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CHANCE CONSTRAINT PROGRAMMING MODEL FOR SUPPLY CHAIN MANAGEMENT WITH FUZZY COST PARAMETERS

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Abstract: Coordination is one of the most critical challenges in supply chain management. Depending on the level of coordination, supply chains can be categorized as either centralized or decentralized. In a centralized model, a single decision-maker seeks to optimize the performance of the entire supply chain by minimizing overall costs and maximizing system-wide efficiency. In contrast, in a decentralized model, each member independently pursues its own profit objectives.

This study examines a two-stage supply chain structure consisting of a supplier and a retailer under fuzzy production cost parameters. To address the uncertainty, the fuzzy chance-constrained programming (FCCP) method is applied to determine the optimal order quantities that maximize the total profit in both centralized and decentralized settings. Unlike most previous studies that analyze these structures separately, this research provides a comparative framework integrating FCCP with credibility theory across both coordination mechanisms. In addition, the decentralized model incorporates a goal programming structure to capture the conflicting objectives of independent members. This unified approach offers both methodological novelty and practical insights for decision-making under uncertainty in supply chain coordination.

Keywords: supply chain, decentralized, centralized, chance constraint programming, credibility theory

Bulanık Maliyet Parametreleri Altında Tedarik Zinciri Yönetimi için Şans Kısıtlı Programlama Modeli

Öz: Tedarik zinciri yönetiminde koordinasyon, sistemin etkinliği açısından en kritik konulardan biridir. Koordinasyon düzeyine bağlı olarak tedarik zincirleri merkezi veya merkezi olmayan (desantralize) yapılar olarak sınıflandırılabilir. Merkezi modelde tek bir karar verici, tüm tedarik zincirinin performansını optimize etmeyi amaçlayarak toplam maliyetleri en aza indirmeye ve sistem genelinde verimliliği artırmaya çalışır. Buna karşılık merkezi olmayan modelde zincirin her bir üyesi kendi kârını maksimize etmeye yönelik bağımsız kararlar alır.

Bu çalışmada, bulanık üretim maliyeti parametreleri altında faaliyet gösteren tedarikçi ve perakendeciden oluşan iki aşamalı bir tedarik zinciri yapısı incelenmiştir. Belirsizliğin ele alınabilmesi amacıyla bulanık şans kısıtlı programlama (Fuzzy Chance-Constrained Programming – FCCP) yöntemi kullanılarak hem merkezi hem de merkezi olmayan yapılar için toplam kârı maksimize eden optimal sipariş miktarları belirlenmiştir. Literatürde çoğu çalışma bu iki yapıyı ayrı ayrı ele alırken, bu araştırmada FCCP yöntemi güvenilirlik (credibility) teorisi ile kullanılarak her iki koordinasyon mekanizmasını karşılaştırmalı bir çerçevede inceleyen bütünleşik bir yaklaşım sunulmuştur. Ayrıca merkezi olmayan modelde, bağımsız karar vericilerin çatışan hedeflerini temsil edebilmek amacıyla hedef programlama yapısı kullanılmıştır. Önerilen bu bütünleşik yaklaşım, belirsizlik altında tedarik zinciri koordinasyonuna yönelik karar verme süreçlerine hem yöntemsel yenilik hem de uygulamaya dönük önemli katkılar sağlamaktadır.

Anahtar Kelimeler: tedarik zinciri, merkezi olmayan yapı, merkezi yapı, şans kısıtlı programlama, güvenilirlik teorisi

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1. INTRODUCTION

The supply chain is a network of firms that must cooperate with each other and have conflicting objectives. The supply chain starts with the raw material and continues until the final product reaches the customer. It may even cover the after-sales services. The presence of members with conflicting objectives in the supply chain makes coordination between supply chain members difficult. Depending on the level of coordination, there are centralized and decentralized supply chain models in the literature. In a centralized supply chain model, there is only one decision-maker aiming to optimize the performance of the entire supply chain. The goal of this decision-maker is to minimize overall costs and maximize overall performance. On the other hand, in a decentralized supply chain model, all members want to optimize their performance separately. In other words, the purpose of each supply chain member is to minimize their costs and to maximize their profits.

Many parameters are subject to uncertainty in supply chain (SC) problems such as demand, production cost, transportation cost, etc. In literature, many researchers address these uncertainties by using probability theory (Giri and Sarker, 2019; Taleizadeh, Cardenas-Barron and Sohani, 2019; Raza and Govindaluri, 2019; Lee and Billington, 1993). However, in real-life problems, the probability distributions of the specified parameters cannot be determined in some situations such as the absence of data, incorrect data, etc. In these cases, the fuzzy set theory is used. Fuzzy set theory was first described by Lotfi A. Zadeh in 1965. Especially in recent years, many studies have been done on the combination of supply chain coordination and fuzzy set theory. Some of these studies are as follows: According to Petrovic et al.(1999), supply chain members are trying to ensure coordination in an uncertain environment, and this uncertainty is related to three conditions such as customer demand, supply deliveries and external or market supply. Different approaches to improve SC performance in an uncertain environment have been simulated and analyzed. Ryu and Yücesan (2010) considered a fuzzy approach to the newsvendor problem by using several fuzzy parameters such as demand, wholesale price and market sales price. Moreover, they used three different supply chain contracts to solve the problem. Bilgen (2010) proposed a combined optimization model for production and distribution planning with the aimed of optimally coordinating important and interrelated logistics decisions. These fuzzy models account for fuzziness in capacity constraints. Arshinder et al. (2007) suggested a model to measure the effect of coordination mechanisms. They combined fuzzy logic with the analytic hierarchy process (AHP) to evaluate coordination. The proposed methodology is demonstrated through a case study of a supply chain.

In addition to these earlier contributions, several recent studies have further advanced the literature on supply chain coordination under uncertainty. Xu et al. (2024) conducted a bibliometric analysis of supply chain management research based on uncertainty theory, highlighting the growing focus on sustainability and multi-objective optimization. Gholami et al.(2022) proposed a robust-fuzzy optimization model for designing sustainable and lean supply chain networks, incorporating uncertain demand and cost parameters. Safari and Sahraeian (2023) developed a chance-constrained optimization model for a multi-echelon, multi-product closed-loop supply chain using an accelerated Benders decomposition approach. Wu et al. (2024) examined a green multimodal routing problem with soft time windows under twofold uncertainty using chance-constrained programming. Furthermore, Choi and Guo (2023) analyzed the concept of credibility in supply chain relationships, linking it to firms' operational performance in the presence of institutional and technological factors. These recent contributions demonstrate that while the handling of uncertainty in supply chain management has become more sophisticated, the application of fuzzy chance-constrained programming (FCCP) combined with credibility theory in both centralized and decentralized supply chain structures remains underexplored.

Beyond these contributions, a growing stream of post-2015 research has explicitly combined fuzzy optimization with supply chain planning and coordination decisions. Tuan et al. (2021) developed a fuzzy credibility-based chance-constrained optimization model for multi-objective aggregate production planning in a supply chain, showing how credibility theory can be used to treat demand and capacity uncertainty within an FCCP framework. Sahin et al. (2021) proposed a fuzzy goal-programming formulation for maritime supply chain optimization with triangular fuzzy numbers, using membership functions and satisfaction levels to balance conflicting logistics objectives under imprecise data. Gupta et al. (2018) introduced a probabilistic fuzzy goal multi-objective supply chain network model that couples fuzziness in transportation cost and delivery time with randomness in demand and supply parameters. In parallel, several hybrid stochastic–fuzzy and robust credibility-based models have been proposed for sustainable or resilient supply chains, where fuzzy parameters are integrated with stochastic programming or data-driven robust optimization to capture multiple sources of uncertainty. Recent bibliometric studies on fuzzy techniques in supply chain management also confirm the increasing use of credibility-based models and fuzzy goal programming in coordination and network design problems (Lu,Lao and Zavadskas, 2020).

Although these recent studies demonstrate that credibility-based FCCP, fuzzy goal programming and hybrid stochastic–fuzzy optimization have become important tools for handling uncertainty in supply chain design and planning, they typically focus on single coordination structures (such as aggregate production planning, network design or maritime logistics) and do not explicitly compare centralized and decentralized coordination within a unified FCCP–credibility framework. Therefore, in this study we propose an integrated approach that applies FCCP to both centralized and decentralized supply chain structures under fuzzy production cost parameters. Unlike previous studies that generally focus on either centralized or decentralized models in isolation, our work presents a comparative modeling framework that includes both structures simultaneously. Additionally, the decentralized model incorporates a multi-objective goal programming structure to reflect the conflicting profit objectives of independent members, which has rarely been addressed in existing literature.

In this study, a two-stage supply chain structure consisting of a supplier and a retailer, with fuzzy demand parameters, is examined. In the study, the fuzzy chance constraint programming method is used to determine the optimal order quantities that provide a maximum total supply chain profit in centralized and decentralized supply chain structures with fuzzy production cost parameters. We investigate the problem with credibility theory as the basis of the fuzzy chance-constrained programming (FCCP) method. Also, the decentralized supply chain model has more than one objective function because there are multiple decision-makers. Therefore, a goal programming approach is also employed to solve this model. For simplicity, shortage costs for all members have been ignored.

The remainder of this paper is organized into six sections. In the second section, basic information about the fuzzy set theory and credibility theory is given. In the third section, chance-constrained programming is discussed. In the fourth section, mathematical models for decentralized and centralized supply chain models are illustrated using chance-constrained programming in the fuzzy environment. The next section presents a sample problem illustrating the application of the model. The last section discusses the results and offers recommendations for future research.

2. METHODOLOGY

2.1. Fuzzy Set Theory, Credibility Theory

Fuzzy set theory, originally introduced by Zadeh (1965), provides a mathematical foundation for modeling uncertainty arising from imprecise or subjective information. Unlike classical set theory where an element either fully belongs to a set or does not, fuzzy set theory allows for partial membership. Each element in a fuzzy set is assigned a membership degree between 0 and 1, representing the extent to which it belongs to the set (Klir and Yuan, 1995).

Mathematically, a fuzzy set $\tilde{A}$ in a universal set X is defined by the membership function $\mu_{\tilde{A}}(x)$:

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)), \forall x \in X\}$$

where $\mu_{\tilde{A}}(x) \in [0,1]$ denotes the degree of membership of element x (Zadeh, 1978).

To handle uncertainty within the fuzzy environments in a decision-making context, the credibility theory proposed by Liu et al. (2002) offers an alternative to the traditional possibility and necessity measures. Unlike possibility measures, which lack the self-duality property, credibility measures fulfil this condition, making them more suitable for chance-constrained under fuzziness.

A credibility measure Cr is a function defined over a fuzzy event space that satisfies several axioms such as:

a. (Normality) : $Cr(\odot) = 1$;
b. (Monotonicity) : $Cr(A) \leq Cr(B)\ whenever\ A \subset B$;
c. (Self-duality) : $Cr\{A\} + Cr\{A^C\} = 1\ for\ any\ event\ A$;
d. (Maximality) : $Cr\{\cup_i A_i\} = sup_i\ Cr\{A_i\}\ for\ any\ events\ \{A_i\}\ with\ sup_i\ Cr\{A_i\} \leq 0{,}5$.

Based on this measure, a credibility space is formed as a triplet $(\odot, \mathrm{P}(\odot), Cr)$, where $\odot$ is the universe of discourse, $\mathrm{P}(\odot)$ its power set, and Cr the credibility measure. Within this framework, a fuzzy variable is defined as a function from credibility space to the set of real numbers (Liu, 2007).

Definition: Let ε be a fuzzy variable with membership function μ. Then for any set A of real numbers, we have (Liu, 2007);

$$Cr\{\varepsilon \in A\} = \frac{1}{2}\left(\sup_{t \in A}\mu(t) + 1 - \sup_{t \in A^c}\mu(t)\right) \tag{1}$$

Definition: Let ε be a fuzzy variable with membership function μ. Then it follows from Equation (1) that the following Equations hold (Huang,2010):

$$Cr\{\varepsilon = t\} = \frac{1}{2}\left(\mu(t) + 1 - \sup_{y \neq t}\mu(y)\right), \forall t \in \Re \tag{2}$$

$$Cr\{\varepsilon \leq t\} = \frac{1}{2}\left(\sup_{y \leq t}\mu(t) + 1 - \sup_{y > t}\mu(y)\right), \forall t \in \Re \tag{3}$$

$$Cr\{\varepsilon \geq t\} = \frac{1}{2}\left(\sup_{y \geq t}\mu(t) + 1 - \sup_{y < t}\mu(y)\right), \forall t \in \Re \tag{4}$$

The credibility function increases on the x- axis and the inverse function of the credibility function is a unique function for any $\propto$ confidence level and it is also a strictly increasing on the x-axis.

Example: Let $\mu(x)$ be the membership function for the triangular fuzzy number expressed by Equation (5); the credibility measure of this variable is shown in Equation (6) and the inverse credibility measure of this variable is shown in Equation (7) (Arık, 2019);

$$\mu_{\tilde{X}}(x) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{u-x}{u-m} & m \leq x \leq u \\ 0 & otherwise \end{cases} \tag{5}$$

$$\theta(x) = Cr\{\tilde{X} \leq x\} = \begin{cases} 0 & x \leq l \\ \frac{x-l}{2(m-l)} & l \leq x \leq m \\ \frac{u+x-2l}{2(u-l)} & m \leq x \leq u \\ 1 & otherwise \end{cases} \tag{6}$$

$$\theta^{-1}(\alpha) = \begin{cases} 2\alpha(m-l)+l & 0 \leq \alpha \leq 0{,}5 \\ u-(2-2\alpha)(u-m) & 0{,}5 \leq \alpha \leq 1 \end{cases} \tag{7}$$

Credibility theory provides a rigorous structure for formulating and evaluating fuzzy events, and its particularly valuable in optimization problems where parameters are not crisply defined. In such cases, chance constrained programming can incorporate credibility measures to define constraints and objectives based on a predetermined confidence level.

2.2. Chance Constrained Programming in a Fuzzy Environment

Charnes and Cooper (1959) suggested a method for solving stochastic mathematical models. Liu and Iwamura (1996) developed this method for the fuzzy environment and proposed a crisp auxiliary model for solving problems.

We can formulate mathematical modelling with fuzzy variable as shown in Equation (8);

$$\begin{cases} \max f(x,\varepsilon) \\ subject\ to \\ g_i(x,\varepsilon) \leq 0, i = 1,2,\ldots,p \end{cases} \tag{8}$$

where x is a decision variable, ε is a fuzzy variable, $f(x,\varepsilon)$ is the objective function, $g_i(x,\varepsilon)$ are constraint function, for $i = 1,2,\ldots,p$ (Liu and Ivamura, 1996) .

In this mathematical modelling, we have to convert the fuzzy functions (objective and constraint) to their crisp values. A chance-constrained programming model with a fuzzy variable can be written by using credibility measure of fuzzy variable as follows:

$$\begin{cases} \max f(x,\varepsilon) \\ subject\ to \\ Cr\{\varepsilon | g_i(x,\varepsilon) \leq 0, i = 1,2,\ldots,p\} \geq \alpha \end{cases} \tag{9}$$

where α is a predetermined confidence level, $Cr\{\cdot\}$ is the credibility of event in $\{\cdot\}$.

In addition, the multi-objective chance constrained mathematical model can be modelled as follows:

$$\begin{cases} \max[f_1(x), f_2(x), \ldots, f_m(x)] \\ subject\ to \\ Cr\{\varepsilon | g_i(x,\varepsilon) \leq 0, i = 1,2,\ldots,p\} \geq \alpha \end{cases} \tag{10}$$

Also, we can formulate this mathematical model according to the priority structure and target levels decided by decision makers as shown in Equation (11):

$$\begin{cases} \min \sum_{j=1}^{l} P_j \sum_{i=1}^{m} \left(u_{ij} d_i^+ + v_{ij} d_i^-\right) \\ subject\ to \\ f_i(x) + d_i^- - d_i^+ = b_i \,, i = 1,2, \ldots, m \\ Cr\{\varepsilon | g_j(x,\varepsilon) \leq 0,\ j = 1,2, \ldots, p\} \geq \alpha \\ d_i^-, d_i^+ \geq 0 \,, i = 1,2, \ldots, m \end{cases} \tag{11}$$

where P_j is the priority factor for each objective, u_{ij} is the weighting factor corresponding to positive deviation for goal i with priority j assigned, v_{ij} is the weighting factor corresponding to negative deviation for goal i with priority j assigned, d_i^+ is the positive deviation from the target of goal i, d_i^- is the negative deviation from the target of goal i, b_i is the target value according to goal i, l is the number of priorities, m is the number of goal constraints, and p is the number of real constraints.

Liu and Iwamura (26) used the inverse credibility function to convert the fuzzy model to a crisp model. For any confidence level α_i, $\theta^{-1}(\alpha)$ can be calculated according to Equation (7). And the model converted to the crisp one is as shown:

$$\begin{cases} \max f(x,\varepsilon) \\ subject\ to \\ \theta^{-1}(\alpha) \end{cases} \tag{12}$$

After the model becomes a crisp model; the mathematical model can be solved by classical methods (simplex algorithm, packet programs, etc.).

2.3. Chance Constrained Programming Models for Centralized and Decentralized Supply Chain Structure

Let us consider a two-stage supply chain consisting of a supplier and a retailer. The retailer buys the product from the supplier and sells it to the end customer. The retailer must determine the amount of the order (Q) that will be made to the supplier before the start of the selling season. The retail price at which the retailer sells the product to the end customer is p. The supplier production cost per unit is c_s and the marginal cost for the retailer is c_r. The goodwill penalty costs for the unmet demand have been ignored for computational ease. For notational convenience, $c = c_s + c_r$. At the end of the selling season, the retailer earns the salvage value for the unsold products, and the salvage value(s) must be lower than production costs $(s < c)$. The wholesale price from supplier to retailer is w. The demand occurring during the selling season is deterministic and shown as D. Also, the cost parameters are considered as a triangular fuzzy variable:

$\widetilde{c_s} = \left(c_s^a, c_s^b, c_s^c\right)$,

$\widetilde{c_r} = \left(c_r^a, c_r^b, c_r^c\right)$.

The profit functions of the supply chain members can be obtained as follows:

$The\ profit\ of\ the\ retailer = Sales\ Revenue + Salvage\ Income - Marginal\ Cost - Wholesale\ Outcome$

$$\Pi_r(Q) = p * D + s * (Q - D) - \tilde{c_r} * Q - w * Q \quad (13)$$

$$The\ profit\ of\ the\ supplier = -Production\ Cost + Wholesale\ Income$$
$$\Pi_s(Q) = -\tilde{c_s} * Q + w * Q \quad (14)$$

According to the coordination between the members, the supply chain is divided into two groups: such as centralized and decentralized. In a centralized supply chain model, there is only one decision-maker aiming to optimize the performance of the entire supply chain. The goal of this decision-maker is to *maximize the total profit of the supply chain.* On the other hand, in a decentralized supply chain model; all of the members want to optimize their performance separately. In other words, the purpose of each supply chain member is *to maximize their profits.*

The optimum order quantity, according to these supply chain structures, can be determined by using mathematical modelling. The chance-constrained models with fuzzy cost parameters for the centralized and decentralized supply chain structures are as shown in Model 1 and Model 2:

(Model 1)

Centralized Supply Chain Model (an objective function)

$$\max f(Q, \tilde{c}) = \Pi_T(Q) = -\tilde{c_s}Q - \tilde{c_r}Q + pD - s(Q - D) \quad (15)$$
$$Subject\ to$$
$$Q \geq D \quad (16)$$
$$Q\ is\ integer$$

(Model 2)

Decentralized Supply Chain Model (two objective functions)

$$\max f_1(Q, \tilde{c}) = \Pi_s(Q) = -\tilde{c_s}Q + wQ \quad (17)$$
$$\max f_2(Q, \tilde{c}) = \Pi_r(Q) = pD - s(Q - D) - \tilde{c_r}Q - wQ \quad (18)$$
$$Subject\ to$$
$$Q \geq D \quad (19)$$
$$Q\ is\ integer$$

The objective function of the centralized supply chain model (Equation 15) is to maximize the total profit of the supply chain. Furthermore, the crisp equivalent of this function can be obtained by using Equation (7). The constraints of this model are;

i. $Q \geq D$ (Equation 16); The order quantity of the retailer must be higher than the market demand (The goodwill penalty costs for the demand not satisfied have been ignored for computational ease.).
ii. $Q\ is\ integer$; The order quantity of the retailer must be an integer variable.

The objective functions of the decentralized supply chain model (Equation 17-18) are that the profit of each supply chain member is more significant than T. The constraints of this model are;

i. $Q \geq D$ (Equation 19); The order quantity of the retailer must be higher than the market demand (The goodwill penalty costs for the demand not satisfied have been ignored for computational easiness.).
ii. $Q\ is\ integer$; The order quantity of the retailer must be an integer variable.

Also, according to goal programming, goals also need to be added as constraints. So, the constraints of the goals with chance-constrained programming with fuzzy cost parameters are as follows:

i. $$C_r(pD - s(Q - D) - \tilde{c_r}Q - wQ + d_1^- - d_1^+ \geq T) \geq \alpha \quad (20)$$

$$C_r(\tilde{c_s}Q + wQ + d_2^- - d_2^+ \geq T) \geq \alpha \quad (21)$$

Moreover, the crisp equivalents of these functions can be obtained by using Equation (7). If we transform this model as a goal programming model; our objective function will be as follows. The goal of all members' profits being greater than T is considered to be of equal priority.

$$\min\ {d_1}^- + {d_2}^- \quad (22)$$

After transforming to the crisp equivalent of the functions, the centralized and decentralized supply chain models transform as shown in Model 1* and Model 2*:

(Model 1*)

Centralized Supply Chain Model (an objective function)

$$\max f(Q,\tilde{c}) = \Pi_T(Q) = -\theta^{-1}{}_{c_s}(\alpha)Q - \theta^{-1}{}_{c_r}(\alpha)Q + pD - s(Q-D) \quad (23)$$

$Subject\ to$

$$Q \geq D \quad (24)$$

$Q\ is\ integer$

(Model 2*)

Decentralized Supply Chain Model (two objective functions)

$$\min d_1{}^{-} + d_2{}^{-} \quad (25)$$

$Subject\ to$

$$pD - s(Q-D) - \theta^{-1}{}_{c_r}(\alpha)Q - wQ + d_1^- - d_1^+ \geq T \quad (26)$$

$$-\theta^{-1}{}_{c_s}(\alpha)Q + wQ + d_2^- - d_2^+ \geq T \quad (27)$$

$$Q \geq D \quad (28)$$

$Q\ is\ integer$

2.4. List of Notations

The notations employed throughout mathematical formulations are defined in Table 1. For ease of reference, all symbols are collected in the List of Notations.

Table 1. List of Notations

Symbol	Description
Q	Order quantity decided by the retailer
D	Market demand
p	Unit retail price of the product
w	Unit wholesale price charged by the supplier
c_s	Supplier’s unit production cost (fuzzy parameter)
C_r	Retailer’s unit marginal cost (fuzzy parameter)
s	Salvage value per unit of unsold product
Π_s	Profit of the supplier
Π_r	Profit of the retailer
α	Confidence (credibility) level in chance-constrained programming
P_j	Priority factor for objective jj (in goal programming)
T	Target value
u_{ij}	Weight of positive deviation for goal ij
v_{ij}	Weight of negative deviation for goal ij
d_i^+	Positive deviation variable for goal ij
d_i^-	Negative deviation variable for goal ij
Π_T	Total profit of the supply chain (supplier + retailer)

3. RESULTS

In this section, numerical examples are given for the demonstration of the proposed model in the previous section. Firstly, for a confidence level, the centralized and the decentralized supply chain models are compared. After that, the effect of the confidence level is investigated for each supply chain model by changing the confidence level value.

The primary objective of the supply chain members is to increase their profits. To achieve this goal, the members of the supply chain use different coordination mechanisms. In this part of the study, it is tried to determine the optimum order quantity in the centralized and decentralized supply chain models by using chance-constrained programming with fuzzy parameters. The parameters for the sample problem developed for this purpose are shown in Table 2.

Table 2. Some model parameters and their assigned values (All monetary values in USD; demand in units)

Parameters		Values
p	The retail price-deterministic	3000
$\tilde{c_s}$	The supplier's production cost per unit (fuzzy-triangular)	(100,150,190)
$\tilde{c_r}$	The retailer's marginal cost per unit (fuzzy-triangular)	(60,90,150)
s	The salvage value-deterministic	100
D	The demand of end customer-deterministic	1500
w	Wholesale price -deterministic	500
α	The confidence level-deterministic	0.1
T	Minimum value of the members' profit-deterministic	1000000

The fuzzy parameters used in this study (e.g., supplier's production cost, retailer's marginal cost) are hypothetical but representative of realistic cost intervals. Since the primary objective of this paper is methodological illustration, these values were not derived from a specific dataset but designed to demonstrate how the proposed fuzzy chance-constrained programming model operates under plausible uncertainty conditions. Each fuzzy parameter is expressed as a triangular fuzzy number (a, b, c), where $a$and $c$correspond to the minimum and maximum cost levels observed in similar numerical examples in the literature, and $b$represents the most likely or nominal cost level. This approach ensures interpretability while keeping the numerical demonstration fully self-contained and reproducible.

Depending on these parameters, the inverse credibility measure of the fuzzy parameters is calculated according to Equation (7) and the Model 1* and Model 2* are obtained.

For example, when the confidence level is $\alpha = 0.30$, we have $\alpha \leq 0.5$ and thus:

$\mathrm{Cr}^{-1}(0.30) = 100 + 2 \times 0.30 \times (150 - 100) = 100 + 0.60 \times 50 = 100 + 30 = 130.$

Hence, the fuzzy production cost $\tilde{c}_s = (100{,}150{,}190)$ is converted to its crisp counter part $c_s^{(0.30)} = 130$ at $\alpha = 0.30$.

When the confidence level is increased to $\alpha = 0.80 > 0.5$, the second branch of the inverse credibility function applies:

$\mathrm{Cr}^{-1}(0.80) = 190 - 2(1 - 0.80)(190 - 150) = 190 - 2 \times 0.20 \times 40 = 190 - 16 = 174.$

Thus, for $\alpha = 0.80$, the same fuzzy production cost is represented by the higher crisp value $c_s^{(0.80)} = 174$, reflecting a more conservative (risk-averse) assessment of the uncertain cost. These crisp values are then used in the centralized and decentralized models (see Models 1* and 2*) in place of the original fuzzy parameter.

In these models the retailer's order quantity must be at least 1500 units more than the manufacturer's order quantity. And in the decentralized supply chain model, the profits of each supply chain members are greater than 1.000.000. These models are as follows:

(Model 1*)

Centralized Supply Chain Model (an objective function)

$$\max f(Q,\tilde{c}) = \Pi_T(Q) = -182 * Q - 138 * Q + 4500000 - 100 * (Q - 1500)$$

$Subject\ to$

$Q \geq 1500$

$Q\ is\ integer$

(Model 2*)

Decentralized Supply Chain Model (two objective functions)

$$\min d_1^{-} + d_2^{-}$$

$Subject\ to$

$4500000 - 100 * (Q - 1500) - 138 * Q - 500 * Q + d_1^- - d_1^+ = 1000000$

$-182 * Q + 500 * Q + d_2^- - d_2^+ = 1000000$

$Q \geq 1500$

$Q\ is\ integer$

The results of these mathematical models are obtained using the Excel Solver. According to results, in the centralized supply chain model (model 1*), the optimum order quantity is 1500, and the supply chain total profit is 4236000. Furthermore, in the decentralized supply chain model (model 2*), the optimum order quantity is 2565, and the supply chain total profit is 3338400.

3.1. Sensitivity analysis and computational aspects

This subsection presents a detailed sensitivity and computational analysis of the proposed FCCP-based supply chain models. The objective is to evaluate how key parameters—such as the credibility (confidence) level, fuzzy cost spreads, wholesale price, and salvage value—affect the optimal decisions and profit outcomes in both centralized and decentralized structures. By systematically varying these parameters, the robustness and computational efficiency of the developed models can be assessed.

From a computational perspective, the proposed FCCP-based models are small-scale nonlinear optimization problems that can be efficiently solved using standard solvers. In this study, all numerical experiments were implemented in a spreadsheet environment and solved with the built-in Solver tool. For each parameter setting, the solution time was essentially instantaneous on a standard desktop computer, and no convergence or feasibility issues were encountered. This indicates that the centralized and decentralized formulations are computationally tractable and suitable for practical decision-support applications even when extended to larger instances.

The effect of the confidence level is investigated for each supply chain model by changing confidence level value. Table 3 shows the different solutions to the problem having different confidence levels from 0 to 1 with increment 0.05.

Table 3. Supply chain profit values under different confidence levels *(Profit values in $)*

α	DECENTRALIZED MODEL			CENTRALIZED MODEL
	Supplier's Profit ($)	Retailer's Profit ($)	Supply Chain Total Profit ($)	Supply Chain Total Profit ($)
0.1	815670	2522730	3338400	4236000
0.2	836976	2458544	3295520	4212000
0.3	859554	2390526	3250080	4188000
0.4	883404	2318676	3202080	4164000
0.5	908844	2242036	3150880	4140000
0.6	929832	2178808	3108640	4110000
0.7	952410	2110790	3063200	4080000
0.8	975624	2040856	3016480	4050000
0.9	1000110	1967090	2967200	4020000
1.0	1025868	1889492	2915360	3990000

As seen in Table 3, the supply chain total profit in both two cases (in the centralized and decentralized supply chain model) changes according to the different confidence levels. Also, in the decentralized model, as the confidence level increases, the supplier's profit increases and the retailer's profit decreases.

Also, it can be seen from Table 3 that the difference between the total profit of the decentralized and centralized models increases as the confidence level increases. So, we can say that the profit values of the centralized supply chain model are higher than the profit values of the decentralized supply chain model. If there is coordination between the members of the supply chain, the members generate more profit.

To provide a visual interpretation of the impact of the credibility level, Figure 1 plots the total supply chain profit of the centralized and decentralized models as a function of the confidence level α. The figure shows that, for all $\alpha \in [0.1,1.0]$, the centralized model consistently yields higher total profit than the decentralized model. As α increases, both profit curves exhibit a decreasing trend, reflecting the higher conservatism imposed by more stringent credibility requirements. Moreover, the profit gap between the two coordination structures widens with α, indicating that centralized coordination becomes relatively more advantageous under more risk-averse settings.

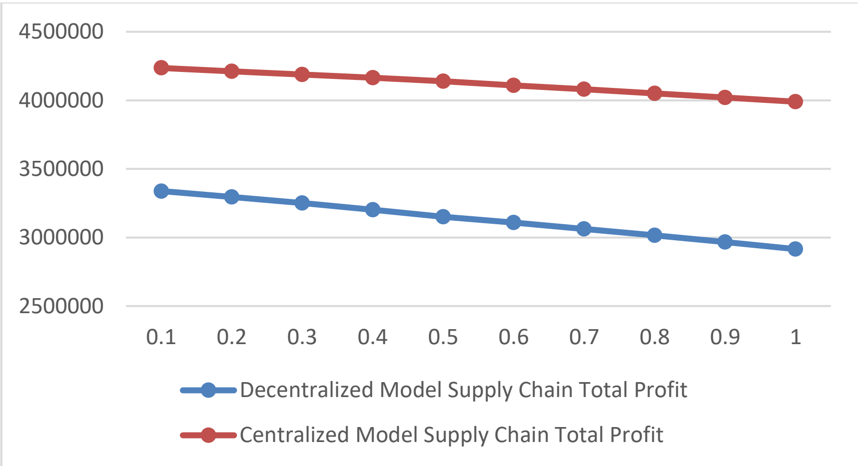

Figure 1: Variation of total profit with confidence level α for centralized and decentralized models

In addition to varying the credibility level, a scenario-based sensitivity analysis was carried out for the fuzzy cost parameters. As summarized in Tables 4 and 5, three alternative scenarios (S1–S3) were constructed by changing the spreads and central values of the triangular fuzzy production and marginal costs. Across all scenarios, the centralized model continues to deliver higher total profit than the decentralized one. At the same time, increases in the upper bounds of the fuzzy cost intervals lead to lower profits and slightly reduced optimal order quantities, as expected. These results confirm that the main managerial insight—namely, the profit advantage of centralized coordination under fuzzy cost uncertainty—remains robust to plausible changes in the fuzzy parameter configurations.

Table 4. Additional scenario parameter values *(costs in \$, demand in units, confidence in %)*

Scenario	α	Production cost (fuzzy)	Retailer cost (fuzzy)
S1	0.3	(120,150,180)	(60,100,140)
S2	0.6	(90,130,180)	(70,110,160)
S3	0.9	(100,140,200)	(80,120,170)

Table 5. Results of the scenarios presented in Table 3 *(profit values in \$)*

Scenarios	Optimal Order Quantity (Centralized) (\$)	Profit (Centralized) (\$)	Optimal Order Quantity (Decentralized) (unit)	Profit (Decentralized) (\$)
S1	1550	4205000	2470	3298000
S2	1490	4125000	2380	3215000
S3	1450	4000000	2300	3090000

As observed, the proposed model adapts well to varying fuzzy parameters and consistently demonstrates that centralized coordination yields higher total profit. These results further confirm the robustness and generalizability of the FCCP-based modeling framework.

To ensure the validity of the selected parameters, a sensitivity-style comparative analysis was performed by varying key inputs (e.g., production cost, marginal cost, confidence level). The results showed that the model behaved consistently across different parameter configurations, validating its structural reliability and practical robustness.

4. CONCLUSION

One of the most critical problems faced in supply chain management is the coordination between supply chain members. Based on the coordination among members, supply chains can be classified into two types: centralized and decentralized. In a centralized supply chain model, a single decision-maker seeks to optimize the performance of the entire supply chain. The objective of this decision-maker is to minimize overall system costs while maximizing overall performance. In contrast, in a decentralized supply chain model, each member focuses on optimizing their own performance independently. In other words, every supply chain member aims to minimize their individual costs and maximize their own profits.

In this study, a two-stage supply chain structure consisting of a supplier and a retailer under fuzzy demand is examined. In the study, the fuzzy chance constraint programming method is used in order to obtain optimum order quantity values that provide a maximum total supply chain profit in centralized and decentralized supply chain structures with fuzzy production costs parameters. We investigate the problem with credibility theory for the basis of the fuzzy chance-constraint programming method. Also, the decentralized supply chain model has more than one objective function because there are multiple decision-makers. Therefore, the goal programming approach is also utilized to solve this model. In order to facilitate the solution of the problem, shortage costs for all members have been ignored.

Firstly, for a confidence level, the centralized and the decentralized supply chain models are compared. According to results, in the centralized supply chain model (model 1*), the optimum order quantity is 1500, and the supply chain total profit is 4236000. Furthermore, in the decentralized supply chain model (model 2*), the optimum order quantity is 2565, and the supply chain total profit is 3338400.

After that, the effect of the confidence level is investigated for each supply chain model by changing confidence level value. The supply chain total profit in both cases (in the centralized and decentralized supply chain model) changes according to the different confidence level. Also, in the decentralized model, as confidence level increases; supplier's profit increases and retailer's profit decreases. Also, it can be seen, the difference between the total profit of decentralized and centralized model increases as the confidence level increases. So, we can say that the profit values of the centralized supply chain model are higher than the profit values of the decentralized supply chain model. If there is coordination between the members of the supply chain, the members generate more profit.

The sensitivity analyses with respect to the credibility level, fuzzy cost spreads, wholesale price, and salvage value further indicate that the qualitative dominance of the centralized coordination scheme is preserved under a wide range of parameter configurations, highlighting the robustness of the proposed FCCP-based framework.

In addition to the initial case study, several new test scenarios were developed to evaluate the robustness and generalizability of the proposed FCCP-based supply chain coordination model. These scenarios were constructed by varying the fuzzy cost parameters and confidence levels in line with real-world structures referenced in the literature. The results of these additional simulations consistently supported the main findings: the centralized model yields higher total supply chain profit compared to the decentralized structure. Furthermore, the model remained stable and interpretable under diverse parameter configurations. These findings reinforce the applicability and reliability of the proposed approach across different supply chain settings under uncertainty.

Moreover, this study contributes to the literature by integrating fuzzy chance constraint programming and credibility theory into both centralized and decentralized supply chain settings, something not previously done in a unified framework. Especially, the use of a goal programming-based FCCP model in the decentralized case allows modeling of multiple independent objectives under fuzzy cost parameters, which brings both theoretical novelty and practical relevance. These aspects demonstrate the originality and applicability of the proposed model.

In the present formulation, shortage and goodwill loss costs were deliberately omitted to simplify the comparative analysis between centralized and decentralized structures. This assumption allows the model to focus on the effect of fuzzy cost parameters and coordination mechanisms without introducing additional stochastic variability. However, neglecting shortage costs may lead to an overestimation of profits and order quantities, since real-world supply chains often face penalties or loss-sales consequences when demand exceeds available stock. Future extensions of the model could incorporate shortage-related costs through additional fuzzy or credibility-based parameters within the objective functions. For example, a fuzzy penalty term could be introduced to represent customer dissatisfaction or backorder costs, allowing the model to balance production, inventory, and service level trade-offs under uncertainty.

In this study, uncertainty was addressed through fuzzy cost parameters. For future research, demand uncertainty could also be considered—either in fuzzy or stochastic form—to further enhance the model's realism and applicability. Several other extensions are also possible. First, incorporating shortage or goodwill loss costs would provide a more comprehensive operational perspective. Second, extending the model to multi-period or rolling horizon settings would increase its managerial relevance by accounting for dynamic decisions and inter-temporal trade-offs. Finally, applying the model to large-scale industry case studies or validating it through simulation-based methods, such as Monte Carlo analysis, would further strengthen its empirical robustness.

The principal novelty of this study lies in the integration of credibility theory with fuzzy chance-constrained programming within a unified framework that simultaneously addresses both centralized and decentralized supply chain coordination. While earlier studies typically examined either coordination structure independently, this research demonstrates how credibility-based measures can model risk perception and confidence levels under fuzzy cost uncertainty. This methodological integration provides a robust analytical foundation for assessing coordination efficiency and decision robustness under imprecise information.

Despite these contributions, the study has several limitations. The analysis is based on a simplified two-stage, single-product supply chain and considers only fuzzy production and marginal cost parameters while ignoring stochastic demand and shortage costs. These assumptions were necessary to isolate the effect of coordination mechanisms and fuzzy uncertainty, but they may limit the direct applicability of the model to highly dynamic or multi-echelon supply chains.

Future research could address these limitations by:

(i) incorporating stochastic or fuzzy demand variables alongside cost uncertainty,

(ii) extending the FCCP-based framework to multi-product and multi-period supply chain systems,

(iii) integrating hybrid fuzzy–stochastic or data-driven robust optimization models to capture multiple layers of uncertainty, and

(iv) validating the proposed approach through real industrial case studies or simulation-based analysis. These directions would further enhance the generalizability and practical relevance of the proposed model.

Beyond the current two-stage, single-product formulation, the proposed FCCP-based coordination framework could be extended to multi-echelon and multi-product supply chains where multiple suppliers, manufacturers, and retailers interact simultaneously. Each echelon could have its own fuzzy production, transportation, and inventory cost parameters, thereby requiring a hierarchical or decomposed optimization structure. Moreover, incorporating uncertain or fuzzy demand would make the model more realistic for practical applications, as demand variability is often a major driver of coordination decisions. In such cases, the FCCP approach can be combined with stochastic programming or scenario-based fuzzy simulation to jointly handle parameters and demand uncertainty. These extensions would allow the framework to capture more complex interdependencies and enhance its relevance for real-world supply chain systems.

5. DISCUSSION

This study contributes to the literature by providing one of the first integrated applications of fuzzy chance-constrained programming (FCCP) and credibility theory to both centralized and decentralized supply chain structures. Academically**,** the work extends prior studies that usually examine either centralized or decentralized models in isolation, by offering a comparative and unified modeling framework. The methodological novelty also lies in incorporating multi-objective goal programming in the decentralized setting, thereby addressing the conflicting objectives of supply chain members.

From a conceptual standpoint, the interaction between fuzzy uncertainty and coordination structure fundamentally influences decision-making behavior within the supply chain. Under higher fuzzy cost uncertainty, decentralized members—operating with individual profit objectives—tend to adopt more conservative ordering decisions because they perceive higher individual risk. Conversely, a centralized decision-maker, who internalizes system-wide information and jointly optimizes all cost components, can offset this uncertainty by pooling risks across the chain. Therefore, the FCCP framework demonstrates that uncertainty amplifies the performance gap between decentralized and centralized systems: as the credibility level increases, decentralized profits diverge more sharply from the coordinated optimum. This finding conceptually reinforces the role of information sharing and integrated optimization as natural hedges against fuzziness in cost parameters.

From a managerial perspective**,** the findings underline the tangible benefits of centralized coordination, which consistently yields higher overall profits, particularly as the confidence level increases. This offers guidance to practitioners in designing contracts and coordination mechanisms under uncertain cost structures. Decision-makers can use the proposed framework as a decision-support tool to balance risk tolerance and profitability across different coordination scenarios.

For industrial practitioners, these insights imply that coordination contracts—such as buy-back, revenue-sharing, or quantity-flexibility agreements—become increasingly valuable in environments characterized by fuzzy or imprecise cost data. Firms can use FCCP-based decision models to determine optimal confidence levels corresponding to their risk tolerance and to design incentive mechanisms that align decentralized objectives with system-level goals. For example, in industries with volatile production costs (e.g., automotive, electronics, or food supply chains), adopting a centralized or contractually coordinated approach can significantly reduce profit volatility and improve responsiveness. Thus, the proposed model serves as a practical decision-support framework for managers seeking to balance profitability and robustness under fuzzy uncertainty.

At the societal level**,** improving coordination in supply chains contributes to economic efficiency and stability, which is critical for industries facing high uncertainty in cost parameters. By promoting more efficient use of resources and enhancing resilience to uncertainty, the proposed approach supports broader societal goals such as sustainability, competitiveness, and consumer welfare.

CONFLICT OF INTEREST

The author(s) declare that there is no known conflict of interest and no financial or personal relationships with any institution, organization, or individual that could have influenced the work reported in this study.

AUTHOR CONTRIBUTIONS

Gülçin Canbulut: Conceptualization, research design, methodology development, analysis and interpretation of the results, and manuscript writing.

REFERENCES

1. Arık, O. A. (2019). Credibility-based chance constrained programming for project scheduling with fuzzy activity durations. *An International Journal of Optimization and Control: Theories & Applications*, 9(2), 208–215. https://doi.org/10.11121/ijocta.01.2019.00631
2. Arshinder, A., Kanda, S. and Deshmukh, G. (2007) Coordination in supply chains: An evaluation using fuzzy logic, *Production Planning & Control*, 18(8), 420–435. https://doi.org/10.1080/09537280701430994.
3. Bilgen, B. (2010) Application of fuzzy mathematical programming approach to the production allocation and distribution supply chain network problem, *Expert Systems with Applications*, 37(6), 4488–4495. https://doi.org/10.1016/j.eswa.2009.12.062.
4. Charles, V., Gupta, S. and Ali, İ. (2018) Fuzzy goal programming approach for solving multi-objective supply chain network problems under probabilistic and fuzzy uncertainty, *Annals of Operations Research*, 269(1–2), 489–512. https://doi.org/10.1007/s10479-017-2524-1.
5. Charnes, A. and Cooper, W.W. (1959) Chance-constrained programming, *Management Science*, 6(1), 73–79. https://doi.org/10.1287/mnsc.6.1.73.
6. Choi, T.Y. and Guo, S. (2023) Manufacturing firms' credibility towards customers and operational performance: The counteracting roles of corruption and ICT readiness,

International Journal of Production Research, 61(15), 5172–5190. https://doi.org/10.1080/00207543.2023.2169666

7. Gholami, Z., Jolai, F. and Torabi, S.A. (2022) Robust-fuzzy optimization approach in design of sustainable lean supply chain network under uncertainty, *Computational and Applied Mathematics*, 41(4), 136. https://doi.org/10.1007/s40314-022-01936-w

8. Giri, B.C. and Sarker, B.R. (2019) Coordinating A Multi-Echelon Supply Chain Under Production Disruption and Price-Sensitive Stochastic Demand, *Journal of Industrial And Management Optimization*, 15,1631-1651. https://doi.org/10.3934/jimo.2018115.

9. Huang, X. (2010) *Portfolio analysis: From probabilistic to credibilistic and uncertain approaches*, *Studies in Fuzziness and Soft Computing*, vol. 250. https://doi.org/10.1007/978-3-642-11214-0.

10. Klir, G.J. and Yuan, B. (1995) *Fuzzy sets and fuzzy logic: Theory and applications*, Prentice Hall PTR, Upper Saddle River, NJ.

11. Lee, H.L. and Billington, C. (1993) Material management in decentralized supply chains, *Operations Research*, 41(3), 835–847. https://doi.org/10.1287/opre.41.5.835.

12. Liu, B. (2007) *Uncertainty theory*, 2nd edn, Springer, Berlin. https://doi.org/10.1007/978-3-540-73165-8.

13. Liu, B. and Iwamura, K. (1996) Chance constrained programming with fuzzy parameters, *Fuzzy Sets and Systems*, 94(2), 227–237. https://doi.org/10.1016/0165-0114(95)00204-4.

14. Liu, B. and Liu, Y.K. (2002) Expected value of fuzzy variable and fuzzy expected value model, *IEEE Transactions on Fuzzy Systems*, 10(4), 445–450. https://doi.org/10.1109/TFUZZ.2002.800692.

15. Lotfi, R., Kargar, B., Rajabzadeh, M., Hesabi, F. and Özceylan,E. (2022) Hybrid fuzzy and data-driven robust optimization for resilience and sustainable healthcare supply chains with a VMI approach, *Environmental Science and Pollution Research*, 29(12), 17645–17663. https://doi.org/10.1007/s11356-021-17053-3.

16. Lu, K., Lao,H. and Zavadskas,E.K. (2020) An overview of fuzzy techniques in supply chain management: Bibliometrics, methodologies, applications and future directions, *Annals of Operations Research*, 290(1), 1–30. https://doi.org/10.1007/s10479-018-2981-5.

17. Petrovic, D., Roy, R. and Petrovic, R. (1999) Supply chain modelling using fuzzy sets, *International Journal of Production Economics*, 59(1–3), 443–453. https://doi.org/10.1016/S0925-5273(98)00076-9.

18. Raza, S.A. and Govindaluri, S.M. (2019) Greening and price differentiation coordination in a supply chain with partial demand information and cannibalization, *Journal of Cleaner Production*, 229(1), 706–726. https://doi.org/10.1016/j.jclepro.2019.04.057.

19. Ryu, K. and Yücesan, E. (2010) A fuzzy newsvendor approach to supply chain coordination, *European Journal of Operational Research*, 200(2), 421–438. https://doi.org/10.1016/j.ejor.2009.01.037.

20. Safari, M. and Sahraeian, R. (2023) A chance-constraint optimization model for a multi-echelon multi-product closed-loop supply chain considering brand diversity: An accelerated Benders decomposition algorithm, *Computers & Operations Research*, 149, 106130. https://doi.org/10.1016/j.cor.2022.106130

21. Sahin, B., Yazir, D., Hamid, A. A., and Abdul Rahman, N. S. F. (2021) Maritime supply chain optimization by using fuzzy goal programming, *Algorithms*, 14(8), 234. https://doi.org/10.3390/a14080234.

22. Taleizadeh, A.A., Cardenas-Barron, L.E. and Sohani,R. (2019) Coordinating The Supplier-Retailer Supply Chain Under Noise Effect with Bundling and Inventory Strategies, *Journal* *of Industrial And Management Optimization*, 15, 1701-1727. https://doi.org/10.3934/jimo.2018153.

23. Tuan, D.H. and Chiadamrong, N. (2021) A fuzzy credibility-based chance-constrained optimization model for multiple-objective aggregate production planning in a supply chain under an uncertain environment, *Engineering Journal*, 25(4), 1–19. https://doi.org/10.4186/ej.2021.25.4.1.

24. Xu, Z., Zhang, Y. and Liu, B. (2024) Supply chain management based on uncertainty theory: A bibliometric analysis and future prospects, *Annals of Operations Research*. https://doi.org/10.1007/s10700-024-09435-9

25. Xue, F., Tang, W. and Zhao, R. (2008) The expected value of a function of a fuzzy variable with a continuous membership function, *Computers & Mathematics with Applications*, 55(6), 1215–1224. https://doi.org/10.1016/j.camwa.2007.05.025.

26. Wu, H., Chen, J. and Li, X. (2024) Chance-constrained optimization for a green multimodal routing problem with soft time window under twofold uncertainty, *Axioms*, 13(3), 200. https://doi.org/10.3390/axioms13030200

27. Zadeh, L.A. (1978) Fuzzy sets as a basis for a theory of possibility, *Fuzzy Sets and Systems*, 1(1), 3–28. https://doi.org/10.1016/0165-0114(78)90029-5.