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Designing sustainable supply chain networks under uncertain environments: Fuzzy multi-objective programming

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ABSTRACT

Sustainable supply chain networks have attracted considerable attention in recent years as a means of dealing with a broad range of environmental and social issues. This paper reports a multi-objective mathematical programming model for use in the design of a sustainable supply chain network under uncertain conditions. The proposed model is aimed at maximizing social benefits while minimizing economic costs and environmental impacts. The objective assists in making decisions concerning the selection of production technologies and materials and determining the number and locations of production and distribution centers and the quantity of product to be transported between facilities. Uncertainty related to customer demand is dealt by using stochastic variables, whereas overall costs, carbon emissions, job opportunities, and the detrimental effects of the resulting solutions are handled using fuzzy numbers. An interactive method based on two-phase stochastic programming and fuzzy probabilistic multi-objective programing is used to overcome problems related to uncertainty. Finally, numerical analysis demonstrates the efficacy and efficiency of the proposed model.

1. Introduction

Supply chain network (SCN) design is a crucial issue under discussion on variable economic cycles and increased globalization, taking into account strategic and political decisions related to the location and capacity of facilities and the flow between these facilities (Melnyk et al., 2014; Devika et al., 2014). Generally, the structure of a supply chain cannot be altered over the short term due to the time and costs associated with such activities. Thus, establishing a well-conceived SCN from the beginning is essential for facilitating sustainable development over the long term.

In the design of a logistics network, sustainable development depends on the following three dimensions: the economy, environment, and society (Hall et al., 2012). Unfortunately, minimizing total costs and/or maximizing profits have been the only objectives in SCN design (Demirel et al., 2014; Ozceylan and Paksoy, 2014; Devika et al., 2014). Sustainable supply chain management takes into account the environmental and social impact of supply chain operations, in addition to economic performance in the management of information, materials, and capital flow (Seuring and Müller, 2008). The objective behind sustainable supply chain network (SSCN) design is achieving a balance among a range of conflictive objectives pertaining to the supply chain. Numerous studies have addressed bi-objective problems dealing with economic and environmental considerations (Pinto-Varela et al., 2011; Pishvaee and Razmi, 2012; Pishvaee et al., 2012b; Baud-Lavigne et al., 2014; Mohammadi et al., 2014; Marufuzzaman et al., 2014; Bradenburg, 2015; Mohammad et al., 2015) or economic and social considerations (Yue et al., 2013; Cruz, 2013; Datta, 2014; Pishvaee et al., 2012a). Very few studies have considered economic, environmental, and social issues collectively (Mota et al., 2015; Devika et al., 2014; Yue et al., 2013) when dealing with design problems pertaining to SSCN. A review by Eskandarpour et al. (2015) on studies related to SSCN design for the period between 1990 and 2014 identified that there are a very limited number of studies dealing with the three indispensable dimensions of a SSCN (economy, environment, and society). Furthermore, most previous work has failed to take into account conditions of uncertainty in the planning of SCNs, which can lead to increased risk over the long term. This paper extends the formulation of models to include a wide range of realistic uncertainty problems.

The dynamic nature of complex supply chains imposes considerable uncertainty on the problem of network design; however,

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several methods have been developed to overcome this issue. The fuzzy interactive approach is one of the most attractive methods for its ability to measure and adjust the satisfaction level associated with each objective function in accordance with the preference of decision-makers (Pishvaee et al., 2012b). Fuzzy interactive methods have been widely used to solve problems related to green supply chain, closed-loop supply chain, and reverse logistics network design. However, to the best of our knowledge, no previous research has applied interactive fuzzy multi-objective programming within the context of SSCN design. Designing a SSCN is invariably a multi-objective problem, and fuzzy multi-objective programming is ideally suited for solving this problem; this approach has the ability to yield both balanced and unbalanced compromised for the conflicting objective functions. This approach also enables the direct measurement of satisfaction levels pertaining to each objective function.

To overcome the issues in considering all the three aspects of sustainable development and applying interactive fuzzy methods under uncertainty decision environment in the SSCN design field, this research considers the problem of SSCN design under conditions of uncertain customer demand and related costs, carbon emissions, job opportunities, and the detrimental effects of selecting inappropriate technology and materials. The following three detrimental effects are considered in this study: potentially hazardous products for customers, workplace hazards, and product-related cost. This paper distinguishes contributions from practical and theoretical perspectives as follows:

- Practical: This paper proposes a multi-objective mathematical model that takes into account three indispensable dimensions of a SSCN (economy, environment, and society). The proposed model is expected to help the planners to determine the number and location of facilities (i.e., production and distribution centers) and the product flows in the network. The CO_2 equivalent emissions and the abatement cost of production centers are used for measuring environmental goals, while the working conditions (i.e., the number of working days lost due to workplace hazards) and social commitments to customers are considered for measuring social objectives. The selection of materials and production technology are strategic decision made in relation to the trade-off between the establishment costs and the environmental and social impacts of the network for achieving the sustainable goal.
- Theoretical: This study proposes an interactive fuzzy multi-objective programming approach, combining two-phase stochastic programming and fuzzy probabilistic programming to formulate a SSCN design problem under an uncertain environment. Subsequently, fuzzy multi-objective programming is used to solve the proposed model. This approach would dominate other approaches used in previous studies owing to its use of fuzzy numbers for discrete distributions and stochastic variables for continuous distributions to deal with uncertainties. It saves considerable time and resources when collecting data to manage probability distribution for practical real-world problems. Furthermore, the two-phase stochastic programing (TSP) is used to divide decision variables into two subsets; this helps to control resource variables in the first subset to ensure feasibility of output variables in the second. The proposed approach also makes it possible to deal with numerous scenarios simultaneously in relation to uncertainties in customer demand.

The remainder of this paper is organized as follows. Section 2 presents a review of the relevant literature on SSCN design. The problem addressed in this study is defined in Section 3. In Section 4, we propose a multi-objective integer linear programming model, and the proposed interactive fuzzy approach to solve the problem is outlined in Section 5. Numerical analysis of the proposed method is presented in Section 6. Concluding remarks and suggestions for future research are given in Section 7.

2. Literature review

A sustainable multi-echelon supply chain must be able to handle multiple objectives related to economic, environmental, and social concerns within an uncertain environment. The following review is based on the characteristics of the design problem; the solutions to this problem are divided into two categories: the three dimensions of a SSCN and the application of fuzzy methods to SCN design.

2.1. Economic and environmental issues associated with sustainable supply chain networks

In the design and operation of a SCN, sustainability is crucial to economic performance, and has a profound impact on the environment society. However, most mathematical models conventionally used in network design fail to consider the environmental objectives. Generally, firms are driven by customers and/or government to address these issues. Ilgin and Gupta (2010) summarized the environmental factors in product design, reverse and closed-loop supply chain, remanufacturing, and disassembly. Chardine-Baumann and Botta-Genoulaz (2014) presented a sustainable performance assessment approach toward supply chain management practices, in which the environmental budget of production centers is considered as a constraint for environmental management (i.e., checking pollution and the use of hazardous materials). You and Wang (2011) sought to optimize the design of biomass-to-liquid supply chains under the economic and environmental criteria based on the CO_2 equivalent greenhouse gas emissions of the total life cycle of product, including acquisition, production, distribution, storage, and sequestration. Pinto-Varela et al. (2011) used a bi-objective optimization method in a supply chain design with the aim of maximizing profits while taking into account environmental issues related to the consumption of utilities, land use, and resource inventory. Pishvaee et al. (2012b) proposed a bi-objective model to minimize the total cost and environmental impact of designing a SCN, where CO_2 equivalent emissions due to production and transportation activities are used to model the environmental impact across the concerned logistics network. Pishvaee and Razmi (2012) dealt with the total cost and total environmental impact of a supply chain; their study uses the Eco-indicator 99 method and life cycle approach to estimate the total environmental impact, including human health, health of the ecosystem, and resource depletion. Mohammadi et al. (2014) formulated a model for sustainable hub location-allocation problem through the integration of economic and environmental decisions, wherein two new environmental factors related to air and noise pollution by vehicles were introduced. Saffar et al. (2015) took into account the CO_2 emissions associated with the production and remanufacturing processes and total cost minimization in the design of a green supply chain network; however, they failed to take into account the effects of transportation on environmental issues.

2.2. Social issues pertaining to sustainable supply chain networks

The social aspect of supply chains is associated with social justice and the rights of stakeholders including employees, customers, and local communities (Eskandarpour et al., 2015). In recent years, far less attention has been paid to social factors than environmental factors in the design of SSCN. In ISO 26000 (Handbook for Implementers of ISO 26000, 2011), social responsibilities are classified into the following seven groups: (1) organizational governance, (2) human rights, (3) labor practices, (4) environment, (5) fair operating practices, (6) consumer issues, and (7) community involvement and development. Chardine-Baumann and Botta-Genoulaz (2014) classified the social and environmental issues into five fields: (1) work conditions, (2) human rights, (3) social commitments, (4) customer issues, and (5) business. The focus of the social problems considered in our study is based on the work of Chardine-Baumann and Botta-Genoulaz (2014), owing to the emphasis on internal stakeholders, particularly employees. For external stakeholders, the social commitments related to the safety of products and regional development are also considered in this study.

The number of jobs created is widely considered a primary social indicator. Pishvaee et al. (2012a) aggregated the number of job opportunities created at the production and distribution centers with consumer safety and environment issues while seeking to minimize total costs in a network. Devika et al. (2014) divided job opportunities into fixed and variable jobs, based on the activity levels of the supply chain. Yue et al. (2013) considered the economy, environment, and society in the design of a sustainable bioelectricity supply chain network, wherein they divided the job opportunities into fixed and variable local jobs; they subsequently sought to maximize the balance in accordance with the tenets of corporate social responsibility.

Beheshtifar and Alimohammadi (2014) considered social commitments, land acquisition-related costs, and land-use incompatibility in relation to the establishment of new healthcare facilities in a SCN. Zhang and Awasthi (2014) investigated social factors related to legal compliance and ethics in the planning of a sustainable supply chain; they used the sustainability function deployment based on the quality function deployment. Mota et al. (2015) proposed a social benefit indicator (SBI) for less developed regions when solving location-allocation problems in designing a SCN. Govindan et al. (2015) conducted the maximization of social benefits, including economic welfare, stakeholder growth, economic contributions, and environmental impact for a generic closed-loop supply chain network.

2.3. Fuzzy methods in the design of supply chain networks

SCN designing is followed by an implementation period, during which operational parameters are determined. Emerging from local issues and global trends, uncertain planning conditions can lead to variability in the business environment. Uncertainty also affects the output and structure of SCN in terms of economy, environment, and society. This has led to the development of numerous fuzzy computation methods, such as fuzzy probabilistic, robust fuzzy, and interactive fuzzy methods. Particularly, fuzzy probability is considered an efficient approach for managing inaccurate data or insufficient historical data that are required for estimating the probability distribution function of uncertain parameters. Pishvaee and Torabi (2010) adopted this approach to minimize the total costs and delivery delays in a closed-loop SCN design. Phuc et al. (2013) applied this method to optimize a closed-loop supply chain for electrical and electronic equipment. You and Wang (2011) formulated a bi-criterion optimization model for centralized networks of biomass supply chains and solved it using the ε-constraint method of fuzzy probabilistic programming. Wang and Hsu (2012) also applied the fuzzy probabilistic approach to the modeling and resolution of uncertain closed-loop logistics with objective functions related to transportation, operation, shortage, and surplus cost. Pinto-Varela et al. (2011) applied the symmetric fuzzy linear programming for the bi-objective functions used for supply chain planning. Xu et al. (2011) proposed a multi-objective model for distribution center locations with random fuzzy coefficient and solved one model by using the probability and possibility measure of the fuzzy theory.

Interactive fuzzy method is known as the combination of methods that is used to convert original mathematical models into equivalent auxiliary crisp model and solve multi-objective problems based on fuzzy approaches. The interactive fuzzy methods do not need complex computation like the stochastic approaches. Pishvaee and Razmi (2012) presented an interactive fuzzy solution approach based on the ε-constraint method and Pishvaee et al. (2012b) presented a solution based on the credibility measure method for the design of SCNs. Pishvaee et al. (2012a) proposed a robust probabilistic programming method based on the expected value concept of fuzzy numbers for the design of a socially responsible supply chain network. Vahdani et al. (2013) proposed an interactive hybrid fuzzy solution method combining fuzzy probabilistic programming, interval programming, and chance-constraint programming for designing a closed-loop supply chain network. Saffar et al. (2015) applied a fuzzy ε-constraint method in the design of a green supply chain network under conditions of uncertainty. Recently, Talaei et al. (2016) proposed a robust fuzzy optimization model with the fuzzy ε-constraint approach to solve the closed-loop SCN design problem under objective functions related to economic and environmental concerns.

Table 1 presents a summary of studies conducted since 2010 on the three primary dimensions of a sustainable supply chain under uncertainty. During this period, only a few studies considered all the three dimensions (i.e., economic, environmental, and social) in the design of a sustainable supply chain. There are no previous studies that have dealt with this problem in an uncertain environment with interactive fuzzy methods.

3. Problem description

The SSCN considered in this paper is a multi-echelon network that comprises four layers: multiple suppliers, production centers, distribution centers, and customer zones. The ultimate objective is to determine the number and locations of production and distribution centers and make decisions concerning the selection of material suppliers and production technologies and the flow of product among the selected facilities to minimize the total cost and environmental impact and maximize the social benefit.

According to Fig. 1, the suppliers offer materials of various quality levels that can have a profound influence on total costs, environmental impacts, and social benefits. A single product is manufactured by different production centers at a set of potential locations using suitable production technology and materials. The product is then shipped to fixed customer zones through multiple distribution centers selected from a pre-determined set of potential locations.

Many researchers have considered the capacity of production and distribution centers in the design of SCNs, owing to their importance in relation to the cost of implementing a distribution network (Mohammad et al., 2015; Pishvaee et al., 2012a, 2012b). This paper also considered a range of capacity levels in the development of a SSCN. It is notable that this paper is the first research to take into account varying levels of quality in terms of material for SSCN design, as this is considers SSCN design to be a critical problem in real-world contexts and one the experts a significant impact on environmental and social initiatives (Ashby, 2013). An important assumption for the effectiveness of SSCN is that the demands of all the customers are satisfied. The following other assumptions must be taken into account in the formulation of the problem:

Table 1
Review of some relevant researches about sustainable supply chain network.

Reference	Aspects of SSCND			Uncertainty decision environment
	Economic contributions	Environmental impacts	Social responsibilities	
Pishvaee and Torabi (2010)	●			●
You and Wang (2011)	●	●		●
Pinto-Varela et al. (2011)	●	●		●
Xu et al. (2011)	●			●
Pishvaee and Razmi (2012)	●	●		●
Pishvaee et al. (2012a)	●		●	●
Pishvaee et al. (2012b)	●	●		●
	●			●
Datta (2014)	●		●	
Wang and Hsu (2012)	●			●
Phuc et al. (2013)	●			●
Vahdani et al. (2013)	●			●
Mohammadi et al. (2014)	●	●		●
Devika et al. (2014)	●	●	●	
Yue et al. (2013)	●	●	●	
Beheshtifar and Alimoahmmadi (2014)	●		●	
Ozceylan and Paksoy (2014)	●			●
Demirel et al. (2014)	●			●
Mota et al. (2015)	●	●	●	
Saffar et al. (2015)	●	●		●
Talaei et al. (2016)	●	●		●
Govindan et al. (2015)	●	●	●	
This research	●	●	●	●

- A single product is produced and distributed throughout the network.
- The locations of customer zones and material supply zones are fixed.
- The potential locations of production and distribution centers are discrete.
- Plants and distribution centers can be configured at various capacity levels.
- Various production technologies are available for the establishment of production centers.
- Material cost depends on the quality of material.
- Material choice also affects the environmental and social cost.

The important uncertainty issues are addressed in SSCN design problems include demand, cost, capacity, CO_2 emissions, and the number of job opportunities, the generation of hazardous by-products, and the average number of workdays lost due to the implementation of new technologies. The design of a SSCN requires that three objective functions be taken into account: the minimization of total costs, environmental impact, and maximization of social benefits. The first objective is related to efficiency, whereas the other two objectives refer to corporate social responsibility. The ultimate goal of this endeavor is to make a reasonable trade-off between the economic benefits of production centers and the social and environmental impacts of customer zones.

4. Model formulation

The SSCN design is formulated as a multi-objective mixed integer linear programming (MOMILP) model. The indices, parameters and variables used in the formulation are illustrated in the following:

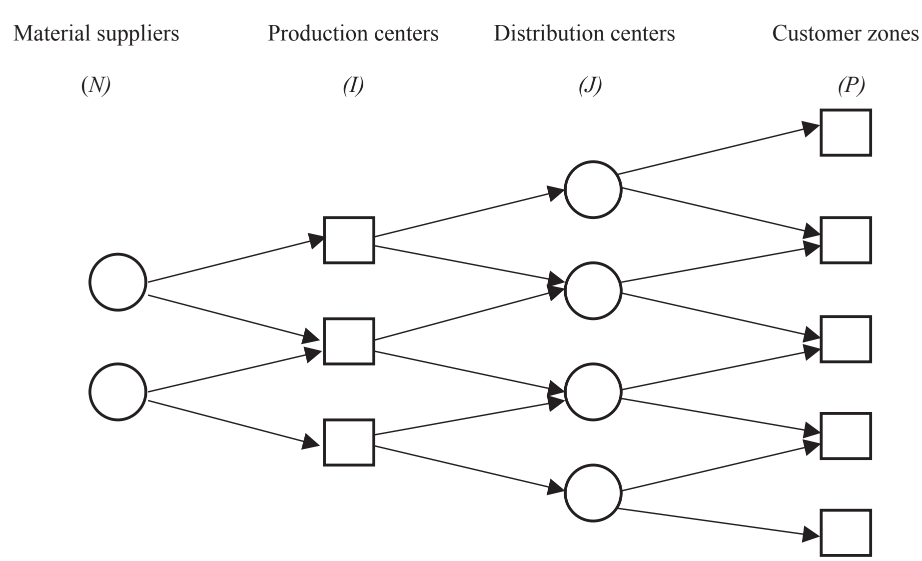

Fig. 1. Underlying structure of proposed sustainable supply chain network.

Indices:

i	index of potential locations for plants, $i = 1, 2 \ldots I$
j	index of potential locations for distribution centers, $j = 1, 2 \ldots J$
p	index of fixed locations for customer zone, $p = 1, 2 \ldots P$
m	index of different production technologies available for plants, $m = 1, 2 \ldots M$
n	index of different type material qualities available for plants, $n = 1, 2 \ldots N$

Parameters:

f_i^m	fixed cost of opening plant i with production technology m
g_j	fixed cost of opening distribution center j
c_{ij}	shipping cost per product unit from plant i to distribution center j
c_{jp}	shipping cost per product unit from distribution center j to customer zone p
p_i^m	production cost per unit of product at plant i with technology m
m_i^n	material cost per product unit at plant j with type material n
h_j	holding cost per product unit at distribution center j
η_i^m	CO_2 equivalent emission per unit product producted at plant i by technology m
$¶_i^n$	CO_2 equivalent emission per unit product producted at plant i by material n
t_{ij}	CO_2 equivalent emission per unit product shipped from plant i to distribution center j
s_{jp}	CO_2 equivalent emission per unit product shipped from distribution center j to customer zone p
δ_i^m	abatement cost of plant i by technology m
β_i^n	abatement cost of plant i by material n
B	budget for environmental problems of plant i
e_c	unit cost of CO_2 equivalent emission trading with the outside market
θ_{lo}	weight factor of total number of produced job opportunities
θ_{lp}	weight factor of total number of potentially hazardous products
θ_{ld}	weight factor of total number of lost days caused from work's damages
o_i^m	number of job opportunities created if a plant is opened at location i with technology m
o_j	number of job opportunities created if a distribution center is opened at location j
s^m	average amount of potentially hazardous products when technology m is used
s^n	average amount of potentially hazardous products when matetail n is used
l^m	average lost days caused from health problems of per worker when technology m is used
l^n	average lost days ccaused from health problems of per worker when material n is used
d_p	demand of customer zone p
ι_i	maximum capacity of plant i
ϕ_j	maximum capacity of distribution center j

Variables:

$$x_i^m = \begin{cases} 1 & \text{if a plant with technology } m \text{ is opened at location } i \\ 0 & \text{otherwise} \end{cases}$$

$$z_i^n = \begin{cases} 1 & \text{if a plant use material } n \text{ to product is opened at location } i \\ 0 & \text{otherwise} \end{cases}$$

$$y_j = \begin{cases} 1 & \text{if a distribution center is opened at location } j \\ 0 & \text{otherwise} \end{cases}$$

q_{ij}^{mn}	quantity of products manufactured at plant i with technology m and material n and shipped to distribution center j
u_{jp}	quantity of products shipped from distribution center j to customer zone p

In terms of the above notation, the SSCND problem can be formulated as follows:

Model

$$\text{Min } W_1 = \sum_{i=1}^{I}\sum_{m=1}^{M}\tilde{f}_i^m x_i^m + \sum_{j=1}^{J}\tilde{g}_j y_j + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\left(\tilde{m}_i^n + \tilde{p}_i^m + \tilde{c}_{ij} + \tilde{h}_j\right) q_{ij}^{mn} + \sum_{j=1}^{J}\sum_{p=1}^{P}\tilde{c}_{jp} u_{jp} \tag{1}$$

$$\text{Min } W_2 = e_c\left(\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{p=1}^{P}\left(\tilde{\eta}_i^m + \tilde{\P}_i^n + \tilde{t}_{ij}\right) q_{ij}^{mn} + \sum_{j=1}^{J}\sum_{p=1}^{P}\tilde{s}_{jp} u_{jp}\right) + \sum_{i=1}^{I}\sum_{m=1}^{M}\tilde{\delta}_i^m x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}\tilde{\beta}_i^n z_i^n \tag{2}$$

$$\text{Max } W_3 = \theta_{lo}\left(\sum_{i=1}^{I}\sum_{m=1}^{M}\tilde{o}_i^m x_i^m + \sum_{j=1}^{J}\tilde{o}_j y_j\right) - \theta_{lp}\left(\sum_{i=1}^{I}\sum_{n=1}^{N}\sum_{j=1}^{J}\tilde{s}^n q_{ij}^{mn} + \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{j=1}^{J}\tilde{s}^m q_{ij}^{mn}\right) - \theta_{ld}\left(\sum_{i=1}^{I}\sum_{m=1}^{M}\tilde{l}^m x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}\tilde{l}^n z_i^n\right) \tag{3}$$

The first objective function (1) is to minimize the total costs of the SSCN. In this objective, the first and second terms are fixed costs incurred during the establishment of production and distribution centers. The installation cost of facilities depends on the capacity level adopted in the network. The third term deals with the costs incurred by a production center on materials, production, storage, and transportation. The material cost depends on the quality of material provided by the suppliers, while the production cost is influenced by the technology adopted for production. The last term calculates the shipping cost from distribution centers to customer zones. It is assumed that the shipping cost depends on the transportation model used in the network.

The second objective function (2) minimizes the environmental impacts of the network. The CO_2 equivalent emissions caused by production and transportation are presented in the first and second terms. The third and last four terms deal with the amount invested in environmental protection at the production centers. Unlike most previous studies, which focused solely on CO_2 emissions, we introduced this new factor in the formulation of the model to facilitate a more comprehensive evaluation of the environmental impact. In this objective function, we assumed that the CO_2 emissions depend on the transportation model, fuel usage, and geographical distances; additionally, it is assumed that the production centers are committed to sustainable development goals.

The third objective function (3) maximizes the number of social benefits earned from establishing the network. The first and second terms of this objective comprise the number of job opportunities created in the network. We assumed that the number of jobs created totally depends on the used capacity and production technology of the facilities. The third and fourth terms show the amount of hazardous by-products associated with the selection of production technology and materials. The two last terms depict the number of workdays lost due to workplace hazards. It strongly depends on the production technology and materials used at the production centers in the network.

The constraints of the model are presented in Eqs. (4)–(13), as follows:

Constraints

$$\sum_{j=1}^{J} u_p^j \geq \tilde{d}_p\ , \forall p \tag{4}$$

$$\sum_{j=1}^{J} q_{ij}^{mn} \leq\ x_i^m \tilde{\iota}_i\ \forall i, m,\ n \tag{5}$$

$$\sum_{j=1}^{J} q_{ij}^{mn} \leq z_i^n \tilde{\iota}_i\ \forall \mathrm{i, m,\ n} \tag{6}$$

$$\sum_{p=1}^{P} u_{jp} \leq \mathrm{y}_j \tilde{\phi}_j\ \forall \mathrm{j} \tag{7}$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\tilde{\delta}_i^m x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}\tilde{\beta}_i^n z_i^n \leq B \tag{8}$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\mathrm{q}_{\mathrm{ij}}^{\mathrm{mn}} = \sum_{p=1}^{P} u_{jp},\ \forall j \tag{9}$$

$$\sum_{n=1}^{N} z_i^n \leq 1\ \forall \mathrm{i} \tag{10}$$

$$\sum_{m=1}^{M} x_i^m \leq 1\ \forall \mathrm{i} \tag{11}$$

$$q_{ij}^{mn},\ u_{jp} \geq\ 0,\ \forall i,\ j,\ m,\ n,\ p \tag{12}$$

$$x_i^m,\ z_i^n,\ \mathrm{y}_j \in (0, 1)\ \forall \mathrm{i,\ j,\ m,\ n} \tag{13}$$

Constraint (4) ensures that the demand of each customer zone is satisfied. It should be noted that minimizing the total cost of the network would result in production output equaling the demand. Constraints (5) and (6) ensure that the output of each production center is less than the designed capacity, as determined by technology and materials, respectively. Constraint (7) is a constraint on the capacity of the distribution centers. Constraints (5), (6), and (7) prohibit the shipping of units between production and distribution centers that have not become operational. Constraint (8) is the budget allocated by production centers to protect the environment, particularly concerning the strategic selection of technologies and materials. Constraint (9) strikes a balance between the input and output of each distribution center. Equations (10) and (11) ensure that no more than one technology and one material are assigned to each production center in a given location. Finally, constraints (12) and (13) guarantee the binary and non-negativity of decision variables.

The dynamic nature of supply chains and the fact that operating parameters cannot be determined when the network is designed indicate that problems related to the design of SCNs are associated with parameters of considerable uncertainty (e.g., demand, capacity, and costs) in real-world circumstances. Furthermore, this uncertainty increases when environmental and social concerns are taken into account. Thus, omitting uncertainty from the design of a sustainable supply chain may impose considerable risk on future operations. This paper developed an interactive fuzzy approach based on fuzzy probabilistic multi-objective programing for the management of uncertain parameters in SSCN design problems. This makes it possible to consider all model parameters as probability distributions and fuzzy numbers. The symbol "~" is used to assign uncertain parameters related to the demand; capacity; and some relevant economic, environmental, and social costs in the objective functions and system constraints. Details pertaining to the proposed interactive fuzzy approach are outlined in the following section.

5. Proposed solution method

Fuzzy programming is increasingly being used to overcome decision-making problems in SCN designing; it can be classified into three groups: (1) fuzzy flexible programming, (2) fuzzy probabilistic programming, and (3) robust programing. Fuzzy flexible programming deals with soft constraints and flexible objective functions; however, it lacks the capability to consider ambiguous coefficient of the objective functions and constraints. Robust programming improves the above disadvantage of fuzzy flexible programming by representing fuzzy numbers in the constraints; however, the main limitation of this method is the assumption about uncertainties in a non-fuzzy decision space. Fuzzy probabilistic programming can successfully overcome ambiguous coefficients in both objective functions and constraints (Vahdani et al., 2013; Pishvaee and Khalaf, 2016). Fuzzy probabilistic programming is more commonly used to handle situations associated with an inability to determine the exact value of the model parameters. In doing so, probability distributions can be used to model fuzzy parameters based on available data and knowledge of the decision-maker. In addition, fuzzy probabilistic programming makes it possible to take into account ambiguous coefficients of objective functions and constraints, which can be exceedingly difficult to achieve using fuzzy flexible programming or robust programing. Numerous methods have been based on this approach to cope with SCN design problems under situations of uncertainty. In this study, we also applied fuzzy probabilistic programming to adjust the objective functions and constraints of the two-phase stochastic programming model for SSCN design.

5.1. Auxiliary multi-objective linear programming model

In SCN design, some stochastic events, such as the demand for a product and cost of resources, can affect decision-making. Thus, we adopted the two-phase stochastic programming (TSP) combined with fuzzy probabilistic programming to transform the MOMILP model into an equivalent crisp model by adjusting the objective functions and constraints.

The compact form of the MOMILP model for SSCN design can be stated as Eq. (14). The process of constructing the equivalent crisp model and solving problem are based on this compact form.

$$\begin{aligned}
&\text{Min} \sum_{k=1}^{3} W_k = \sum_{g=1}^{G}\left(c_g x_g + b_g q_g\right)\\
&\text{s.t.}\\
&\sum_{g=1}^{G} t_g x_g \le v_g\\
&\sum_{g=1}^{G} e_g q_g \le d_g\\
&x_g, q_g \ge 0
\end{aligned} \tag{14}$$

5.1.1. Dealing with a lack of precision in objective functions

The TSP is used to divide the decision variables into two subsets. The first subset denotes the activity levels of resources, such as the number or capacity of facilities, which are determined using random variables. The second subset comprises output variables, such as the number of products or inventory level, which are determined using the realized value of random variables (Sakawa et al., 2011; Li et al., 2014). Decision-makers must assign a cost to the resource variables in the first subset to ensure that the output variables in the second subset are feasible.

The decision variables in this model can be divided into two subsets: (1) the first subset includes recourse-related variables including technologies, materials, and the number of facilities (x_i^m, z_i^n, y_j) and (2) the amount of product that is produced and shipped (q_{ij}^{mn}, u_{jp}), which may be influenced by stochastic variables in the model, such as demand in specific customer zones (d_p). The possibility distribution of these fuzzy parameters in the model can be configured as fuzzy membership functions. In this research, fuzzy parameters are presented in the form of a trapezoidal fuzzy set with four numbers, for example $\tilde{f}_i^m = (\tilde{f}_{i1}^m, \tilde{f}_{i2}^m, \tilde{f}_{i3}^m, \tilde{f}_{i4}^m)$ with $\tilde{f}_{i2}^m < \tilde{f}_{i3}^m$. According to TSP, the objective function in the model (14) can be formulated as Eq (15). The detailed objective function formulations are shown in Appendix A.

$$\text{Min} \sum_{k=1}^{3} W = \sum_{g=1}^{G} \tilde{c}_g x_g + \sum_{h=1}^{H} p_h \sum_{g=1}^{G} \tilde{b}_g q_g \tag{15}$$

In which

- p_h the probability of realization of scenario, with $p_h > 0$ and $\sum_{h=1}^{H} p_h = 1$
- h the number of scenarios are considered, $h = 1, 2, \ldots, H$
- $\tilde{c}_g$ trapezoidal fuzzy parameters for decision variables in the first subset
- x_g decision variables of the first subset
- $\tilde{b}_g$ trapezoidal fuzzy parameters for decision variables in the second subset
- q_g decision variables of the second subset

5.1.2. Dealing with constraints

Fuzzy probabilistic programming makes it possible to alter model constraints under a set of given probabilities to reflect the reliability of the system, according to which the customer demand can be assumed to have uniform distribution $[\tilde{d}_p \sim unifrom\ (x,\ y)]$ and the probability level of each demand is given by a trapezoidal fuzzy number ($\tilde{p}_d = (p_{d1}, p_{d2}, p_{d3}, p_{d4})$). The values on the right-hand side of the remaining constraints are trapezoidal fuzzy numbers. The constraints system in the model (14) can be formulated as Eq (16); all the constraints of MOMILP model are shown in Appendix B.

$$\begin{aligned}&\sum_{g=1}^{G}\tilde{t}_g x_g \le \tilde{v}_g\\&\sum_{g=1}^{G}\tilde{e}_g q_g \le \sum_{h=1}^{H}\mathrm{p_h}\tilde{\mathrm{d}}_g d_p\\&x_g, q_g \ge 0\end{aligned} \tag{16}$$

The α-cut level is defined as "a set of elements that belong to a fuzzy set with a membership grade of at least α." This grade is also referred to as the degree of confidence or the degree of plausibility (Zadel, 1978). Using a trapezoidal fuzzy number, such as $\tilde{\mathrm{a}}_i = (\mathrm{a_{i1}}, \mathrm{a_{i2}}, \mathrm{a_{i3}}, \mathrm{a_{i4}})$, each α-cut level can be presented into a closed interval—$[(1-\alpha)a_{i1} + \alpha a_{i2};\ (1-\alpha)a_{i4} + \alpha a_{i3}]$—for the lower and upper bounds of the objective functions and constraints. This makes it possible to convert the TSP model directly into two deterministic sub-models that accord with the lower and upper bounds of the objective-function value with α-cut level. We have provided the detailed model formulation with lower sub model and upper sub model of SSCN design problem in Appendix C. The general formulation is shown as follows:

Lower sub model

$$\text{Min } W = \sum_{g=1}^{G}[(1-\alpha)c_{g1} + \alpha c_{g2}]x_g + \sum_{h=1}^{H}p_h\sum_{g=1}^{G}[(1-\alpha)b_{i1} + \alpha b_{i2}]q_g$$

Constraints:

$$\begin{aligned}&\sum_{g=1}^{G}[(1-\alpha)\mathrm{d_{g1}}+\alpha\mathrm{d_{g2}}]x_g \le (1-\alpha)\mathrm{e_{g1}}+\alpha\mathrm{e_{g2}}\\&\sum_{g=1}^{G}[(1-\alpha)\mathrm{d_{g1}}+\alpha\mathrm{d_{g2}}]q_g \le \sum_{h=1}^{H}(\mathrm{y}_h-\mathrm{x}_h)(1-\alpha)\mathrm{d_{g1}}+\mathrm{de_{g2}}+x_{g1}\\&q_g, x_g \ge 0\end{aligned}$$

Upper sub model

$$\text{Min } W = \sum_{g=1}^{G}[(1-\alpha)c_{g4} + \alpha c_{g3}]x_g + \sum_{h=1}^{H}p_h\sum_{g=1}^{G}[(1-\alpha)b_{i4} + \alpha b_{i3}]q_g$$

Constraints:

$$\begin{aligned}&\sum_{g=1}^{G}[(1-\alpha)\mathrm{d_{g4}}+\alpha\mathrm{d_{g3}}]x_g \le (1-\alpha)\mathrm{e_{g4}}+\alpha\mathrm{e_{g3}}\\&\sum_{g=1}^{G}[(1-\alpha)\mathrm{d_{g4}}+\alpha\mathrm{d_{g3}}]q_g \le \sum_{h=1}^{H}(\mathrm{y}_h-\mathrm{x}_h)(1-\alpha)\mathrm{d_{g4}}+\mathrm{de_{g3}}+x_h\\&q_g, x_g \ge 0\end{aligned}$$

5.2. Proposed interactive fuzzy programming

SSCN design is a multi-objective programming problem. The interactive fuzzy programming is one of the most attractive methods for this problem under uncertainty situations because of its ability to measure and adjust the satisfaction level of each objective function (Pishvaee et al., 2012b). This study proposes an interactive fuzzy approach toward solving the MOMILP model by combining hybrid TSP and the fuzzy multi-objective programming method proposed by Torabi and Hassini (2008); it is referred to as the TH method. The TH method can produce both unbalanced and balanced efficient solutions with compromise of the objective functions for decision-makers. A solution is considered as balancing when the conflicting objectives reach a common compromise based on the decision-maker's preferences for an optimal solution.

The steps of the proposed method can be summarized in the form of an algorithm, as follows:

Algorithm:

Step 1: Identify all uncertain parameters and decision variables in the two-phase TSP model.

Step 2: Convert the MOMILP model into equivalent crisp model of the fuzzy probabilistic-stochastic with lower and upper sub-model.

Step 3: Determine the α-positive idea solution (α-PIS) by solving the lower and upper sub-models of each objective function. The α-negative idea solution (α-NIS) for each objective function can be then estimated as follows:

$$W_{1,2,3}^{NIS-l} = \mathrm{w}_{1,2,3}^{PIS-l}\left(x_{1,2,3}^{PIS-l}\right); W_{1,2,3}^{NIS-u} = \mathrm{w}_{1,2,3}^{PIS-u}\left(x_{1,2,3}^{PIS-u}\right)$$

This is a feasible region of each objective function

$$\begin{aligned}W_1 &= \left[\left(\mathrm{w}_1^{PIS-l}, w_1^{NIS-l}\right); \left(\mathrm{w}_1^{PIS-u}, w_1^{NIS-u}\right)\right]\\W_2 &= \left[\left(\mathrm{w}_2^{PIS-l}, w_2^{NIS-l}\right); \left(\mathrm{w}_2^{PIS-u}, w_2^{NIS-u}\right)\right]\\W_3 &= \left[\left(\mathrm{w}_3^{PIS-l}, w_3^{NIS-l}\right); \left(\mathrm{w}_3^{PIS-u}, w_3^{NIS-u}\right)\right]\end{aligned}$$

Step 4: Obtain a linear membership function for each objective function,

$$\mu^l_{(W_{1,2,3})}(v) = \begin{cases}1 & w^l_{1,2,3} \le w^{PIS-l}_{1,2,3}\\ \dfrac{w^{NIS-l}_{1,2,3} - w^l_{1,2,3}}{w^{NIS-l}_{1,2,3} - w^{PIS-l}_{1,2,3}} & w^{PIS-l}_{1,2,3} < w^l_{1,2,3} < w^{NIS-l}_{1,2,3}\\ 0 & w^l_{1,2,3} > w^{NIS-l}_{1,2,3}\end{cases}$$

$$\mu^u_{(W_{1,2,3})}(v) = \begin{cases}1 & w^u_{1,2,3} \le w^{PIS-u}_{1,2,3}\\ \dfrac{w^{NIS-u}_{1,2,3} - w^u_{1,2,3}}{w^{NIS-u}_{1,2,3} - w^{PIS-u}_{1,2,3}} & w^{PIS-u}_{1,2,3} < w^u_{1,2,3} < w^{NIS-u}_{1,2,3}\\ 0 & w^u_{1,2,3} > w^{NIS-u}_{1,2,3}\end{cases}$$

In fact, $\mu^{l,u}_{(W_h)}(v)$ denotes the degree of satisfaction associated with the hth objective functions for the given solution vector (v) for each of the sub-models.

Step 5: Transform the equivalent crisp models into a single-objective model.

The equivalent crisp model is transformed into a single-objective model using the TH aggregation function proposed by Torabi and Hassini (2008), which is calculated as follows:

Table 2
Size of test problems.

Problem no.	No. of potential production centers (I)	No. of potential distribution centers (J)	No. of customer zones (P)	No. of production technologies (M)	No. of material suppliers (N)
1	5	7	14	2	2
2	20	30	100	2	2

Table 3
CO2 per utility consumption.

Utility	CO_2	Unit of measure
Electricity	0.7306	kg/kwh
Gasoline	2.392	kg/m^3

$$Max\ \omega(x) = \xi\omega_0 + (1-\xi)\sum_{w=1,2,3} \upsilon_w \mu_w(x)$$

$$\text{S.t.} \quad \omega_0 \le \mu_h(x)\ h = 1,2,3 \quad x \in F(x) \quad \omega_0, \xi \in [0,1]$$

Where :
$\mu_h(x)$: the satisfaction degree of hthobjective function. It is a linear membership function.
$\omega_0 = \min_h\{\mu_h(x)\}$: the minimum satisfaction degree of objective functions.
υ_h : the importance of the h*th*objective function.
ξ : the coefficient of compensation.
The importance of the fuzzy goals (υ_h) and the value of compensation coefficient (ξ) are determined based upon the decision maker preferences.

In the TH method, ξ provides implicit control over the minimum satisfaction level with regard to the objectives as well as the degree to which they have been compromised. Therefore, the balanced and unbalanced compromised solutions for a given problem can be obtained by adjusting the value of ξ by decision makers.

Step 6: Determine the value of the coefficient of compensation (ξ) and the relative importance of the fuzzy objective (υ_{wi}) based on the opinion of experts.

Step 7: Solve each single-objective model using lower and upper sub-models to obtain the following solution:

$$W_i^{l,u} = \left(w_i^l,\ w_i^u\right), (i = 1 \ldots n).$$

If the decision-maker is satisfied with the proposed solution based on goals and priorities, then the algorithm stops. Otherwise, another solution is sought by adjusting the value of one of the controllable parameters (e.g. α-cut level) and then returning to Step 3.

6. Numerical analysis

Numerical analyses were used to evaluate the efficacy and efficiency of the proposed interactive fuzzy programming method. The scale of each test problem is shown in Table 2.

6.1. Data setting

Some of the basic data, such as customer demand, manufacturing capacity, and the costs incurred by opening facilities, were obtained from other SCN design-related studies (Pishvaee et al., 2012a, 2012b). In these studies, demands in customer zones were trapezoidal fuzzy numbers; therefore, they

Table 4
Summary of test results of problem 1.

α-cut level	Objective function values $W^{l,u}_{1,2,3} = (w^l_{1,2,3},\ w^u_{1,2,3})$ and The satisfaction degrees $\mu^{l,u}_{1,2,2} = (\mu^l_{1,2,3},\ \mu^u_{1,2,3})$			No. of opened facilities		CPU time (seconds)
	W_1 and μ_1 (Cost)	W_2 and μ_2 (Cost)	W_3 and μ_3 (Number)	Plants (a; b)	DCs	
$\alpha = 0.1$	(7.07E+06; 1.12E+07)	(1.54E+08; 1.63E+08)	(478; 756)	2	4	13
	(0.88; 0.94)	(0.75; 0.86)	(0.63; 0.71)	(1;1)		
$\alpha = 0.2$	(7.54E+06; 1.15E+07)	(1.75E+08; 1.74E+08)	(487; 765)	2	4	13
	(0.78; 0.87)	(0.75, 0.88)	(0.67; 0.72)	(1;1)		
$\alpha = 0.3$	(8.12E+06; 1.19E+07)	(1.98E+08; 1.95E+08)	(495; 778)	2	5	12
	(0.85; 0.94)	(0.78; 0.83)	(0.65; 0.76)	(2;1)		
$\alpha = 0.4$	(8.86E+06; 1.22E+07)	(2.13E+08; 2.18E+08)	(505; 786)	2	4	10
	(0.86; 0.96)	(0.78; 0.89)	(0.68; 0.75)	(1;2)		
$\alpha = 0.5$	(9.02E+06; 1.26E+07)	(2.25E+08; 2.21E+08)	(510; 790)	3	5	10
	(0.65; 0.78)	(0.74; 0.85)	(0.72; 0.81)	(1;1)		
$\alpha = 0.6$	(9.16E+06; 1.30E+07)	(2.27E+08; 2.45E+08)	(516; 805)	3	6	11
	(0.68; 0.72)	(0.62; 0.74)	(0.78; 0.89)	(1;1)		
$\alpha = 0.7$	(9.22E+06; 1.34E+07)	(2.28E+08; 2.66E+08)	(535; 830)	4	6	10
	(0.52; 0.68)	(0.62; 0.76)	(0.88; 0.91)	(1;2)		
$\alpha = 0.8$	(9.25E+06; 1.68E+07)	(2.30E+08; 2.71E+08)	(541; 837)	4	6	09
	(0.64; 0.77)	(0.63; 0.71)	(0.88; 0.92)	(1;2)		
$\alpha = 0.9$	(9.30E+06; 1.98E+07)	(2.31E+08; 2.76E+08)	(548; 844)	4	6	09
	(0.67; 0.78)	(0.53; 0.68)	(0.85; 0.92)	(2;2)		
$\alpha = 1.0$	(9.35E+06; 2.02E+07)	(2.32E+08; 2.81E+08)	(554; 851)	4	6	08
	(0.61; 0.76)	(0.61; 0.78)	(0.82; 0.89)	(2;2)		

[a] Type of production technology.
[b] Type of material.

Table 5
Summary of test results of problem 2.

α-cut level	Objective function values $W^{l,u}_{1,2,3} = (w^l_{1,2,3}, w^u_{1,2,3})$ and The satisfaction degrees $\mu^{l,u}_{1,2,2} = (\mu^l_{1,2,3}, \mu^u_{1,2,3})$			No. of opened facilities		CPU time (seconds)
	W_1 and μ_1 (Cost)	W_2 and μ_2 (Cost)	W_3 and μ_3 (Number)	Plants (a; b)	DCs	
$\alpha = 0.1$	(2.54E+07; 4.74E+07)	(3.12E+07; 6.89E+07)	(12800; 18700)	12	13	397
	(0.79; 0.89)	(0.85; 0.91)	(0.68; 0.76)	(1;1)		
$\alpha = 0.2$	(2.98E+07; 5.12E+07)	(3.52E+07; 7.52E+07)	(19800; 24100)	12	13	405
	(0.83; 0.92)	(0.74; 0.85)	(0.63; 0.78)	(1;1)		
$\alpha = 0.3$	(3.24E+07; 5.84E+07)	(3.98E+07; 7.84E+07)	(24600; 28300)	12	14	412
	(0.81; 0.92)	(0.75; 0.88)	(0.72; 0.78)	(1;1)		
$\alpha = 0.4$	(3.54E+07; 6.66E+07)	(4.42E+07; 8.21E+07)	(25000; 33400)	12	13	392
	(0.89; 0.92)	(0.85; 0.95)	(0.79; 0.89)	(1;1)		
$\alpha = 0.5$	(3.87E+07; 7.32E+07)	(4.97E+07; 8.69E+07)	(25400; 34400)	12	14	336
	(0.92; 0.97)	(0.75; 0.84)	(0.78; 0.83)	(1;2)		
$\alpha = 0.6$	(4.12E+07; 8.07E+07)	(5.26E+07; 8.96E+07)	(26000; 35300)	16	16	305
	(0.75; 0.83)	(0.61; 0.79)	(0.83; 0.92)	(2;1)		
$\alpha = 0.7$	(4.37E+07; 8.91E+07)	(5.96E+07; 9.21E+07)	(26900; 36200)	15	17	245
	(0.75; 0.82)	(0.68; 0.85)	(0.83; 0.90)	(1;2)		
$\alpha = 0.8$	(4.52E+07; 9.84E+07)	(6.15E+07; 9.49E+07)	(27500; 37200)	16	20	265
	(0.75; 0.82)	(0.62; 0.78)	(0.81; 0.89)	(1;2)		
$\alpha = 0.9$	(4.66E+07; 1.09E+08)	(6.33E+07; 9.73E+07)	(29700; 38100)	16	20	254
	(0.74; 0.83)	(0.63; 0.75)	(0.85; 0.92)	(2;2)		
$\alpha = 1.0$	(4.82E+07; 1.20E+08)	(6.52E+07; 9.97E+07)	(30700; 39100)	16	20	246
	(0.73; 0.82)	(0.62; 0.71)	(0.85; 0.92)	(2;2)		

[a] Type of production technology.
[b] Type of material.

had to be modified into a uniformly distributed and trapezoidal fuzzy numbers to estimate the probability of each demand distribution. Data related to environmental impact were estimated as follows. We assumed that each production technology would consume electrical energy and that CO_2 emissions would depend on the transportation model, fuel used, and geographical distances (e.g., gasoline would be used for road transport delivery). Table 3 shows the CO_2 emissions for electric energy and gasoline fuel (ECTA, 2011; McKinnon, 2007) used in the numerical analysis.

The number of jobs created depends on the number of facilities, their capacity, and their production technology (Pishvaee et al., 2012a; Devika et al., 2014). Generally, decision-makers or experts define the weights assigned to CSR-related factors, such as job creation, the creation of hazardous materials, and the number of workdays lost due to workplace hazards. However, these weights should consider goals pertaining to regional development. For example, in a region with high unemployment, the weight assigned to the number of jobs created should be higher than the weights assigned to other factors. Based on this, the parameters related to social aspects were estimated. The remaining parameters were based on assumptions pertaining to production technologies and the quality of materials used in manufacturing. For instance, if a production technology would be considered superior to other similar technologies, then the production cost, CO_2 equivalent emissions, number of jobs created, potentially hazardous products, and workdays lost of that would be lower when compared to other production technologies.

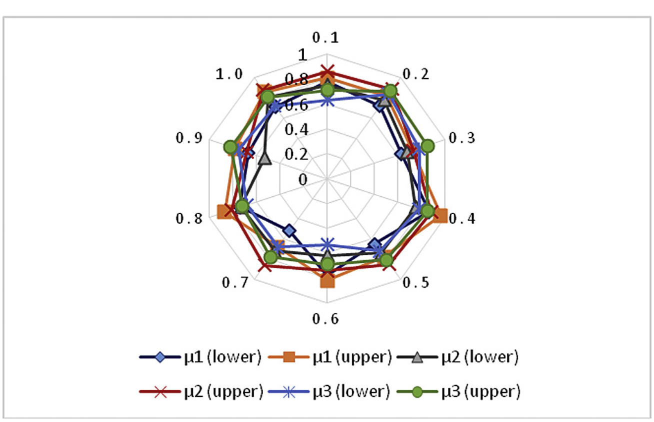

Fig. 2. Interaction between the lower and upper satisfaction degrees and the confidence levels for test problem 1.

6.2. Sensitivity analysis for three objective functions

Sensitivity analysis was conducted for α-cut levels from 0.1 to 1.0, under two demand scenarios with probability $p_1 = 0.4$ and $p_2 = 0.6$, to assess the applicability of the proposed model based on the interactive fuzzy programming approach. We used weight vectors $\upsilon_1 = 0.5, \upsilon_1 = 0.3, \upsilon_2 = 0.2$ and the compensation coefficient $\xi = 0.5$ in both the test problems. All tests were coded using LINGO 10.0 optimization software running on a Pentium dual-core 2.90 GHz computer with 4.0 GB RAM. The main results for various α-cut values, including the objective values, degree of satisfaction, number of plants and distribution centers, and CPU time are presented in Tables 4 and 5. As shown in the tables, the optimal solution for all the objective functions is sensitive to α-cut values,

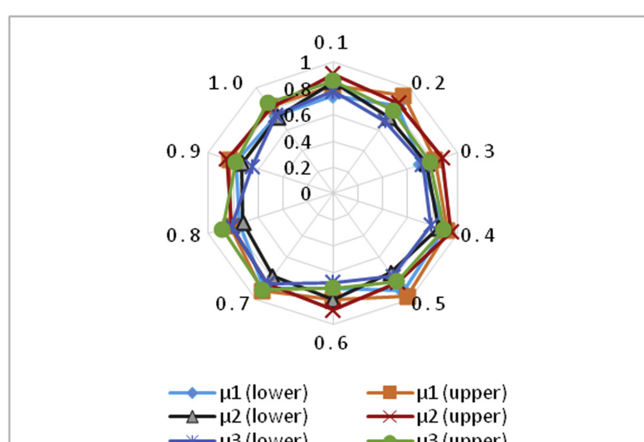

Fig. 3. Interaction between the lower and upper satisfaction degrees and the confidence levels for test problem 2.

Table 6
Aggregate time for two set problems.

Problem no.	Number of decision variables	Number of constraints	Aggregate time (second)
1	504	587	105
2	10911	11325	3257

which tends to increase with the α-cut value. In this case, the decision-makers must use more resources to satisfy demand in customer zones under higher α-levels. In other words, they must respond to uncertainty with a higher confidence level. Nevertheless, the minimum acceptable value can be varied based on the selections of decision-maker at the end of each iteration.

As shown in the results in Tables 4 and 5, the values of the first and second objective functions (W_1, W_2) tend toward a centralized supply chain network in minimizing total costs and environmental costs because fewer plants and distribution centers are opened in areas with a higher degree of satisfaction. This is contrary to previous studies in which it was concluded that environmental impact tends to be lower in a decentralized network (Pishvaee et al., 2012a). This can be explained by the fact that the environmental budget factor in the second objective function affects decisions concerning the number of new plants and distribution centers that are to be opened in the network. Furthermore, we sought to quantify environmental impact more comprehensively than most previous studies, which based this indicator only on CO_2 equivalent emissions that tend to be lower in a centralized network. For example, in test problem 1, only two plants and four distribution centers are opened when $\mu_1 = (0.88;\ 0.94)$ at $\alpha = 0.1$ and $\mu_2 = (0.78;\ 0.89)$ at $\alpha = 0.2$, whereas four plants and six distribution centers are opened when $\mu_1 = (0.61;\ 0.76)$ at $\alpha = 1.0$ and μ_2 $(0.53;\ 0.68)$ at $\alpha = 0.9$. The same trend can be observed in test problem 2.

In contrast, in Tables 4 and 5, the third objective function (W_3) of maximizing social benefits tends toward a decentralized network in which a large number of facilities, which create more job opportunities, are opened. Production technology and materials are allocated at each facility; although these resources decrease the hazardous effects of bi-products on the health of workers and customers, they increase the costs of establishing a network. For instance, the number of new facilities opened in a given supply chain network is maximized when $\mu_3 = (0.82;\ 0.89)$ in test problem 1 and $\mu_3 = (0.85;\ 0.92)$ in test problem 2 at $\alpha = 1.0$.

Decisions concerning the selection of production technologies and material qualities are performed by evaluating their effects on cost, CO_2 emissions, potentially hazardous products, and the number of workdays lost. These factors are expressed through three objective functions; thus, the final efficient solution strongly relies on the compromise of the objective functions.

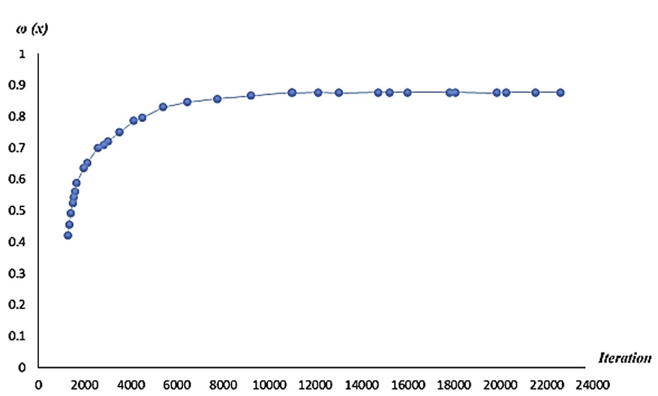

Fig. 4. Fluctuation of overall objective value with the number of iterations for test problem 2.

As it can be seen from Tables 4 and 5, the value of the three objective functions increases when the α-cut value is increased. The result could be simply explained by the need for spending more on resources (material cost, products, etc.) for selecting and procuring high quality material and production technology. At the small α-cut values, the production technology and quality material type 1 are used for minimizing economic costs and environmental impacts; however, they do not contribute toward maximizing social benefits. In higher α-cut values, the production technology and quality material type 2 are adopted to maximize the social benefits; however, it leads to increased economic costs and environmental impacts because the production technology type 2 and quality material type 2 are assumed to be superior to production technology type 1 and quality material type 1. Briefly, the selection of the right quality of materials and production technologies to achieve a balanced solution between the three objectives function depends on the decision-maker's confidence levels to deal with flexible constraints through the value of α-cut level in the model. The α-cut value can be varied based on the decision-maker's preferences; however, at a certain α-cut value, only one type of material and production technology is selected that satisfies all the three objective functions.

Figs. 2 and 3 illustrate changes in the lower and upper degrees of satisfaction associated with the three objective functions, wherein decision-makers express different levels of confidence in dealing with the conditions of uncertainty. Thus, the highest overall satisfaction is achieved when α-cut $= 0.4$, which provides a balanced solution with compromise of the objective functions.

6.3. Evaluation of performance of the proposed model

The last column in Tables 4 and 5 present the CPU times pertaining to the implementation of the proposed method. We opted not to conduct a direct comparison of the proposed method and those used in previous studies due to differences between the models, computer configuration, and size of the input data. The test problem 1 included 504 decision variables and 587 constraints, whereas test problem 2 included 10,911 decision variables and 11,325 constraints. The CPU time is shorter when the α-cut value is higher, which requires fewer iterations to arrive at an optimal solution.

The aggregate times in Table 6 indicate that the proposed solution approach is suitable for large-scale problems associated with the design of a SSCN. Using decision variables and constraints as a proxy for problem size, the CPU time in test problem 2 was found to be 30 times higher than that in test problem 1, whereas the decision number of variables and constraints increased approximately 20 times. Obtaining the optimal solution for a large-scale problem (test problem 2) resulted in an average CPU time of 325.7 s, which would be acceptable for the development of a reliable SSCN in an uncertain environment.

We conducted a fluctuation analysis of the overall objective value ($\omega(x)$) with the number of iterations for test problem 2 at α-cut $= 0.4$. As shown in the results in Fig. 4, the number of required iterations is 22,690 times and CPU time is 392 s. The overall objective value begins to reach a steady state at the 11,023th iteration. Later, the stability of the overall objective value in 11,667 (22,690−11,023) iterations assures high accuracy of decisions related to the structure of the SSCN. The little variation in the number of plants and distribution centers through each iteration reveals that the proposed model is capable of making the correct decision for the SSCN design problem under uncertainty situations. The number of variables and constraints in the test problem 2 are 10,911 and 11,325, respectively; the proposed algorithm requires 392 s to obtain an optimization solution. It is evident that the proposed algorithm is useful for solving large-sized SSCN design problems.

These numerical analyses also provide the following managerial insights. First, when decision-makers respond to uncertainty with a higher confidence level, they allocate more resources to ensure the sustainability of SCNs. Second, a centralized supply chain network can minimize total costs and environmental costs; however, it cannot maximize social benefits. Therefore, decision-makers should consider supply chain strategy (network centralization or network decentralization) to achieve balanced solutions for the multi-objective functions.

7. Conclusion

Environmental and social issues are important aspects of the SSCN design. They involve complex decisions related to strategic design and tactical operation within a dynamic and uncertain environment. This paper studies the SSCN planning under uncertain environment of customer demands and economic, social, and environmental parameters. An interactive multi-objective fuzzy programming approach based on combining the two-phase stochastic programming and fuzzy multi-objective programing is employed to consider economic costs, environmental impacts, and social benefits of the network simultaneously. The CO_2 emissions and the abatement cost of production centers driven by the choice of production technology and materials are taken into account for measuring environmental goals; the number of job creation opportunities, hazardous by-products, and workdays lost due to workplace hazards are used for measuring social objectives.

The numerical analyses indicate that the proposed approach is a very promising multi-objective problem under uncertainty decision environment that can provide unbalanced and balanced efficient solutions for decision-makers with compromise of the conflicting objectives. This approach can also be used for solving large-scaled problems due to its computational advantages. However, this approach strongly relies on the decision-maker's preferences for parameters, such as the compensation coefficient of objectives and their confidence level to deal with flexible constraints, such as the α-cut level in selecting the final preferred compromise solution. The proposed model only considers for designing SSCN with single product and environmental and social impacts highly depend on capacity of facilities opened on the network.

There are some possible directions for further research. One possible direction is to test the proposed approach on a complete real life problem, such as industrial products SCN where the social and environmental issues are common. In addition, future research can also involve the extension of the proposed model to SSCN with multiple products and considering other impacts on environmental and social issues. Finally, developing efficient genetic algorithms and metaheuristic approaches under uncertain environment should be conducted in the SSCN design field.

Appendix A

In this appendix we provide detail formulation of these objective functions in the proposed model with TSP method.

$$
\begin{aligned}
&\text{Min } W_1 = \sum_{i=1}^{I}\sum_{m=1}^{M}(f_{i1}^m, f_{i2}^m, f_{i3}^m, f_{i4}^m)x_i^m + \sum_{j=1}^{J}\Big(g_{j1}, g_{j2}, g_{j3}, g_{j4})y_j \\
&+\sum_{h=1}^{2}p_h\left[\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\Big[(m_{i1}^n, m_{i2}^n, m_{i3}^n, m_{i4}^n) + (p_{i1}^m, p_{i2}^m, p_{i3}^m, p_{i4}^m) + (c_{ij1}, c_{ij2}, c_{ij3}, c_{ij4}) + (h_{j1}, h_{j2}, h_{j3}, h_{j4})\Big]q_{ij}^{mn}\Big)\right. \\
&\left.+\sum_{j=1}^{J}\sum_{p=1}^{P}(c_{jp1}, c_{jp2}, c_{jp3}, c_{jp4})u_{jp}\right] \\
&\text{Min } W_2 = \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}[(\delta_{i1}^m, \delta_{i2}^m, \delta_{i3}^m, \delta_{i4}^m) + (\beta_{i1}^n, \beta_{i2}^n, \beta_{i3}^n, \beta_{i4}^n)]x_i^m z_i^n \\
&\sum_{h=1}^{2}p_h\left[\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\Big(\eta_{i1}^m, \eta_{i2}^m, \eta_{i3}^m, \eta_{i4}^m) + (¶_{i1}^n, ¶_{i2}^n, ¶_{i3}^n, ¶_{i4}^n) + (t_{ij1}, t_{ij2}, t_{ij3}, t_{ij4})e_c q_{ij}^{mn}\right. \\
&\left.+\sum_{j=1}^{J}\sum_{p=1}^{P}(s_{jp1}, s_{jp2}, s_{jp3}, s_{jp4})e_c u_{jp}\right] \\
&\text{Min } -W_3 = -\left[\theta_{lo}\left[\sum_{i=1}^{I}\sum_{m=1}^{M}(o_{i1}^m, o_{i2}^m, o_{i3}^m, o_{i4}^m)x_i^m + \sum_{j=1}^{J}\Big(o_{j1}, o_{j2}, o_{j3}, o_{j4})y_j\right]+\right. \\
&\theta_{ld}\left[\sum_{i=1}^{I}\sum_{m=1}^{M}(l_1^m, l_2^m, l_3^m, 1_4^m)x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}(l_1^n, l_2^n, l_3^n, 1_4^n)z_i^n\right] + \sum_{h=1}^{2}p_h[\theta_{lp}\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\Big(s_1^n, s_2^n, s_3^n, s_4^n) + (s_1^m, s_2^m, s_3^m, s_4^m)q_{ij}^{mn}]
\end{aligned}
$$

Appendix B

In this appendix we provide all constraints of TSP model with trapezoidal fuzzy number form and stochastics variables form.

$$\sum_{j=1}^{J} u_p^j \geq \tilde{d}_{p(h=1)}^{\tilde{d}_p} = \begin{cases} \tilde{d}_p = (d_{p1}, d_{p2}, d_{p3}, d_{p4}) \\ \tilde{d}_{p(h=1)} \sim unifrom\ (x_1, y_1) \end{cases}, \forall p \ for\ h = 1$$
$$\sum_{j=1}^{J} u_p^j \geq \tilde{d}_{p(h=2)}^{\tilde{d}_p} = \begin{cases} \tilde{d}_p = (d_{p1}, d_{p2}, d_{p3}, d_{p4}) \\ \tilde{d}_{p(h=2)} \sim unifrom\ (x_2, y_2) \end{cases}, \forall p \ for\ h = 2$$
$$\sum_{j=1}^{J} q_{ij}^{mn} \leq x_i^m(\iota_{i1}, \iota_{i2}, \iota_{i3}, \iota_{i4})\ \forall i, m, n$$
$$\sum_{j=1}^{J} q_{ij}^{mn} \leq z_i^n(\iota_{i1}, \iota_{i2}, \iota_{i3}, \iota_{i4})\ \forall i, m, n$$
$$\sum_{p=1}^{P} u_{jp} \leq y_j(\phi_{j1},\ \phi_{j2}, \phi_{j3}, \phi_{j4}) \forall j$$
$$\sum_{i=1}^{I} \sum_{m=1}^{M} (\delta_{i1}^m, \delta_{i2}^m, \delta_{i3}^m, \delta_{i4}^m) x_i^m + \sum_{i=1}^{I} \sum_{n=1}^{N} (\beta_{i1}^n, \beta_{i2}^n, \beta_{i3}^n, \beta_{i4}^n) z_i^n \leq (B_1, B_2, B_3, B_4)$$
$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} q_{ij}^{mn} = \sum_{p=1}^{P} u_{jp},\ \forall j$$
$$\sum_{m=1}^{M} x_i^m \leq 1\ \forall i$$
$$\sum_{n=1}^{N} z_i^n \leq 1\ \forall i$$
$$q_{ij}^{mn},\ u_{jp} \geq\ 0,\ \forall i,\ j, m, n, p$$
$$x_i^m,\ z_i^n,\ y_j \in (0, 1)\ \forall i,\ j, m, n$$

Appendix C

In this appendix we provide MOMILP model with the lower sub model and upper sub model.

Lower sub model

$$\text{Min } W_1 = \sum_{i=1}^{I} \sum_{m=1}^{M} [(1-\alpha) f_{i1}^m + \alpha f_{i2}^m] x_i^m + \sum_{j=1}^{J} \Big[(1-\alpha) g_{j1} + \alpha g_{j2}\Big] y_j$$
$$+ \sum_{h=1}^{2} p_h \left[\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{J} \Big[(1-\alpha) m_{i1}^n + \alpha m_{i2}^n) + (1-\alpha) p_{i1}^m + \alpha p_{i2}^m) + (1-\alpha) c_{ij1} + \alpha c_{ij2}) + (1-\alpha) h_{j1} +\ \alpha h_{j2}) \Big] q_{ij}^{mn} \right.$$
$$\left. + \sum_{j=1}^{J} \sum_{p=1}^{P} (1-\alpha) c_{jp1}\ + \alpha c_{jp2}) u_{jp} \right]$$
$$\text{Min } W_2 = \sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} [(1-\alpha)\delta_{i1}^m\ +\ \alpha\delta_{i2}^m + (1-\alpha)\ \beta_{i1}^n + \alpha\beta_{i2}^n] x_i^m z_i^n$$
$$\sum_{h=1}^{2} p_h \left[\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{J} \Big[(1-\alpha)\eta_{i1}^m\ + \alpha\eta_{i2}^m + (1-\alpha)¶_{i1}^n + \alpha¶_{i2}^n + (1-\alpha) t_{ij1}\ +\ \alpha t_{ij2} \Big] e_c q_{ij}^{mn} \right.$$
$$\left. + \sum_{j=1}^{J} \sum_{p=1}^{P} [(1-\alpha) s_{jp1} + \alpha s_{jp2})] e_c u_{jp} \right]$$
$$\text{Min } -W_3 = -\left[\theta_{lo} \left[\sum_{i=1}^{I} \sum_{m=1}^{M} ((1-\alpha) o_{i1}^m + \alpha o_{i2}^m) x_i^m\ + \sum_{j=1}^{J} \Big((1-\alpha) o_{j1} + \alpha o_{j2}) y_j \right] - \right.$$
$$\theta_{ld} \left[\sum_{i=1}^{I} \sum_{m=1}^{M} ((1-\alpha) l_1^m\ +\ \alpha l_2^m) x_i^m + \sum_{i=1}^{I} \sum_{n=1}^{N} ((1-\alpha) l_1^n + \alpha l_2^n) z_i^n - \right.$$
$$\sum_{h=1}^{2} p_h \left[\theta_{lp} \sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{J} \Big((1-\alpha) s_1^n + \alpha s_2^n + (1-\alpha) s_1^m + \alpha s_2^m) q_{ij}^{mn} \right]$$

Constraints

$$\sum_{j=1}^{J} u_p^j \geq \left[(\mathrm{y}_1 - \mathrm{x}_1)\{(1-\alpha)\mathrm{d}_{\mathrm{p}1} + \alpha \mathrm{d}_{\mathrm{p}2}\} + \mathrm{x}_1\right], \forall p \text{ for h} = 1$$

$$\sum_{j=1}^{J} u_p^j \geq \left[(\mathrm{y}_2 - \mathrm{x}_2)\{(1-\alpha)\mathrm{d}_{\mathrm{p}1} + \alpha \mathrm{d}_{\mathrm{p}2}\} + \mathrm{x}_2\right], \forall p \text{ for h} = 2$$

$$\sum_{j=1}^{J} q_{ij}^{mn} \leq \mathrm{x}_i^m[(1-\alpha)\iota_{i1} + \alpha\iota_{i2}] \ \forall \mathrm{i, m, n}$$

$$\sum_{j=1}^{J} q_{ij}^{mn} \leq \mathrm{z}_i^n[(1-\alpha)\iota_{i1} + \alpha\iota_{i2}] \ \forall \mathrm{i, m, n}$$

$$\sum_{p=1}^{P} u_{jp} \leq \mathrm{y}_j[(1-\alpha)\phi_{j1} + \alpha\phi_{j2}] \ \forall \mathrm{j}$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M}((1-\alpha)\delta_{i1}^m + \alpha\delta_{i2}^m)\mathrm{x}_\mathrm{i}^\mathrm{m} + \sum_{i=1}^{I}\sum_{n=1}^{N}((1-\alpha)\beta_{i1}^n + \alpha\beta_{i2}^n)\mathrm{z}_\mathrm{i}^\mathrm{n} \leq (1-\alpha)\mathrm{B}_1 + \alpha\mathrm{B}_2$$

$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\mathrm{q}_{\mathrm{ij}}^{\mathrm{mn}} = \sum_{p=1}^{P} u_{jp}, \ \forall j$$

$$\sum_{m=1}^{M} x_i^m \leq 1 \ \forall \mathrm{i}$$

$$\sum_{n=1}^{N} z_i^n \leq 1 \ \forall \mathrm{i}$$

$$q_{ij}^{mn}, \ \mathrm{u}_{jp} \geq 0, \ \forall \mathrm{i, j, m, n, p}$$

$$x_i^m, \ \mathrm{z}_i^n, \ \mathrm{y}_j \in (0,1) \ \forall \mathrm{i, j, m, n}$$

Upper sub model

$$\text{Min } W_1 = \sum_{i=1}^{I}\sum_{m=1}^{M}\left[(1-\alpha)f_{i4}^m + \alpha f_{i4}^m\right]x_i^m + \sum_{j=1}^{J}\left[(1-\alpha)g_{j4} + \alpha g_{j3}\right]y_j$$

$$+\sum_{h=1}^{2} p_h\left[\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\left[(1-\alpha)m_{i4}^n + \alpha m_{i3}^n) + (1-\alpha)p_{i4}^m + \alpha p_{i3}^m) + (1-\alpha)c_{ij4} + \alpha c_{ij3}) + (1-\alpha)h_{j4} + \alpha h_{j3})\right]q_{ij}^{mn}\right.$$

$$\left.+\sum_{j=1}^{J}\sum_{p=1}^{P}(1-\alpha)c_{jp4} + \alpha c_{jp3})u_{jp}\right]$$

$$\text{Min } W_2 = \sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\left[(1-\alpha)\delta_{i4}^m + \alpha\delta_{i3}^m + (1-\alpha)\beta_{i4}^n + \alpha\beta_{i3}^n\right]x_i^m z_i^n$$

$$\sum_{h=1}^{2} p_h\left[\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\left[(1-\alpha)\eta_{i4}^m + \alpha\eta_{i3}^m + (1-\alpha)¶_{i4}^n + \alpha¶_{i3}^n + (1-\alpha)t_{ij4} + \alpha t_{ij3}\right]e_c q_{ij}^{mn}\right.$$

$$\left.+\sum_{j=1}^{J}\sum_{p=1}^{P}\left[(1-\alpha)s_{jp4} + \alpha s_{jp3})\right]e_c u_{jp}\right]$$

$$\text{Min } -W_3 = -\left[\theta_{lo}\left[\sum_{i=1}^{I}\sum_{m=1}^{M}((1-\alpha)o_{i4}^m + \alpha o_{i3}^m)x_i^m + \sum_{j=1}^{J}\left((1-\alpha)o_{j4} + \alpha o_{j3})y_j\right]\right.\right. -$$

$$\theta_{ld}\left[\sum_{i=1}^{I}\sum_{m=1}^{M}((1-\alpha)l_4^m + \alpha l_3^m)x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}((1-\alpha)l_4^n + \alpha l_3^n)z_i^n -\right.$$

$$\left.\sum_{h=1}^{2} p_h[\theta_{lp}\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\left((1-\alpha)s_4^n + \alpha s_3^n + (1-\alpha)s_4^m + \alpha s_3^m)q_{ij}^{mn}\right]$$

Constraints

$$\sum_{j=1}^{J} u_p^j \geq [(y_1 - x_1)\{(1-\alpha)d_{p4} + \alpha d_{p3}\} + x_1], \forall p \text{ for } h = 1$$
$$\sum_{j=1}^{J} u_p^j \geq [(y_2 - x_2)\{(1-\alpha)d_{p4} + \alpha d_{p3}\} + x_2], \forall p \text{ for } h = 2$$
$$\sum_{j=1}^{J} q_{ij}^{mn} \leq x_i^m[(1-\alpha)\iota_{i4} + \alpha\iota_{i3}] \ \forall i, m, n$$
$$\sum_{j=1}^{J} q_{ij}^{mn} \leq z_i^n[(1-\alpha)\iota_{i4} + \alpha\iota_{i3}] \ \forall i, m, n$$
$$\sum_{p=1}^{P} u_{jp} \leq y_j[(1-\alpha)\phi_{j4} + \alpha\phi_{j3}] \ \forall j$$
$$\sum_{i=1}^{I}\sum_{m=1}^{M}((1-\alpha)\delta_{i4}^m + \alpha\delta_{i3}^m)x_i^m + \sum_{i=1}^{I}\sum_{n=1}^{N}((1-\alpha)\beta_{i4}^n + \alpha\beta_{i3}^n)z_i^n \leq (1-\alpha)B_4 + \alpha B_3$$
$$\sum_{i=1}^{I}\sum_{m=1}^{M}\sum_{n=1}^{N} q_{ij}^{mn} = \sum_{p=1}^{P} u_{jp}, \ \forall j$$
$$\sum_{m=1}^{M} x_i^m \leq 1 \ \forall i$$
$$\sum_{n=1}^{N} z_i^n \leq 1 \ \forall i$$
$$q_{ij}^{mn}, \ u_{jp} \geq 0, \ \forall i, j, m, n, p$$
$$x_i^m, \ z_i^n, \ y_j \in (0,1) \ \forall i, j, m, n$$

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