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Article

A Fuzzy Credibility-Based Chance-Constrained Optimization Model for Multiple-Objective Aggregate Production Planning in a Supply Chain under an Uncertain Environment

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Abstract. In this study, a Multiple-Objective Aggregate Production Planning (MOAPP) problem in a supply chain under an uncertain environment is developed. The proposed model considers simultaneously four different conflicting objective functions. To solve the proposed Fuzzy Multiple-Objective Mixed Integer Linear Programming (FMOMILP) model, a hybrid approach has been developed by combining Fuzzy Credibility-based Chance-constrained Programming (FCCP) and Fuzzy Multiple-Objective Programming (FMOP). The FCCP can provide a credibility measure that indicates how much confidence the decision-makers may have in the obtained optimal solutions. In addition, the FMOP, which integrates an aggregation function and a weight-consistent constraint, is capable of handling many issues in making decisions under multiple objectives. The consistency of the ranking of objective's important weight and satisfaction level is ensured by the weight-consistent constraint. Various compromised solutions, including balanced and unbalanced ones, can be found by using the aggregation function. This methodology offers the decision makers different alternatives to evaluate against conflicting objectives. A case experiment is then given to demonstrate the validity and effectiveness of the proposed formulation model and solution approach. The obtained outcomes can assist to satisfy the decision-makers' aspiration, as well as provide more alternative strategy selections based on their preferences.

Keywords: Aggregate production planning, supply chain, credibility, chance-constrained modelling, fuzzy multiple-objective optimization, weight-consistent solution.

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1. Introduction

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 [1].

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 [2, 3].

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 [4]. Therefore, it is necessary to address these two problems when designing and operating a supply chain.

The main contribution of this study is to address the two main issues. Firstly, a multiple-objective model for APP in an SC under uncertainty including multiple suppliers, a production plant, and multi-customers that integrate the plan of procurement, production, and distribution is addressed. Secondly, a hybrid approach that integrates the defuzzification method (Credibility-based Fuzzy Chance-constrained Programming (CFCCP) and Fuzzy Multiple-Objective Programming (FMOP) is proposed. This can help decision-makers to cope with the fuzziness of data under a multiple-objective problem. Fuzzy chance-constrained programming 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. To the best of the authors' knowledge, so far, there has been little research using CFCCP as the optimization method in production planning problems. With fuzzy multiple-objective programming, some approaches have been researched and applied, but one of the common approaches is fuzzy programming with several objective functions that was proposed by Zimmermann [5]. 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 is not suitable for making decisions for multiple objectives in a practical environment. Being aware of a deficiency in the above problem, Tiwari et al. [6] 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 [7], Li et al. [8], Selim and Ozkarahan [9], and Torabi and Hassini [10], 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. Considering this matter, a weight-consistent constraint is further proposed in this study to add to the fuzzy multiple-objective programming. This ensures that the obtained solution can be more consistent with DM expectations.

The remainder of this paper is arranged as follows: A review of the related literature is presented in Section 2. The description, assumption, notation, and mathematical formulation of the APP problem in an SC are described in Sections 3 and 4. The proposed methodology for solving the multiple-objective APP model in an SC under uncertainty is developed in Section 5. Then, an illustration of a case experiment is shown in Section 6. Subsequently, the results of the proposed mathematical model are provided in Section 7. Finally, the conclusions and directions for further work are presented in Section 8.

2. Literature Review

According to the content of our research in this paper, the literature review can be divided into two parts. The first part focuses on the relevant studies, which define the structure of the APP model. The second part attempts to review past research that is related to the application of the single-objective and multiple-objective optimizations under uncertainty.

2.1. Aggregate Production Planning (APP) Models

An Aggregate Production Planning (APP) problem is an intermediate-time capacity plan that identifies the cost minimization of the production plan and the human resources to fulfill market needs in the most effective way. Its purpose is to determine a suitable quantity of production and the inventory level in a term of aggregation. The time-period range of APP is from 2 to 12 (or even 18 months) [11]. APP brings a connection between strategic and operations management. Besides, APP operating strategies play a significant role in organizational integration and enterprise resource planning. The target of making APP in a manufacturing enterprise is to acquire the minimum cost or the maximum profit by determining the quantity of produced products, the quantity of subcontracting products, the levels of labor, etc., to fulfill the market demand [12].

Based on the uncertainty level in the APP model, the APP model can be categorized into two different groups. The input data are used in the APP model could change from a deterministic value to a fuzzy value, or a stochastic value. There is another significant criterion that can also impact the structure of the APP model. This criterion 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: deterministic models with a single objective, deterministic models with multiple objectives, fuzzy models with a single objective, fuzzy models with multiple objectives, stochastic models with a single objective, and stochastic models with multiple objectives [13].

2.1.1. Number of Objective Functions

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 et al. [14] 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 et al. [15] 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 [16] 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).

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 [1, 17]. 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 [18] 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 et al. [19] 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 et al. [20] 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.

2.1.2. Type of Data

As mentioned earlier, 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 et al. [21] 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 [22-24].

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. [25]. 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 [26, 27].

Stochastic data are uncertain data that can be described by the theory of randomness and probability. The stochastic model and its method are restricted to tackling uncertainties with probability distributions [28]. Besides, its method requires a large amount of collected historical data, which is hard to obtain for an APP problem. Lai and Hwang [29] argued that the application of stochastic models can lead to a lack of computational efficiency. The theory of probability could not provide the correct means for solving several decision-making problems in practice. Most stochastic data are used in simulation-based optimization problems as these data can be modeled and captured by the simulation processor. Therefore, the stochastic model and its method are not mentioned in this study since the main optimization algorithm of this study is focused on the mathematical or analytical optimization model.

2.1.3. 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 [30]. 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 DMs 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 et al. [13]. 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 under Uncertainty

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 [26] 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 [27] 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 [25] 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 [31] 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.

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 et al. [32] 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 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 [33] 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. Chen and Huang [34] 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.

Credibility-based Fuzzy Chance-constrained Programming (CFCP) is known as a fuzzy optimization approach that is based on the credibility measure of fuzzy numbers in the theory of fuzzy sets (as the average of possibility and necessity measures). This method is used to ensure that the satisfaction of the fuzzy objectives and fuzzy constraints can be solved at a minimum allowed confidence level [35]. Currently, CFCP has been applied to solve some uncertain problems in a practical environment. Zhu and Zhang [36] 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 et al. [37] studied an APP model with uncertain information in the realistic conditions of a manufacturing company. To solve the proposed fuzzy APP model, a fuzzy chance-constrained programming model 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. Zhang et al. [38] presented a comprehensive credibility-based chance-constrained programming approach by applying the concept of credibility theory to the fuzzy mathematical optimization model. The proposed approach can cope with the imprecise parameters in the right-hand side and the left-hand-side of fuzzy constraints. It also yields a level of credibility that represents how much confidence the DMs are able to trust the obtained solution.

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 et al. [39] 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 [40] 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 [41] 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.

Fuzzy Goal Programming (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 [42] 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 [43] 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. Mosadegh et al. [44] 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 et al. [45] 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.

Taking into 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-importance weight of its goal. In other words, the ranking of achieved satisfaction levels for a fuzzy goal must be the same as the ranking of the goal's weight. For instance, it is assumed that the goal's weights (θ_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 has the ranking of the achieved satisfaction levels of goals (μ_h) as follows: $\mu_1 \geq \mu_2 \geq \mu_3 \geq \mu_4$. Generally, if a goal is assigned with a high-importance weight, that means the DMs want to obtain a high satisfaction level for that goal, and otherwise.

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

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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, we propose a hybrid approach that integrates Fuzzy Chance-constrained Programming (FCCP) and Fuzzy Multiple-Objective Programming (FMOP) 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 FMOP, we apply an aggregation function and integrate for the 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 1.

3. 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:

Our 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 Fig. 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.

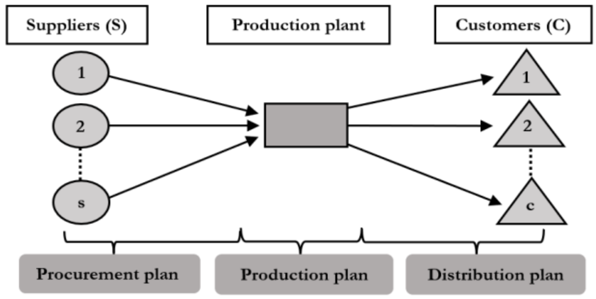

Fig. 1. Structure of a supply chain network.

3.1. 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 production plant produces many types of products to meet customer demand during the planning horizon.
- A set of qualified suppliers is given.
- 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.

3.2. Problem Notation

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

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Table 1. Summary of the literature on APP problems.

Articles	No. objectives	Type of data	Chance constraint	Important issues in APP						Consistent solution	Mathematical Modeling	Solution approaches
				Multiple Products	Product characteristics	Labor characteristics	Supply Chain concept	Multiple period planning	Satisfaction of solution			
Chiadamrong and Sutthibutr [2]	Single	F	–	✓	–	–	–	✓	✓	–	MILP	PLP
Techawiboonwong and Yenradee [11]	Single	D	–	✓	–	–	–	✓	–	–	MILP	LDR
Iris and Cevikcan [12]	Single	F	–	✓	–	–	–	✓	–	–	FMILP	ParP
Sillekens et al. [14]	Single	D	–	✓	–	✓	–	✓	–	–	MILP	H
Zhang et al. [15]	Single	D	–	✓	–	✓	–	✓	–	–	MILP	H
Wang and Yeh [16]	Single	D	–	–	–	✓	–	✓	–	–	MILP	PSO
Da Silva and Marins [18]	Multiple	D	–	✓	✓	–	S-P	✓	–	–	MOMILP	SS
Entezaminia et al. [19]	Multiple	D	–	✓	–	–	S-P-C-Co-R	✓	–	–	MOMILP	SS
Mehdizadeh et al. [20]	Multiple	D	–	✓	–	–	–	✓	–	–	MOMILP	GA
Paiva and Morabito [22]	Single	D	–	✓	✓	–	S-P	✓	–	–	MILP	SS
Chaturvedi and Bandyopadhyay [23]	Single	D	–	–	–	–	–	–	–	–	MILP	H
Tang et al. [32]	Single	F	–	✓	–	–	–	✓	✓	–	FMILP	FLP
Wang and Fang [33]	Multiple	F	–	✓	–	–	–	✓	✓	–	FMOMILP	FLP
Chen and Huang [34]	Single	F	–	✓	–	–	–	✓	–	–	FMILP	ParP
Zhu and Zhang [36]	Single	F	✓	✓	–	–	–	✓	–	–	FMILP	FCCP
Zhang et al. [37]	Single	F	✓	✓	–	–	–	✓	–	–	FMILP	FCCP
Leung et al. [39]	Multiple	D	–	✓	–	–	–	✓	✓	–	MOMILP	GP
Leung and Ng [40]	Multiple	D	–	✓	✓	–	–	✓	–	–	MOMILP	GP
Leung and Chan [41]	Multiple	D	–	✓	–	–	–	✓	–	–	MOMILP	GP
Jamalnia and Soukhakian [42]	Multiple	F	–	✓	–	–	–	✓	✓	–	FMONILP	FLP+GA
Liang and Cheng [43]	Multiple	F	–	✓	–	–	–	✓	✓	–	FMOMILP	FGP
Mosadegh et al. [44]	Multiple	F	–	✓	–	–	–	✓	✓	–	FMOMILP	FGP
Chauhan et al. [45]	Multiple	F	–	✓	✓	–	S-P-C	✓	✓	–	FMOMILP	FLP
This study	Multiple	F	✓	✓	✓	✓	S-P-C	✓	✓	✓	FMOMILP	FCCP+FGP

Notes: D: Deterministic, F: Fuzzy, S: Supplier, P: Production plant, C: Customer, Co: Collection center, R: Recycling center, MILP: Mixed-integer linear programming, FMILP: Fuzzy mixed-integer linear programming, MOMILP: Multiple-objective mixed-integer linear programming, FMOMILP: Fuzzy multiple-objective mixed-integer linear programming, FMONILP: Fuzzy multiple-objective mixed-integer non-linear programming, PLP: Possibilistic 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-constrained programming.

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Set of Indices:

R Index of raw materials $\{r = 1,\dots,R\}$
S Index of suppliers $\{s = 1,\dots,S\}$
J Index of customers $\{j = 1,\dots,J\}$
N Index of finished products $\{n = 1,\dots,N\}$
K Index of worker levels $\{k = 1,\dots,K\}$
T Index of periods in planning horizon $\{t = 1,\dots,T\}$

Fuzzy Parameters:

$\widetilde{RTPC}_t$ 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)
$\widetilde{STPC}_t$ Fuzzy subcontracting production unit cost at the production plant in period t (\$/min)
$\widetilde{RMSC}_{srt}$ Fuzzy purchasing unit cost of supplier s for raw material r in period t (\$/unit)
$\widetilde{SC}_{kt}$ 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)
$\widetilde{IRMC}_{rt}$ 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)
$\widetilde{TRMC}_{st}$ 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)
$\widetilde{PSC}_{njt}$ Fuzzy penalty unit cost of shortage of product n for customer j in period t (\$/unit)
$\widetilde{AFRS}_{sr}$ 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 finished 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 a unit of product n (units)
$NoL^0{}_k$ 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)
$Prod_k$ Worker's productivity at level k $(0 < Prod < 1)$
FWV Acceptable fraction of workforce variation (%)
$TSSQ_s$ Total score of supplier s by considering the 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 at the end of period t (units)
QSP_{njt} Shortage of product n for customer j in period t (units)

4. Problem Formulation

The FMOMILP model for the APP problem in a SC is formulated below.

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.

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:

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

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

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

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:

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

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

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

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:

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

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

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

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

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

Minimizing the shortages of product to improve the customer's 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:

$$Min\ CS = \textstyle\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} QSP_{njt} \tag{2}$$

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 Eq. (2).

Minimizing the rate of change 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:

$$Min\ RCW = \sum_{t}^{K}\sum_{t=1}^{T}(QWH_{kt} + QWF_{kt}) \quad (3)$$

Equation (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.

Maximizing the total value of purchasing (Z_4):
The fourth objective function shown in Eq. (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:

$$Max\ TVP = \sum_{s=1}^{S} TSSQ_s \times \sum_{r=1}^{R}\sum_{t=1}^{T} QRMS_{srt} \quad (4)$$

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 Analytic Hierarchy Process (AHP) is an efficient approach that can help the DMs to calculate the appropriate score (weight) of each supplier [46, 47].

4.2. Constraints

Constraint on finished product inventory:

$$IP_{nt} = IP_{n(t-1)} + QRTP_{nt} + QOTP_{nt} + QSTP_{nt} - \sum_{j=1}^{J} QPSC_{njt}\ ;\ \forall\, n,t \quad (5)$$

Equation (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:

$$IRM_{rt} = IRM_{r(t-1)} + \sum_{s=1}^{S} QRMS_{srt} - \sum_{n=1}^{N}(QRTP_{nt} + QOTP_{nt} + QSTP_{nt}) \times NoRM_{rn};\ \forall\, r,t \quad (6)$$

Equation (6) presents the balance of the raw material inventory at the production plants. This constraint shows that the inventory quantity of raw materials in period t is equal to the inventory quantity 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:

$$QW_{kt} = NoL^{0}{}_{k};\qquad \forall\, k, t < 2 \quad (7)$$

Equation (7) corresponds to one of assumptions that assigns the initial workforce level to the first period of planning $(t-2)$.

Constraint on balancing the workforce level:

$$QW_{kt} = QW_{k(t-1)} + QWH_{kt} - QWF_{kt};\ \forall\, k, t > 1 \quad (8)$$

Equation (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 the available production time due to the limited workforce:

$$\sum_{k=1}^{K} QW_{kt} \times Prod_k \times (RTPA_t + OTPA_t) \geq \sum_{n=1}^{N}(QRTP_{nt} + QOTP_{nt}) \times PTP_n;\ \forall\, t \quad (9)$$

Constraint (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:

$$\sum_{n=1}^{N} QSTP_{nt} \times PTP_n \leq STPA_t;\qquad \forall\, t \quad (10)$$

Equation (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:

$$QSTP_{nt} \leq MaxPS_{nt};\qquad \forall\, n,t \quad (11)$$

Equation (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:

$$MHU_{nt} \times (QRTP_{nt} + QOTP_{nt}) \leq MaxMA_{nt};\ \forall\, n,t \quad (12)$$

Equation (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:

$$QSP_{njt} = QSP_{nj(t-1)} + \widetilde{D}_{njt} - QPSC_{njt}; \quad \forall\, n, j, t \quad (13)$$

Equation (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:

$$\sum_{n=1}^{N}(WSP_{nt} \times IP_{nt}) + \sum_{r=1}^{R}(WSRM_{rt} \times IRM_{rt}) \leq MaxWSA_t; \quad \forall\, t \quad (14)$$

Equation (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:

$$\sum_{r=1}^{R} IRM_{rt} \leq SCRM; \quad \forall\, t \quad (15)$$

Constraint on limiting the storage capacity of the final products:

$$\sum_{n=1}^{N} IP_{nt} \leq SCP; \quad \forall\, t \quad (16)$$

Equations (15) and (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 ratio of worker in each period:

$$\sum_{k=1}^{K}(QWH_{kt} + QWF_{kt}) \leq FWV \times \sum_{k=1}^{K} QW_{k(t-1)}; \quad \forall\, t \quad (17)$$

Equation (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:

$$QRMS_{srt} \leq MaxRS_{srt}; \quad \forall\, s, r, t \quad (18)$$

Equation (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 plant:

$$\sum_{n=1}^{N} NoRM_{rn} \times (QRTP_{nt} + QOTP_{nt} + QSTP_{nt}) \leq \sum_{s=1}^{S} QRMS_{srt}; \quad \forall\, r, t \quad (19)$$

Equation (19) displays the flow balances of raw materials from the suppliers to the production plant.

Constraint on the quality of raw materials:

$$\sum_{s=1}^{S} \widehat{AFRS}_{sr} \times QRMS_{srt} \leq \widehat{AFRP}_r \times \sum_{s=1}^{S} QRMS_{srt}; \quad \forall\, r, t \quad (20)$$

Constraint on service level (on-time delivery):

$$\sum_{r=1}^{R}\sum_{s=1}^{S} \widehat{ASL}_s \times QRMS_{srt} \geq \widehat{ASLP} \times \sum_{r=1}^{R}\sum_{s=1}^{S} QRMS_{srt}; \quad \forall\, t \quad (21)$$

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 Eq.s (20) and (21).

Constraints on non-negativity of decision variables:

$$\begin{aligned}
&QW_{kt}, QWH_{kt}, QWF_{kt} \geq 0 \;\&\; interger; \;\forall k, t \\
&QRTP_{nt}, QOTP_{nt}, QSTP_{nt} \geq 0; \;\forall n, t \\
&QRMS_{srt} \geq 0; \;\forall s, r, t \\
&QPSC_{njt} \geq 0; \;\forall n, j, t \\
&IRM_{rt} \geq 0; \;\forall r, t\text{: } IP_{nt} \geq 0; \;\forall n, t \\
&QSP_{njt} \geq 0; \;\forall n, j, t
\end{aligned} \quad (22)$$

Constraint (22) shows that most of the decision variables are non-negative, and some of them are non-negative and integer.

5. Solution Methodology

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) [48]. 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 section, an appropriate hybrid solution approach for solving the Fuzzy Multi-Objective Mixed-Integer Linear Programming (FMOMILP) model (as explained in Section 4) 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.

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5.1. First Phase: Transforming the FMOMILP Model into the Equivalent Crisp Model Based on FCCP with Credibility Measure

5.1.1. Credibility-Based Fuzzy Chance-constrained Programming (CFCCP)

CFCCP is an efficient fuzzy mathematical programming approach based on the credibility measure of fuzzy numbers [49, 50]. 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 [35]. 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.

5.1.1.1. Credibility Fundamentals

The theory of fuzzy sets was introduced by Zadeh [26]. 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 [51]. 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 [52].

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

$$Pos\{\xi \le R\} = \sup_{u \le R} \mu(u) \tag{23}$$

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

$$Nec\{\xi \le R\} = 1 - Pos\{\xi \le R\} = 1 - \sup_{u > R} \mu(u) \tag{24}$$

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

$$Cr\{\xi \le R\} = \frac{1}{2}(Pos\{\xi \le R\} = 1 + Nec\{\xi \le R\}) \tag{25}$$

Let the fuzzy variable ξ be fully determined by the triplet $(\underline{a},\ a,\ \overline{a})$ of crisp numbers with $(\underline{a} \le a \le \overline{a})$ (Fig. 2.a), whose membership function is presented as follows:

$$\mu(R) = \begin{cases} \dfrac{R-\underline{a}}{a-\underline{a}} & \text{if } \underline{a} \le R < a \\ \dfrac{R-\overline{a}}{a-\overline{a}} & \text{if } a \le R \le \overline{a} \\ 0 & \text{otherwise.} \end{cases} \tag{26}$$

According to Eqs. (23)–(25), the possibility, necessity, and credibility of $\{\xi \le R\}$ and $\{\xi \ge R\}$ are as follows:

$$Pos\{\xi \le R\} = \begin{cases} 0, & R \le \underline{a} \\ \dfrac{R-\underline{a}}{a-\underline{a}}, & \underline{a} \le R \le a\,; \\ 1, & R \ge \mathrm{a} \end{cases} \quad Nec\{\xi \le R\} = \begin{cases} 0, & R \le a \\ \dfrac{R-a}{\overline{a}-a}, & a \le R \le \overline{a} \\ 1, & R \ge \overline{a} \end{cases} \tag{27}$$

$$Pos\{\xi \ge R\} = \begin{cases} 0, & R \ge \overline{a} \\ \dfrac{\overline{a}-R}{\overline{a}-a}, & a \le R \le \overline{a}\,; \\ 1, & R \le \mathrm{a} \end{cases} \quad Nec\{\xi \ge R\} = \begin{cases} 0, & R \ge a \\ \dfrac{a-R}{a-\underline{a}}, & \underline{a} \le R \le a \\ 1, & R \le \underline{a} \end{cases} \tag{28}$$

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:

$$Cr\{\xi \le R\} = \begin{cases} 0, & R \le \underline{a} \\ \dfrac{R-\underline{a}}{2(a-\underline{a})}, & \underline{a} \le R \le a \\ \dfrac{\overline{a}-2a+R}{2(\overline{a}-a)}, & a \le R \le \overline{a} \\ 1, & R \ge \overline{a} \end{cases} \quad Cr\{\xi \ge R\} = \begin{cases} 0, & R \ge \overline{a} \\ \dfrac{\overline{a}-R}{2(\overline{a}-a)}, & a \le R \le \overline{a} \\ \dfrac{2a-\underline{a}-R}{2(a-\underline{a})}, & \underline{a} \le R \le a \\ 1, & R \le \underline{a} \end{cases} \tag{29}$$

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 Fig 2.

Figure 2 shows the triangular fuzzy variable $\xi = (\underline{a},\ a,\ \overline{a})$ as a specific case. Let $Pos\{\xi \le R\} = 1$ when $R \ge a$. Nevertheless, it is obvious that the event $\{\xi \le R\}$ 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 $\underline{a} \leq a_1 \leq a_2 \leq \overline{a}$, 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.

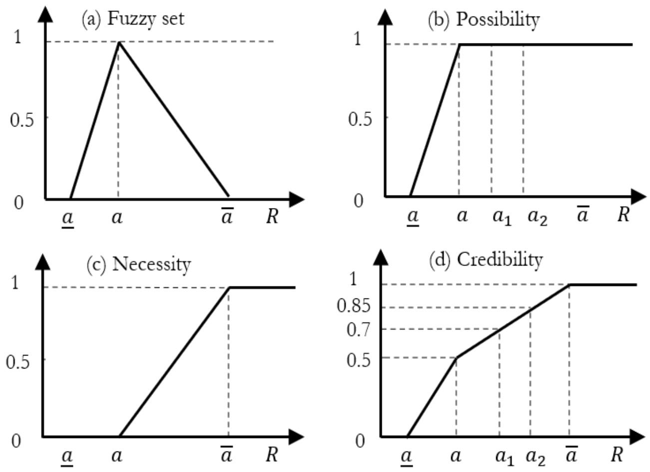

Fig. 2. Measures of fuzzy events: (a) fuzzy set, (b) possibility, (c) necessity, and (d) credibility.

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:

$$Cr\{\xi \leq \tilde{R}\} = \begin{cases} 1, & \overline{a} \leq \underline{b} \\ \dfrac{\overline{a} - 2a + 2b - \underline{b}}{2(\overline{a} - a + b - \underline{b})}, & a \leq b, \overline{a} > \underline{b} \\ \dfrac{\overline{b} - \underline{a}}{2(\overline{b} - b + a - \underline{a})}, & a > b, \underline{a} < \overline{b} \\ 0, & \underline{a} \geq \overline{b} \end{cases}$$
$$Cr\{\xi \geq \tilde{R}\} = \begin{cases} 1, & \underline{a} \geq \overline{b} \\ \dfrac{\overline{b} - 2b + 2a - \underline{a}}{2(\overline{b} - b + a - \underline{a})}, & a > b, \underline{a} < \overline{b} \\ \dfrac{\overline{a} - \underline{b}}{2(\overline{a} - a + b - \underline{b})}, & a \leq b, \overline{a} > \underline{b} \\ 0, & \overline{a} \leq \underline{b} \end{cases} \tag{30}$$

The credibility measure may display the satisfaction degree of an event when parametric information is shown as fuzzy sets. Fig 3 demonstrates four credibility situations between two fuzzy sets.

Based on Eqs. (29) and (30), it can be shown that for $(0 \leq \alpha \leq 0.5)$:

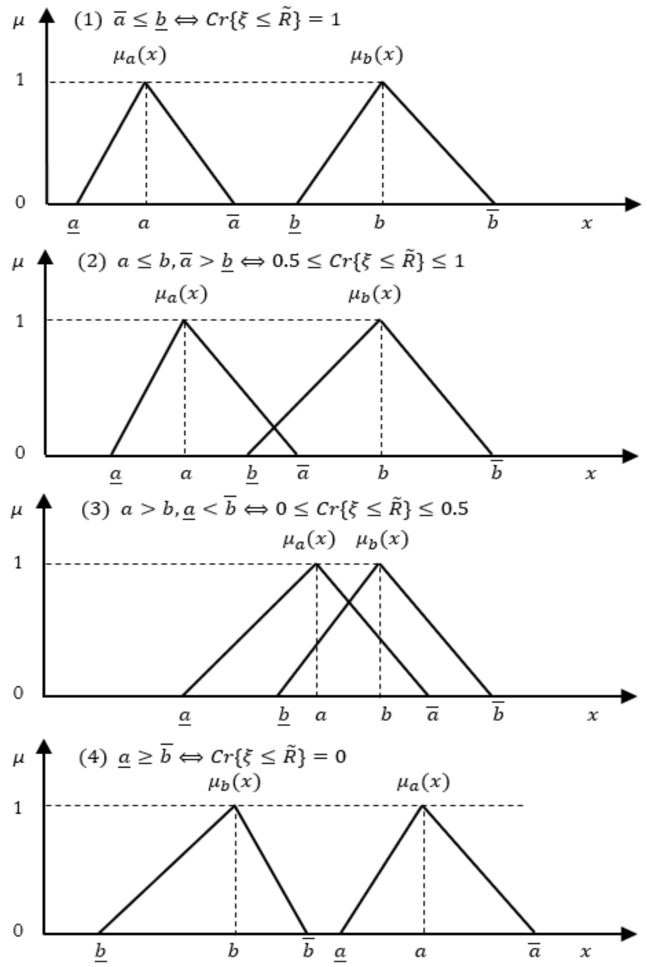

Fig. 3. Relative positions of two fuzzy sets are based on credibility measures.

$$Cr\{\xi \leq R\} \geq \alpha \Leftrightarrow R \geq (1 - 2\alpha)\underline{a} + (2\alpha)a \tag{31}$$
$$Cr\{\xi \geq R\} \geq \alpha \Leftrightarrow R \leq (2\alpha)a + (1 - 2\alpha)\overline{a} \tag{32}$$
$$Cr\{\xi \leq \tilde{R}\} \geq \alpha \Leftrightarrow (1 - 2\alpha)\underline{a} + (2\alpha)a \leq (2\alpha)b + (1 - 2\alpha)\overline{b} \tag{33}$$
$$Cr\{\xi \geq \tilde{R}\} \geq \alpha \Leftrightarrow (2\alpha)a + (1 - 2\alpha)\overline{a} \geq (1 - 2\alpha)\underline{b} + (2\alpha)b \tag{34}$$

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

$$Cr\{\xi \leq R\} \geq \alpha \Leftrightarrow R \geq (2 - 2\alpha)a + (2\alpha - 1)\overline{a} \tag{35}$$
$$Cr\{\xi \geq R\} \geq \alpha \Leftrightarrow R \leq (2\alpha - 1)\underline{a} + (2 - 2\alpha)a \tag{36}$$
$$Cr\{\xi \leq \tilde{R}\} \geq \alpha \Leftrightarrow (2 - 2\alpha)a + (2\alpha - 1)\overline{a} \leq (2\alpha - 1)\underline{b} + (2 - 2\alpha)b \tag{37}$$
$$Cr\{\xi \geq \tilde{R}\} \geq \alpha \Leftrightarrow (2\alpha - 1)\underline{a} + (2 - 2\alpha)a \geq (2 - 2\alpha)b + (2\alpha - 1)\overline{b} \tag{38}$$

5.1.1.2. Fuzzy Chance-constrained Programming Model

The Chance-constrained Programming (CCP) model was first introduced by Charnes and Cooper [53]. Then, it was modified and improved in a fuzzy environment [51, 52, 54]. 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:

$$\begin{aligned} & min\ \bar{f} \\ & s.t. \quad Cr\{\textstyle\sum_{j=1}^{n} \tilde{c}_{ij}x_j \le \bar{f}\} \ge \alpha \\ & \qquad\ Cr\{\textstyle\sum_{j=1}^{n} \tilde{a}_{ij}x_j \ge \tilde{b}_i\} \ge \alpha \\ & \qquad\ x_j \ge 0 \end{aligned} \tag{39}$$

Applying Eqs. (31)–(38), the credibility-based fuzzy chance-constrained programming model is shown in Eq. (39). They can be converted to the following crisp equivalent equations with confidence levels as follows:

$$\begin{aligned} & min\ \bar{f} \\ & s.t. \\ & \textstyle\sum_{j=1}^{n}\left[(1-2\alpha)\underline{c}_j + (2\alpha)c_j\right]x_j \le \bar{f}; \quad if\ \ \alpha \le 0.5 \\ & \textstyle\sum_{j=1}^{n}\left[(2-2\alpha)c_j + (2\alpha-1)\overline{c}_j\right]x_j \le \bar{f}; \quad if\ \ \alpha \ge 0.5 \\ & \textstyle\sum_{j=1}^{n}\left[(2\alpha)a_{ij} + (1-2\alpha)\overline{a}_{ij}\right]x_j \\ & \qquad \ge (1-2\alpha)\underline{b}_i + (2\alpha)b_i; \ \ if\ \alpha\ \le 0.5 \\ & \textstyle\sum_{j=1}^{n}\left[(2\alpha-1)\underline{a}_{ij} + (2-2\alpha)a_{ij}\right]x_j \\ & \qquad \ge (2-2\alpha)b_i + (2\alpha-1)\overline{b}_i; \ \ if\ \alpha\ \ge 0.5 \\ & x_j\ \ge 0;\ j = 1,\ldots,n;\ 0 \le \alpha \le 1 \end{aligned} \tag{40}$$

5.1.2. Equivalent Crisp Multiple-Objective Linear Programming Model

In relation to Eqs. (31)–(39), 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:

$$Min\ Z_1 \tag{41}$$
$$Min\ Z_2 = \textstyle\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} QSP_{njt} \tag{42}$$
$$Min\ Z_3 = \textstyle\sum_{k=1}^{K}\sum_{t=1}^{T}(QWH_{kt} + QWF_{kt}) \tag{43}$$
$$Max\ Z_4 = \textstyle\sum_{s=1}^{S} TSSQ_s \sum_{r=1}^{R}\sum_{t=1}^{T} QRMS_{srt} \tag{44}$$

$Subject\ to$:

$$Cr\{TC \le Z_1\} \ge \alpha \tag{45}$$
$$Cr\left\{QSP_{njt} = QSP_{nj(t-1)} + \widetilde{D}_{njt} - QPSC_{njt}\right\} \ge \alpha \quad \forall\, n, j, t \tag{46}$$
$$\begin{aligned} & Cr\{\textstyle\sum_{s=1}^{S} \widehat{AFRS}_{srt} \times QRMS_{srt} \\ & \qquad \le \widehat{AFRP}_r \times \textstyle\sum_{s=1}^{S} QRMS_{srt}\} \ge \alpha; \ \ \forall\, r, t \end{aligned} \tag{47}$$
$$\begin{aligned} & Cr\{\textstyle\sum_{r=1}^{R}\sum_{s=1}^{S} \widehat{ASL}_s \times QRMS_{srt} \ge \\ & \qquad \widehat{ASLP} \times \textstyle\sum_{r=1}^{R}\sum_{s=1}^{S} QRMS_{srt}\} \ge \alpha; \ \forall\, r, t \end{aligned} \tag{48}$$

Other constraints are the same as the constraints in the FMOMILP model. If $(\alpha > 0.5)$, this means that the chance constraints must be met at a level of confidence that is greater than 0.5. Then, according to Eqs. (39)–(40), the fuzzy chance constraints (Eqs. (45)–(48)) can be converted into the following crisp equivalents with the confidence level α as follows:

$$\begin{aligned} (45) \Leftrightarrow & \textstyle\sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times RTPC_t^m \\ & \qquad +(2\alpha-1) \times RTPC_t^p] \times QRTP_{nt} \\ & + \textstyle\sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times OTPC_t^m \\ & \qquad +(2\alpha-1) \times OTPC_t^p] \times QOTP_{nt} \\ & + \textstyle\sum_{n=1}^{N}\sum_{i=1}^{T} PTP_n \times [(2-2\alpha) \times STPC_{it}^m \\ & \qquad +(2\alpha-1) \times STPC_{it}^p] \times QSTP_{nt} \\ & + \textstyle\sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{i=1}^{T}[(2-2\alpha) \times RMSC_{srt}^m \\ & \qquad +(2\alpha-1) \times RMSC_{srt}^p] \times QRMS_{srt} \\ & + \textstyle\sum_{k}^{K}\sum_{t=1}^{T}[(2-2\alpha) \times SC_{kt}^m \\ & \qquad +(2\alpha-1) \times SC_{kt}^p] \times QW_{kt} \\ & + \textstyle\sum_{k}^{K}\sum_{t=1}^{T}[(2-2\alpha) \times HC_{kt}^m \\ & \qquad +(2\alpha-1) \times HC_{kt}^p] \times QWH_{kt} \\ & + \textstyle\sum_{k}^{K}\sum_{t=1}^{T}[(2-2\alpha) \times FC_{kt}^m \\ & \qquad +(2\alpha-1) \times FC_{kt}^p] \times QWF_{kt} \\ & + \textstyle\sum_{r=1}^{R}\sum_{t=1}^{T}[(2-2\alpha) \times IRMC_{rt}^m \\ & \qquad +(2\alpha-1) \times IRMC_{rt}^p] \times IRM_{rt} \\ & + \textstyle\sum_{n=1}^{N}\sum_{t=1}^{T}[(2-2\alpha) \times IPC_{nt}^m \\ & \qquad +(2\alpha-1) \times IPC_{nt}^p] \times IP_{nt} \\ & + \textstyle\sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{t=1}^{T}[(2-2\alpha) \times TRMC_{st}^m \\ & \qquad +(2\alpha-1) \times TRMC_{st}^p] \times QRMS_{srt} \\ & + \textstyle\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\left[(2-2\alpha) \times TPC_{jt}^m \right. \\ & \qquad \left. +(2\alpha-1) \times TPC_{jt}^p\right] \times QPSC_{njt} \\ & + \textstyle\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\left[(2-2\alpha) \times PSC_{njt}^m \right. \\ & \qquad \left. +(2\alpha-1) \times PSC_{njt}^p\right] \times QSP_{njt} \le Z_1 \end{aligned} \tag{49}$$

$$\begin{aligned} (46) \Leftrightarrow & QSP_{njt} = QSP_{nj(t-1)} + \left[(2-2\alpha) \times D_{njt}^m \right. \\ & \left. +(2\alpha-1) \times D_{njt}^p\right] - QPSC_{njt}; \quad \forall\, n, t \end{aligned} \tag{50}$$

$$\begin{aligned} (47) \Leftrightarrow & \textstyle\sum_{s=1}^{S}[(2-2\alpha) \times AFRS_{srt}^m \\ & +(2\alpha-1) \times AFRS_{srt}^p] \times QRMS_{srt} \\ & \le [(2\alpha-1) \times AFRP_r^o + (2-2\alpha) \times AFRP_r^m] \\ & \qquad \times \textstyle\sum_{s=1}^{S} QRMS_{srt}\ ; \ \ \forall\, r, t \end{aligned} \tag{51}$$

$$\begin{aligned} (48) \Leftrightarrow & \textstyle\sum_{r=1}^{R}\sum_{s=1}^{S}[(2\alpha-1) \times ASL_s^o \\ & +(2-2\alpha) \times ASL_s^m] \times QRMS_{srit} \\ & \ge (2-2\alpha) \times ASLP^m + (2\alpha-1) \times ASLP^p] \\ & \qquad \times \textstyle\sum_{r=1}^{R}\sum_{s=1}^{S} QRMS_{srt}\ ; \ \ \forall\, t \end{aligned} \tag{52}$$

5.2. Second Phase: Fuzzy Multiple-Objective Programming (FMOP)

Fuzzy Multiple-Objective Programming (FMOP) 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 FMOP 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 Fig. 4:

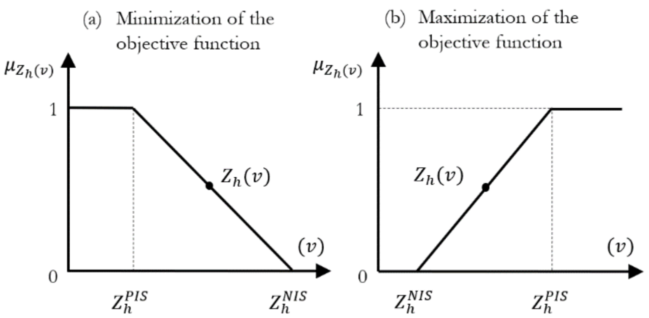

Fig. 4. Membership function representing the (a) minimum objective and (b) maximum objective.

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 2.

Table 2. Payoff table for achieving positive and negative ideal solutions.

Z_h	v_k^*			
	v_1^*	v_2^*	v_3^*	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 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:

$$Z_h^{NIS} = max\{Z_h(v_k^*); h \neq k\} \tag{53}$$

Note that: Eq. (53) 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:

$$Z_h^{NIS} = min\{Z_h(v_k^*); h \neq k\} \tag{54}$$

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

$$\mu_{z_h(v)} = \begin{cases} 1 & , z_h(v) \leq z_h^{PIS} \\ \dfrac{z_h^{NIS} - z_h(v)}{z_h^{NIS} - z_h^{PIS}} & , z_h^{PIS} \leq z_h(v) \leq z_h^{NIS} \\ 0 & , z_h(v) \geq z_h^{NIS} \end{cases} \tag{55}$$

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

$$\mu_{z_h(v)} = \begin{cases} 1 & , z_h(v) \geq z_h^{PIS} \\ \dfrac{z_h(v) - z_h^{NIS}}{z_h^{PIS} - z_h^{NIS}} & , z_h^{NIS} \leq z_h(v) \leq z_h^{PIS} \\ 0 & , z_h(v) \leq z_h^{NIS} \end{cases} \tag{56}$$

The FGP model can be formed after all the membership functions have been formulated.

5.2.1. 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:

$$\begin{aligned} &Max && \lambda \\ &s.t && \lambda \leq \mu_h(v), \quad h = 1, \dots, H, \\ & && v \in F(v), \quad \lambda \in [0,1]. \end{aligned} \tag{57}$$

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

5.2.2. 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:

$$\begin{aligned} &Max && \lambda(v) = \gamma \times \lambda_0 + (1-\gamma) \times \textstyle\sum_h^H \theta_h \times \mu_h(v) \\ &s.t && \lambda_0 \leq \mu_h(v), \quad h = 1, \dots, H, \\ & && \textstyle\sum_h^H \theta_h = 1, \quad \theta_h \geq 0 \\ & && v \in F(v), \quad \lambda_0 \; and \; \gamma \in [0,1]. \end{aligned} \tag{58}$$

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 (λ_0). The weighting summation of these obtained satisfaction levels $\mu_h(v)$ could be adjusted to bring unbalanced compromise solutions. In addition, γ and θ_h are the coefficients of compensation and the relative importance weight of the $h-th$ objective, respectively. The weighted values θ_h are specified by the DMs based on their preferences so that

$\sum_h \theta_h = 1, \theta_h \geq 0$. Besides that, γ 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 γ. In relation to this problem, a higher value of γ implies that the DMs pay more attention to getting the higher bound of the satisfaction level for objectives (λ_0) with more balanced compromise solutions (symmetric fuzzy decision-making). In contrast, the lower value of γ 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).

5.2.3. 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:

$$\begin{array}{lll} Max & \lambda(v) = \gamma \times \lambda_0 + (1-\gamma)\sum_h^H \theta_h \times \mu_h & \\ s.t & \lambda_0 \leq \mu_h(v), & h = 1, \dots, H, \\ & \sum_h^H \theta_h = 1, & \theta_h \geq 0 \\ & \mu_h \geq \dfrac{\theta_h}{\theta_{h+1}} \times \mu_{h+1} & \forall h \\ & v \in F(v), & \lambda_0 \ and\ \gamma \in [0,1]. \end{array} \tag{59}$$

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 (θ_h) must be larger than the weight value of the objective (θ_{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.

5.3. 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 FMOMILP model into the corresponding crisp MOMILP model by applying credibility-based fuzzy chance-constrained programming references to Eq. (40).
- **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 5.2.
- **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 5.2.
- **Step 8:** Implement the sensitivity analysis by modifying some parameters (the confidence level (α) and the coefficient compensation (γ)).

6. Experimental Case

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 section. 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 3. The consumption rate of the raw materials for producing these types of products is described in Table 4. 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 3. Scope of the problem.

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

Table 4. Bill of Materials (BOM).

Product	Raw materials (r)									
(n)	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 supposed to be the same price at the medium level, the service level of supplier 2 is better than supplier 1. However, the quality of supplier 2 is poorer than supplier 1. To sum up, the overall score of each supplier (representing their performance) is determined by using the AHP method. The information of setting problem for supplier selection and the outcome of the overall weighted score for each supplier is shown in Table 5.

Table 5. 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, it can be seen that supplier 1 has the best performance (the highest weighted score) and supplier 3 has the poorest performance (the lowest weighted score). The performance weighted score of suppliers 1, 2, 3, and 4 are 0.44, 0.20, 0.14, 0.22, respectively.

The available time and production costs for the regular time, overtime, and subcontracting production are presented in Table 6. Table 7 shows the purchasing cost and maximum capacity of all raw materials that are provided by suppliers. Table 8 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 both raw materials, and the finished products are given in Table 9. The transportation cost from suppliers to the production plant, and from the production plant to the customers are provided in Table 10. 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 11.

Table 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)

The relevant data for the quality and service level of the suppliers (evaluated by the manufacturer) are summarized in Table 12. 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 13. 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 14. In Table 15, 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.

Table 7. Purchasing cost of raw materials and the maximum quantity of raw materials provided by suppliers.

Raw material (r)	Purchasing cost of raw materials from supplier (s) ($/unit)				Maximum quantity of raw materials provided by suppliers (s) (units)			
	s1	s2	s3	s4	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)	3,500	3,000	3,500	3,000
r2	(2, 2.2, 2.6)	(2, 2.2, 2.6)	(1, 1.1, 1.3)	(1.5, 1.65, 1.95)	3,500	3,000	3,000	3,500
r3	(1, 1.1, 1.3)	(1, 1.1, 1.3)	(1, 1.1, 1.3)	(1, 1.1, 1.3)	3,500	3,000	4,500	3,500
r4	(3, 3.3, 3.9)	(3, 3.3, 3.9)	(2, 2.2, 2.6)	(2, 2.2, 2.6)	3,500	3,500	4,000	3,000
r5	(2, 2.2, 2.6)	(2, 2.2, 2.6)	(1.5, 1.65,1.95)	(2, 2.2, 2.6)	3,500	3,000	4,000	3,000
r6	(1, 1.1, 1.3)	(1, 1.1, 1.3)	(2, 2.2, 2.6)	(1, 1.1, 1.3)	2,500	3,000	3,500	3,500
r7	(2, 2.2, 2.6)	(2, 2.2, 2.6)	(1.5, 1.65, 1.95)	(1, 1.1, 1.3)	4,000	3,500	3,500	3,500
r8	(1, 1.1, 1.3)	(1, 1.1, 1.3)	(1, 1.1, 1.3)	(1, 1.1, 1.3)	3,500	3,500	4,500	3,500
r10	(2, 2.2, 2.6)	(2, 2.2, 2.6)	(1.5, 1.65, 1.95)	(1.5, 1.65, 1.95)	3,000	3,500	3,500	3,500

Table 8. Workforce costs at the production plant ($/person).

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

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Table 9. Inventory cost, warehouse space limitation, initial units of raw material, and finished products.

Raw material (r)	Inventory costs ($/unit)	Initial raw material inventory (units)	Warehouse space for a unit of product (m^2/unit)	Product (n)	Inventory costs ($/unit)	Initial finished product inventory (units)	Warehouse space for a unit of raw material (m^2/unit)
r1	(4, 5, 7)	20	1	n1	(5, 6, 8)	2	3
r2	(4, 5, 7)	20	1.5				
r3	(4, 5, 7)	20	1.5	n2	(7, 8, 10)	2	2
r4	(4, 5, 7)	12	0.5				
r5	(4, 5, 7)	15	1.5	n3	(9, 10, 12)	20	3
r6	(5, 6, 8)	20	0.5				
r7	(5, 6, 8)	20	1	n4	(11, 12, 14)	10	2
r8	(5, 6, 8)	20	1				
r9	(5, 7, 9)	15	1.5	n5	(13, 14, 16)	10	6
r10	(5, 7, 9)	20	1.5				

Table 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)

Table 11. Penalty cost of product shortages ($/unit).

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

Table 12. Relevant data for the quality and the service level of suppliers evaluated by the manufacturer.

Raw materials (r)	Average defect rate of raw materials from suppliers (%)				Acceptable defect rate of production plant for raw materials (%)
	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)	(4.48, 5.6, 6.72)
r2	(2, 2.01, 2.03)	(2.2, 2.21, 2.23)	(2.8, 2.81, 2.83)	(2.465, 2.465, 2.265)	(4.64, 5.8, 6.96)
r3	(2, 2.01, 2.03)	(2.1, 2.11, 2.13)	(2.18, 2.19, 2.21)	(2.31, 2.31, 231)	(4.8, 6, 7.2)
r4	(2, 2.01, 2.03)	(2.3, 2.31, 2.33)	(2.4, 2.41, 2.43)	(2.22, 2.22, 2.22)	(4.48, 5.6, 6.72)
r5	(2, 2.01, 2.03)	(2.2, 2.21, 2.23)	(2.6, 2.61, 2.63)	(2.82, 2.82, 2.82)	(4.4, 5.5, 6.6)
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)	(4.72, 5.9, 7.08)
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)	(5.04, 6.3, 7.56)
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)	(4.4, 5.5, 6.6)
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)	(4.72, 5.9, 7.08)
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)	(4.88, 6.1, 7.32)
	Average service level of suppliers (%)				Acceptable service level of production plant (%)
	(75, 94, 100)	(72, 90, 100)	(69, 86, 100)	(70, 87, 100)	(69, 86, 100)

Table 13. 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 14. 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)					
Raw material	Finished product	k1	k2	k3	k4	k5	
10,000	15,000	21	34	36	8	2	20

Table 15. Forecasted demand of customers in the optimistic case (units).

Customer (j)	Product (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

7. Results and Discussions

7.1. Obtained Outcome from the Crisp MOMILP model

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 Section 6 are used to find the positive and negative ideal solutions (following the description in Section 5) by IBM ILOG CPLEX Optimization Studio (version 12.4) software. The crisp MOMILP model is 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 16.

According to the result in Table 16 and Eqs. (53)–(54), the obtained positive and negative ideal solutions of each objective function are presented in Table 17.

7.2. Fuzzy Goal Programming

7.2.1. Obtained Outcome from 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 18.

From Table 18, the overall goal satisfaction (as denoted by λ), 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.

Table 16. 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

Table 17. 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

Table 18. Optimal solution of Zimmerman's method.

Implications	Symbol	Value	Unit
Overall satisfaction	λ	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 level	Z_3	19	persons
Maximizing the total value of purchasing	Z_4	331,053	units
Satisfaction of the first objective function	μ_{Z_1}	77.37	%
Satisfaction of the second objective function	μ_{Z_2}	91.01	%
Satisfaction of the third objective function	μ_{Z_3}	77.65	%
Satisfaction of the fourth objective function	μ_{Z_4}	77.36	%
Confidence level	α	90	%

7.2.2. Obtained Outcome from Applying TH's Method

TH's method allows 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 19.

According to the obtained results from Table 19, as compared to the obtained results of Zimmerman's method, it was found that the overall satisfaction level (λ) 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 we need 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.

Table 19. 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	λ	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 level	Z_3	0	persons
Maximizing the total value of purchasing	Z_4	326,843	units
Satisfaction of the first objective function	μ_{Z_1}	77.47	%
Satisfaction of the second objective function	μ_{Z_2}	100	%
Satisfaction of the third objective function	μ_{Z_3}	100	%
Satisfaction of the fourth objective function	μ_{Z_4}	73.31	%
Confidence level	α	90	%

Table 20. 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	λ	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 level	Z_3	39	persons
Maximizing the total value of purchasing	Z_4	289,451	units
Satisfaction of the first objective function	μ_{Z_1}	97.94	%
Satisfaction of the second objective function	μ_{Z_2}	83.93	%
Satisfaction of the third objective function	μ_{Z_3}	54.12	%
Satisfaction of the fourth objective function	μ_{Z_4}	40.59	%
Confidence level	α	90	%

7.2.3. Obtained Outcome from the Proposed Method

As mentioned earlier, by taking into consideration of the consistency of the obtained solutions, a consistent-weight constraint $\mu_h \times \theta_{h+1} \geq \theta_h \times \mu_{h+1}$ 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 20.

Based on Table 20, 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.

In each period, the quantity of each type of raw material is bought from suppliers, the production quantity of each product (produced in regular time, overtime, and subcontracted), the quantity of each product that is distributed to customers, the inventory levels of the raw material type, the product type, and the number of each workforce level are the operational decision variables of the model. For example, there are 3,500 and 3,000 units of raw material Type 1 that are purchased from Suppliers 1, and 2, respectively. The number of Product 1 units, produced in regular time production, is 1,699 units. The distributed quantities of Product 1 to Customers 1, 2, 3, and 4 are 118, 236, 177, and 295 units, respectively. For more information, these main values of the operational decision variables in Period 1, which are obtained from solving the proposed model with confidence level ($\alpha = 0.9$), importance weights of the 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 in Table 21.

Table 21. Aggregate plan (Period 1) from solving the proposed model

Procurement plan

	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10
s1	3,500	3,500	1,084	3,500	3,085	2,500	2,005	3,269	2,585	3,293
s2	3,000	219	221	146	0	1,646	0	3,500	0	3,500
s3	0	3,000	207	4,000	3,748	0	343	0	3,489	1,954
s4	0	2,987	2,563	3,000	0	3,313	3,500	1,732	3,500	0
Inventory	20	20	20	12	15	20	20	20	15	20

Production plan

	Regular time	Overtime	Subcontracted	Inventory
n1	1,699	0	0	1,052
n2	1,178	0	0	0
n3	747	0	0	0
n4	1,701	0	0	0
n5	1,075	0	0	0

Distribution plan

	j1	j2	j3	j4
n1	118	236	177	295
n2	224	330	248	354
n3	106	71	106	224
n4	201	543	236	838
n5	118	236	177	295

Workforce plan

	k1	k2	k3	k4	k5
Labor	21	34	36	8	2
Hiring	0	0	0	0	0
Firing	0	0	0	0	0

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 22.

Table 22. Varied ordering patterns of the importance weights of objectives.

Cases	Order patterns	θ_1	θ_2	θ_3	θ_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 22 for solving the proposed multiple-objective model, the optimal obtained results of TH's model (integrating the consistent-weight constraints) are shown in Table 23.

Throughout the obtained solutions as presented in Table 23, 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 24.

Table 24. 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 24, 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.

7.3. 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 γ are varied while the other parameters are fixed.

Table 23. Optimal solutions of the proposed model.

Case	γ	α	Order patterns	λ	μ_1(%)	μ_2(%)	μ_3(%)	μ_4(%)	Consistent solutions
1	0.2	0.9	$\theta_1 > \theta_2 > \theta_3 > \theta_4$	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

Table 25. 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	λ	μ_1(%)	μ_2(%)	μ_3(%)	μ_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

Usually, in credibility-based fuzzy chance-constrained programming, the confidence level is set by 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 *a* 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 25 and illustrated graphically in Fig. 5.

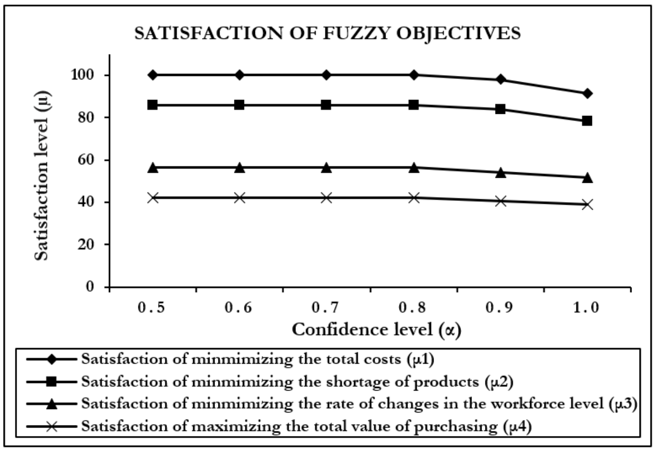

Fig. 5. Satisfaction levels of each objective function according to the different values of (α).

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

Table 26. Results of sensitivity analysis by varying the compensation coefficient (γ).

γ-value	λ(%)	μ_1(%)	μ_2(%)	μ_3(%)	μ_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

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 26. A spectrum of unbalanced and balanced compromise solutions based on the preferences of DMs is illustrated graphically in Fig. 6.

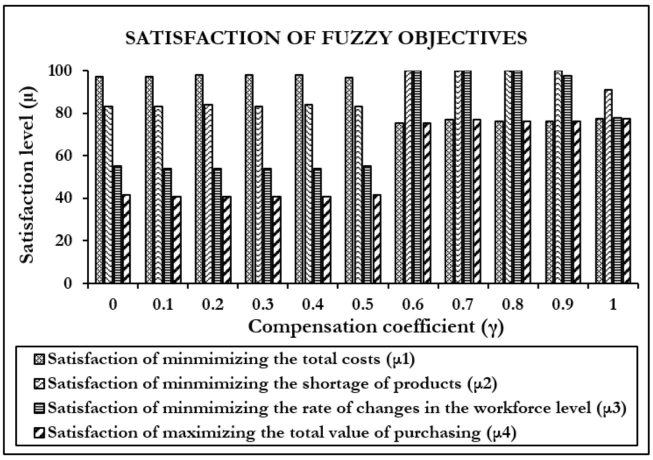

Fig. 6. Satisfaction levels of each objective function according to the different values of (γ).

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.
- The approach can be used for different types of fuzzy numbers (i.e. triangular, trapezoidal). It can also be used for nonlinear membership functions, and both in symmetric and asymmetric forms.
- 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 (θ_h), confidence levels (α), and compensatory coefficient (γ), it can yield many efficient solutions. This feature is evidence to show the high flexibility of the proposed approach.

7.4. 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 (α) 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 (α), 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 (α), 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.

8. Conclusions, Limitations, and Further Work

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 Fuzzy Multiple-Objective Mixed-Integer Linear Programming (FMOMILP) 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 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 Programming (FMOP) 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 FMOP 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.

Any parameter that may affect the results of planning can be considered as a fuzzy number. In fact, there are 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 several parameters in the constraints that are considered to be fuzzy numbers. This is also a limitation of this 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 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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