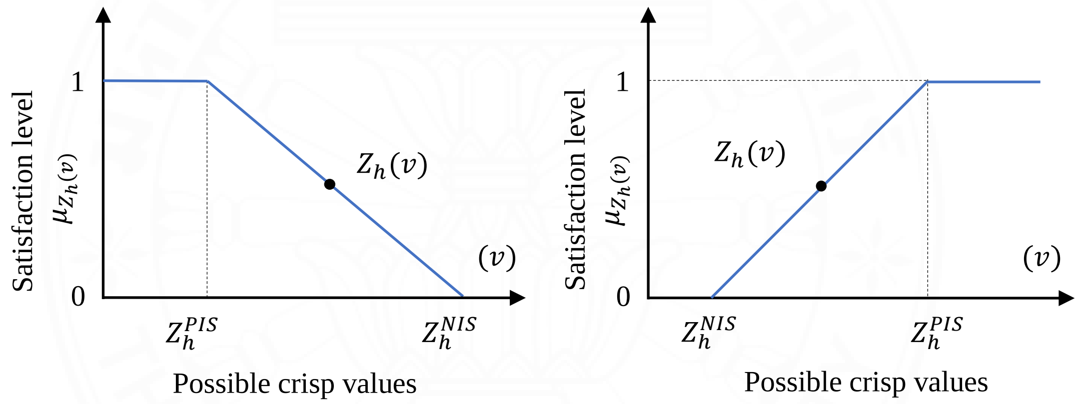


**Figure 4.4** Membership function representing the (a) minimum objective and (b) maximum objective.

The results of the model are presented in tabular form, commonly referred to as the "Payoff" table. The "Payoff" table includes the positive ideal solution ($Z_h^{PIS}$) and the negative ideal solution ($Z_h^{NIS}$) of the objective functions. A typical payoff table is shown in Table 4.1.

**Table 4.1** Payoff table for achieving positive and negative ideal solutions.

| $\boldsymbol{Z_h}$ | $\boldsymbol{v_k^*}$ | | | |
|---|---|---|---|---|
| | $\boldsymbol{v_1^*}$ | $\boldsymbol{v_2^*}$ | $\boldsymbol{v_3^*}$ | $\boldsymbol{v_4^*}$ |
| $Z_1$ | $Z_1(v_1^*)$ | $Z_1(v_2^*)$ | $Z_1(v_3^*)$ | $Z_1(v_4^*)$ |
| $Z_2$ | $Z_2(v_1^*)$ | $Z_2(v_2^*)$ | $Z_2(v_3^*)$ | $Z_2(v_4^*)$ |
| $Z_3$ | $Z_3(v_1^*)$ | $Z_3(v_2^*)$ | $Z_3(v_3^*)$ | $Z_3(v_4^*)$ |
| $Z_4$ | $Z_4(v_1^*)$ | $Z_4(v_2^*)$ | $Z_4(v_3^*)$ | $Z_4(v_4^*)$ |

in which $v_1^*, v_2^*, v_3^*$, and $v_4^*$ are the Positive Ideal Solutions (PISs) for objective functions $Z_1$, $Z_2$, $Z_3$, and $Z_4$, respectively. Based on the results in Table 4.1, the PIS and NIS for each objective function of the model can be defined. $Z_h^{PIS}$ is the optimal result of the *h*-th objective function when neglecting the remaining objective functions, while $Z_h^{NIS}$ is selected by the following equation:

$$Z_h^{NIS} = max\{Z_h(v_k^*); h \neq k\} \tag{4.31}$$

Note that: Equation (4.31) is only correct for the minimum of the objective function. In contrast, if the objective function is maximum, $Z_h^{NIS}$ is selected based on the following equation:

$$Z_h^{NIS} = min\{Z_h(v_k^*); h \neq k\} \tag{4.32}$$

Based on the $Z_h^{PIS}$ and $Z_h^{NIS}$values defined in the "Payoff" table and the membership functions in Figure 4, the linear membership function for having a minimum objective is formulated as follows:

$$\mu_{z_h(v)} = \begin{cases} 1 & , z_h(v) \leq z_h^{PIS} \\ \frac{z_h^{NIS} - z_h(v)}{z_h^{NIS} - z_h^{PIS}} & , z_h^{PIS} \leq z_h(v) \leq z_h^{NIS} \\ 0 & , z_h(v) \geq z_h^{NIS} \end{cases} \tag{4.33}$$

The linear membership function for having a maximum objective is formulated as follows:

$$\mu_{z_h(v)} = \begin{cases} 1 & , z_h(v) \geq z_h^{PIS} \\ \frac{z_h(v) - z_h^{NIS}}{z_h^{PIS} - z_h^{NIS}} & , z_h^{NIS} \leq z_h(v) \leq z_h^{PIS} \\ 0 & , z_h(v) \leq z_h^{NIS} \end{cases} \tag{4.34}$$

The Fuzzy Goal Programming (FGP) model can be formed after all the membership functions have been formulated.

### 4.2.1 Zimmerman’s method

This approach was first developed by Zimmermann [3] for dealing with MOLP problems. It attempts to maximize the lowest or minimum satisfaction level of objective functions. This ensures that the satisfaction levels of objective functions are equal or higher than the level of the lowest objective functions. The mathematical model of Zimmermann’s method is presented as follows:

$$\begin{aligned} & Max \quad \lambda \\ & s.t \quad \lambda \le \mu_h(v), \quad h = 1, \dots, H, \\ & \qquad v \in F(v), \qquad \lambda \in [0, 1]. \end{aligned} \tag{4.35}$$

where $\lambda$ represents the minimum satisfaction level of objective functions, and $F(v)$ denotes the feasible region for the constraints of the equivalent crisp model.

### 4.2.2 Torabi and Hassini (TH) method

This approach is known as a hybrid method. An aggregate function is proposed in this method that can yield balanced and unbalanced compromise solutions (symmetric and asymmetric solutions). The TH model is formulated as follows:

$$\begin{aligned} & Max \quad \lambda(v) = \gamma \times \lambda_0 + (1 - \gamma) \times \textstyle\sum_h^H \theta_h \times \mu_h(v) \\ & s.t \quad \lambda_0 \le \mu_h(v), \qquad h = 1, \dots, H, \\ & \qquad \textstyle\sum_h^H \theta_h = 1 \qquad \theta_h \ge 0 \\ & \qquad v \in F(v), \qquad \lambda_0 \; and \; \gamma \in [0, 1]. \end{aligned} \tag{4.36}$$

where $\lambda_0 = min_h\{\mu_h(v)\}$ represents the minimum satisfaction level of objectives, while $\mu_h(v)$ indicates the satisfaction level of the $h$-th objective function. The objective function of this approach is defined as an integration of the lowest bound for obtaining the satisfaction level of objectives ($\lambda_0$). The weighting summation of these obtained satisfaction levels ($\mu_h(v)$) could be adjusted to bring balanced compromise solutions. In addition, $\gamma$ and $\theta_h$ are the coefficients of compensation and the relative importance weight of the $h$-th objective, respectively. The weighted values $\theta_h$ are specified by the DMs based on their preferences so that $\sum_h \theta_h = 1, \theta_h \ge 0$. Besides that, $\gamma$ can be used as an aligning parameter to control the minimum satisfaction level of objectives and the compromise level among the objectives. As a result, this approach could generate and provide balanced and unbalanced compromised solutions by adjusting the value of $\gamma$. In relation to this problem, a higher value of $\gamma$ implies that the DMs pay more attention to getting the higher bound of the satisfaction level for objectives ($\lambda_0$) with more balanced compromise solutions (symmetric fuzzy decision-making). In contrast, the lower value of $\gamma$ means that the DMs get more concerned about the solutions with a high satisfaction level of some objectives in connection with the relative importance of objectives. This can help for providing unbalanced compromise solutions (asymmetric fuzzy decision-making).

### 4.2.3 Proposed consistency method

Taking into consideration of the weight consistency of solutions, the proposed model uses a ranking constraint (weigh-consistence constraint) to ensure that the achieved solution of the aspiration level of objectives and its assigned weights will be homogeneous. The proposed model is as follows:

$$\begin{aligned} Max \quad & \lambda(v) = \gamma \times \lambda_0 + (1-\gamma) \textstyle\sum_h^H \theta_h \times \mu_h \\ s.t \quad & \lambda_0 \leq \mu_h(v), \qquad h = 1, \dots, H, \\ & \mu_h \geq \frac{\theta_h}{\theta_{h+1}} \times \mu_{h+1} \quad \forall h \\ & \textstyle\sum_h^H \theta_h = 1 \\ & v \in F(v), \lambda_0 \qquad and\ \gamma \in [0,1]. \end{aligned} \tag{4.37}$$

where $\mu_h \times \theta_{h+1} \geq \theta_h \times \mu_{h+1}$ is a weight-consistent constraint. It is supplemented to ensure that the ratio of the satisfaction level of each objective function matches their allocated importance weights. It is highly noted that the weight value of objective ($\theta_h$) must be larger than the weight value of the objective ($\theta_{h+1}$). If $\theta_h \geq \theta_{h+1}$ then $\mu_h \geq \mu_{h+1}$ Therefore, it is guaranteed that the weight-consistent solution can be obtained.

### 4.3 Solution Procedure

In summary, the proposed Fuzzy Multiple Objective Mixed Integer Linear Programming (FMOMILP) can be solved by following these steps:

- Step 1: Identify suitable triangular fuzzy numbers for the imprecise parameters and formulate the original fuzzy model for the APP problem in the supply chain.
- Step 2: Give the minimum acceptable confidence level for each fuzzy chance constraints and assign the relative importance weight to each objective.
- Step 3: Convert the fuzzy MOMILP model into the corresponding crisp MOMILP model by applying credibility-based fuzzy chance-constrained programming references to Equation 4.18.
- Step 4: Optimize each objective in the crisp MOMILP model as a single-objective problem.
- Step 5: Determine the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) for each objective function according to the description in Sub-section 4.1.
- Step 6: Construct the linear membership function of the objective functions.
- Step 7: Convert the crisp MOMILP model into a crisp single-objective MILP model by applying Fuzzy Goal Programming (FGP) that is presented in Sub-section 4.2.
- Step 8: Implement the sensitivity analysis by modifying some parameters (the confidence level ($\alpha$) and the coefficient compensation ($\gamma$)).

# CHAPTER 5
# EXPERIMENTAL CASE

An experimental case is given in this chapter to demonstrate the validity and effectiveness of the model and algorithm are proposed in Chapters 3 and 4, respectively.

## 5.1 Description of input data

To illustrate and evaluate the usefulness of the proposed FMOMILP model and the solution methodology, an industrial case from a manufacturing company is provided in this chapter. The supply chain of the manufacturing company consists of four suppliers, a production plant, and four customers. The company produces five types of products by assembling ten types of raw materials. The planning horizon of the APP in the supply chain is 12 months. The scope of the problem is shown in Table 5.1. The consumption rate of the raw materials for producing these types of products is described in Table 5.2. Production costs, labor costs, transportation costs, purchasing cost, customer demand, and some types of data related to the quality of the provided raw materials, and the service level, are all fuzzy data and follow the triangular possibility distribution. The remained data are deterministic data. All data are presented in the tables below.

**Table 5.1** Scope of the problem.

| R | S | J | N | K | T |
|---|---|---|---|---|---|
| 10 | 4 | 4 | 5 | 5 | 12 |

**Table 5.2** Bill of Materials (BOM).

| Product (*n*) | Raw materials (*r*) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | r1 | r2 | r3 | r4 | r5 | r6 | r7 | r8 | r9 | r10 |
| n1 | 2 | 3 | 0 | 4 | 0 | 0 | 1 | 2 | 3 | 0 |
| n2 | 2 | 3 | 1 | 2 | 2 | 2 | 0 | 0 | 0 | 0 |
| n3 | 1 | 0 | 1 | 2 | 0 | 0 | 1 | 0 | 0 | 2 |
| n4 | 0 | 0 | 0 | 0 | 2 | 3 | 2 | 3 | 2 | 3 |
| n5 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 0 | 1 | 2 |

The qualifications of these selected suppliers have been evaluated throughout a screening process based on some criteria such as the price, quality of raw materials, and service level (on-time delivery). In this regard, the provided raw materials from supplier 1 are assessed as having the highest selling price, the best quality, and the best service level. As opposed to supplier 1, supplier 3 has the cheapest selling price, the lowest quality, and the poorest service level. While the selling price of raw materials from suppliers 2 and 3 are set to be the same price at the medium level, the service level of supplier 2 is higher than the service level of supplier 1. However, the quality of supplier 2 is poorer than supplier 1. To sum up, the overall score of each supplier (representing their performances) is determined by using the TOPSIS method. The information of setting this supplier selection problem and the outcome of the overall weighted score for each supplier are shown in Table 5.3.

**Table 5.3** Relative performance of suppliers.

| Supplier *(s)* | Criteria | | | Weighted score of the supplier |
|---|---|---|---|---|
| | Price | Quality | Service level | |
| s1 | Expensive | Excellent | Excellent | 0.44 |
| s2 | Medium | Low | Good | 0.20 |
| s3 | Cheap | Low | Low | 0.14 |
| s4 | Medium | Good | Low | 0.22 |

From Table 5.3, it can be seen that supplier 1 has the best performance (with the highest weighted score) and supplier 3 has the poorest performance (with the lowest weighted score). The performance weighted scores of suppliers 1, 2, 3, and 4 are 0.44, 0.20, 0.14, 0.22, respectively.

Tables 5.4 and 5.5 show the purchasing cost and maximum quantity of all raw materials that are provided by suppliers. To reflect uncertain market condition in reality, the purchasing cost of raw materials from each supplier are determined to be fuzzy.

**Table 5.4** Purchasing cost for raw materials by suppliers ($/unit).

| R (*r*) | Supplier (*s*) | | | |
|---|---|---|---|---|
| | s1 | s2 | s3 | s4 |
| r1 | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (1.5, 1.65, 1.95) | (1.5, 1.65, 1.95) |
| r2 | (2, 2.2, 2.6) | (2, 2.2, 2.6) | (1, 1.1, 1.3) | (1.5, 1.65, 1.95) |
| r3 | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (1, 1.1, 1.3) |
| r4 | (3, 3.3, 3.9) | (3, 3.3, 3.9) | (2, 2.2, 2.6) | (2, 2.2, 2.6) |
| r5 | (2, 2.2, 2.6) | (2, 2.2, 2.6) | (1.5, 1.65,1.95) | (2, 2.2, 2.6) |
| r6 | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (2, 2.2, 2.6) | (1, 1.1, 1.3) |
| r7 | (2, 2.2, 2.6) | (2, 2.2, 2.6) | (1.5, 1.65, 1.95) | (1, 1.1, 1.3) |
| r8 | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (1, 1.1, 1.3) | (1, 1.1, 1.3) |
| r10 | (2, 2.2, 2.6) | (2, 2.2, 2.6) | (1.5, 1.65, 1.95) | (1.5, 1.65, 1.95) |

**Table 5.5** Maximum quantity of raw materials provided by suppliers (units).

| Raw material (*r*) | Supplier (*s*) | | | |
|---|---|---|---|---|
| | s1 | s2 | s3 | s4 |
| r1 | 3,500 | 3,000 | 3,500 | 3,000 |
| r2 | 3,500 | 3,000 | 3,000 | 3,500 |
| r3 | 3,500 | 3,000 | 4,500 | 3,500 |
| r4 | 3,500 | 3,500 | 4,000 | 3,000 |
| r5 | 3,500 | 3,000 | 4,000 | 3,000 |
| r6 | 2,500 | 3,000 | 3,500 | 3,500 |
| r7 | 4,000 | 3,500 | 3,500 | 3,500 |
| r8 | 3,500 | 3,500 | 4,500 | 3,500 |
| r10 | 3,000 | 3,500 | 3,500 | 3,500 |

The available time and production costs for the regular time, overtime, and subcontracting production are presented in Table 5.6.

**Table 5.6** Available time and production costs.

| Period *(t)* | Regular time (hours/period) | Overtime (hours/period) | Subcontracting (hours/period) |
|---|---|---|---|
| t1 | 144 | 50 | 200 |
| t2 | 160 | 50 | 220 |
| t3 | 168 | 50 | 230 |
| t4 | 176 | 60 | 240 |
| t5 | 120 | 40 | 170 |
| t6 | 192 | 60 | 270 |
| t7 | 200 | 60 | 280 |
| t8 | 200 | 60 | 280 |
| t9 | 192 | 60 | 270 |
| t10 | 176 | 60 | 240 |
| t11 | 184 | 60 | 260 |
| t12 | 160 | 50 | 220 |
| Regular time cost ($/min) | | (0.5, 0.55, 0.65) | |
| Overtime cost ($/min) | | (0.9, 0.95, 1.05) | |
| Subcontracting cost ($/min) | | (1.25, 1.30, 1.40) | |

Table 5.7 presents the related workforce cost for each level including salary, hiring, and firing costs. Besides that, the worker's productivity at each level is also presented. The inventory cost, warehouse storage-space limitation, initial units for the finished products and raw materials are given in Tables 5.8 and 5.9. The transportation cost from suppliers to the production plant, and from the production plant to the customers are provided in Table 5.10.

**Table 5.7** Workforce costs at the production plant ($/person).

| Labor level (*k*) | Types of cost | | | Productivity (%) |
|---|---|---|---|---|
| | Salary | Firing cost | Hiring cost | |
| k1 | (180, 190, 210) | (70, 80, 100) | (40, 50, 70) | 65 |
| k2 | (200, 210, 230) | (80, 90, 110) | (40, 50, 70) | 70 |
| k3 | (220, 230, 250) | (90, 100, 120) | (40, 50, 70) | 75 |
| k4 | (240, 250, 270) | (100, 110, 130) | (40, 50, 70) | 85 |
| k5 | (260, 270, 290) | (110, 120, 140) | (40, 50, 70) | 95 |

**Table 5.8** Inventory cost, warehouse space limitation, initial units of finished products.

| Product (*n*) | Inventory costs ($/unit) | Initial finished product inventory (units) | Warehouse space for a unit of raw material (m2/unit) |
|---|---|---|---|
| n1 | (5, 6, 8) | 2 | 3 |
| n2 | (7, 8, 10) | 2 | 2 |
| n3 | (9, 10, 12) | 20 | 3 |
| n4 | (11, 12, 14) | 10 | 2 |
| n5 | (13, 14, 16) | 10 | 6 |

**Table 5.9** Inventory cost, warehouse space limitation, initial units of raw material.

| Raw material (*r*) | Inventory costs ($/unit) | Initial raw material inventory (units) | Warehouse space for a unit of product ($m^2$/unit) |
|---|---|---|---|
| r1 | (4, 5, 7) | 20 | 1 |
| r2 | (4, 5, 7) | 20 | 1.5 |
| r3 | (4, 5, 7) | 20 | 1.5 |
| r4 | (4, 5, 7) | 12 | 0.5 |
| r5 | (4, 5, 7) | 15 | 1.5 |
| r6 | (5, 6, 8) | 20 | 0.5 |
| r7 | (5, 6, 8) | 20 | 1 |
| r8 | (5, 6, 8) | 20 | 1 |
| r9 | (5, 7, 9) | 15 | 1.5 |
| r10 | (5, 7, 9) | 20 | 1.5 |

**Table 5.10** Transportation cost ($/unit).

| Suppliers (*s*) | Production plant | Customers (*j*) | Production plant |
|---|---|---|---|
| s1 | (0.014, 0.016, 0.024) | j1 | (0.036, 0.040, 0.060) |
| s2 | (0.029, 0.032, 0.048) | j2 | (0.058, 0.064, 0.096) |
| s3 | (0.079, 0.088, 0.132) | j3 | (0.072, 0.080, 0.120) |
| s4 | (0.101, 0.112, 0.168) | j4 | (0.065, 0.072, 0.108) |

If the quantity of produced products is not enough to fulfill a customer's demand, the customer will be compensated by a determined penalty cost based on the quantity of product shortages. The penalty unit cost of every type of product is shown in Table 5.11.

**Table 5.11** Penalty cost of product shortages ($/unit).

| Product (*n*) | Customer (*j*) | | | |
|---|---|---|---|---|
| | j1 | j2 | j3 | j4 |
| n1 | (2, 2.25, 2.75) | (3, 3.25, 3.75) | (2, 2.25, 2.75) | (2, 2.25, 2.75) |
| n2 | (2, 2.25, 2.75) | (4, 4.25, 4.75) | (2, 2.25, 2.75) | (2, 2.25, 2.75) |
| n3 | (2, 2.25, 2.75) | (4, 4.25, 4.75) | (2, 2.25, 2.75) | (3, 3.25, 3.75) |
| n4 | (3, 3.25, 3.75) | (4, 4.25, 4.75) | (2, 2.25, 2.75) | (2, 2.25, 2.75) |
| n5 | (1, 1.25, 1.75) | (2, 2.25, 2.75) | (2, 2.25, 2.75) | (2, 2.25, 2.75) |

The maximum allowable quantity of produced products by subcontracting and the machine usage for producing each product at the production plant, and the maximum operating machine time and production time for producing different types of products are given in Table 5.12. The number of initially available workforce levels, the storage capacity, and the allowed variation in changing workforce levels at the production plant are summarized in Table 5.13.

**Table 5.12** Subcontracting limitations and machine-hour usage.

| Product (*n*) | Maximum quantity of subcontracting (unit-periods) | Machine hour usage for products (machine-hours/ unit period) | Maximum machine time (machine-hours) | Production time (min/unit) |
|---|---|---|---|---|
| n1 | 140 | 1 | 1,400 | 35 |
| n2 | 150 | 2 | 1,500 | 48 |
| n3 | 160 | 3 | 1,600 | 40 |
| n4 | 130 | 2 | 1,300 | 45 |
| n5 | 140 | 8 | 1,400 | 62 |

**Table 5.13** Storage capacity and workforce information at the production plant.

| Storage capacity at the production plant (units) | | Initial workforce (persons) | | | | | Variation of workforce (%) |
|---|---|---|---|---|---|---|---|
| | | Worker level (*k*) | | | | | |
| RM | Finished product | k1 | k2 | k3 | k4 | k5 | |
| 10,000 | 15,000 | 21 | 34 | 36 | 8 | 2 | 20 |

The relevant data for the quality and service level of the suppliers (evaluated by the manufacturer) are summarized in Tables 5.14 and 5.15.

**Table 5.14** Average defect rate of raw materials from suppliers (%).

| RM (*r*) | Suppliers (*s*) | | | |
|---|---|---|---|---|
| | s1 | s2 | s3 | s4 |
| r1 | (2, 2.01, 2.03) | (2.1, 2.11, 2.13) | (2.65, 26.6, 2.68) | (2.265, 2.265, 2.265) |
| r2 | (2, 2.01, 2.03) | (2.2, 2.21, 2.23) | (2.8, 2.81, 2.83) | (2.465, 2.465, 2.265) |
| r3 | (2, 2.01, 2.03) | (2.1, 2.11, 2.13) | (2.18, 2.19, 2.21) | (2.31, 2.31, 231) |
| r4 | (2, 2.01, 2.03) | (2.3, 2.31, 2.33) | (2.4, 2.41, 2.43) | (2.22, 2.22, 2.22) |
| r5 | (2, 2.01, 2.03) | (2.2, 2.21, 2.23) | (2.6, 2.61, 2.63) | (2.82, 2.82, 2.82) |
| r6 | (2.1, 2.11, 2.13) | (2.1, 2.11, 2.13) | (2.3, 2.31, 2.33) | (2.71, 2.71, 2.71) |
| r7 | (2.2, 2.21, 2.23) | (2.2, 2.21, 2.23) | (2.365, 2.366, 2.38) | (2.91, 2.91, 2.91) |
| r8 | (2.1, 2.11, 2.13) | (2.1, 2.11, 2.13) | (2.41, 2.42, 2.44) | (2.91, 2.91, 2.91) |
| r9 | (2.2, 2.21, 2.23) | (2.2, 2.21, 2.23) | (2.26, 2.27, 2.29) | (2.66, 2.66, 2.66) |
| r10 | (2.1, 2.11, 2.13) | (2.1, 2.11, 2.13) | (2.51, 2.52, 2.54) | (2.82, 28.2, 2.82) |

**Table 5.15** Acceptable defective rate of production plant for raw materials, average service level of suppliers and acceptable service level of production plant.

| RM (*r*) | Acceptable defect rate of production plant for raw materials (%) | Suppliers (*s*) | Average service level of suppliers (%) | Acceptable service level of production plant (%) |
|---|---|---|---|---|
| r1 | (4.48, 5.6, 6.72) | s1 | (75, 94, 100) | (69, 86, 100) |
| r2 | (4.64, 5.8, 6.96) | s2 | (72, 90, 100) | |
| r3 | (4.8, 6, 7.2) | s3 | (69, 86, 100) | |
| r4 | (4.48, 5.6, 6.72) | s4 | (70, 87, 100) | |
| r5 | (4.4, 5.5, 6.6) | | | |
| r6 | (4.72, 5.9, 7.08) | | | |
| r7 | (5.04, 6.3, 7.56) | | | |
| r8 | (4.4, 5.5, 6.6) | | | |
| r9 | (4.72, 5.9, 7.08) | | | |
| r10 | (4.88, 6.1, 7.32) | | | |

In Table 5.16, the forecasted demand of each customer in the optimistic case is reported. The most likely and pessimistic cases of forecasted demand are estimated by multiplying the optimistic case of forecasted demand by 1.2 and 1.3, respectively. For instance, the forecasted demand of customer (*j*1) for product (*n*1) in period (*t*1), in optimistic case, are 100 units. As a result, the estimated demand of the most likely and pessimistic cases will be 120 and 130 units, respectively.

**Table 5.16** Forecasted demand of customers in the optimistic case (units).

| (*j*) | (*n*) | Period (*t*) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | t1 | t2 | t3 | t4 | t5 | t6 | t7 | t8 | t9 | t10 | t11 | t12 |
| j1 | n1 | 100 | 250 | 350 | 300 | 100 | 200 | 250 | 0 | 100 | 150 | 100 | 100 |
| | n2 | 200 | 250 | 300 | 350 | 200 | 200 | 200 | 350 | 400 | 450 | 500 | 350 |
| | n3 | 150 | 200 | 250 | 300 | 100 | 50 | 0 | 100 | 200 | 250 | 300 | 400 |
| | n4 | 250 | 100 | 300 | 250 | 200 | 100 | 200 | 300 | 400 | 400 | 400 | 300 |
| | n5 | 150 | 200 | 200 | 400 | 300 | 350 | 100 | 100 | 150 | 100 | 100 | 100 |
| j2 | n1 | 190 | 350 | 540 | 590 | 120 | 320 | 380 | 200 | 180 | 190 | 130 | 110 |
| | n2 | 280 | 330 | 320 | 570 | 370 | 330 | 290 | 690 | 670 | 650 | 950 | 430 |
| | n3 | 210 | 370 | 490 | 400 | 150 | 70 | 100 | 160 | 330 | 380 | 400 | 620 |
| | n4 | 300 | 180 | 370 | 410 | 310 | 130 | 270 | 460 | 770 | 780 | 520 | 590 |
| | n5 | 290 | 400 | 220 | 690 | 420 | 380 | 170 | 190 | 190 | 120 | 170 | 140 |
| j3 | n1 | 90 | 190 | 30 | 80 | 40 | 300 | 140 | 100 | 130 | 50 | 60 | 20 |
| | n2 | 60 | 250 | 530 | 140 | 150 | 80 | 160 | 190 | 330 | 290 | 560 | 450 |
| | n3 | 90 | 70 | 140 | 400 | 10 | 60 | 80 | 100 | 160 | 260 | 200 | 610 |
| | n4 | 190 | 130 | 230 | 40 | 160 | 20 | 100 | 180 | 540 | 510 | 300 | 20 |
| | n5 | 80 | 170 | 150 | 290 | 280 | 300 | 80 | 20 | 240 | 50 | 120 | 110 |
| j4 | n1 | 170 | 580 | 750 | 880 | 290 | 350 | 560 | 0 | 230 | 310 | 250 | 330 |
| | n2 | 460 | 620 | 470 | 710 | 680 | 540 | 570 | 920 | 830 | 660 | 1,260 | 810 |
| | n3 | 200 | 500 | 300 | 830 | 160 | 90 | 0 | 140 | 620 | 540 | 550 | 850 |
| | n4 | 710 | 240 | 530 | 810 | 620 | 180 | 260 | 520 | 980 | 460 | 810 | 710 |
| | n5 | 400 | 310 | 490 | 600 | 630 | 1,110 | 320 | 200 | 170 | 180 | 250 | 190 |

# CHAPTER 6
# RESULTS AND DISCUSSIONS

The mathematical models, which have been developed and proposed in the previous chapters, are coded by Optimization Programming Language (OPL), and presented in Appendix D. All computations are solved by IBM ILOG CPLEX Optimization Studio (version 12.6) software. The obtained results of the discussed approaches in this study are shown in this chapter. The obtained results are compared, analyzed, and discussed to figure out the pros and cons of the proposed methodology.

## 6.1 Obtained outcome from solving crisp multiple-objective mixed-integer linear programming

As a primary stage of identifying the goal values for each objective to construct its membership function, the credibilistic MOMILP model is transformed into the equivalent crisp model with a given minimum confidence level ($\alpha = 0.9$). The gathered data from the case study in Chapter 5 are used to find the positive and negative ideal solutions (following the description in Chapter 4) by IBM ILOG CPLEX Optimization Studio (version 12.6) software. The crisp multiple-objective mixed-integer linear programming model is then solved to attain the positive and negative ideal solutions. As a result, a payoff table for determining the positive and negative ideal solutions of each objective function is formed, as shown in Table 6.1.

**Table 6.1** Payoff table for achieving positive and negative ideal solutions.

| Objective functions | $v_1^*$ | $v_2^*$ | $v_3^*$ | $v_4^*$ |
|---|---|---|---|---|
| $Z_1$ ($) | 4,842,557.76 | 6,334,476.88 | 6,483,751.24 | 9,605,972.20 |
| $Z_2$ (units) | 2,357 | 0 | 5,886 | 4,479 |
| $Z_3$ (persons) | 85 | 0 | 0 | 0 |
| $Z_4$ (units) | 271,887 | 270,139 | 243,074 | 357,345 |

According to the results in Table 6.1 and Equations (4.31) – (4.32), the obtained positive and negative ideal solutions of each objective function are presented in Table 6.2.

**Table 6.2** Achieved positive and negative ideal solutions for each objective function.

| Objective functions | PIS | | NIS | |
|---|---|---|---|---|
| | Type | Value | Type | Value |
| $Z_1$ ($) | Min | 4,842,557.76 | Max | 9,605,972.20 |
| $Z_2$ (units) | Min | 0 | Max | 5,886 |
| $Z_3$ (persons) | Min | 0 | Max | 85 |
| $Z_4$ (units) | Max | 357,345 | Min | 243,074 |

In relation to Equations (4.33) – (4.34) and Figure 4.4, the achieved positive and negative ideal solutions of each objective function in Table 6.2 is applied. The membership function of each objective function is depicted and formulated, as shown as below:

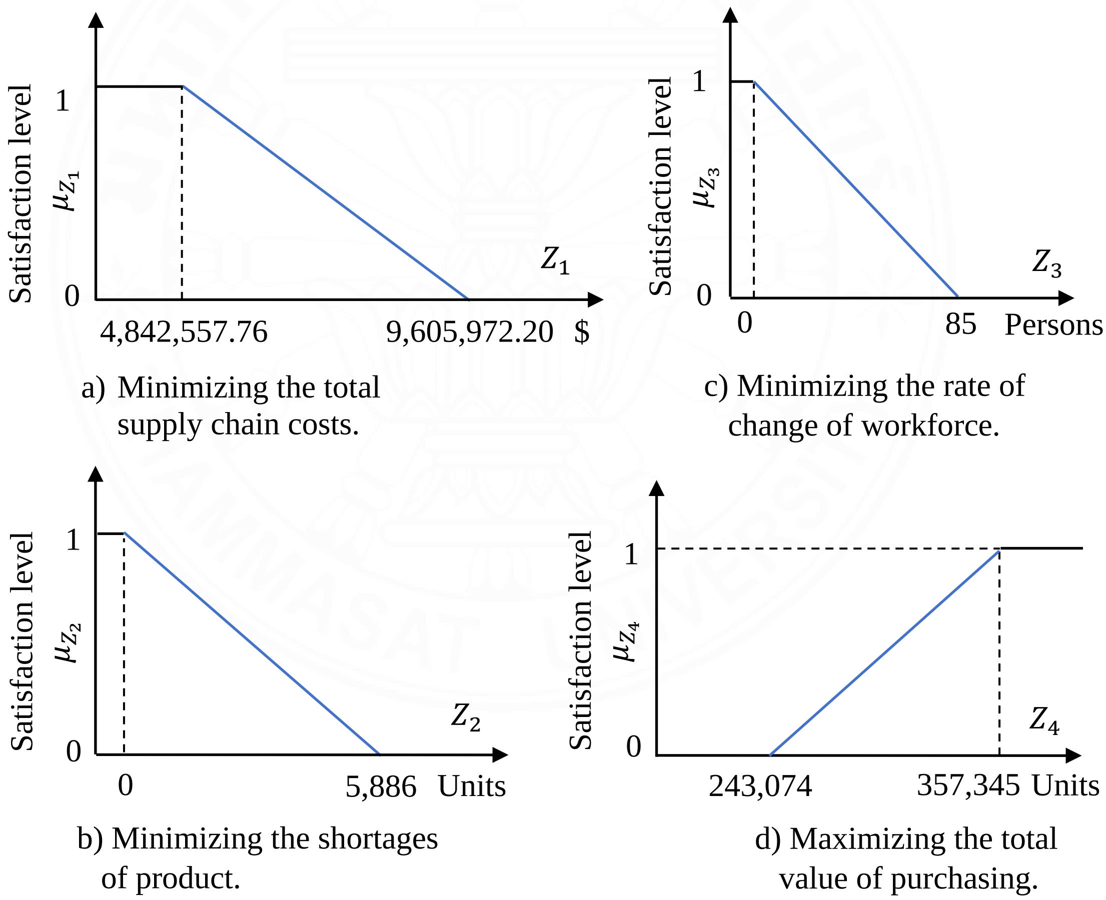


**Figure 6.1** Membership functions of objective functions.

$$\mu_{Z_1} = \begin{cases} 1, & Z_1 \leq 4{,}842{,}557.76 \\ \dfrac{9{,}605{,}972.20 - Z_1}{9{,}605{,}972.20 - 4{,}842{,}557.76} & 4{,}842{,}557.76 \leq Z_1 \leq 9{,}605{,}972.20 \\ 0, & 9{,}605{,}972.20 \geq Z_1 \end{cases}$$

$$\mu_{z_2} = \begin{cases} 1, & Z_2 \le 0 \\ \dfrac{5{,}886 - Z_2}{5{,}886 - 0} & 0 \le Z_2 \le 5{,}886 \\ 0, & 5{,}886 \ge Z_2 \end{cases}$$

$$\mu_{z_3} = \begin{cases} 1, & Z_3 \le 0 \\ \dfrac{85 - Z_3}{85 - 0} & 0 \le Z_3 \le 85 \\ 0, & 85 \ge Z_3 \end{cases}$$

$$\mu_{z_4} = \begin{cases} 1, & Z_4 \ge 357{,}345 \\ \dfrac{Z_4 - 234{,}074}{357{,}345 - 234{,}074} & 234{,}074 \le Z_4 \le 357{,}345 \\ 0, & Z_4 \le 234{,}074 \end{cases}$$

## 6.2 Fuzzy goal programming

### 6.2.1 Obtained outcome from applying Zimmerman's method

For Zimmerman's method, each objective function is considered to have the same relative importance (there is no priority for any objective function). That is why it is known as a symmetric model. The objective function of this method maximizes the minimum value of the satisfaction level. As a result, the outcome of this method is the balanced efficient compromise solutions. By applying Zimmerman's method for solving the proposed MOMILP model, the obtained results are presented in Table 6.3.

**Table 6.3** Optimal solution of Zimmerman's method.

| Implications | Symbol | Value | Unit |
|---|---|---|---|
| Overall satisfaction | $(\lambda)$ | 77.36 | % |
| Minimizing the total supply chain costs | $(Z_1)$ | 5,920,829.06 | $ |
| Minimizing the shortages of product | $(Z_2)$ | 530 | units |
| Minimizing the rate of changes in the workforce | $(Z_3)$ | 19 | persons |
| Maximizing the total value of purchasing | $(Z_4)$ | 331,053 | units |
| Satisfaction of the first objective function | $(\mu_{z_1})$ | 77.37 | % |
| Satisfaction of the second objective function | $(\mu_{z_2})$ | 91.01 | % |
| Satisfaction of the third objective function | $(\mu_{z_3})$ | 77.65 | % |
| Satisfaction of the fourth objective function | $(\mu_{z_4})$ | 77.36 | % |
| Confidence level | $(\alpha)$ | 90 | % |

From Table 6.3, the overall goal satisfaction (as denoted by $\lambda$), which represents the maximum degree of the minimum satisfaction of all the objective functions is 77.36%. Under this circumstance, the satisfaction degree of the first, second, third, and fourth objective function is 77.37%, 91.01%, 77.65%, and 77.36%, respectively. The total cost of aggregate production planning for the entire supply chain is $ 5,920,829.06, while the total number of products that could not be manufactured to fulfill customer demand is 530 units. The total number for the changed workforce level is 19 persons, and the maximum value of total purchasing is 331,053 units.

### 6.2.2 Obtained outcome from applying TH's method

TH's method allows decision-makers (DMs) to allocate the different weights to the objective functions based upon their importance level (asymmetric model). In this study, according to the DM preferences, the relative importance weight of the objective functions are given as $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$. Furthermore, the distribution of weights for each objective function means that the DMs pay more attention to the unbalanced compromise solutions (the higher satisfaction level of the objective that is indicated by its higher weight importance will be more concern). That is why the value of the coefficient of compensation is set to a low value ($\gamma = 0.2$). The optimal results of the proposed model after being solved by using TH's method is shown in Table 6.4.

**Table 6.4** Optimal results from TH's method with $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$, and $\gamma = 0.2$.

| Implications | Symbol | Value | Unit |
|---|---|---|---|
| Overall satisfaction | $(\lambda)$ | 84.87 | % |
| Minimizing the total supply chain costs | $(Z_1)$ | 5,963,618.11 | $ |
| Minimizing the shortages of product | $(Z_2)$ | 0 | units |
| Minimizing the rate of changes in the workforce | $(Z_3)$ | 0 | persons |
| Maximizing the total value of purchasing | $(Z_4)$ | 326,843 | units |
| Satisfaction of the first objective function | $(\mu_{z_1})$ | 77.47 | % |
| Satisfaction of the second objective function | $(\mu_{z_2})$ | 100 | % |
| Satisfaction of the third objective function | $(\mu_{z_3})$ | 100 | % |
| Satisfaction of the fourth objective function | $(\mu_{z_4})$ | 73.31 | % |
| Confidence level | (α) | 90 | % |

According to the obtained results from Table 6.4, as compared to the obtained results of Zimmerman's method, it was found that the overall satisfaction level ($\lambda$) of DMs for TH's method is 84.87%. This is higher than the overall satisfaction level of DMs for Zimmerman's method (77.36%). The obtained satisfaction values of each objective from TH's method are better than the obtained satisfaction values of each objective from Zimmerman's method except for the fourth objective. This implies that there is a trade-off among these objectives (Once one of these objectives gets better, at least one other objective must be worse). As can be seen that there is only the satisfaction value of the first objective and the fourth objectives meet the DM preferences ($\mu_{z_1} > \mu_{z_4}$ agrees with $\theta_1 > \theta_4$). While the second and third objectives are supposed to be less important than the first objective $\theta_1 > \theta_2 > \theta_3$ the obtained satisfaction values of the second and the third objective are still better than the satisfaction values of the first objective. Hence, the DM preferences cannot be satisfied totally although most objectives can get better results. That is why it is necessary to improve the model so that the model can be able to generate consistent solutions (the satisfaction level of each objective must be compatible with the expected importance weight of its objective) that can totally satisfy the DM expectations. In relation to the above satisfaction value of each objective function, the actual total cost of aggregate production planning for the entire supply chain ($Z_1$) is \$ 5,963,618.11, while there is no shortage of product ($Z_2$= 0 units). There is also no change in the workforce level ($Z_3$ = 0 persons), and the maximum value of total purchasing ($Z_4$) is 326,843 units.

### 6.2.3 Obtained outcome from applying the proposed method

As mentioned earlier, by taking into consideration of the consistency of the obtained solutions, a ranking constraint $\mu_h \times \theta_{h+1} \geq \theta_h \times \mu_{h+1}$ (consistent-weight constraint) is added to TH's model. The consistent-weight constraint can ensure that the achieved solution of the satisfaction level of objectives and the assigned weights (based on DM preferences) is homogeneous (i.e. $\mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$ agrees with $\theta_1 \geq \theta_2 \geq \theta_3 \geq \theta_4$). The optimal weight-consistent solutions of the proposed model are shown in Table 6.5.

**Table 6.5** Optimal results from proposed method with $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$, and $\gamma = 0.2$.

| Implications | Symbol | Value | Unit |
|---|---|---|---|
| Overall satisfaction | $(\lambda)$ | 69.21 | % |
| Minimizing the total supply chain costs | $(Z_1)$ | 4,940,544.27 | $ |
| Minimizing the shortages of product | $(Z_2)$ | 946 | units |
| Minimizing the rate of changes in the workforce | $(Z_3)$ | 39 | persons |
| Maximizing the total value of purchasing | $(Z_4)$ | 289,451 | units |
| Satisfaction of the first objective function | $(\mu_{z_1})$ | 97.94 | % |
| Satisfaction of the second objective function | $(\mu_{z_2})$ | 83.93 | % |
| Satisfaction of the third objective function | $(\mu_{z_3})$ | 54.12 | % |
| Satisfaction of the fourth objective function | $(\mu_{z_4})$ | 40.59 | % |
| Confidence level | $(\alpha)$ | 90 | % |

Based on Table 6.5, the obtained overall satisfaction level is 69.21%, while the satisfaction levels of four objectives $Z_1, Z_2, Z_3$, and $Z_4$ are 97.94%, 83.93%, 54.12%, and 40.59%, respectively. It is clear that the obtained satisfaction levels of objectives are totally consistent with DM preferences for all the objective functions ($\mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$ agrees with $\theta_1 \geq \theta_2 \geq \theta_3 \geq \theta_4$). However, it is found that the overall satisfaction level of this method is lower than the overall satisfaction levels of Zimmerman's method and TH's method that were previously presented. This is explained by the trade-off among these four objectives (to get improvement from any objective, at least one other objective must be worse). As a result, the value of the overall satisfaction level of the proposed method can be low. Regarding the above-mentioned percentages of satisfaction of each objective function, the actual total cost of aggregate production planning for the entire supply chain ($Z_1$) is $ 4,940,544.27. The total shortage of product ($Z_2$) is 946 units. The total number of the changed workforce level ($Z_3$) is 39 persons, and the maximum value of total purchasing ($Z_4$) is 289,451 units.

Some main values of decision variables (aggregation plan) from solving the proposed model with the confident level ($\alpha$ = 0.9), the important weight of objectives ($\theta_1 = 0.35,\ \theta_2 = 0.3,\ \theta_3 = 0.2,\ \theta_4 = 0.15$), and compensation coefficient ($\gamma = 0.2$) are shown as Tables in the Appendix A.

To verify the efficiency of the proposed model for the consistency of solutions, a full of possible cases for different ordering pattern values of the importance weights of objectives are generated by factorial design. These possible cases are used for testing the proposed model. There are four objectives considered in the proposed model. Therefore, there are twenty-four possible cases that are generated from four factorial (4!). All the possible cases of the ordering pattern weights of objectives are presented in Table 6.6.

**Table 6.6** Varied ordering patterns of the importance weights of objectives.

| Cases | Order patterns | $\theta_1$ | $\theta_2$ | $\theta_3$ | $\theta_4$ |
|---|---|---|---|---|---|
| 1 | $\theta_1 > \theta_2 > \theta_3 > \theta_4$ | 0.37 | 0.31 | 0.21 | 0.11 |
| 2 | $\theta_1 > \theta_2 > \theta_4 > \theta_3$ | 0.3 | 0.29 | 0.15 | 0.26 |
| 3 | $\theta_1 > \theta_3 > \theta_2 > \theta_4$ | 0.28 | 0.24 | 0.26 | 0.22 |
| 4 | $\theta_1 > \theta_3 > \theta_4 > \theta_2$ | 0.6 | 0.07 | 0.18 | 0.15 |
| 5 | $\theta_1 > \theta_4 > \theta_2 > \theta_3$ | 0.4 | 0.2 | 0.08 | 0.32 |
| 6 | $\theta_1 > \theta_4 > \theta_3 > \theta_2$ | 0.27 | 0.23 | 0.24 | 0.26 |
| 7 | $\theta_2 > \theta_1 > \theta_3 > \theta_4$ | 0.26 | 0.29 | 0.24 | 0.21 |
| 8 | $\theta_2 > \theta_1 > \theta_4 > \theta_3$ | 0.3 | 0.4 | 0.1 | 0.2 |
| 9 | $\theta_2 > \theta_3 > \theta_1 > \theta_4$ | 0.23 | 0.3 | 0.25 | 0.22 |
| 10 | $\theta_2 > \theta_3 > \theta_4 > \theta_1$ | 0.21 | 0.34 | 0.29 | 0.25 |
| 11 | $\theta_2 > \theta_4 > \theta_1 > \theta_3$ | 0.18 | 0.51 | 0.03 | 0.28 |
| 12 | $\theta_2 > \theta_4 > \theta_3 > \theta_1$ | 0.17 | 0.4 | 0.2 | 0.23 |
| 13 | $\theta_3 > \theta_1 > \theta_2 > \theta_4$ | 0.27 | 0.22 | 0.32 | 0.19 |
| 14 | $\theta_3 > \theta_1 > \theta_4 > \theta_2$ | 0.34 | 0.1 | 0.4 | 0.16 |
| 15 | $\theta_3 > \theta_2 > \theta_1 > \theta_4$ | 0.22 | 0.27 | 0.3 | 0.21 |
| 16 | $\theta_3 > \theta_2 > \theta_4 > \theta_1$ | 0.03 | 0.06 | 0.87 | 0.04 |
| 17 | $\theta_3 > \theta_4 > \theta_1 > \theta_2$ | 0.19 | 0.18 | 0.42 | 0.21 |
| 18 | $\theta_3 > \theta_4 > \theta_2 > \theta_1$ | 0.15 | 0.19 | 0.38 | 0.28 |
| 19 | $\theta_4 > \theta_1 > \theta_2 > \theta_3$ | 0.25 | 0.13 | 0.08 | 0.54 |
| 20 | $\theta_4 > \theta_1 > \theta_3 > \theta_2$ | 0.33 | 0.13 | 0.18 | 0.36 |
| 21 | $\theta_4 > \theta_2 > \theta_1 > \theta_3$ | 0.25 | 0.25 | 0.15 | 0.35 |
| 22 | $\theta_4 > \theta_2 > \theta_3 > \theta_1$ | 0.21 | 0.26 | 0.24 | 0.29 |
| 23 | $\theta_4 > \theta_3 > \theta_1 > \theta_2$ | 0.22 | 0.16 | 0.28 | 0.34 |
| 24 | $\theta_4 > \theta_3 > \theta_2 > \theta_1$ | 0.18 | 0.22 | 0.28 | 0.32 |

Applying the data set in Table 6.6 for solving the proposed multiple-objective model, the optimal obtained results of TH’s model (integrating the consistent-weight constraints) are shown in Table 6.7.

**Table 6.7** Optimal solutions of the proposed model with $\alpha$ = 0.9 and $\gamma$ = 0.2.

| Case | Order patterns | λ | $\mu_1$(%) | $\mu_2$(%) | $\mu_3$(%) | $\mu_4$(%) | Consistent solutions |
|---|---|---|---|---|---|---|---|
| 1 | $\theta_1 > \theta_2 > \theta_3 > \theta_4$ | 66.60 | 97.95 | 82.06 | 54.12 | 28.35 | Yes |
| 2 | $\theta_1 > \theta_2 > \theta_4 > \theta_3$ | 68.35 | 94.89 | 91.71 | 35.29 | 62.55 | Yes |
| 3 | $\theta_1 > \theta_3 > \theta_2 > \theta_4$ | 76.44 | 93.76 | 80.36 | 87.06 | 58.25 | Yes |
| 4 | $\theta_1 > \theta_3 > \theta_4 > \theta_2$ | 56.18 | 96.84 | 10.98 | 28.24 | 23.53 | Yes |
| 5 | $\theta_1 > \theta_4 > \theta_2 > \theta_3$ | 57.11 | 87.24 | 43.61 | 16.47 | 69.79 | Yes |
| 6 | $\theta_1 > \theta_4 > \theta_3 > \theta_2$ | 71.63 | 79.27 | 66.51 | 69.41 | 75.20 | Yes |
| 7 | $\theta_2 > \theta_1 > \theta_3 > \theta_4$ | 82.09 | 89.65 | 100.00 | 81.18 | 67.00 | Yes |
| 8 | $\theta_2 > \theta_1 > \theta_4 > \theta_3$ | 64.92 | 75.00 | 100.00 | 24.71 | 50.00 | Yes |
| 9 | $\theta_2 > \theta_3 > \theta_1 > \theta_4$ | 81.66 | 75.76 | 100.00 | 82.35 | 72.47 | Yes |
| 10 | $\theta_2 > \theta_3 > \theta_4 > \theta_1$ | 84.02 | 61.34 | 99.98 | 84.71 | 73.02 | Yes |
| 11 | $\theta_2 > \theta_4 > \theta_1 > \theta_3$ | 59.50 | 35.29 | 100.00 | 5.88 | 54.90 | Yes |
| 12 | $\theta_2 > \theta_4 > \theta_3 > \theta_1$ | 64.60 | 42.00 | 100.00 | 49.41 | 57.50 | Yes |
| 13 | $\theta_3 > \theta_1 > \theta_2 > \theta_4$ | 76.82 | 84.37 | 68.74 | 100.00 | 59.37 | Yes |
| 14 | $\theta_3 > \theta_1 > \theta_4 > \theta_2$ | 67.24 | 85.00 | 24.99 | 100.00 | 40.00 | Yes |
| 15 | $\theta_3 > \theta_2 > \theta_1 > \theta_4$ | 82.10 | 73.33 | 89.99 | 100.00 | 69.99 | Yes |
| 16 | $\theta_3 > \theta_2 > \theta_4 > \theta_1$ | 70.85 | 3.44 | 6.88 | 100.00 | 4.59 | Yes |
| 17 | $\theta_3 > \theta_4 > \theta_1 > \theta_2$ | 63.62 | 45.24 | 42.85 | 100.00 | 50.00 | Yes |
| 18 | $\theta_3 > \theta_4 > \theta_2 > \theta_1$ | 67.14 | 39.47 | 50.00 | 100.00 | 73.68 | Yes |
| 19 | $\theta_4 > \theta_1 > \theta_2 > \theta_3$ | 55.37 | 44.03 | 22.87 | 11.76 | 95.10 | Yes |
| 20 | $\theta_4 > \theta_1 > \theta_3 > \theta_2$ | 56.20 | 72.80 | 28.03 | 38.82 | 79.42 | Yes |
| 21 | $\theta_4 > \theta_2 > \theta_1 > \theta_3$ | 61.19 | 62.50 | 62.50 | 36.47 | 87.56 | Yes |
| 22 | $\theta_4 > \theta_2 > \theta_3 > \theta_1$ | 73.25 | 62.79 | 77.90 | 71.76 | 86.91 | Yes |
| 23 | $\theta_4 > \theta_3 > \theta_1 > \theta_2$ | 63.83 | 56.39 | 40.98 | 71.76 | 89.67 | Yes |
| 24 | $\theta_4 > \theta_3 > \theta_2 > \theta_1$ | 70.33 | 51.40 | 62.83 | 80.00 | 92.45 | Yes |

Throughout the obtained solutions as presented in Table 6.7, it can be seen that all satisfaction values of the objectives match their allocated importance weights. The proposed model is optimized so that the satisfaction levels of objectives $\mu_h \geq \mu_{h+1}$ agree with their allocated important weights $\theta_h \geq \theta_{h+1}$. This is also evidence that the proposed model can ensure the weight-consistent solutions. The number of weight-consistent solutions from the three approaches is summarized in Table 6.8. The satisfaction level and the actual value of all objectives of these three approaches are presented in the Appendix B.

**Table 6.8** Weight-consistent solutions of three approaches.

| Approaches | Weight-consistent solutions | Percentages |
|---|---|---|
| Zimmerman's model | 1/24 | 4.1% |
| TH's model | 3/24 | 12.5% |
| Proposed model | 24/24 | 100% |

Based on the aggregated results as shown in Table 6.8, it is a highlight that only the proposed model can guarantee 100% for the generated weight-consistent solutions while the other two approaches hardly achieve the weight-consistent solutions.

### 6.3 Sensitivity analysis

In this section, a sensitivity analysis is conducted to investigate the impacts of the confidence level (α) and the coefficient of compensation (γ) on the optimal solution of the proposed model. The values of α and $\gamma$ are varied while the other parameters are fixed.

Usually, in credibility-based fuzzy chance-constrained programming, the confidence level is set by the decision-makers (DMs). The confidence levels (credibility levels) have a significant impact on the attainment of solutions because they are used to control the allowable satisfaction level of imprecise objective functions and imprecise constraints. Thus, it is necessary to find how uncertainty affects the optimal solutions through the different confidence levels. In this sensitivity analysis, the confidence levels of $\alpha$ are varied with a step size of 0.1 (from 0.5 to 1), the value of the compensatory coefficient is set to 0.2, and the importance weights of the objectives are $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$. The result of sensitivity analysis with the variation of the confidence level (α) is shown in Table 6.9 and illustrated graphically in Figure 6.2.

**Table 6.9** Obtained solutions with different values of α with $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$, and $\gamma = 0.2$.

| α-value | $\lambda$ | $\mu_1$(%) | $\mu_2$(%) | $\mu_3$(%) | $\mu_4$(%) | $Z_1$($) | $Z_2$ (units) | $Z_3$ (persons) | $Z_4$ (units) |
|---|---|---|---|---|---|---|---|---|---|
| 0.5 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,468 |
| 0.6 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,471 |
| 0.7 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,567.11 | 841 | 37 | 291,471 |
| 0.8 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,571.76 | 841 | 37 | 291,471 |
| 0.9 | 69.21 | 97.94 | 83.93 | 54.12 | 40.59 | 4,940,544.27 | 946 | 39 | 289,451 |
| 1 | 65.14 | 91.48 | 78.41 | 51.76 | 38.82 | 5,248,346.32 | 1,271 | 41 | 287,438 |

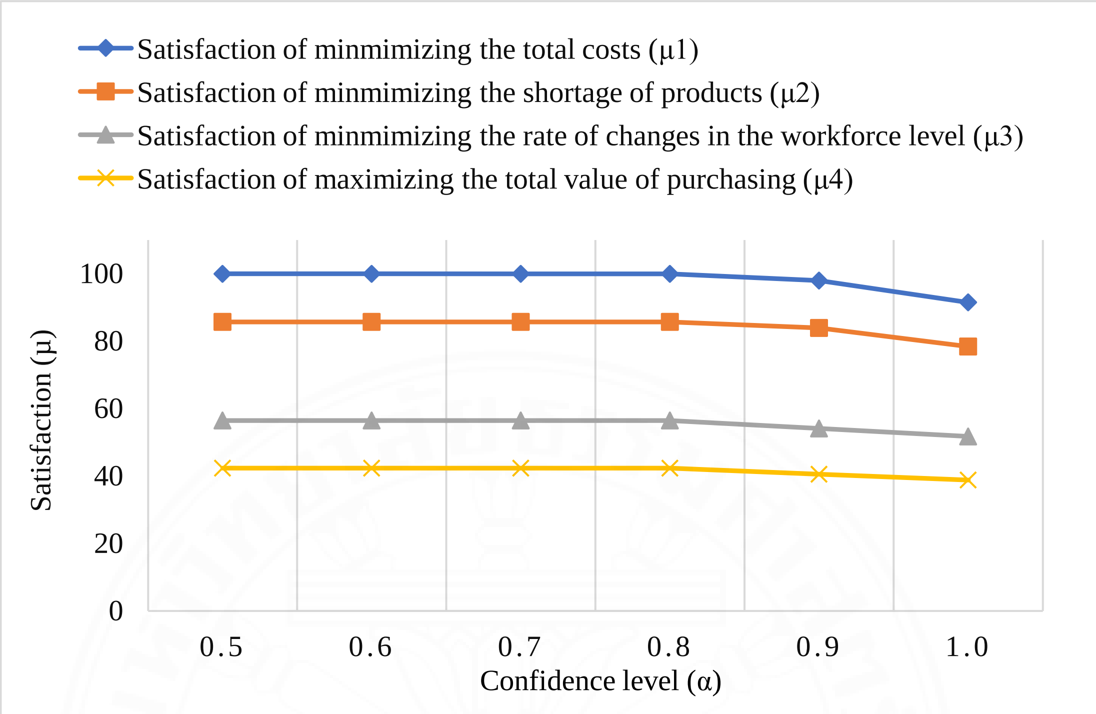


**Figure 6.2** Satisfaction levels of each objective function according to the different values of ($\alpha$).

According to the obtained outcomes in Table 25, it highlights that an increment of the confidence level will lead to a decrease in the satisfaction levels of all objectives. This implies that the actual values of all objectives can get worse. The reasons for obtaining worse solutions when the confidence level is higher can be explained as follows:

- When DMs allocate a higher confidence level (high credibility) for the fuzzy parameters, the DMs focus on the upper point of the fuzzy parameter. In other words, if the confidence level is set to 1, the used value of the fuzzy parameter will be the largest value (pessimistic case). As a result, the value of the objectives will be worse in the pessimistic case.
- In addition, there is a trade-off between the satisfaction of constraints (the risk of violating constraints) and the optimal value of objectives. When the satisfaction levels of constraints are high, the feasible solution set will be smaller. As a result, the optimal objectives become worse. The confidence level (here) is denoted as the satisfaction level of the constraints. Thus, when the

confidence level is high (low violation of constraints), the value of the optimal objective becomes worse.

Regarding the obtained results of different confidence levels, it can help DMs to estimate the possible results from the optimistic situation to the pessimistic situation. Knowing that, the DMs can take necessary actions and with better preparation for these situations in the future.

To explore and realize the influence of the coefficient compensation (γ) on the optimal solutions, the value of coefficient compensation is varied from 0 to 1 with a step size of 0.1, the confidence level (α) is set to 0.9, and the importance weights of the objective function are $\theta_1 = 0.35, \theta_2 = 0.3, \theta_3 = 0.2, \theta_4 = 0.15$. Moreover, in the process of the sensitivity analysis, as the value of the compensation coefficient is set larger than 0.5, this means that the DMs will pay more attention to the balanced solutions (there is no priority for any objective – all objectives are treated equally). Thus, the consistency of the solutions is not considered. In contrast, if the value of the compensation coefficient is set smaller at 0.5, this implies that the DMs are interested in the unbalanced solution (The priority of objectives is considered). Therefore, the consistency of the solutions will be taken into account. The obtained satisfaction levels and the actual values for all objective functions by doing sensitivity analysis with the compensation coefficient are presented in Table 6.10. A spectrum of unbalanced and balanced compromise solutions based on the preferences of DMs is illustrated graphically in Figure 6.3.

**Table 6.10** Results of sensitivity analysis by varying the compensation coefficient ($\gamma$).

| γ-value | $\lambda$(%) | $\mu_1$(%) | $\mu_2$(%) | $\mu_3$(%) | $\mu_4$(%) | $Z_1$($) | $Z_2$ (units) | $Z_3$ (persons) | $Z_4$ (units) |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 76.34 | 97.29 | 83.37 | 55.29 | 41.47 | 4,971,733.43 | 979 | 38 | 290,459 |
| 0.1 | 72.34 | 97.11 | 83.23 | 54.12 | 40.59 | 4,980,150.77 | 987 | 39 | 289,454 |
| 0.2 | 69.21 | 97.94 | 83.93 | 54.12 | 40.59 | 4,940,544.27 | 946 | 39 | 289,451 |
| 0.3 | 65.47 | 97.91 | 83.20 | 54.12 | 40.59 | 4,942,033.27 | 989 | 39 | 289,455 |
| 0.4 | 62.11 | 98.10 | 84.06 | 54.12 | 40.58 | 4,933,022.55 | 938 | 39 | 289,451 |
| 0.5 | 58.77 | 96.84 | 82.98 | 55.29 | 41.47 | 4,993,245.57 | 1,002 | 38 | 290,460 |
| 0.6 | 80.33 | 75.43 | 99.90 | 100.00 | 75.43 | 6,012,784.80 | 6 | 0 | 329,269 |
| 0.7 | 80.43 | 76.98 | 99.97 | 100.00 | 76.98 | 5,938,946.62 | 2 | 0 | 331,038 |
| 0.8 | 78.46 | 76.06 | 100.00 | 100.00 | 76.06 | 5,982,793.50 | 0 | 0 | 329,991 |
| 0.9 | 77.13 | 75.98 | 100.00 | 97.65 | 75.98 | 5,986,879.89 | 0 | 2 | 329,897 |
| 1 | 77.36 | 77.36 | 91.00 | 77.65 | 77.36 | 5,920,829.06 | 530 | 19 | 331,479 |

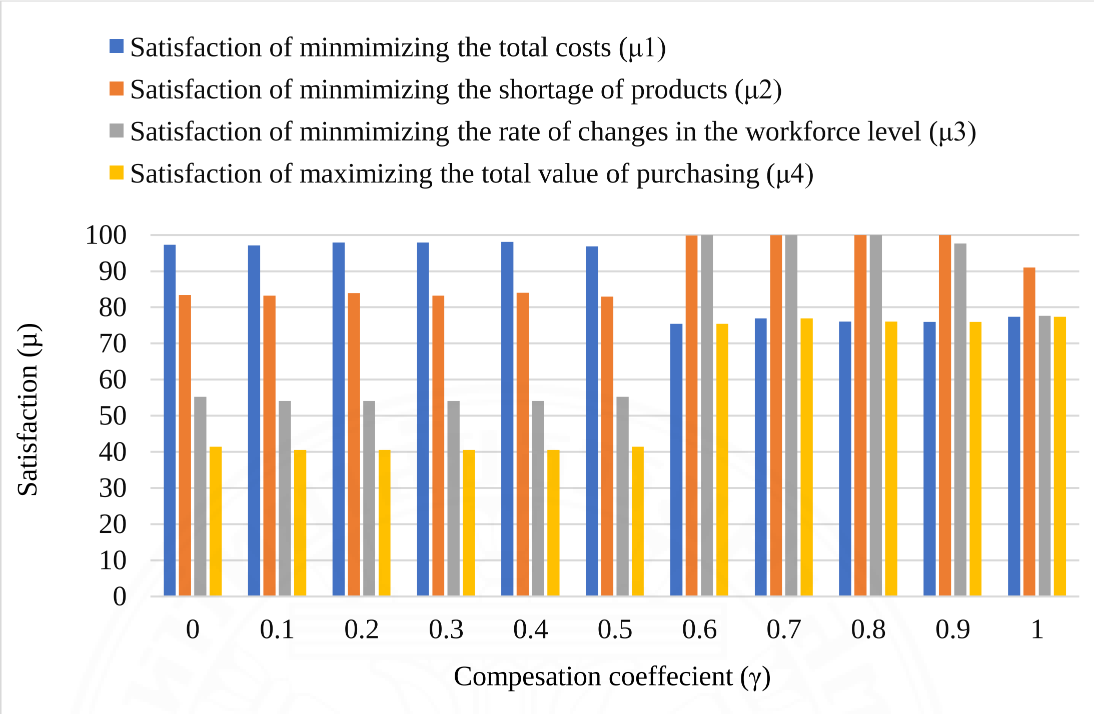


**Figure 6.3** Satisfaction levels of each objective function according to the different values of ($\gamma$).

According to Table 6.10 and Figure 6.3, it is noted that when a higher value of $\gamma$ is used, a smaller gap between the lowest and highest satisfaction levels of objective functions can be obtained. Particularly, at the highest compensation coefficient value of 1, the lowest and highest satisfaction levels of objectives are 77.36% and 91%, respectively (the gap is 13.64%). It implies that the DMs pay more attention to obtaining the higher bound of the satisfaction level for objective functions ($\lambda_0$) with more balanced compromise solutions (symmetric fuzzy decision-making). In contrast, as a lower value of $\gamma$ is used, the gap between the lowest and highest satisfaction levels of objective functions becomes larger. Particularly, the lowest and highest satisfaction levels of objectives are 41.47% and 97.29%, respectively, at the lowest compensation coefficient value of 0 (the gap is 55.82%). It also means that the DMs get more concerned about the solutions with a high satisfaction level of some objectives in connection with the relative importance of objectives. It yields unbalanced compromise solutions (asymmetric fuzzy decision-making).

Based on the obtained outcomes and the above discussion, it could be concluded that the proposed approach possesses some advantages as follows:

- As compared with traditional defuzzification methods (e.g. fuzzy ranking method, average weight method), the fuzzy ranking method can separate the fuzzy numbers into different corresponding scenarios. The weighted average method just converts a fuzzy number into a crisp number by assigning weights to the possible values of fuzzy numbers. Since these methods are conducted at the beginning of FLP process (too early), therefore, the attributes of fuzzy data totally disappear and no information about the likely violation of constraints (feasibility concept) is provided. In contrast, based on the relation of the two fuzzy sets under the credibility measure, FCCP used in this study can assist DMs in controlling and analyzing the fuzziness level of fuzzy constraints (the risk of constraint violation) by a sensitivity analysis or interactive decision-making process.
- The approach brings computational efficiency because it still maintains the linearity and does not increase the number of objective functions and constraints. Therefore, it can be used for solving a large scope of fuzzy programming models.
- This is a robust and reliable approach because the obtained solutions are always consistent with the expectation of DMs for the matter of the homogeneity between the satisfaction level of the objectives and their importance weights.
- The approach can generate efficient solutions and yield both unbalanced and balanced compromise solutions according to the preferences of the DMs.
- By using different sets of controllable parameters such as the importance weight of objectives($\theta_h$),confidence levels ($\alpha$), and compensatory coefficient ($\gamma$), it can yield many efficient solutions. This feature is evidence to show the high flexibility of the proposed approach.

# CHAPTER 7
# CONCLUSION

## 7.1 Managerial Implications

Throughout this study, several managerial and business insights for operational planners or managers could be drawn as follows:

In practical applications, the credibility level ($\alpha$) can be used to reflect the occurrence of a fuzzy event and can represent the uncertain parameters in the fuzzy model. By setting credibility levels ($\alpha$), the uncertain parameters can be converted into crisp analogous parameters, and all of the crisp parameters can create a deterministic system scenario. With each credibility level ($\alpha$), there is a corresponding scenario and a set of optimal results (operational decision variables). Being aware of many scenarios, the planners or managers can make effective operational and strategic management plans for any changes in the future.

In general, the higher the credibility level is, the more satisfied the DMs are with the constraints. This leads to higher confidence in the planners or managers for the obtained optimal results. In the credibility theory, decreasing the credibility level in the fuzzy chance constraints will lead to an increase in the right-hand side parameters and a decrease in the left-hand side parameters of the constraints. Hence, the feasible solution region will be extended. As a result, better optimal solutions can be more easily found. Usually, the right-hand side parameters of the constraints represent the available resources of the company, but the resources are not free. They have costs. To enhance the available resources, the company needs to spend more on investing in the company's resources. Consequently, there exists a trade-off between the credibility level and the gained benefits. Based on the trade-off analysis, the planners or managers can choose a suitable plan or policy by considering comprehensively between the acceptable credibility levels and the gained benefits.

From the perspective of making decisions under the consideration of multiple conflicting objectives at the same time (there exists a trade-off between objectives), this study provided a fuzzy solution that can achieve both balanced, unbalanced, and consistent compromise solutions among the conflicting objectives. Hence, it is very helpful for the planners or managers in selecting satisfactory solutions under a company's policies.

## 7.2 Conclusions

Uncertainty of data and conflicting objectives are two main features that should be addressed in the aggregate supply chain planning problem. In this study, a multiple-objective optimization model in an uncertain environment for aggregate production planning in a supply chain was investigated. To make the APP problem more effective, informative, and compatible with a real-life environment, the APP problem was integrated into a Supply Chain (SC) including a production plant, multiple suppliers, and multiple customers. Besides, several important problems such as multiple products, product characteristics, and labor characteristics, are embedded in the proposed model. Since the APP problem was considered in the SC, the aggregate plan has not only production plan, but also includes procurement plan and distribution plan. The proposed APP model considered simultaneously four conflicting objective functions, which minimize the total cost of the SC, minimize the total shortage of products, minimize the variation in the workforce, and maximize the total value of purchasing. The proposed model is formulated as a Multiple-Objective Mixed-Integer Linear Programming (MOMILP) model.

A comprehensive Credibility-based Fuzzy Chance-constrained Programming (CFCCP) approach for dealing with the uncertainty of data was presented. It indicated that CFCCP can handle the uncertain parameters that appear in any positions in the fuzzy optimization model such as the objective function and constraints (one side and both two-sides of the constraints). In addition, it also yields a confidence level for the obtained optimal solutions.

In practical applications, the importance of objectives is not treated equally. Therefore, it is necessary to assign importance weights to the different objectives. Although the weights are assigned to indicate the importance of the objectives, they still cannot ensure that the obtained solutions totally satisfy the decision-makers as their expectations (the obtained solutions are not consistent with the preference of the decision-makers (DMs)). In the proposed model, weight-consistent constraints were integrated to guarantee that the obtained solutions are consistent with the DM expectations (the ranking of the objective satisfaction levels must be the same as the ranking of the objective importance weights).

In summary, to cope with the proposed fuzzy MOMILP model in this study, a hybrid approach with a two-phase solution was developed. In the first phase, to deal with the fuzziness of parameters, Credibility-based Fuzzy Chance-constrained Programming (CFCCP) was applied to transform the fuzzy multiple-objectives optimization model into the corresponding crisp multiple objectives model. With CFCCP, it not only deals with imprecise parameters represented as fuzzy sets, but also controls the different confidence levels in the satisfaction of the imprecise objective functions and imprecise constraints. In the second phase, Fuzzy Multiple Objective Linear Programming (FMOLP) integrating the concept of the weight-consistent solutions was applied to solve the crisp credibilistic multiple-objective model. Adding the weight-consistent constraint into the model can ensure that the obtained results will totally satisfy the expectations of decision-makers in terms of the consistency between the objective satisfaction and the objective importance weight (i.e. $\mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$ in accordance with $\theta_1 \geq \theta_2 \geq \theta_3 \geq \theta_4$). Moreover, the objective function of FMOLP is an aggregation function. Thus, the proposed model can generate both balanced and unbalanced compromise solutions.

From the obtained outcomes of the proposed model, it showed that the proposed hybrid approach is very effective. For the matter of optimizing under uncertainty, this method can solve and bring efficient solutions with pre-determined confidence levels in an uncertain environment. For the matter of conflicting objectives, this method can produce consistent-solutions, balanced solutions, and unbalanced compromise solutions based on the preferences of the DMs. Besides that, it also offers high flexibility for yielding different efficient solutions to support decision-makers in selecting the final preferred satisfactory solution.

### 7.3 Limitations

The limitations of this study are as follows:

The triangular possibility distribution is assumed to represent the uncertain parameters of the proposed fuzzy model. Based on incomplete available data, subjective knowledges or experiences of the DMs/experts, other appropriate distribution forms can be generated and then applied for the proposed model.

Any parameter that may affect the results of planning can be considered as a fuzzy number. In fact, there is no restrictions on the number of fuzzy parameters that can appear in the proposed approach. However, except for the operational costs in the objective function, there are other parameters in the constraints (e.g. machine capacity, machine's hours, warehouse capacity) that can be considered to be fuzzy numbers.

### 7.4 Further study

In future research, it is possible to embed some more important issues of APP in the proposed model such as multiple production plants, varying lead time, labor skills, time value of money, etc. Also, taking into account the modeling perspectives of the supply chain, one more echelon (distribution centers) can be added to the supply chain network. This is because the final products should be delivered from the distribution centers instead of being transferred directly from the production plant. From the perspective of solution methodology, once the complete data is available and the problem becomes more complicated or is too large, various heuristic or evolutionary approaches such as genetic algorithms should be considered in future research work.

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# APPENDICES

# APPENDIX A
# OBTAINED SOLUTIONS (AGGREGATION PLAN) FROM SOLVING THE PROPOSED MATHEMATICAL MODEL

In this appendix, the obtained aggregation plan which includes procurement plan, production plan, and distribution plan are presented.

**Table A.1** Production plan.

| Product | M | Period | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | R | 1,699 | 1,551 | 1,848 | 1,317 | 649 | 1,381 | 1,586 | 337 | 754 | 826 | 637 | 661 |
| | O | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | S | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | | |
| 2 | R | 1,178 | 1,711 | 1,912 | 2,089 | 1,652 | 1,356 | 1,440 | 2,537 | 2,925 | 2,740 | 3,244 | 2,407 |
| | O | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | S | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | | |
| 3 | R | 747 | 1,346 | 1,392 | 2,277 | 496 | 319 | 212 | 590 | 1,546 | 1,687 | 2,238 | 2,400 |
| | O | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | S | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | | |
| 4 | R | 1,701 | 766 | 1,687 | 1,783 | 1,522 | 874 | 1,950 | 1,950 | 1,950 | 1,950 | 1,950 | 1,950 |
| | O | 0 | 0 | 0 | 0 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | S | 0 | 0 | 0 | 0 | 0 | 0 | 32 | 0 | 0 | 390 | 54 | 0 |
| | | | | | | | | | | | | | |
| 5 | R | 1,075 | 1,605 | 1,666 | 1,666 | 1,666 | 1,666 | 1,320 | 602 | 885 | 531 | 756 | 602 |
| | O | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | S | 0 | 0 | 0 | 0 | 183 | 329 | 0 | 0 | 0 | 0 | 0 | 0 |
| M: Method, R: Regular time, O: overtime, S: Subcontracted | | | | | | | | | | | | | |

**Table A.2** Worker plan

| | Levels | Period | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Labor | 1 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 | 21 |
| | 2 | 34 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 | 27 |
| | 3 | 36 | 36 | 19 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 | 14 |
| | 4 | 8 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 5 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | | | | | | | | | | | | |
| Firing | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0 | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 3 | 0 | 0 | 17 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 4 | 0 | 7 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 5 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table A.3** Inventory level of raw materials and final products

| | | Period | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Raw material | 1 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 2 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 3 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 4 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| | 5 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| | 6 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 7 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 8 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | 9 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 | 15 |
| | 10 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 |
| | | | | | | | | | | | | | |
| Product | 1 | 1,052 | 987 | 865 | 0 | 0 | 0 | 17 | 0 | 0 | 0 | 0 | 0 |
| | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 294 | 615 | 0 | 0 |
| | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 527 | 0 |
| | 4 | 0 | 0 | 0 | 1 | 7 | 374 | 1,376 | 1,603 | 379 | 182 | 0 | 0 |
| | 5 | 0 | 330 | 745 | 75 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

**Table A.4** Procurement plan

| | | Period | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Supplier | RM | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | 1 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 2 | 3,500 | 3,500 | 3,500 | 3,500 | 2,975 | 3,500 | 3,500 | 2,724 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 3 | 1,084 | 3,500 | 3,136 | 3,500 | 3,500 | 3,500 | 792 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 4 | 3,500 | 3,500 | 3,500 | 3,500 | 0 | 3,279 | 3,279 | 602 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 5 | 3,085 | 3,085 | 3,500 | 3,500 | 3,500 | 2,455 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 6 | 2,500 | 2,269 | 2,385 | 2,500 | 2,500 | 2,500 | 2,498 | 2,500 | 2,500 | 2,500 | 2,500 | 2,500 |
| | 7 | 2,005 | 0 | 3,585 | 3,585 | 360 | 0 | 0 | 0 | 0 | 3,350 | 3,040 | 0 |
| | 8 | 3,269 | 3,500 | 3,269 | 3,500 | 3,500 | 3,293 | 3,498 | 3,500 | 3,500 | 3,500 | 3,500 | 3,269 |
| | 9 | 2,585 | 2,585 | 3,000 | 2,585 | 2,779 | 2,585 | 3,000 | 2,475 | 2,585 | 2,585 | 2,585 | 3,000 |
| | 10 | 3,293 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,498 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | | | | | | | | | | | | | |
| 2 | 1 | 3,000 | 3,000 | 3,000 | 3,000 | 1,598 | 2,293 | 2,764 | 2,838 | 3,000 | 3,000 | 3,000 | 3,000 |
| | 2 | 219 | 1,391 | 2,946 | 1,884 | 0 | 206 | 398 | 0 | 1,922 | 1,229 | 2,399 | 219 |
| | 3 | 221 | 2,767 | 0 | 3,000 | 221 | 221 | 0 | 831 | 2,741 | 1,989 | 3,000 | 2,511 |
| | 4 | 146 | 1,818 | 3,500 | 3,500 | 0 | 0 | 0 | 0 | 1,458 | 1,658 | 3,012 | 1,758 |
| | 5 | 0 | 0 | 1,364 | 1,910 | 474 | 0 | 665 | 2,076 | 3,000 | 3,000 | 3,000 | 474 |
| | 6 | 1,646 | 3,000 | 3,000 | 3,000 | 2,078 | 2,834 | 2,633 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 |
| | 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 8 | 3,500 | 1,900 | 3,500 | 983 | 2,385 | 0 | 126 | 3,024 | 358 | 3,500 | 3,500 | 3,500 |
| | 9 | 0 | 0 | 584 | 0 | 0 | 0 | 43 | 0 | 0 | 0 | 0 | 0 |
| | 10 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 2,743 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | | | | | | | | | | | | | |
| 3 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2256 | 0 | 3352 | 0 |
| | 2 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 |
| | 3 | 207 | 0 | 0 | 0 | 207 | 207 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 4 | 4,000 | 4,000 | 4,000 | 4,000 | 3,892 | 2,595 | 3,369 | 4,000 | 4,000 | 4,000 | 4,000 | 4,000 |
| | 5 | 3,748 | 3,474 | 4,000 | 4,000 | 4,000 | 4,000 | 3,999 | 4,000 | 4,000 | 4,000 | 4,000 | 4,000 |
| | 6 | 0 | 0 | 0 | 527 | 0 | 0 | 195 | 1,924 | 2,700 | 3,500 | 3,500 | 1,664 |
| | 7 | 343 | 929 | 0 | 75 | 343 | 0 | 2,263 | 1,327 | 3,026 | 343 | 343 | 3,461 |
| | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 1,994 | 0 | 0 | 1,672 | 286 | 0 |
| | 9 | 3,489 | 1,705 | 3,500 | 3,098 | 575 | 1,801 | 3,499 | 0 | 962 | 1,604 | 590 | 0 |
| | 10 | 1,954 | 1,200 | 3,000 | 3,000 | 2,277 | 250 | 2,769 | 1,234 | 3,000 | 3,000 | 3,000 | 3,000 |
| | | | | | | | | | | | | | |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1 | 0 | 1,370 | 2,412 | 2,589 | 0 | 0 | 0 | 0 | 148 | 2,319 | 148 | 2,036 |
| | 2 | 2,987 | 3,500 | 3,500 | 3,500 | 2,777 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,087 |
| | 3 | 2,563 | 0 | 3,500 | 1,198 | 1,918 | 1,737 | 3,500 | 0 | 0 | 0 | 494 | 0 |
| | 4 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 | 3,000 |
| | 5 | 0 | 0 | 0 | 0 | 237 | 0 | 0 | 0 | 135 | 191 | 752 | 1,342 |
| | 6 | 3,313 | 451 | 3,500 | 3,500 | 3,313 | 0 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 |
| | 7 | 3,500 | 3,500 | 3,029 | 3,500 | 3,500 | 3,448 | 3,499 | 3,500 | 3,174 | 3,500 | 3,500 | 3,500 |
| | 8 | 1,732 | 0 | 1,988 | 3,500 | 0 | 2,091 | 3,500 | 0 | 3,500 | 0 | 0 | 403 |
| | 9 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,500 | 3,038 | 3,500 | 3,500 | 3,500 | 3,485 |
| | 10 | 0 | 0 | 1,177 | 3,235 | 0 | 0 | 0 | 0 | 712 | 1,456 | 2,000 | 1,854 |

**Table A.5** Distribution plan

| | | Period | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Customer | Product | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | 1 | 118 | 295 | 413 | 354 | 118 | 236 | 295 | 0 | 118 | 177 | 118 | 118 |
| | 2 | 236 | 295 | 354 | 413 | 236 | 236 | 236 | 413 | 472 | 531 | 590 | 413 |
| | 3 | 177 | 236 | 295 | 354 | 118 | 59 | 0 | 118 | 236 | 295 | 354 | 472 |
| | 4 | 295 | 118 | 354 | 295 | 236 | 118 | 236 | 354 | 472 | 472 | 472 | 354 |
| | 5 | 177 | 236 | 236 | 472 | 354 | 290 | 241 | 118 | 177 | 118 | 118 | 83 |
| | | | | | | | | | | | | | |
| 2 | 1 | 224 | 413 | 637 | 696 | 142 | 378 | 448 | 236 | 212 | 224 | 153 | 130 |
| | 2 | 330 | 389 | 378 | 673 | 437 | 389 | 342 | 814 | 791 | 767 | 1121 | 507 |
| | 3 | 248 | 437 | 578 | 472 | 177 | 83 | 118 | 189 | 389 | 448 | 472 | 732 |
| | 4 | 354 | 212 | 437 | 484 | 366 | 153 | 319 | 543 | 909 | 920 | 614 | 696 |
| | 5 | 342 | 472 | 260 | 814 | 496 | 314 | 335 | 224 | 224 | 142 | 201 | 165 |
| | | | | | | | | | | | | | |
| 3 | 1 | 106 | 224 | 35 | 94 | 47 | 354 | 165 | 118 | 153 | 59 | 71 | 24 |
| | 2 | 71 | 295 | 625 | 165 | 177 | 94 | 189 | 224 | 389 | 342 | 661 | 531 |
| | 3 | 106 | 83 | 165 | 472 | 12 | 71 | 94 | 118 | 189 | 307 | 236 | 720 |
| | 4 | 224 | 153 | 271 | 47 | 189 | 24 | 118 | 212 | 637 | 602 | 248 | 123 |
| | 5 | 94 | 201 | 177 | 342 | 330 | 354 | 94 | 24 | 283 | 59 | 142 | 130 |
| | | | | | | | | | | | | | |
| 4 | 1 | 201 | 684 | 885 | 1038 | 342 | 413 | 661 | 0 | 271 | 366 | 295 | 389 |
| | 2 | 543 | 732 | 555 | 838 | 802 | 637 | 673 | 1086 | 979 | 779 | 1487 | 956 |
| | 3 | 236 | 590 | 354 | 979 | 189 | 106 | 0 | 165 | 732 | 637 | 649 | 1003 |
| | 4 | 838 | 283 | 625 | 956 | 732 | 212 | 307 | 614 | 1156 | 543 | 852 | 777 |
| | 5 | 472 | 366 | 578 | 708 | 743 | 1038 | 650 | 236 | 201 | 212 | 295 | 224 |

# APPENDIX B
# OPTIMAL SATISFACTION LEVEL OF EACH OBJECTIVE FROM THE THREE APPROACHES

**Table B.1** Optimal satisfaction level of each objective from the three approaches

| Scenario | The order of weight importance for each objective function | Model | TC ($\mu_1$) | CS ($\mu_1$) | RCW ($\mu_1$) | TVP ($\mu_1$) | Weight-consistent solutions |
|---|---|---|---|---|---|---|---|
| 1 | θ1 > θ2 > θ3 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.8990 | 1.0000 | 1.0000 | 0.6023 | No |
| | | Proposed | 0.9795 | 0.8206 | 0.5412 | 0.2835 | Yes |
| 2 | θ1 > θ2 > θ4 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7652 | 0.9997 | 1.0000 | 0.7658 | No |
| | | Proposed | 0.9489 | 0.9171 | 0.3529 | 0.6255 | Yes |
| 3 | θ1 > θ3 > θ2 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7513 | 1.0000 | 1.0000 | 0.7512 | No |
| | | Proposed | 0.9376 | 0.8036 | 0.8706 | 0.5825 | Yes |
| 4 | θ1 > θ3 > θ4 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.9314 | 1.0000 | 1.0000 | 0.5905 | No |
| | | Proposed | 0.9684 | 0.1098 | 0.2824 | 0.2353 | Yes |
| 5 | θ1 > θ4 > θ2 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7822 | 0.9997 | 1.0000 | 0.7361 | No |
| | | Proposed | 0.8724 | 0.4361 | 0.1647 | 0.6979 | Yes |
| 6 | θ1 > θ4 > θ3 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7682 | 0.9988 | 1.0000 | 0.7681 | No |
| | | Proposed | 0.7927 | 0.6651 | 0.6941 | 0.7520 | Yes |
| 7 | θ2 > θ1 > θ3 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7484 | 1.0000 | 1.0000 | 0.7483 | No |
| | | Proposed | 0.8965 | 1.0000 | 0.8118 | 0.6700 | Yes |
| 8 | θ2 > θ1 > θ4 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7728 | 0.9997 | 1.0000 | 0.7404 | No |
| | | Proposed | 0.7500 | 1.0000 | 0.2471 | 0.5000 | Yes |
| 9 | θ2 > θ3 > θ1 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7612 | 1.0000 | 1.0000 | 0.7612 | Yes |
| | | Proposed | 0.7576 | 1.0000 | 0.8235 | 0.7247 | Yes |
| 10 | θ2 > θ3 > θ4 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | Yes |
| | | TH | 0.7563 | 0.9998 | 1.0000 | 0.7576 | No |
| | | Proposed | 0.6134 | 0.9998 | 0.8471 | 0.7302 | Yes |
| 11 | θ2 > θ4 > θ1 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7599 | 0.9993 | 1.0000 | 0.7598 | No |
| | | Proposed | 0.3529 | 1.0000 | 0.0588 | 0.5490 | Yes |
| 12 | θ2 > θ4 > θ3 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7604 | 1.0000 | 1.0000 | 0.7604 | No |
| | | Proposed | 0.4200 | 1.0000 | 0.4941 | 0.5750 | Yes |
| 13 | θ3 > θ1 > θ2 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7407 | 1.0000 | 1.0000 | 0.7407 | No |
| | | Proposed | 0.8437 | 0.6874 | 1.0000 | 0.5937 | Yes |
| 14 | θ3 > θ1 > θ4 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.8064 | 0.9998 | 1.0000 | 0.7435 | No |
| | | Proposed | 0.8500 | 0.2499 | 1.0000 | 0.4000 | Yes |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 15 | θ3 > θ2 > θ1 > θ4 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7640 | 1.0000 | 1.0000 | 0.7640 | Yes |
| | | Proposed | 0.7333 | 0.8999 | 1.0000 | 0.6999 | Yes |
| 16 | θ3 > θ2 > θ4 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7127 | 1.0000 | 1.0000 | 0.7164 | Yes |
| | | Proposed | 0.0344 | 0.0688 | 1.0000 | 0.0459 | Yes |
| 17 | θ3 > θ4 > θ1 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7587 | 0.9997 | 1.0000 | 0.7606 | No |
| | | Proposed | 0.4524 | 0.4285 | 1.0000 | 0.5000 | Yes |
| 18 | θ3 > θ4 > θ2 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7507 | 1.0000 | 1.0000 | 0.7506 | No |
| | | Proposed | 0.3947 | 0.5000 | 1.0000 | 0.7368 | Yes |
| 19 | θ4 > θ1 > θ2 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7606 | 1.0000 | 1.0000 | 0.7605 | No |
| | | Proposed | 0.4403 | 0.2287 | 0.1176 | 0.9510 | Yes |
| 20 | θ4 > θ1 > θ3 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7683 | 1.0000 | 1.0000 | 0.7682 | No |
| | | Proposed | 0.7280 | 0.2803 | 0.3882 | 0.7942 | Yes |
| 21 | θ4 > θ2 > θ1 > θ3 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7616 | 1.0000 | 1.0000 | 0.7615 | No |
| | | Proposed | 0.6250 | 0.6250 | 0.3647 | 0.8756 | Yes |
| 22 | θ4 > θ2 > θ3 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7632 | 1.0000 | 1.0000 | 0.7631 | No |
| | | Proposed | 0.6279 | 0.7790 | 0.7176 | 0.8691 | Yes |
| 23 | θ4 > θ3 > θ1 > θ2 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7606 | 1.0000 | 1.0000 | 0.7606 | No |
| | | Proposed | 0.5639 | 0.4098 | 0.7176 | 0.8967 | Yes |
| 24 | θ4 > θ3 > θ2 > θ1 | Zimmerman | 0.7696 | 0.9101 | 0.7765 | 0.7699 | No |
| | | TH | 0.7577 | 1.0000 | 1.0000 | 0.7576 | No |
| | | Proposed | 0.5140 | 0.6283 | 0.8000 | 0.9245 | Yes |

# APPENDIX C
# OBTAINED SOLUTIONS OF DIFFERENT VALUE OF α AND γ

**Table C.1** Obtained solutions of different value of α and γ

| γ | α | $\lambda$ | $\mu_1$(%) | $\mu_2$(%) | $\mu_3$(%) | $\mu_4$(%) | $Z_1$($) | $Z_2$ (units) | $Z_3$ (workers) | $Z_4$(TVP) |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.5 | 78.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.05 |
| | 0.6 | 78.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,464.45 |
| | 0.7 | 78.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,568.19 | 841 | 37 | 291,471.10 |
| | 0.8 | 78.10 | 100.00 | 85.71 | 56.47 | 40.61 | 4,842,557.76 | 841 | 37 | 289,477.75 |
| | 0.9 | 76.34 | 97.29 | 83.37 | 55.29 | 41.47 | 4,971,733.43 | 979 | 38 | 290,459.40 |
| | 1 | 71.60 | 91.28 | 78.24 | 51.76 | 38.82 | 5,257,894.80 | 1281 | 41 | 287,436.25 |
| | | | | | | | | | | |
| 0.1 | 0.5 | 74.76 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,471.10 |
| | 0.6 | 74.76 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,465.10 |
| | 0.7 | 74.76 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.75 |
| | 0.8 | 74.76 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,561.58 | 841 | 37 | 291,469.80 |
| | 0.9 | 72.34 | 97.11 | 83.23 | 54.12 | 40.59 | 4,980,150.77 | 987 | 39 | 289,454.25 |
| | 1 | 69.26 | 93.01 | 79.71 | 51.76 | 38.82 | 5,175,313.82 | 1194 | 41 | 287,437.80 |
| | | | | | | | | | | |
| 0.2 | 0.5 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,467.65 |
| | 0.6 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.95 |
| | 0.7 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,567.11 | 841 | 37 | 291,471.05 |
| | 0.8 | 71.16 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,571.76 | 841 | 37 | 291,471.00 |
| | 0.9 | 69.21 | 97.94 | 83.93 | 54.12 | 40.59 | 4,940,544.27 | 946 | 39 | 289,451.15 |
| | 1 | 65.14 | 91.48 | 78.41 | 51.76 | 38.82 | 5,248,346.32 | 1271 | 41 | 287,437.95 |
| | | | | | | | | | | |
| 0.3 | 0.5 | 67.56 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,469.95 |
| | 0.6 | 67.56 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.85 |
| | 0.7 | 67.55 | 100.00 | 85.69 | 56.47 | 42.35 | 4,842,557.76 | 842 | 37 | 291,467.90 |
| | 0.8 | 67.55 | 100.00 | 85.69 | 56.47 | 42.35 | 4,842,669.84 | 842 | 37 | 291,469.45 |
| | 0.9 | 65.47 | 97.91 | 83.20 | 54.12 | 40.59 | 4,942,033.27 | 989 | 39 | 289,454.55 |
| | 1 | 62.12 | 92.13 | 78.95 | 51.76 | 38.82 | 5,217,276.76 | 1239 | 41 | 287,436.50 |
| | | | | | | | | | | |
| 0.4 | 0.5 | 63.96 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.50 |
| | 0.6 | 63.95 | 100.00 | 85.69 | 56.47 | 42.35 | 4,842,557.76 | 842 | 37 | 291,469.90 |
| | 0.7 | 63.96 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,471.10 |
| | 0.8 | 63.96 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,471.10 |
| | 0.9 | 62.11 | 98.10 | 84.06 | 54.12 | 40.58 | 4,933,022.55 | 938 | 39 | 289,450.60 |
| | 1 | 58.58 | 91.54 | 78.44 | 51.76 | 38.82 | 5,245,758.76 | 1269 | 41 | 287,436.30 |
| | | | | | | | | | | |
| 0.5 | 0.5 | 60.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,470.50 |
| | 0.6 | 60.35 | 100.00 | 85.71 | 56.47 | 42.34 | 4,842,557.76 | 841 | 37 | 291,461.75 |
| | 0.7 | 60.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,648.90 | 841 | 37 | 291,470.85 |
| | 0.8 | 60.36 | 100.00 | 85.71 | 56.47 | 42.35 | 4,842,557.76 | 841 | 37 | 291,469.25 |
| | 0.9 | 58.77 | 96.84 | 82.98 | 55.29 | 41.47 | 4,993,245.57 | 1002 | 38 | 290,460.05 |
| | 1 | 55.57 | 92.48 | 79.26 | 51.76 | 38.82 | 5,200,875.81 | 1221 | 41 | 287,438.00 |
| | | | | | | | | | | |
| 0.6 | 0.5 | 85.74 | 82.18 | 100.00 | 100.00 | 82.17 | 5,691,625.66 | 0 | 0 | 336,972.00 |
| | 0.6 | 85.05 | 81.32 | 100.00 | 100.00 | 81.30 | 5,732,351.60 | 0 | 0 | 335,981.30 |
| | 0.7 | 83.54 | 79.43 | 100.00 | 100.00 | 79.43 | 5,822,386.95 | 0 | 0 | 333,836.75 |
| | 0.8 | 82.48 | 78.10 | 100.00 | 100.00 | 78.10 | 5,885,657.17 | 0 | 0 | 332,321.25 |
| | 0.9 | 80.33 | 75.43 | 99.90 | 100.00 | 75.43 | 6,012,784.80 | 6 | 0 | 329,269.05 |
| | 1 | 79.62 | 74.53 | 100.00 | 100.00 | 74.53 | 6,055,775.82 | 0 | 0 | 328,236.60 |
| | | | | | | | | | | |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.7 | 0.5 | 85.34 | 82.76 | 99.97 | 100.00 | 82.75 | 5,663,890.42 | 2 | 0 | 337,633.40 |
| | 0.6 | 83.31 | 80.37 | 100.00 | 100.00 | 80.36 | 5,777,462.18 | 0 | 0 | 334,904.05 |
| | 0.7 | 81.63 | 78.39 | 100.00 | 100.00 | 78.39 | 5,871,781.86 | 0 | 0 | 332,651.50 |
| | 0.8 | 81.68 | 78.45 | 100.00 | 100.00 | 78.45 | 5,869,227.82 | 0 | 0 | 332,715.05 |
| | 0.9 | 80.43 | 76.98 | 99.97 | 100.00 | 76.98 | 5,938,946.62 | 2 | 0 | 331,037.75 |
| | 1 | 78.12 | 74.27 | 99.97 | 100.00 | 74.26 | 6,068,399.42 | 2 | 0 | 327,936.20 |
| | | | | | | | | | | |
| 0.8 | 0.5 | 84.76 | 83.08 | 99.95 | 100.00 | 83.07 | 5,648,499.37 | 3 | 0 | 338,004.10 |
| | 0.6 | 83.02 | 81.13 | 100.00 | 100.00 | 81.13 | 5,741,177.21 | 0 | 0 | 335,781.15 |
| | 0.7 | 81.07 | 78.96 | 100.00 | 100.00 | 79.00 | 5,844,611.94 | 0 | 0 | 333,347.80 |
| | 0.8 | 80.36 | 78.18 | 100.00 | 100.00 | 78.17 | 5,881,754.34 | 0 | 0 | 332,404.95 |
| | 0.9 | 78.46 | 76.06 | 100.00 | 100.00 | 76.06 | 5,982,793.50 | 0 | 0 | 329,991.20 |
| | 1 | 76.68 | 74.10 | 99.97 | 100.00 | 74.09 | 6,076,140.95 | 2 | 0 | 327,743.25 |
| | | | | | | | | | | |
| 0.9 | 0.5 | 82.62 | 81.72 | 99.93 | 100.00 | 81.71 | 5,713,162.35 | 4 | 0 | 336,441.80 |
| | 0.6 | 81.64 | 80.68 | 100.00 | 100.00 | 80.67 | 5,762,997.83 | 0 | 0 | 335,258.55 |
| | 0.7 | 79.72 | 78.70 | 100.00 | 97.65 | 78.70 | 5,857,283.09 | 0 | 2 | 333,004.50 |
| | 0.8 | 79.38 | 78.36 | 99.95 | 97.65 | 78.35 | 5,873,540.08 | 3 | 2 | 332,600.45 |
| | 0.9 | 77.13 | 75.98 | 100.00 | 97.65 | 75.98 | 5,986,879.89 | 0 | 2 | 329,897.15 |
| | 1 | 75.04 | 73.98 | 99.97 | 88.24 | 73.97 | 6,082,055.55 | 2 | 10 | 327,602.80 |
| | | | | | | | | | | |
| 1 | 0.5 | 83.06 | 83.06 | 97.11 | 83.53 | 83.07 | 5,649,288.92 | 170 | 14 | 338,003.30 |
| | 0.6 | 81.18 | 81.66 | 96.31 | 81.18 | 81.64 | 5,715,933.80 | 217 | 16 | 336,364.10 |
| | 0.7 | 80.00 | 80.34 | 92.46 | 80.00 | 80.31 | 5,779,232.37 | 444 | 17 | 334,844.45 |
| | 0.8 | 78.82 | 79.03 | 91.73 | 78.82 | 79.02 | 5,841,280.87 | 487 | 18 | 333,371.25 |
| | 0.9 | 77.36 | 77.36 | 91.00 | 77.65 | 77.36 | 5,920,829.06 | 530 | 19 | 331,479.25 |
| | 1 | 75.98 | 75.98 | 90.27 | 76.47 | 76.00 | 5,986,784.48 | 573 | 20 | 329,919.60 |

# APPENDIX D

# IBM CPLEX CODING FOR FUZZY MULTIPLE OBJECTIVE CREDIBILITY BASED CHANCE CONSTRAINED PROGRAMMING MODEL

```
/*One-demensional*/
/*********************************************/
{string} Rset = ...; //Number types of raw materials         (r=1…R)
{string} Sset = ...; //Number of suppliers                   (s=1…S)
{string} Jset = ...; //Number of customers,                  (j=1…J)
{string} Nset = ...; //Number types of product               (n=1…N)
{string} Kset = ...; //Number of worker levels               (k=1…K)
{int}    Tset = ...; //Number of periods in planning horizon (t=1…T)

/*Two-demensional*/
/*********************************************/
tuple TwoIndex{
string Index1;
string Index2;
};
{TwoIndex} SRset = ...;
{TwoIndex} NJset = ...;
{TwoIndex} RNset = ...;

/*Fuzzy Parameters*/
/*******************************************************************/
float   RTPC_o[t in Tset] = ...;
float   RTPC_m[t in Tset] = ...;
float   RTPC_p[t in Tset] = ...;

float   OTPC_o[t in Tset] = ...;
float   OTPC_m[t in Tset] = ...;
float   OTPC_p[t in Tset] = ...;

float   STPC_o[t in Tset] = ...;
float   STPC_m[t in Tset] = ...;
float   STPC_p[t in Tset] = ...;

float   RMSC_o[<s,r> in SRset, t in Tset] = ...;
float   RMSC_m[<s,r> in SRset, t in Tset] = ...;
float   RMSC_p[<s,r> in SRset, t in Tset] = ...;

float   SC_o[k in Kset, t in Tset] = ...;
float   SC_m[k in Kset, t in Tset] = ...;
float   SC_p[k in Kset, t in Tset] = ...;

float   HC_o[k in Kset, t in Tset] = ...;
float   HC_m[k in Kset, t in Tset] = ...;
float   HC_p[k in Kset, t in Tset] = ...;

float   FC_o[k in Kset, t in Tset] = ...;
float   FC_m[k in Kset, t in Tset] = ...;
```

```
float   FC_p[k in Kset, t in Tset] = ...;
float   IRMC_o[r in Rset, t in Tset] = ...;
float   IRMC_m[r in Rset, t in Tset] = ...;
float   IRMC_p[r in Rset, t in Tset] = ...;

float   IPC_o [n in Nset, t in Tset] = ...;
float   IPC_m [n in Nset, t in Tset] = ...;
float   IPC_p [n in Nset, t in Tset] = ...;

float   TRMC_o[s in Sset, t in Tset] = ...;
float   TRMC_m[s in Sset, t in Tset] = ...;
float   TRMC_p[s in Sset, t in Tset] = ...;

float   TPC_o [j in Jset, t in Tset] = ...;
float   TPC_m [j in Jset, t in Tset] = ...;
float   TPC_p [j in Jset, t in Tset] = ...;

float   PSC_o [<n,j> in NJset, t in Tset] = ...;
float   PSC_m [<n,j> in NJset, t in Tset] = ...;
float   PSC_p [<n,j> in NJset, t in Tset] = ...;

float   AFRS_o[<s,r> in SRset] = ...;
float   AFRS_m[<s,r> in SRset] = ...;
float   AFRS_p[<s,r> in SRset] = ...;

float   AFRP_o[r in Rset] = ...;
float   AFRP_m[r in Rset] = ...;
float   AFRP_p[r in Rset] = ...;

float   ASL_o [s in Sset] = ...;
float   ASL_m [s in Sset] = ...;
float   ASL_p [s in Sset] = ...;

float   ASLP_o = ...;
float   ASLP_m = ...;
float   ASLP_p = ...;

float   D_o [<n,j> in NJset, t in Tset] = ...;
float   D_m [<n,j> in NJset, t in Tset] = ...;
float   D_p [<n,j> in NJset, t in Tset] = ...;

/*Deterministic Parameters*/
/*******************************************************************/
float   MaxPS[n in Nset, t in Tset] = ...;
float   MaxMA[n in Nset, t in Tset] = ...;
float   MaxWSA[t in Tset] = ...;
float   MaxRS[<s,r> in SRset, t in Tset] = ...;
float   MHU[n in Nset, t in Tset] = ...;
float   WSP[n in Nset, t in Tset] = ...;
float   WSRM[r in Rset, t in Tset] = ...;
float   NoRM [<r,n> in RNset] = ...;
float   NoL_0[k in Kset] = ...;
float   RTPA[t in Tset] = ...;
float   OTPA[t in Tset] = ...;
float   STPA[t in Tset] = ...;
float   PTP[n in Nset] = ...;
float   SCRM = ...;
float   SCP  = ...;
```

```
float   Prod[k in Kset] = ...;
float   FWV  = ...;
float   TSSQ[s in Sset] = ...;
int     IP_0 [n in Nset] = ...;
int     IRM_0[r in Rset] = ...;

float   Z1NIS = ...; //NIS of objecive function Z1
float   Z2NIS = ...; //NIS of objecive function Z2
float   Z3NIS = ...; //NIS of objecive function Z2
float   Z4NIS = ...; //NIS of objecive function Z4

float   Z1PIS = ...; //PIS of objecive function Z1
float   Z2PIS = ...; //PIS of objecive function Z2
float   Z3PIS = ...; //PIS of objecive function Z3
float   Z4PIS = ...; //PIS of objecive function Z4

float   W1 = ...; //Weighted additive importance for Z1
float   W2 = ...; //Weighted additive importance for Z2
float   W3 = ...; //Weighted additive importance for Z3
float   W4 = ...; //Weighted additive importance for Z4

float   Alpha = ...; //Acceptable feasible degree
float   Gamma = ...; //Coefficient compensation

/*Decision Variables*/
/*****************************************************************/
dvar int+ QRTP[n in Nset, t in Tset];
dvar int+ QOTP[n in Nset, t in Tset];
dvar int+ QSTP[n in Nset, t in Tset];
dvar int+ QRMS[<s,r> in SRset, t in Tset];
dvar int+ QPSC[<n,j> in NJset, t in Tset];
dvar int+ QW [k in Kset, t in Tset];
dvar int+ QWH[k in Kset, t in Tset];
dvar int+ QWF[k in Kset, t in Tset];
dvar int+ IP [n in Nset, t in Tset];
dvar int+ IRM[r in Rset, t in Tset];
dvar int+ QSP[<n,j> in NJset, t in Tset];
dvar float+ U;
dvar float+ Z1; //TotalCostSC

/*Objective Functions*/
/*Credibility-Based Fuzzy Chance-Constrained*/
/*****************************************************************/
dexpr float ProductionCost_CFCCP=sum(n in Nset, t in
Tset)PTP[n]*((((2-2*Alpha)*RTPC_m[t])+((2*Alpha-
1)*RTPC_p[t]))*QRTP[n,t])+sum(n in Nset, t in Tset)PTP[n]*((((2-
2*Alpha)*OTPC_m[t])+((2*Alpha-1)*OTPC_p[t]))*QOTP[n,t])+sum(n in
Nset, t in Tset)PTP[n]*((((2-2*Alpha)*STPC_m[t])+((2*Alpha-
1)*STPC_p[t]))*QSTP[n,t]);

dexpr float PurchasingCost_CFCCP=sum(<s,r> in SRset, t in Tset)(((2-
2*Alpha)*RMSC_m[<s,r>,t])+((2*Alpha-
1)*RMSC_p[<s,r>,t]))*QRMS[<s,r>,t];

dexpr float LaborWage_CFCCP=sum(k in Kset, t in Tset)10*(((2-
2*Alpha)*SC_m[k,t])+((2*Alpha-1)*SC_p[k,t]))*QW[k,t];
```

```
dexpr float FiringCost_CFCCP=sum(k in Kset, t in Tset)10*(((2-
2*Alpha)*FC_m[k,t])+((2*Alpha-1)*FC_p[k,t]))*QWF[k,t];
dexpr float HiringCost_CFCCP=sum(k in Kset, t in Tset)10*(((2-
2*Alpha)*HC_m[k,t])+((2*Alpha-1)*HC_p[k,t]))*QWH[k,t];

dexpr float HoldingCostRM_CFCCP=sum(r in Rset, t in Tset)(((2-
2*Alpha)*IRMC_m[r,t])+((2*Alpha-1)*IRMC_p[r,t]))*IRM[r,t];

dexpr float InventoryFinalProduct_CFCCP=sum(n in Nset, t in
Tset)(((2-2*Alpha)*IPC_m[n,t])+((2*Alpha-1)*IPC_p[n,t]))*IP[n,t];

dexpr float TransportationCostRM_CFCCP=sum(<s,r> in SRset, t in Tset)
(((2-2*Alpha)*TRMC_m[s,t])+((2*Alpha-1)*TRMC_p[s,t]))*QRMS[<s,r>,t];

dexpr float TransportationCostFP_CFCCP=sum(<n,j> in NJset, t in Tset)
(((2-2*Alpha)*TPC_m[j,t])+((2*Alpha-1)*TPC_p[j,t]))*QPSC[<n,j>,t];

dexpr float ShortageCost_CFCCP=sum(<n,j> in NJset, t in Tset)(((2-
2*Alpha)*PSC_m[<n,j>,t])+((2*Alpha-1)*PSC_p[<n,j>,t]))*QSP[<n,j>,t];

dexpr float TotalCostSC_CFCCP=ProductionCost_CFCCP
                             +PurchasingCost_
                             +LaborWage_CFCCP
                             +FiringCost_CFCCP
                             +HiringCost_CFCCP
                             +HoldingCostRM_CFCCP
                             +InventoryFinalProduct_CFCCP
                             +TransportationCostRM_CFCCP
                             +TransportationCostFP_CFCCP
                             +ShortageCost_CFCCP;
/*********************************************************************/
/*Shortage of product*/
dexpr float ShortageProduct=sum(<n,j> in NJset, t in
Tset)QSP[<n,j>,t];
dexpr float Z2 = ShortageProduct;

/*Rate of changes in the workforce level*/
dexpr float RateChangeWorkforce=sum(k in Kset, t in
Tset)(QWH[k,t]+QWF[k,t]);
dexpr float Z3 = RateChangeWorkforce;

/*Total value of purchasing*/
dexpr float TotalValuePurchasing=sum(s in Sset)TSSQ[s]*sum(r in Rset,
t in Tset)QRMS[<s,r>,t];
dexpr float Z4 = TotalValuePurchasing;

//Membership function
dexpr float U_Z1 = (Z1NIS-Z1)/(Z1NIS-Z1PIS);
dexpr float U_Z2 = (Z2NIS-Z2)/(Z2NIS-Z2PIS);
dexpr float U_Z3 = (Z3NIS-Z3)/(Z3NIS-Z3PIS);
dexpr float U_Z4 = (Z4-Z4NIS)/(Z4PIS-Z4NIS);

dexpr float satisfaction=Gamma*U+((1-
Gamma)*(W1*U_Z1+W2*U_Z2+W3*U_Z3+W4*U_Z4));

//Objective function (satisfaction)
maximize satisfaction;
```

```
/*Constraint*/
/*******************************************************************/
subject to {
Z1 >= TotalCostSC_CFCCP;

/*Constraint (5): final product inventory*/
forall(n in Nset, t in
Tset:t==1)IP[n,t]==IP_0[n]+QRTP[n,t]+QOTP[n,t]+QSTP[n,t]-sum(j in
Jset:<n,j> in NJset)QPSC[<n,j>,t];

forall(n in Nset, t in Tset: t>1)IP[n,t]==IP[n,t-
1]+QRTP[n,t]+QOTP[n,t]+QSTP[n,t]-sum(j in Jset:<n,j> in
NJset)QPSC[<n,j>,t];

/*******************************************************************/
/*Constraint (6): raw materials inventory*/
forall(r in Rset, t in Tset:t==1)IRM[r,t]==IRM_0[r]+sum(s in
Sset:<s,r> in SRset)QRMS[<s,r>,t]-sum(n in Nset:<r,n> in
RNset)(QRTP[n,t]+QOTP[n,t]+QSTP[n,t])*NoRM[<r,n>];

forall(r in Rset, t in Tset:t>1)IRM[r,t]==IRM[r,t-1]+sum(s in
Sset:<s,r> in SRset)QRMS[<s,r>,t]-sum(n in Nset:<r,n> in
RNset)(QRTP[n,t]+QOTP[n,t]+QSTP[n,t])*NoRM[<r,n>];

/*Constraint (7): initial workforce*/
forall(k in Kset, t in Tset:t==1)QW[k,t]==NoL_0[k];

/*Constraint (8): the workforce level*/
forall(k in Kset, t in Tset: t>1)QW[k,t]==QW[k,t-1]+QWH[k,t]-
QWF[k,t];

/*Constraint (9): available production time*/
forall(t in Tset)sum(k in
Kset)QW[k,t]*Prod[k]*(RTPA[t]+OTPA[t])>=(1/60)*sum(n in
Nset)(QRTP[n,t] + QOTP[n,t])*PTP[n];

/*Constraint (10): available time for the subcontractor */
forall(t in Tset)(1/60)*sum(n in Nset)QSTP[n,t]*PTP[n]<=STPA[t];

/*Constraint (11): maximum allowable of the subcontracting*/
forall(n in Nset, t in Tset)QSTP[n,t]<=MaxPS[n,t];

/*Constraint (12): the machine capacity*/
forall(n in Nset, t in
Tset)MHU[n,t]*(QRTP[n,t]+QOTP[n,t])<=MaxMA[n,t];

/*Credibility based chance constrained*/
/*******************************************************************/
/*Constraint (13): shortage in demand*/
forall(<n,j> in NJset, t in Tset:t==1)QSP[<n,j>,t]==round((2-
2*Alpha)*D_m[<n,j>,t]+(2*Alpha-1)*D_p[<n,j>,t])-QPSC[<n,j>,t];
forall(<n,j> in NJset, t in Tset: t>1)QSP[<n,j>,t]==QSP[<n,j>,t-
1]+round((2-2*Alpha)*D_m[<n,j>,t]+(2*Alpha-1)*D_p[<n,j>,t])-
QPSC[<n,j>,t];

forall(<n,j> in NJset, t in Tset)QSP[<n,j>,t]<=0.3*round((2-
2*Alpha)*D_m[<n,j>,t]+(2*Alpha-1)*D_p[<n,j>,t]);
/*******************************************************************/
```

```
/*Constraint (14): warehouse space*/
forall(t in Tset)sum(n in Nset:n in Nset)WSP[n,t]*IP[n,t]+sum(r in 
Rset)WSRM[r,t]*IRM[r,t]<=MaxWSA[t];

/*Constraint (15): raw materials inventory storage capacity*/
forall(t in Tset)sum(r in Rset)IRM[r,t]<=SCRM;

/*Constraint (16): final product inventory storage capacity*/
forall(t in Tset)sum(n in Nset)IP[n,t]<=SCP;

/*Constraint (17): the proportion of workforces*/
forall(t in Tset:t==1)sum(k in Kset)(QWH[k,t]+QWF[k,t])<=FWV*sum(k in 
Kset)QW[k,t];

forall(t in Tset:t >1)sum(k in Kset)(QWH[k,t]+QWF[k,t])<=FWV*sum(k in 
Kset)QW[k,t-1];

/*Constraint (18): supplier capacity*/
forall(<s,r> in SRset, t in Tset)QRMS[<s,r>,t]<=MaxRS[<s,r>,t];

/*Constraint (19): raw materials flow*/
forall(r in Rset, t in Tset)sum(n in 
Nset)NoRM[<r,n>]*(QRTP[n,t]+QOTP[n,t]+QSTP[n,t])<=sum(s in 
Sset)QRMS[<s,r>,t];

/*Credibility based chance constrained
/*****************************************************************/
/*Constraint (20): the minimum acceptable levels of raw materials 
quality provided by each supplier*/
forall(r in Rset, t in Tset)sum(s in Sset)(((2-
2*Alpha)*AFRS_m[<s,r>])+((2*Alpha-
1)*AFRS_p[<s,r>]))*QRMS[<s,r>,t]<=(((2*Alpha-1)*AFRP_o[r])+((2-
2*Alpha)*AFRP_m[r]))*sum(s in Sset)QRMS[<s,r>,t];

/*Constraint (21): the minimum acceptable levels of on time delivery 
of each supplier*/
forall(t in Tset)sum(<s,r> in SRset)(((2*Alpha-1)*ASL_o[s])+((2-
2*Alpha)*ASL_m[s]))*QRMS[<s,r>,t]>=(((2-2*Alpha)*ASLP_m)+((2*Alpha-
1)*ASLP_p))*sum(<s,r> in SRset)QRMS[<s,r>,t];
/*****************************************************************/

/*Ranking constraint*/
//Case 1
U_Z1 >= (W1/W2)*U_Z2;
U_Z2 >= (W2/W3)*U_Z3;
U_Z3 >= (W3/W4)*U_Z4;
//Case 2
U_Z1 >= (W1/W2)*U_Z2;
U_Z2 >= (W2/W4)*U_Z4;
U_Z4 >= (W4/W3)*U_Z3;
//Case 3
U_Z1 >= (W1/W3)*U_Z3;
U_Z3 >= (W3/W2)*U_Z2;
U_Z2 >= (W2/W4)*U_Z4;
//Case 4
U_Z1 >= (W1/W3)*U_Z3;
U_Z3 >= (W3/W4)*U_Z4;
U_Z4 >= (W4/W2)*U_Z2;
```

```
//Case 5
U_Z1 >= (W1/W4)*U_Z4;
U_Z4 >= (W4/W2)*U_Z2;
U_Z2 >= (W2/W3)*U_Z3;
//Case 6
U_Z1 >= (W1/W4)*U_Z4;
U_Z4 >= (W4/W3)*U_Z3;
U_Z3 >= (W3/W2)*U_Z2;
//Case 7
U_Z2 >= (W2/W1)*U_Z1;
U_Z1 >= (W1/W3)*U_Z3;
U_Z3 >= (W3/W4)*U_Z4;
//Case 8
U_Z2 >= (W2/W1)*U_Z1;
U_Z1 >= (W1/W4)*U_Z4;
U_Z4 >= (W4/W3)*U_Z3;
//Case 9
U_Z2 >= (W2/W3)*U_Z3;
U_Z3 >= (W3/W1)*U_Z1;
U_Z1 >= (W1/W4)*U_Z4;
//Case 10
U_Z2 >= (W2/W3)*U_Z3;
U_Z3 >= (W3/W4)*U_Z4;
U_Z4 >= (W4/W1)*U_Z1;
//Case 11
U_Z2 >= (W2/W4)*U_Z4;
U_Z4 >= (W4/W1)*U_Z1;
U_Z1 >= (W1/W3)*U_Z3;
//Case 12
U_Z2 >= (W2/W4)*U_Z4;
U_Z4 >= (W4/W3)*U_Z3;
U_Z3 >= (W3/W1)*U_Z1;
//Case 13
U_Z3 >= (W3/W1)*U_Z1;
U_Z1 >= (W1/W2)*U_Z2;
U_Z2 >= (W2/W4)*U_Z4;
//Case 14
U_Z3 >= (W3/W1)*U_Z1;
U_Z1 >= (W1/W4)*U_Z4;
U_Z4 >= (W4/W2)*U_Z2;
//Case 15
U_Z3 >= (W3/W2)*U_Z2;
U_Z2 >= (W2/W1)*U_Z1;
U_Z1 >= (W1/W4)*U_Z4;
//Case 16
U_Z3 >= (W3/W2)*U_Z2;
U_Z2 >= (W2/W4)*U_Z4;
U_Z4 >= (W4/W1)*U_Z1;
//Case 17
U_Z3 >= (W3/W4)*U_Z4;
U_Z4 >= (W4/W1)*U_Z1;
U_Z1 >= (W1/W2)*U_Z2;
//Case 18
U_Z3 >= (W3/W4)*U_Z4;
U_Z4 >= (W4/W2)*U_Z2;
U_Z2 >= (W2/W1)*U_Z1;
```

```
//Case 19
U_Z4 >= (W4/W1)*U_Z1;
U_Z1 >= (W1/W2)*U_Z2;
U_Z2 >= (W2/W3)*U_Z3;
//Case 20
U_Z4 >= (W4/W1)*U_Z1;
U_Z1 >= (W1/W3)*U_Z3;
U_Z3 >= (W3/W2)*U_Z2;
//Case 21
U_Z4 >= (W4/W2)*U_Z2;
U_Z2 >= (W2/W1)*U_Z1;
U_Z1 >= (W1/W3)*U_Z3;
//Case 22
U_Z4 >= (W4/W2)*U_Z2;
U_Z2 >= (W2/W3)*U_Z3;
U_Z3 >= (W3/W1)*U_Z1;
//Case 23
U_Z4 >= (W4/W3)*U_Z3;
U_Z3 >= (W3/W1)*U_Z1;
U_Z1 >= (W1/W2)*U_Z2;
//Case 24
U_Z4 >= (W4/W3)*U_Z3;
U_Z3 >= (W3/W2)*U_Z2;
U_Z2 >= (W2/W1)*U_Z1;

/*Satisfaction*/
U <= U_Z1;
U <= U_Z2;
U <= U_Z3;
U <= U_Z4;

0 <= U <= 1;
0 <= U_Z1 <= 1;
0 <= U_Z2 <= 1;
0 <= U_Z3 <= 1;
0 <= U_Z4 <= 1;
}
```

# BIOGRAPHY

| | |
|---|---|
| Name | Mr. Doan Hoang Tuan |
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Publications

Doan, T., & Chiadamrong, N., (2020). Solving an aggregate production planning problem by using interactive fuzzy linear programming. *Asia-Pacific Journal of Science and Technology (APST). 26*(1). Article ID: APST-26-01-05.

Doan, T., & Chiadamrong, N., (Submitted). A Fuzzy Credibility-based Chance-constrained Optimization Model for Multiple-Objective Aggregate Production Planning in a Supply Chain under an Uncertain Environment. *Engineering Journal (EJ).*