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Hybrid Model of IVFRN-BWM and Robust Goal Programming in Agile and Flexible Supply Chain, a Case Study: Automobile Industry

AYAD HENDALIANPOUR[1,2], MAHNAZ FAKHRABADI[3], XIAOBO ZHANG[1], MOHAMMAD REZA FEYLIZADEH[4], MEHDI GHEISARI[5,6], PEIDE LIU[7], AND NEGAR ASHKTORAB[4]

[1]Faculty of Automation, Guangdong University of Technology, Guangzhou 510006, China
[2]School of Industrial Engineering, College of Engineering, University of Tehran, Tehran 1439955961, Iran
[3]Department of Industrial Engineering and System Management, Amirkabir University of Technology, Tehran 1591634311, Iran
[4]Department of Industrial Engineering, Shiraz Branch, Islamic Azad University, Shiraz 71987-74731, Iran
[5]Department of Computer science, Guangzhou university, Guangzhou, China
[6]Young Researchers and Elite Club, Parand Branch, Islamic Azad University, Parand, Iran
[7]School of Management Science and Engineering, Shandong University of Finance and Economics, Jinan Shandong 250014, China.

Corresponding authors: Xiaobo Zhang (zxb_leng@gdut.edu.cn), Mohammad Reza Feylizadeh (feylizadeh@iaushiraz.ac.ir), and Mehdi Gheisari (mehdi.gheisari61@gmail.com)

ABSTRACT The main purpose of this paper is the allocation of orders to suppliers in an agile and flexible manner suitable to the automobile industry. In this paper, parts supplied by a single source were eliminated from the set of parts. Using mathematical modeling and through the interval-valued fuzzy-rough numbers best worst method (IVFRN-BWM), we try to achieve the results that can meet the proposed model's needs and provide the ideal results by introducing new modes. This paper addressed some new aspects of the subject and achieved robust results by considering five objective functions. These five functions are as follows: minimization of production line disruptions due to the performance of suppliers, minimization of the complaints of production line about supplied parts, minimization of defective parts received from suppliers (PPM), maximization of on-time delivery services, and minimization of overall costs of supplied parts. Reviewing the literature, the originality of this study are as follows: 1) identifying the structure of a supply chain (SC) in general and particularly in an automobile industry SC; 2) investigating the modeling techniques of the existing SC models for coordinating all the members of a product SC; 3) building a hybrid model of IVFRN-BWM and a robust goal programming agile and flexible supply chain in an uncertain situation; and 4) identifying the suitable scenarios/cases for testing the proposed models to validate the models. This paper can help decision makers and managers to opt for the best suppliers and also allocate the right numbers of parts to those supplier(s) based on a real situation of each firm.

INDEX TERMS Robust optimizations, IVFRN-BWM, allocation, agile and flexible SC, automobile industry.

I. INTRODUCTION

Being able to compete in a rapidly changing environment would require agility in matters such as awareness of observations and information, awareness of developing opportunities for innovation and their appropriate usage, improved response to disruptions and increased flexibility against external threats [1]. Therefore, business models need to be continuously updated in order to be able to compete with competitors in today's complex world and achieve a robust value [2].

Since market, conditions are becoming more and more unpredictable and competitive every day, agility in the supply chain, as well as in the organization, is considered as a key factor for survival in a competitive market [3], [4]. Technically speaking, agility of a supply chain is its ability to react to the changes in different environments in an appropriate and timely fashion [5]; this would help companies gain a competitive advantage. Braunscheidel and Suresh [6] believe

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that organizations may face various barriers in gaining the advantage of agility, such as low level of cooperation between chain members, lack of necessary information, inadequate level of union and cooperation between chain members in designing considering the environmental concerns and inability to meet the expectations of customers. All of which could create a gap between organization and competitive advantage.

Considering the circumstances, researchers and industry practitioners became interested in surveys in the field with focus on concepts such as complexity, uncertainty, risk and flexibility [7]. Uncertainty and risk in a supply chain would affect the decision makers in the supply chain and may lead to inefficiency and ineffectiveness, which may consequently influence the organization's performance [8]. In order to grow in such conditions, modern companies quickly came up with solutions such as variety in the provided products and services to meet the dynamic needs of customers [9], [10]. Through this strategy, they could gain the advantage of agile production and remain in the competitive market. However, modern companies have developed more extensive design of the market, one that can provide their services and products to sporadic customers. As supply, chains became bigger at first and were weakened later, their management created a wide array of challenges. By comparing the current research with previous studies in the literature review, the contributions of this study can be summarized as follows:

– Identification of the structure of an SC in general and that of an automobile industry SC in particular.
– Investigation of the modeling techniques used in the literature and review of the existing SC models and their limitations for coordinating all the members of a product SC.
– Proposing a hybrid model of IVFRN-BWM and a robust goal programming in agile and flexible supply chain under an uncertain situation.
– Identification of suitable scenarios/cases for testing the proposed models, as well as the success criteria to validate the models.

Considering the above mentioned, the rest of the article is structured as follows: In section 2, we review the previous works conducted on the subject. Our proposed model is presented in section 3, which also contains a description of the five objective functions and the IVFRN-BWM approach used in this research. Section four presents the case study and problem-solving results and the fifth section comprises the results obtained in this study. In the current research, we tend toward agile and flexible optimization of the supply chain using these five objective functions and the modified BWM method.

II. RELATED WORKS

Different papers working on this area can be divided to different clusters based on methods or factors employed. To select supplier considering uncertainty, Zhou et al. [11] evaluated the supplier risk assessment consistency during the supplier selection process and employed document analysis and questionnaires for a case study conducted by triangulation and pattern matching in a train manufacturer in South Africa, Zhao and Wang [12] proposed the sustainable criteria based on the supplier selection hybrid approaches for a printing business with three phrases: 1) using SWOT[1] analysis, 2) determining and ranking the weight of each criterion by AHP[2], 3) evaluating and selecting suppliers using TOPSIS,[3] and Quan *et al.* [13] designed a feedback control law for inventory control of three-echelon inventory system. The results revealed that customer satisfaction is optimized using mixed inventory control procedures while the hybrid supply chain is changed by order uncertainty. However, concepts such as agility and flexibility omitted in these papers may have major influence on reducing uncertainty.

On the other hand, there are different multi-criteria/ attributes decision-making methods employed to rank, select and determine the weights of the alternatives and attributes [14]–[18]. Also, some researches are done to select the appropriate supplier(s) such as Wang et al. [19] applied AHP in order to develop a model for a case-study of car seat manufacturer. Ali et al. [20] employed AHP for supplier selection and found that price/cost, product quality, and manufacturing capability are the top three criteria for selecting supplier. Yusuf et al. [21] using K-Means and intuitionistic fuzzy TOPSIS with the criteria of price, purchase method, delivery order, delivery speed, stock availability, and quality of service. Ngai et al. [22] proposing MULTIMOORA approach and employing it to rank the alternative suppliers, and Gligor et al. [23] using an immune genetic algorithm.

The concepts of agility and flexibility are two factors providing profit and new opportunities for a supply chain. Zhang et al. [24] designated that Supply Chain Finance (SCF) has an important influence on SCF. Moreover, all proposed circumstances of SCF adoption have a definite and notable impact on SCF. Changes in customer and technological needs have compelled the manufacturers to develop agile capabilities in their supply chains in order to remain in the competitive scene [25]. Vinodh et al. [10] presented an ASC assessment model using fuzzy logic to evaluate the performance of agile supply chains. This ASC assessment model allows ranking computations, which subsequently help the organization identify the factors affecting improvement and development. Moreover, the Fuzzy Delphi method is one of the approaches used to screen the unnecessary attributes. A method presented for designing an agile and flexible supply chain is the AHP method, which is used to assess the factors affecting flexibility [26]. In another research, the indicator of agility was used to study agility and leanness in the automobile industry [9]. We can say that the agility of an organization depends on the agility of its supply chain. Nevertheless, achieving an agile supply chain would depend

[1] Strengths, Weaknesses, Opportunities and Threats
[2] Analytic Hierarchy Process
[3] Technique for Order Preference by Similarity to Ideal Solution

on other intra-organizational capabilities [2], especially integration of supply chain flexibility and information technology (IT). Agility in a supply chain creates a high amount of value, helps in managing disruptive risks and ensures continuous services to customers [27]. As an attribute, agility can influence the effectiveness of supply chain management. Cost-focused strategies can be suitable for higher-level development of Firm Agility Supply Chain (FASC), none of which is mutually unique [28]. Agility Supply Chain (ASC) is a tool that enables companies to gain a competitive advantage [4]. One of the factors affecting ASC is the supplier's innovation, which has positive effects on information exchange and supply chain agility, but does not have a significant relationship with strategic sourcing. Both information exchange and strategic sourcing have a positive role in development of supply chain agility [3].

In order to evaluate the production flexibility, analysis of the relationships between qualifications, capabilities and customer satisfaction is needed. Significant and rapid changes in customer and market expectations [4], competition and novel technologies would create an increasingly uncertain environment. Production flexibility, as a critical dimension of value chain flexibility, refers to the ability to produce a variety of products based on the level of customer demands, while maintaining a high performance. Production flexibility is an integral part of value chain flexibility, expressing its key sub-dimensions [29]. Flexibility of supply chain must be considered from two aspects: resource flexibility and vendor (supplier) flexibility. Concerning the supplier, network coordinators can classify their suppliers in three categories, namely framework contract suppliers, preferred suppliers and confirmed suppliers, each under different flexibility concepts [30]. Two organizational factors, strategic flexibility and manufacturing flexibility, are vital precursors for supply chain agility. Furthermore, supply chain agility, strategic flexibility and manufacturing flexibility are all important factors in a company's performance [31]. We can categorize flexibility into subcategories such as sourcing flexibility, operating system flexibility, distribution flexibility and information system flexibility [32]. On the other hand, four dimensions are also defined for agility, including: customer enrichment, cooperating to compete, mastering change and uncertainty, and leveraging the impact of people and information; we must also add to this list the relative characteristics for competition and high business performance in the oil and gas industry [33]. An in-depth review of experimental research conducted on flexibility in manufacturing and production revealed the highly scattered nature of this body of work. Factors such as proper compatibility between the environment and internal strategies, organizational variables and technology can equip a company with advanced performance and a competitive advantage. Addressing these issues will help us reach a full understanding of the complex process encompassing the flexibility of manufacturing and production.

After reviewing the previous works in this field and analyzing of previously used methods and their results, we observed that some papers involved questionnaire-based research did not even present a computational model (such as [11], [13]). What is more, some other studies tried to improve the company's performance by considering the conditions static, and did not practically consider the inherent environmental uncertainty present in both internal and external environments of each organization, mostly using Multi-criteria decision making (MCDM), Multi-attribute Decision Making (MADM) methods (such as [19], [21]–[23]). However, to the best of our knowledge, BWM-IVFRN as a strong and new MADM method has not been employed in literature for this subject. Also, the others, in spite of considering agility (such as [3], [4], [10], [24], [25], [31], [32]), and flexibility (such as [4], [26], [34]–[35]) just try to improve a supply chain with predetermined parameters without any attempt to achieve more accurate parameters using strong decision making methods. Certain traditional methods might be able to produce relatively acceptable results under static conditions; however, their results will not be reliable under different conditions.

In order to consider environmental uncertainty in the present research, we tried to first identify the indicators affecting supply chain agility and flexibility using uncertainty and verbal variables. Next, we assigned weights to the extracted indicators using the combined IVFRN-BWM method and robust goal programming, and then, in order to achieve our study's objectives, we used the novel IVFRN-BWM method to assign weights to the extracted criteria. In the next step, the objectives defined based on our five indicators, namely minimization of production line interruptions, minimization of complaints of production line about supplied parts, minimization of defective parts, minimization of overall costs and maximization of on-time deliveries, were designed and executed in the form of a robust goal programming model.

III. PROPOSED MODEL

The need for organizational flexibility is well understood when trying to adapt to a changing world. Today's fast-paced and competitive markets apply greater pressure toward rapid decision-making and performance at high levels. Technology provides new solutions for competition, and at the same time abolishes old solutions. Here, the issue is the changes, which often occur instantaneously and rapidly, and thus, taking effective measures in this regard would play a significant role in achieving success in today's business world. Speed has a considerable influence on business, as time-based strategies can have a positive impact on firm performances. Therefore, in order to gain the advantages of an agile supply chain, organizations need to identify the dimensions and indicators of agility, as well as their level of influence on each other, and be able to measure the agility of their own supply chain. The main question is, then, how can organizations reach agility in their supply chains?

The criteria of flexibility assessment, the most significant of which include flexibility in products, routing, transportation (between supplier's location and warehouses), resources, supply and demand, are often general and mainly evaluate agile capabilities rather than all agility dimensions. The present study aimed at presenting a comprehensive approach of supply chain agility assessment indicators and criteria, with consideration to all dimensions of agility.

Mixed-integer optimization will be used in the present research, and turns our method to the model into a robust one, consistent with Bertsimas and Sim's approach [26]. In this study, we first try to determine the indicators affecting agility and flexibility in the supply chain using the variables of uncertainty and verbal variables. Then, using the combined method of IVFRN-BWM and robust goal programming, we assign weights to the extracted indicators. Next, to reach our objectives, we first assigned weights to the extracted criteria using the novel IVFRN-BWM method, and then, the defined objectives will be designed and executed within the framework of a robust goal programming model based on the five extracted indicators which include minimization of production line interruptions, minimization of complaints of production line about supplied parts, minimization of defective parts, minimization of overall costs of supplied parts and maximization of on-time deliveries.

A. MODIFIED BEST-WORST METHOD (IVFRN-BWM)

Multi-criteria decision making (MCDM) is a field of operational research wherein the decision alternatives are analyzed with respect to a set of multiple (and often conflicting) criteria [32].

Generally, decision-making processes follow eight steps: define the problem, determine the requirements, establish the goals, identify alternatives, develop evaluation criteria, selecting decision-making tool, apply the tool, and check the response. To achieve pre-determined goals, opting the appropriate decision making method which fits the problem type is the first step [33]. Some of MCDM methods are such as ANP,[4] AHP, TOPSIS, and BWM [32].

The advantage of BWM compared with other MCDM methods is higher reliability and lower need for comparison [34]. As one of the common MCDM-based methods, AHP requires n(n-1)/2 comparisons while BWM approach needs 2n-3 comparisons. Pamu ar et al. [35] modified the method through adjusted interval-valued fuzzy-rough numbers method and it consists of the following seven steps.

a)First, the set of criteria affecting the decision is characterized by experts (m) as C = {C1, C2, …., Cn}, where n refers to number of criteria.

b)Then, experts select the best (the most significant) and the worst (the least significant) criterion. If more than one criterion is introduced as the best or the worst criterion, one of them will be selected optionally.

c)M experts determine priority of the best-selected criterion (B) over other criteria (j). Priority of criterion B over j-th criterion is represented as $a^e_{B_j}$ $(j = 1, 2, \ldots, n; 1 \leq e \leq m)$,

[4]Analytic Network Process

TABLE 1. Fuzzy scale for evaluation of criteria.

No.	Linguistic terms	Triangular fuzzy numbers
1	Equally (E)	(1,1,1)
2	Low (L)	(2/3,1,3/2)
3	Medium (M)	(3/2,2,5/2)
4	High (H)	(5/2,3,7/2)
5	Very high (VH)	(7/2,4,9/2)

where e refers to expert. The value of each $a^e_{B_j}$ is represented as triangular fuzzy number in Table 1 [26].

The fuzzy vector of the effects of the best criterion on other criteria is as shown in Eq. (1).

$$A^e_B = \left(a^e_{B_1}, a^e_{B_2}, \ldots, a^e_{B_n}\right) \quad 1 \leq e \leq m \tag{1}$$

where $\tilde{a}^e_{Bj}$ refers to priority of the best criterion B over criterion j. This vector is developed for each expert.

d)The previous step can also be repeated for the worst criterion (W) but the difference is that the extent of priority of other criteria over the worst criterion W should be defined as the vector of Eq. (2).

$$A^e_W = \left(a^e_{1w}, a^e_{2w}, \ldots, a^e_{nw}\right) \quad 1 \leq e \leq m \tag{2}$$

where $\tilde{a}^e_{jw}$ refers to extent of priority of criterion j over the worst criterion W.

e)The vector IVFRN-BO for mean responses of experts is shown as $A^e_B = [a^e_{Bj}]_{\times n}$, where a^e_{Bj} is equal to the triangular fuzzy number $\left(l^e_{Bj}, S^e_{Bj}, u^e_{Bj}\right)$. The integrated vectors A^{*el}_B, A^{*es}_B and A^{*eu}_B are defined as Eqs. (3)-(5).

$$A^{*el}_B = \Big[l^1_{B1}, l^2_{B1}, \ldots, l^m_{B1};\ l^1_{B2}, l^2_{B2}, \ldots, l^m_{B2}; \ldots; l^1_{Bn}, l^2_{Bn}, \ldots, l^m_{Bn}\Big]_{1\times n} \tag{3}$$

$$A^{*es}_B = \Big[s^1_{B1}, s^2_{B1}, \ldots, s^m_{B1};\ s^1_{B2}, s^2_{B2}, \ldots, s^m_{B2}; \ldots; s^1_{Bn}, s^2_{Bn}, \ldots, s^m_{Bn}\Big]_{1\times n} \tag{4}$$

$$A^{*eu}_B = \Big[u^1_{B1}, u^2_{B1}, \ldots, u^m_{B1};\ u^1_{B2}, u^2_{B2}, \ldots, u^m_{B2}; \ldots; u^1_{Bn}, u^2_{Bn}, \ldots, u^m_{Bn}\Big]_{1\times n} \tag{5}$$

where l^e_{Bj}, S^e_{Bj} and u^e_{Bj} are fuzzy components of the number a^e_{Bj}. Based on the suggestion of Meng and Chen [35], l^e_{Bj}, S^e_{Bj} and u^e_{Bj} are respectively transferred to Eqs. (6) to (8).

$$RN\left(l^e_{Bj}\right) = \left\lfloor \underline{\lim}\left(l^e_{Bj}\right), \overline{\lim}\left(l^e_{Bj}\right), \right\rfloor \tag{6}$$

$$RN\left(S^e_{Bj}\right) = \left\lfloor \underline{\lim}\left(S^e_{Bj}\right), \overline{\lim}\left(S^e_{Bj}\right), \right\rfloor \tag{7}$$

$$RN\left(u^e_{Bj}\right) = \left\lfloor \underline{\lim}\left(u^e_{Bj}\right), \overline{\lim}\left(u^e_{Bj}\right), \right\rfloor \tag{8}$$

where $\underline{\lim}\left(l_{Bj}^{e}\right)$ and $\underline{\lim}\left(u_{Bj}^{e}\right)$ are lower bounds and $\overline{\lim}\left(l_{Bj}^{e}\right)$, $\overline{\lim}\left(s_{Bj}^{e}\right)$, and $\overline{\lim}\left(u_{Bj}^{e}\right)$ signify upper bounds of RN $\left(l_{Bj}^{e}\right)$, RN $\left(s_{Bj}^{e}\right)$, and RN $\left(u_{Bj}^{e}\right)$. Therefore, for each of the three tails, a BO vector will be obtained for which means of rough tail are as Eq. (9):

$$\mathrm{RN}\left(\overline{l_{\mathrm{B}j}}\right) = RN\left(l_{Bj}^{1}, l_{Bj}^{2}, \ldots, l_{Bj}^{e}\right) = \left\{\begin{array}{l} l_{Bj}^{-L} = \frac{1}{m}\sum_{e=1}^{m} l_{Bj}^{eL} \\ l_{Bj}^{-u} = \frac{1}{m}\sum_{e=1}^{m} l_{Bj}^{eu} \end{array}\right\} \quad (9)$$

where RN $\left(l_{Bj}^{e}\right)$, RN $\left(s_{Bj}^{e}\right)$, and RN $\left(u_{Bj}^{e}\right)$ are the rough tail and as Eq (10) to (12):

$$\mathrm{RN}\left(\overline{s_{\mathrm{B}j}}\right) = RN\left(s_{Bj}^{1}, s_{Bj}^{2}, \ldots, s_{Bj}^{e}\right) = \left\{\begin{array}{l} s_{Bj}^{-L} = \frac{1}{m}\sum_{e=1}^{m} s_{Bj}^{eL} \\ s_{Bj}^{-u} = \frac{1}{m}\sum_{e=1}^{m} s_{Bj}^{eu} \end{array}\right\} \quad (10)$$

$$\mathrm{RN}\left(\overline{u_{\mathrm{B}j}}\right) = RN\left(u_{Bj}^{1}, u_{Bj}^{2}, \ldots, u_{Bj}^{e}\right) = \left\{\begin{array}{l} u_{Bj}^{-L} = \frac{1}{m}\sum_{e=1}^{m} u_{Bj}^{eL} \\ u_{Bj}^{-u} = \frac{1}{m}\sum_{e=1}^{m} u_{Bj}^{eu} \end{array}\right\} \quad (11)$$

$$\mathrm{IVFRN}_{\overline{\overline{\mathrm{a}}}Bj} = \left[(l_{Bj}^{-L}, l_{Bj}^{-U}), (s_{Bj}^{-L}, s_{Bj}^{-U}), (u_{Bj}^{-L}, u_{Bj}^{-U})\right] \quad (12)$$

The mean vector IVFRN-BO refers to mean response $\overline{\overline{A_B}}$, which is determined through Eq. (13).

$$\overline{\overline{A_B}} = \left\lfloor \overline{\overline{a_{B1}}}, \overline{\overline{a_{B2}}}, \ldots, \overline{\overline{a_{Bn}}} \right\rfloor_{1\times n} \quad (13)$$

f)In this step, IVFRN-OW vector refers to mean response of experts but the difference from step 5 is that the vector is developed for the worst criterion. Finally, the mean vector IFRN-OW refers to mean response $\overline{\overline{A_B}}$, which is determined through Eq. (14).

$$\overline{\overline{A_W}} = \left\lfloor \overline{\overline{a_{1W}}}, \overline{\overline{a_{2W}}}, \ldots, \overline{\overline{a_{nW}}} \right\rfloor_{1\times n} \quad (14)$$

g)This step is concerned with calculation of optimal IVFRN values of weight coefficients of the criteria $\left[\overline{\overline{w_1}}, \overline{\overline{w_2}}, \ldots, \overline{\overline{w_n}}\right]$. The optimal value of evaluation criteria should be minimized for each j as shown in Eq. (15).

$$\left|\frac{\overline{\overline{w_B}}}{\overline{\overline{w_j}}} - \overline{\overline{a_{Bj}}}\right| \quad and \quad \left|\frac{\overline{\overline{w_j}}}{\overline{\overline{W_W}}} - \overline{\overline{a_{jW}}}\right| \quad (15)$$

The value of w for each j has the order $l_j^{wL} \le l_j^{wu} \le s_j^{wL} \le w_j \le s_j^{wu} \le u_j^{wL} \le u_j^{wu}$. As a result, the min-max equation is developed as Eq. (16).

$$\min\max\left\{\left|\frac{\overline{\overline{w_B}}}{\overline{\overline{w_j}}} - \overline{\overline{a_{Bj}}}\right|, \left|\frac{\overline{\overline{w_j}}}{\overline{\overline{w_W}}} - \overline{\overline{a_{jW}}}\right|\right\} \quad (16)$$

$$\left\{\begin{array}{l} \sum_{j=1}^{n} l_j^{wL}, \sum_{j=1}^{n} l_j^{wu}, \sum_{j=1}^{n} s_j^{wL} \le 1 \\ \sum_{j=1}^{n} s_j^{wu}, \sum_{j=1}^{n} u_j^{wL}, \sum_{j=1}^{n} u_j^{wu} \ge 1 \\ l_j^{wL} \le l_j^{wu} \le s_j^{wL} \le s_j^{wu} \le u_j^{wL} \le u_j^{wu}, \quad \forall j = 1, 2, \ldots, n \\ l_j^{wL}, l_j^{wu}, s_j^{wL}, s_j^{wu}, u_j^{wL}, u_j^{wu}, \quad \forall j = 1, 2, \ldots, n \end{array}\right. \quad (17)$$

where $\overline{\overline{w_j}} = \left[(l_j^{wL}, l_j^{wu}), (s_j^{wL}, s_j^{wu}), (u_j^{wL}, u_j^{wu})\right]$ refers to IVFRN-based weight coefficient of each criterion.

B. MATHEMATICAL MODELING

In this section, we introduce our mathematical model based on the problem presented in this research. There are several researches have used multi-objective programming methods [36]–[41]. Before defining our model, which is based on a robust multi-objective goal-programming model, first the subscripts, parameters and decision-making variables used in the model are introduced.

1) SETS AND INDEXES

i	Number of products
j	Number of manufacturing sites
m	Number of parts
n	Number of suppliers
t	Time period

2) PARAMETERS

IS_{mt}	Inventory of the m^{th} part within the t^{th} time period
IS_{mjt}	Inventory of the m^{th} part within the t^{th} time period in the j^{th} factory (site)
IS_{mnjt}	Inventory of the m^{th} part received from supplier nwithin the t^{th} time period in the j^{th} factory (site)
P_{it}	Production rate of the i^{th} automobile within the t^{th} time period
P_{ijt}	Production rate of the i^{th} automobile in the j^{th} factory within the t^{th} time period
CS_{mnt}	Cost of part m bought from the n^{th} supplier within the t^{th} time period
CS_{mnjt}	Maintenance cost of part m bought from the n^{th} supplier in factory j within the t^{th} time period
St_{jmnt}	Duration of production line disruptions due to the performance of supplier n for part m produced in the j^{th} factory within the t^{th} time period
COM_{jmnt}	Rate of production line complaints for part m supplied by the n^{th} supplier in factory j within the t^{th} time period
PPM_{mnjt}	Parts per million (PPM) returned to supplier n for part m from the j^{th} factory within the t^{th} time period

VC_{imt} Rate of consumption of part m in the ^{ith} product within the th time period

DP_{mnjt} On-time delivery performance for the ^{mth} part from supplier n in the ^{jth} factory within the ^{tth} time period

LT_{mnjt} Processing time for supply of part m by the ^{nth} supplier in factory j within the ^{tth} time period

Se_{mnjt} Processing time for procurement of part m by the ^{nth} supplier in factory j within the ^{tth} time period

X_{ijt} Production rate of product i in the ^{jth} factory during period t

α_{mnjt} Confidence level determining allowed levels of inventory of part m from the ^{nth} supplier in the ^{jth} factory during period t

β_{mnjt} Confidence level determining minimum purchases of part m from the ^{nth} supplier in the ^{jth} factory during period t

μ_j Flexibility coefficient of the ^{jth} factory (production site)

CT_{mnjt} Transportation costs for part m from the ^{nth} supplier in the ^{jth} factory during period t

Ch_{mnjt} Cost of changes in demand for part m from the ^{nth} supplier in the ^{jth} factory during period t

Γ Desired robustness level (Ratio)

Z Objective function value

3) DECISION VARIABLES

S_{mnjit} Supplied amount of part m from supplier n in the ^{jth} factory for product ^{ith} within ^{tth} time period

S_{mjt} Supplied amount of part m in the ^{jth} factory within ^{tth} time period

4) MODEL DESIGN WITH FIVE OBJECTIVES

According to the problem presented in this research, the objectives were to minimize production line disruptions, complaints of production line about suppliers' parts, defective parts and overall costs, and maximize on-time delivery services. Therefore, our five objective functions are defined as will follow.

a: FIRST OBJECTIVE: MINIMIZATION OF PRODUCTION LINE DISRUPTIONS DUE TO THE PERFORMANCE OF SUPPLIERS

One of the significant factors affecting order allocation is the performance of suppliers on disruptions of production line. Untimely delivery of products or defects in the parts leads to a disruption in the production line, or in other words, the production line stops. Production line disruptions impose intangible costs on the company; therefore, we have:

$$Min \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} St_{jmnt}S_{mnjit} \tag{18}$$

b: SECOND OBJECTIVE: MINIMIZATION OF COMPLAINTS OF THE PRODUCTION LINE ABOUT SUPPLIED PARTS

The logistics sector of the automobile industry may face complaints of the production line about suppliers' parts, which can be considered as an effective factor in order allocation. A supplier with better performance than others would receive a larger number of orders. Thus, we have:

$$Min \sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} COM_{jmnt}S_{mnjit} \tag{19}$$

c: THIRD OBJECTIVE: MINIMIZATION OF DEFECTIVE PARTS RETURNED (PPM)

PPM is an important indicator in evaluation and allocation of orders. In summary, the significance of this indicator is beyond its role in taking the number of defective parts into account. This indicator is mainly important because it calculates the number of defective parts in relation to the volume of the shipment sent by the supplier. Therefore, suppliers with lower PPM will receive a larger amount of orders. In this regard, the modeling will be as follows:

$$Min \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} PPM_{mnjt}S_{mnjit} \tag{20}$$

d: FOURTH OBJECTIVE: MAXIMIZATION OF ON-TIME DELIVERIES

On-time delivery is one of the indicators emphasized greatly in the literature on supplier selection, as well as by many experts in various industries. In terms of modeling of this objective function, suppliers with a higher coefficient in this indicator get a higher level of order allocation; thus, we have:

$$Max \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} DP_{mnjt}S_{mnjit} \tag{21}$$

e: FIFTH OBJECTIVE: OVERALL COSTS OF SUPPLIED PARTS

In the supply chain of this study, overall supply cost included three types of costs: cost of purchased parts, cost of transportation to the production site, and cost of inventory holding at each production site. Based on the parameters and variables defined for the mathematical model, overall cost of supplied parts for all time-periods is calculated as follows:

$$Min \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnjt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnt}S_{mnjit}$$

$$+\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} CT_{mnjt}S_{mnjit}$$
$$+\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} Ch_{mnjt}IS_{mnjt} \tag{22}$$

5) CONSTRAINTS

The constraints of the proposed model are as follows:

$$S_{mjt} = \sum_{n=1}^{n} S_{mnjit} - \sum_{t=1}^{t} VC_{im}P_{ijt} - \sum_{n=1}^{n} IS_{mjt-1} + \sum_{n=1}^{t} IS_{mjt} \quad \forall j, m, t \tag{23}$$

$$\sum_{i=1}^{I} IS_{mntj} \geq VC_{im} \times X_{ijt} \times Se_{mnjt} \times \alpha_{mnjt} \times LT_{mnjt} \quad \forall j, m, t$$
$$\sum_{i=1}^{I} IS_{mntj} \leq VC_{im} \times X_{ijt} \times Se_{mnjt} \times (1+\alpha_{mnjt}) \times LT_{mnjt} \quad \forall j, m, t \tag{24}$$

$$\sum_{j=1}^{J} S_{mnjit} \leq \sum_{m}^{M}\sum_{n}^{N}\sum_{j}^{J}\sum_{t}^{T} CT_{mnjt} + Ch_{mnjt} \quad \forall m, n, j, t \tag{25}$$

$$\sum_{j=1}^{J} S_{mnjit} \geq \beta_{mnjt} \times \sum_{n=1}^{n}\sum_{j=1}^{J} S_{mnjt} \quad \forall m, n, t \tag{26}$$

$$\sum_{j=1}^{J} \mu_j \leq 0.7 \tag{27}$$

Demand depends on four factors in each period: rate of production in that period, rate of consumption of parts by each product, inventory at the beginning of the period and required inventory at the end of the period. In this respect, constraint (23) shows the rate of demand for part m produced in the j^{th} site during period t. Furthermore, according to experts' opinions, constraint (24) indicates the existing inventory during this period. This constraint is a multiplication of production rate in that period, consumption rate of parts, processing time for supplied parts and the confidence level denoted by α. Thus, minimum and maximum inventory limits are ensured by equation (24).

Constraint (25), holds the assumption that supplier i can only meet a limited amount of demand for part m. In other words, annual production capacity, or maximum annual capacity that supplier i allocates to the purchaser, must be less than or equal to C_i during each year. Constraint (26) is in accordance with company's policies to purchase from all suppliers of any given part, and by considering a coefficient denoting minimum purchases from each supplier. Constraint (27) indicates the minimum level of production system flexibility in factory j. The value of the production system flexibility level is a number between zero and one, which suggests a higher level of flexibility, the closer it gets to one. In addition, according to experts' opinions, the optimal value for this flexibility level is considered as 0.7 [35].

a: GOAL PROGRAMMING MODEL

Based on the study conducted by Seifbarghy and Esfandiari [33], in order to simplify the solving process for the presented model we rewrote our five objective functions within the framework of goal programming as equation (28).

$$MinZ = \sum_{r=1}^{r} w_r(d_r^+, d_r^-) = w_1d_1^+ + w_2d_2^+ + w_3d_3^+ + w_4d_4^+ + w_5d_5^+ \tag{28}$$

Furthermore, constraints presented in equations (23) to (27) are rewritten based on equation (28) as equations (29) to (39).

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} St_{jmnt}S_{mnjit} + d_1^- - d_1^+ = G_1 \tag{29}$$

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} COM_{jmnt}S_{mnjit} + d_2^- - d_2^+ = G_2 \tag{30}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} PPM_{mnjt}S_{mnjit} + d_3^- - d_3^+ = G_3 \tag{31}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} DP_{mnjt}S_{mnjit} + d_4^- - d_4^+ = G_4 \tag{32}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnjt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} CT_{mnjt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} Ch_{mnjt}IS_{mnjt} + d_5^- - d_5^+ = G_5 \tag{33}$$

$$S_{mtj} = \sum_{n=1}^{n} S_{mntj} = \sum_{t=1}^{t} VC_{im}P_{tjt} - \sum_{n=1}^{n} IS_{mjt=1} + \sum_{n=1}^{t} IS_{mjt} \quad \forall j, m, t \tag{34}$$

$$\sum_{i=1}^{I} IS_{mntj} \geq VC_{im} \times X_{ijt} \times Se_{mnjt} \times \alpha_{mnjt} \times LT_{mnjt} \quad \forall j, m, t$$
$$\sum_{i=1}^{I} IS_{mntj} \leq VC_{im} \times X_{ijt} \times Se_{mnjt} \times (1+\alpha_{mnjt}) \times LT_{mnjt} \quad \forall j, m, t \tag{35}$$

$$\sum_{j=1}^{J} S_{mnjit} \leq \sum_{m}^{M}\sum_{n}^{N}\sum_{j}^{J}\sum_{t}^{T} CT_{mnjt} + Ch_{mnjt} \quad \forall m,n,j,t \tag{36}$$

$$\sum_{j=1}^{J} S_{mnjit} \geq \beta_{mnjt} \times \sum_{n=1}^{n}\sum_{j=1}^{J} S_{mnjit} \quad \forall m,n,t \tag{37}$$

$$S_{mnjit}, IS_{mtj} \geq 0, int \quad \forall m,n,j,t \tag{38}$$

$$\sum_{j=1}^{J} \mu_j \leq 0.7 \tag{39}$$

b: A ROBUST MATHEMATICAL MODEL

Problems related to decision-making are often faced with uncertainties due to the lack of accuracy, continuous changes and the inability to predict future events. Model robustness is an important subject in the fields of modeling and operations research. If a model is robust, there will be a significantly lower risk of its incorrect use. In a robust model, output(s) is not very sensitive to an exact value(s) of model inputs [34], [35]. Robust optimization is the modeling of optimization problems with ambiguous data, and their solutions are satisfactory for all or most uncertain arguments. Robust optimization can be considered as a complementary option for sensitivity analysis and stochastic programming.

Considering the abovementioned, in order to increase our model's accuracy, the robust model, and the goal programming model, equation (28) and constraints (29) to (39) will be rewritten within the framework of a robust goal-programming model as equations (40) to (52).

$$MinZ = \sum_{r=1}^{r} w_r(d_r^+, d_r^-) = w_1d_1^+ + w_2d_2^+ + w_3d_3^+ + w_4d_4^+ + w_5d_5^+ \tag{40}$$

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} St_{jmnt}S_{mnjit} + d_1^- - d_1^+ = G_1 \tag{41}$$

$$\sum_{j=1}^{J}\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} COM_{jmnt}S_{mnjit} + d_2^- - d_2^+ = G_2 \tag{42}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} PPM_{mnjt}S_{mnjit} + d_3^- - d_3^+ = G_3 \tag{43}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} DP_{mnjt}S_{mnjit} + d_4^- - d_4^+ = G_4 \tag{44}$$

$$\begin{aligned}&\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnjt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{i=1}^{I} CS_{mnt}S_{mnjit} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{j=1}^{J}\sum_{i=1}^{I} CT_{mnjt}S_{mnjit}\\ &+ \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} Ch_{mnjt}IS_{mnjt} + \sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{j=1}^{J}\sum_{t=1}^{T} PP_{mnjt} + Z \times \Gamma_1 - d_5^+ \leq G_5\end{aligned} \tag{45}$$

$$S_{mtj} = \sum_{n=1}^{n} S_{mnjit} = \sum_{t=1}^{t} VC_{im}P_{ijt} - \sum_{n=1}^{n} IS_{mjt=1} + \sum_{n=1}^{t} IS_{mjt} \quad \forall j,m,t \tag{46}$$

$$\sum_{i=1}^{I} IS_{mntj} \geq VC_{im} \times X_{ijt} \times Se_{mnjt} \times \alpha_{mnjt} \times LT_{mnjt} \quad \forall j,m,t$$

$$\sum_{i=1}^{I} IS_{mntj} \leq VC_{im} \times X_{ijt} \times Se_{mnjt} \times (1+\alpha_{mnjt}) \times LT_{mnjt} \quad \forall j,m,t \tag{47}$$

$$\sum_{j=1}^{J} S_{mnjit} \geq \beta_{mnjt} \times \sum_{n=1}^{n}\sum_{j=1}^{J} S_{mnjt} \quad \forall m,n,t \tag{48}$$

$$PP_{mnjt} + ZZ \geq CT_{mnjt}S_{mnjit} \quad \forall m,n,j,t \tag{49}$$

$$ZZ_{mnt} + PPM_{mntj} \geq \sum_{m}^{M}\sum_{n}^{N}\sum_{j}^{J}\sum_{t}^{T} CT_{mnjt} + Ch_{mnjt} \quad \forall m,n,j,t \tag{50}$$

$$\sum_{j=1}^{J} \mu_j \leq 0.7 \tag{51}$$

$$S_{mnjit}, IS_{mtj} \geq 0, int \quad \forall m,n,j,t \tag{52}$$

IV. CASE STUDY

Automobile manufacturing is one of the significant parts of business and industry throughout the world. The supply chain of this industry is one of the most dynamic supply chains currently existing. Given this fact, we selected one of the automobile manufacturing company for the purposes of this study, which has an active supply chain. In this supply chain, each automobile contains thousands of parts. Regardless of certain parts that have a single source, many parts are supplied from multiple sources. In other words, proper planning for supply of parts taking different criteria and high levels of uncertainty in some indicators into consideration has added to the importance of robust programming in this supply chain. In this study, we considered robust programming in supply of parts for two automobile models (Peugeot 405 and Peugeot Pars). These parts include over 70% of the overall value of each automobile. Planning for supplying these parts was done based on the production plans of that company. However, our model was developed in a general form so that it could be applied to multiple factories.

In the present research, we used the alternatives of experts in the automobile industry to determine the priorities of our goals. For this purpose, we collected the alternatives from

TABLE 2. Matrix of final weights for the criteria under study based on the supplier's choice.

Row	Component	IVFRN-BWM
1	Production line disruption	0.213
2	Complaint of Production line about parts	0.233
3	Defective parts	0.114
4	On-time delivery	0.316
5	Overall cost of supplied parts	0.124

15 managers and experts working in this field. In this respect, based on the first part of our proposed model, we first analyzed the results obtained by solving the finalized indicators. To achieve our objectives, pairwise comparison questionnaires were designed and then distributed among the experts. After solving the problem using the model proposed in the first step of the article, i.e. IVFRN-BWM, the results of the final weights of the criteria based on the operation of suppliers were obtained and presented in Table 2.

Since the main subject of this research was allocation of order to suppliers in an agile and flexible manner suitable to the automobile industry, parts supplied by a single source were eliminated from the set of parts selected for the purposes of the study. Finally, four suppliers were evaluated in this research. Moreover, the robust model was done at a tactical level based on production plans for the two automobile models (Peugeot 405 and Peugeot Pars) at the automobile manufacturing site Q for three periods (monthly).

Various methods can be used to solve this problem, such as mathematical analysis, experimental observation and other research techniques. Naturally, there are strengths and limitations for each of these methods, and employing all of them for one specific system may be neither possible nor will it produce similar results. One of the methods proposed for understanding the current situation and improving system's performance to solve the proposed model is simulation. Simulation is one of the most powerful and beneficial tools for performance analysis of complex processes in different systems.

Due to the specifications of the proposed model in terms of the number of variables, constraints and data, the model will be programmed in the GAMS software (linked with Microsoft Excel). Hence, the input data of the model could be called from Microsoft Excel, and this would increase the computational efficiency. Next, the robust model will be solved 11 times per 11 modes of robustness levels. After each solving stage, the values of the obtained variables will be considered as fixed ones and uncertain parameters in each interval will be produced randomly and simulated in the form of a uniform probability distribution function for 10000 times. In each simulation, how many constraints were violated will be determined. In other words, by obtaining the ratio of all violated constraints to the whole constraints with uncertain parameters, the risk of each desired robustness level will be specified. A summary of results will be provided in Table 3.

TABLE 3. Objective function values.

Situation	Γ_1	Γ_2	Objective value
1	0	0	819122
2	39	0.1	1057305
3	78	0.2	1288788
4	117	0.3	1518428
5	156	0.4	1744630
6	195	0.5	1979347
7	234	0.6	2204116
8	273	0.7	2430908
9	312	0.8	2662562
10	351	0.9	2889888
11	387	1	3164133

TABLE 4. Percentage of deviations from each goal based on the value of that goal in each mode.

situation	Γ_1	Γ_2	A	B	C	D	E
1	0	0	0.057	47.196	22.684	532.768	1.740
2	39	0.1	0.260	47.383	22.708	540.073	1.860
3	78	0.2	0.466	47.591	22.734	547.501	1.888
4	117	0.3	0.670	47.140	22.765	554.973	1.905
5	156	0.4	0.872	48.035	22.794	562.439	1.917
6	195	0.5	1.057	48.262	22.828	570.010	1.927
7	234	0.6	1.283	48.481	22.857	577.410	1.934
8	273	0.7	1.483	48.699	22.886	584.875	1.940
9	312	0.8	1.696	48.922	22.922	592.375	1.919
10	351	0.9	1.897	49.146	22.955	599.838	1.950
11	387	1	2.143	49.491	22.999	607.355	1.954

TABLE 5. Possibility of constraint violations based on the two defined indicators.

Situation	Γ_1	Γ_2	A	B	C	D	E
1	0	0	0.001	0.107	0.532	0.893	0.477
2	39	0.1	0	0.097	0.436	0.903	0.564
3	78	0.2	0	0.086	0.388	0.914	0.612
4	117	0.3	0	0.075	0.339	0.925	0.661
5	156	0.4	0	0.065	0.291	0.935	0.709
6	195	0.5	0	0.055	0.246	0.945	0.754
7	234	0.6	0	0.044	0.196	0.956	0.804
8	273	0.7	0	0.033	0.149	0.967	0.851
9	312	0.8	0	0.023	0.099	0.977	0.901
10	351	0.9	0	0.011	0.049	0.989	0.951
11	387	1	0	0	0	1	1

In Table 4 columns A to E indicate the ratios of deviations from goals one to five to each goal's value, respectively.

Table 5 shows the risk (possibility) of constraint violations. The fifth goal constraint has 387 uncertain parameters, and a desired robustness level of Γ_1. Other constraints have

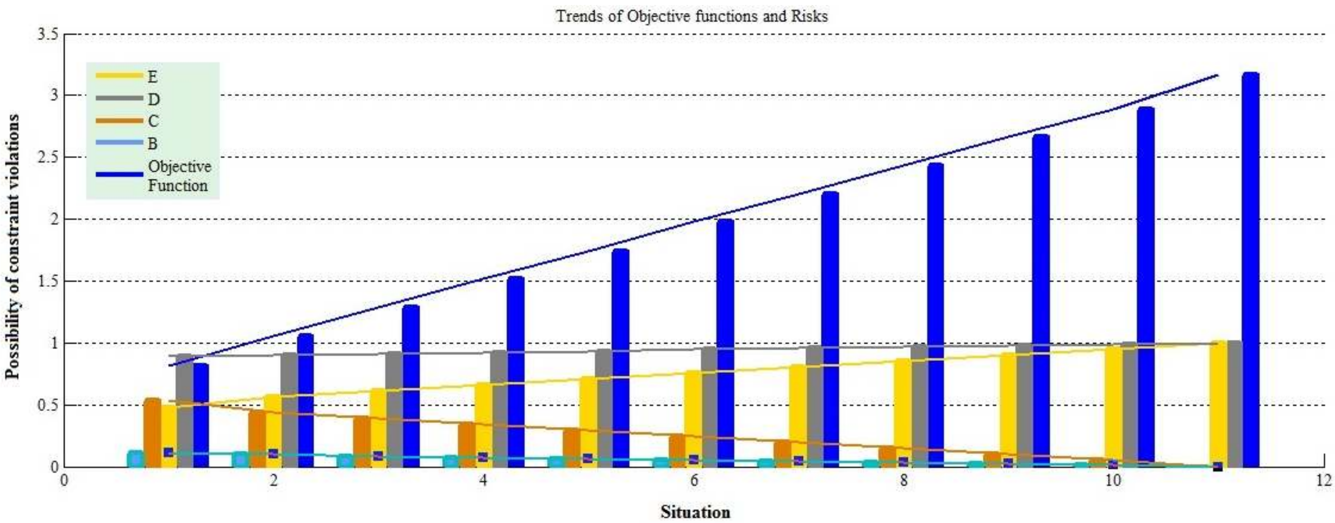

FIGURE 1. Comparison of diagrams for trends of objective functions and risks.

uncertain parameters including 387 constraints related to capacity and have desired robustness level of Γ_2. Results of the simulation reveal that only a number of capacity constraints (86 cases) may be violated. It is because some capacities are higher than the required amounts, or the model has allocated to them a value lower than their true capacity, and thus, fluctuations in the considered interval have no effect on them. Based on the abovementioned, two indicators were considered for calculation of risk levels.

- Indicator 1: Dividing the number of all violated cases by the number of all possible cases.
- Indicator 2: Dividing the number of all violated cases by the number of all cases dependent on constraints that can be violated.

Indicator 2 is stricter, and indicator 1 is generally more logical. In Table 3, modes 1 and 11 are the most optimistic and the most pessimistic cases, respectively. Columns A and B present the violation risk for the fifth goal constraint (based on indicators 1 and 2), columns C and D indicate the violation risk for capacity constraints (based on indicators 1 and 2), and columns E and F provide the overall confidence levels (based on indicators 1 and 2).

As can be observed in Figure 1, the objective function values are linear and have an upward trend. In addition, the Figure 1 simultaneously shows the possibility of constraints' violations in each mode. Due to consistency between objective functions values and risk values in terms of size, the objective function diagram was drawn in the scale of millions. The diagram demonstrates that the more we move towards mode 11, the lower the risk levels will be and the worse the objective function will get.

Based on Table 4 and Figure 1, it can be concluded that by reducing risk-taking (increase in desired robustness level), the minimization objective function got worse. For finding the values of variables within the specified interval, technically, the more the robustness level increases, the stricter the model is. In this regard, the possibility of constraint violations decreases, and the objective function's solution gets worse. This can itself be a confirmation for the accurate robust model and its performance.

In addition, based on Table 4 and the coefficients of goals, despite the highest coefficients for goals 1 to 5, respectively, the model is able to reduce the deviations of the mentioned goals. On the other hand, the percentages of reduced deviations of goals 1, 3 and 5 are considerable based on the value of each goal.

In Table 5, desired robustness levels have the highest values in the pessimistic mode. Furthermore, the value of zero for the possibility of constraint violations in the results of this mode means that no constraints being violated, and hence, the worst value is obtained for the objective function. If this situation does not occur (all of the fluctuations do not occur together), choosing this alternative can compensate the losses caused by lost opportunities. On the other hand, over-optimism can lead to more costs and losses.

Finally, this paper was faced two constraints to implementing the proposed model for a real case of the automobile industry. Those two limitations were 1) lacking workforce interest to cooperate with this practical research for compelling the tables of criteria importance and 2) difficulty to achieve real data from this industry.

V. CONCLUSION

In this study, we conducted an analysis on results obtained from solving and simulating the proposed model and diagrams. Table 4 and the slope of diagram 1 show that the changes in risk or desired robustness level has a significant increasing effect on the slope of the objective function line values. In other words, turning the model into a robust one is quite necessary and effective for reducing the decision-making risk. According to Table 4, deviation from the first goal, which has the highest level of importance, is able to get very close to zero. On the other hand, this goal has the lowest percentage of deviation comparing to other goals, which shows the accurate performance of the proposed model in the presence of multiple and contradictory goals.

The values in Table 5 are the results of the simulation and indicate that these values decreased by increasing the levels of desired robustness. This trend shows the proper performance of the robust model and the simulation. Also, this table shows that the best scenario for the decision-maker is to accept a level of risk, and in practice, utilize the values of variables obtained by the model based on that level. If a decision maker accepts a risk of around 5%, then according to Table 5 and based on indicator 1, solutions obtained from mode 7 can ensure a 95% confidence, in other words, they create a balance between risk and revenue.

As expressed in section IV, there are 387 constraints containing uncertain parameters, and only some of these constraints can be violated. Thus, observing the result obtained, we can conclude that 86 violable constraints are active. Therefore, for future research, provision of an algorithm that can reduce these constraints before model solving can be recommended. In the current research, in addition to modeling and solving the model, we presented some new indicators in terms of supplier selection, such as production line interruptions due to the performance of suppliers and complaint of production line about supplied parts. Overall, the proposed model has a high level of reliability, taking the robustness of the solutions, interview-oriented modeling and the important indicators into account based on the decision maker's opinion.

REFERENCES

[1] R. Vernic, "Optimal investment with a constraint on ruin for a fuzzy discrete-time insurance risk model," *Fuzzy Optim. Decis. Making*, vol. 15, no. 2, pp. 195–217, 2016.

[2] C. Battistella, A. F. De Toni, G. De Zan, and E. Pessot, "Cultivating business model agility through focused capabilities: A multiple case study," *J. Bus. Res.*, vol. 73, pp. 65–82, Apr. 2017.

[3] M. Kim and S. Chai, "The impact of supplier innovativeness, information sharing and strategic sourcing on improving supply chain agility: Global supply chain perspective," *Int. J. Prod. Econ.*, vol. 187, pp. 42–52, May 2017.

[4] K.-J. Wu, M.-L. Tseng, A. S. F. Chiu, and M. K. Lim, "Achieving competitive advantage through supply chain agility under uncertainty: A novel multi-criteria decision-making structure," *Int. J. Prod. Econ.*, vol. 190, pp. 96–107, Aug. 2017.

[5] A. Rojo, M. Stevenson, F. J. L. Montes, and M. N. Perez-Arostegui, "Supply chain flexibility in dynamic environments: The enabling role of operational absorptive capacity and organisational learning," *Int. J. Oper. Prod. Manage.*, vol. 38, no. 3, pp. 636–666, Mar. 2018.

[6] M. J. Braunscheidel and N. C. Suresh, "Cultivating supply chain agility: Managerial actions derived from established antecedents," in *Supply Chain Risk Management*. Singapore: Springer, 2018, pp. 289–309.

[7] A. M. T. Thomé, L. F. Scavarda, A. Scavarda, and F. E. S. S. de Thomé, "Similarities and contrasts of complexity, uncertainty, risks, and resilience in supply chains and temporary multi-organization projects," *Int. J. Project Manage.*, vol. 34, no. 7, pp. 1328–1346, Oct. 2016.

[8] M. Wang, F. Jie, and A. Abareshi, "The measurement model of supply chain uncertainty and risk in the australian courier industry," *Oper. Supply Chain Manage.*, vol. 7, no. 3, pp. 89–96, Sep. 2014.

[9] S. G. Azevedo, K. Govindan, H. Carvalho, and V. Cruz-Machado, "An integrated model to assess the leanness and agility of the automotive industry," *Resour., Conservation Recycling*, vol. 66, pp. 85–94, Sep. 2012.

[10] S. Vinodh, S. R. Devadasan, K. E. K. Vimal, and D. Kumar, "Design of agile supply chain assessment model and its case study in an Indian automotive components manufacturing organization," *J. Manuf. Syst.*, vol. 32, no. 4, pp. 620–631, Oct. 2013.

[11] X. Zhou, X. Zhong, H. Lin, Z. Qin, and X. Yang, "Lexicographic maximum solution of min-product fuzzy relation inequalities for modeling the optimal pricing with fixed priority grade in supply chain," *IEEE Access*, vol. 6, pp. 71306–71316, 2018.

[12] W. Zhao and D. Wang, "Simulation-based optimization on control strategies of three-echelon inventory in hybrid supply chain with order uncertainty," *IEEE Access*, vol. 6, pp. 54215–54223, 2018. doi: 10.1109/ACCESS.2018.2870856.

[13] M.-Y. Quan, Z.-L. Wang, H.-C. Liu, and H. Shi, "A hybrid MCDM approach for large group green supplier selection with uncertain linguistic information," *IEEE Access*, vol. 6, pp. 50372–50383, 2018.

[14] M. R. Feylizadeh and M. Bagherpour, "Manufacturing performance measurement using fuzzy multi-attribute utility theory and Z-number," *Trans. FAMENA*, vol. 42, no. 1, pp. 37–49, 2018.

[15] A. Zare, M. R. Feylizadeh, A. Mahmoudi, and S. Liu, "Suitable computerized maintenance management system selection using grey group TOPSIS and fuzzy group VIKOR: A case study," *Decis. Sci. Lett.*, vol. 7, no. 4, pp. 341–358, 2018.

[16] M. R. Feylizadeh and M. A. Dehghani, "Priority determination of the renewable energies using fuzzy group VIKOR method; Case study iran," in *Proc. Int. Conf. Ind. Eng. Oper. Manage.*, Kuala Lumpur, Malaysia, 2016, pp. 3280–3287.

[17] N. Jamali and M. R. Feylizadeh, "Performance evaluation of aircraft maintenance department using integration fuzzy AHP and BSC approach in iran," *Int. J. Manage., Accoutning Econ.*, vol. 2, no. 9, pp. 977–993, 2015.

[18] S. Parsaei, M. Keramati, F. Zorriassatine, and M. R. Feylizadeh, "An order acceptance using FAHP and TOPSIS methods: A case study of iranian vehicle belt production industry," *Int. J. Ind. Eng. Comput.*, vol. 3, no. 2, pp. 211–224, 2012.

[19] Y. Wang, X. Geng, F. Zhang, and J. Ruan, "An immune genetic algorithm for multi-echelon inventory cost control of IOT based supply chains," *IEEE Access*, vol. 6, pp. 8547–8555, 2018.

[20] Z. G. Zacharia, N. W. Nix, and R. F. Lusch, "An analysis of supply chain collaborations and their effect on performance outcomes," *J. Bus. Logistics*, vol. 30, no. 2, pp. 101–123, 2009.

[21] Y. Y. Yusuf, A. Gunasekaran, E. O. Adeleye, and K. Sivayoganathan, "Agile supply chain capabilities: Determinants of competitive objectives," *Eur. J. Oper. Res.*, vol. 159, no. 2, pp. 379–392, Dec. 2004.

[22] E. W. T. Ngai, D. C. K. Chau, and T. L. A. Chan, "Information technology, operational, and management competencies for supply chain agility: Findings from case studies," *J. Strategic Inf. Syst.*, vol. 20, no. 3, pp. 232–249, Sep. 2011.

[23] D. M. Gligor, C. L. Esmark, and M. C. Holcomb, "Performance outcomes of supply chain agility: When should you be agile?" *J. Oper. Manage.*, vols. 33–34, pp. 71–82, Jan. 2015.

[24] Q. Zhang, M. A. Vonderembse, and J.-S. Lim, "Manufacturing flexibility: Defining and analyzing relationships among competence, capability, and customer satisfaction," *J. Oper. Manage.*, vol. 21, no. 2, pp. 173–191, Mar. 2003.

[25] J. Gosling, L. Purvis, and M. M. Naim, "Supply chain flexibility as a determinant of supplier selection," *Int. J. Prod. Econ.*, vol. 128, no. 1, pp. 11–21, Nov. 2010.

[26] A. T. L. Chan, E. W. T. Ngai, and K. K. L. Moon, "The effects of strategic and manufacturing flexibilities and supply chain agility on firm performance in the fashion industry," *Eur. J. Oper. Res.*, vol. 259, no. 2, pp. 486–499, Jun. 2017.

[27] K. K.-L. Moon, C. Y. Yi, and E. W. T. Ngai, "An instrument for measuring supply chain flexibility for the textile and clothing companies," *Eur. J. Oper. Res.*, vol. 222, no. 2, pp. 191–203, Oct. 2012.

[28] Y. Y. Yusuf, A. Musa, M. Dauda, N. El-Berishy, D. Kovvuri, and T. Abubakar, "A study of the diffusion of agility and cluster competitiveness in the oil and gas supply chains," *Int. J. Prod. Econ.*, vol. 147, pp. 498–513, Jan. 2014.

[29] N. M. Galal and A. F. A. Moneim, "Developing sustainable supply chains in developing countries," *Procedia CIRP*, vol. 48, pp. 419–424, Jan. 2016.

[30] J. Rezaei, O. Kothadiya, L. Tavasszy, and M. Kroesen, "Quality assessment of airline baggage handling systems using SERVQUAL and BWM," *Tourism Manage.*, vol. 66, pp. 85–93, Jun. 2018.

[31] D. Pamu ar, I. Petrović, and G. Ćirović, "Modification of the best–worst and MABAC methods: A novel approach based on interval-valued fuzzy-rough numbers," *Expert Syst. Appl.*, vol. 91, pp. 89–106, Jan. 2018.

[32] L. Li and Z. B. Zabinsky, "Incorporating uncertainty into a supplier selection problem," *Int. J. Prod. Econ.*, vol. 134, no. 2, pp. 344–356, 2011.

[33] M. Seifbarghy and N. Esfandiari, "Modeling and solving a multi-objective supplier quota allocation problem considering transaction costs," *J. Intell. Manuf.*, vol. 24, no. 1, pp. 201–209, Feb. 2013.

[34] J. P. C. Kleijnen, "Ethical issues in modeling: Some reflections," *Eur. J. Oper. Res.*, vol. 130, no. 1, pp. 223–230, 2001.

[35] F. Meng and X. Chen, "A robust additive consistency-based method for decision making with triangular fuzzy reciprocal preference relations," *Fuzzy Optim. Decis. Making*, vol. 17, no. 1, pp. 49–73, 2018.

[36] L. Wu, Y. Chen, and M. R. Feylizadeh, "Study on the estimation, decomposition and application of China's provincial carbon marginal abatement costs," *J. Cleaner Prod.*, vol. 207, pp. 1007–1022, Jan. 2019.

[37] M. R. Feylizadeh, N. Karimi, and D. F. Li, "Multi-stage production planning using fuzzy multi-objective programming with consideration of maintenance," *J. Intell. Fuzzy Syst.*, vol. 34, no. 4, pp. 2753–2769, Jan. 2018.

[38] M. R. Feylizadeh, A. Mahmoudi, M. Bagherpour, and D.-F. Li, "Project crashing using a fuzzy multi-objective model considering time, cost, quality and risk under fast tracking technique: A case study," *J. Intell. Fuzzy Syst.*, vol. 35, no. 3, pp. 3615–3631, 2018.

[39] M. Bagherpour, M. R. Feylizadeh, and D. F. Cioffi, "Time, cost, and quality trade-offs in material requirements planning using fuzzy multi-objective programming," *Proc. Inst. Mech. Eng., B, J. Eng. Manuf.*, vol. 226, no. 3, pp. 560–564, 2012.

[40] S. Noori, M. R. Feylizadeh, M. Bagherpour, F. Zorriassatine, and R. M. Parkin, "Optimization of material requirement planning by fuzzy multi-objective linear programming," *Proc. Inst. Mech. Eng., B, J. Eng. Manuf.*, vol. 222, no. 7, pp. 887–900, 2008.

[41] A. Mahmoudi, M. R. Feylizadeh, D. Darvishi, and S. Liu, "Grey-fuzzy solution for multi-objective linear programming with interval coefficients," *Grey Syst., Theory Appl.*, vol. 8, no. 3, pp. 312–327, 2018.