Journal of Applied Research on Industrial Engineering



www.journal-aprie.com

J. Appl. Res. Ind. Eng. Vol. 10, No. 2 (2023) 273-285.



Paper Type: Research Paper

Robust Optimization Model to Improve Supply Chain Network Productivity under Uncertainty

Seyed Farid Mousavi¹, Arash Apornak^{2,*}, Mohammad Reza Pourhassan³

¹Department of Information Technology and Operations Management, Kharazmi University, Tehran, Iran; mousavifarid@khu.ac.ir.

²Department of Industrial Engineering, University of Tehran, Tehran, Iran; arash.apornak@ut.ac.ir

³ Department of Industrial Engineering, Ershad University of Damavand, Tehran, Iran; st_m_poorhassan@azad.ac.ir.

Citation:



Mousavi, S. F., Apornak, A., & Pourhassan, M. R. (2023). Robust optimization model to improve supply chain network productivity under uncertainty. *Journal of applied research on industrial engineering*, 10(2), 273-285.

Received: 22/11/2021

Reviewed: 22/12/2021

Revised: 11/01/2022

Accepted: 08/02/2022

Abstract

Although the importance of supply chain agility considering the necessity of speed of action, response to customers, progressive changes in the market, consumers' needs, etc. in many industries is clear both scientifically and experimentally, today organizations have found that the benefit from this cooperation is greater than cases performed without collaboration with relevant organizations. Meanwhile, supply chain management refers to integration of all processes and activities in the supply chain through improving the relations and implementing the organizational processes in order to achieve competitive advantages. On the other hand, uncertainty in the supply chain results in non-optimality of decisions that are made with assumption of certainty. Accordingly, the main aim of this research is to provide a model for supply chain in an agile and flexible state based on uncertainty variables. The method of research has been based on a mathematical model, whose stages of implementation are investigated by breaking down this model step-by-step. For this purpose, in the first stage and after getting familiar with the intended modeling industry, solution and simulation were done. Eventually the results were compared indicating that through reducing the risk-taking (increasing the protection levels), the objective function which was of minimization type worsened. This study also showed that model robustification is very important in order to reduce the risk of decision-making.

Keywords: Supply chain, Robust optimization, Uncertainty, Productivity.

1 | Introduction

CC Licensee Journal of Applied Research on Industrial Engineering. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons. org/licenses/by/4.0). In order to remain in a competitive environment, it is essential to design a flexible-responsive manufacturing system with automatic material handling systems [1]. Over the first two decades of 21st-century, organizations and people have been experiencing new events and phenomena, whose roots may have been growing from many years ago. Introduction of the information technology element in any area, the necessity of speed of action in response to customers as well as the progressive change of market and needs of consumers, and the need to have flexibility in organizations and production all entail moving towards the concept of productivity in organizations [2]. This concept which arises from the needs of organizations is indeed creating a network in physical and virtual areas as well as eliminating losses in the organization including the most important transformations and novel approaches in management [3].

Corresponding Author: arash.apornak@ut.ac.ir https://doi.org/10.22105/jarie.2022.316357.1402 One of the concepts and paradigms propounded within the last two decades is the concept of Productivity, which arises from the needs of the organizations following development of previous approaches such as manual production, mass production, and lean production [4]. Meanwhile, over the last two decades, supply chain management has been propounded as one of the key factors of competition and success of organizations, and has attracted attention of various researchers as well as scholars of production and operations management [5]. Dealing with productivity in supply chain as a hybrid concept has also become very popular these days, and researchers are trying to provide new angles of this newly emerging concept [6].

Although within the last decade, many individuals have dealt with providing the elements and indicators of assessing the supply chain Productivity, generally a group of researchers have centralized the main stages of supply chain including procurement, production, and distribution and propounded productivity indicators [7]. On the other hand, another group has focused on the elements affecting productivity including stimuli, competences, and empowers, and has been trying to provide an indicator for these elements in the supply chain [8]. The present research tries to provide the elements and indicators of supply chain productivity assessment comprehensively. In other words, the assessment indicators of each of the productivity indicators in every major step of the supply chain have been determined and validated [9].

The important point is that the indicators and criteria for flexibility assessment, with the most important ones mentioned in the previous section, are usually very general and have mostly measured the Productivity competences rather than all of its dimensions [10]. The present research tries to present the criteria and indicators of supply chain productivity assessment comprehensively and based on all of its dimensions [11]. In classic examples of mathematical programming, the input data of the model (parameters) are considered certain (definite) and equivalent to nominal values [12]. This attitude neglects the effect of uncertainty on the quality and justification of the model. Indeed, the data that adopt different values from their nominal values may cause some limitations to be violated. Also, the optimal solution in the long run may not remain optimal or even its justification may be lost. This conveys the fact that solution methods (models) should be designed that creates immunity and protection against data uncertainty [13]. These solution methods are called "robust". The first step in this regard was in the form of a linear programming model for generating solutions that would be justified for all data belonging to a convex set. The mentioned model offers solutions that are very conservative with regards to optimality of the nominal problem in order to ensure robustness. Indeed, this problem is one of the first problems of robust optimization [14]. Thereafter, other important steps were taken independently to develop the robust optimization theory including Ben-Tal and Nemirovski [34], and Bertsimas and Sim [5]. Since optimization of this research is of mixed integer number type, the model robustification is in line with the approach of "Bertsimas and Sim [5]" model [15]. A compelling, productive and strong supply chain may be an economical competitive advantage for countries and firms and makes a difference them to manage with increasing environmental turbulences and more seriously competitive weights [16]. A supply chain could be a organize of provider, generation, conveyance centers and channels between them organized to obtain crude materials, change over them to wrapped up products, and disseminate last items in an effective way to clients [17]. Supply chain arranges plan is one of the foremost critical key choices in supply chain administration. In common, organize plan choices incorporate deciding the numbers, areas and capacities of offices and the amount of stream between them [18].

In the present research, in addition to a brief review on the literature about supply chain productivity and its assessment indicators, expert opinion has been investigated, operational indicators of supply chain productivity assessment have been provided, and a model has been developed to enhance productivity as well as flexibility in the form of a case study. This research attempts to present a model that fits the real-world setting using uncertainty variables and applying verbal variables. The important point is that the indicators and criteria for flexibility assessment, the most important of which were mentioned in the previous section, are typically very general and have mostly measured productivity competences rather than all of its dimensions. The present research tries to provide criteria and indicators for assessing the supply chain productivity comprehensively and based on all of its dimensions.

This paper is structured as follows: Section 2 presents a literature survey. In Section 3, the proposed method is provided generally. Section 4 illustrated the simulation method that is used in this paper, in Section 5 discussed results and discussion on a selected case study. Finally, in Section 6 the conclusion, future research and managerial implementation delivered.

2 | Literature Review

The theoretical basis and research background associated with the subject of the present research are discussed further. The most important condition for survival in today's competitive world is uniqueness and eliminating losses, delivering suitable products, with proper price at the proper time. It is very important for customers to receive their desired product as they wish with a reasonable price as soon as possible. Nevertheless, it should be noted that today and considering the rapid changes in the world, the interests, needs, and demands of customers are also changing equally fast, and considering the uncertainties in the competitive market and in the decision-making system, these issues can no longer be solely relied upon for success and to expend the whole energy for that. Market has shown that even if we provide the product with a very high quality and reasonable price, there are many competitors who would replace us rapidly in the market if our product is not available or not according to the customers' needs. Thus, in this competitive market, productivity is a major and undeniable principle. Accordingly, companies should have productivity in their production and establish integrity with their suppliers and customers. This helps them maintain their position in the competitive world and take effective steps for progress by creating an integrated supply chain [19].

Similar studies have mostly been conducted by foreign researchers. Here, the most important research studies on indicators of supply chain productivity assessment are reviewed. However, delivery flexibility is able to manage a flexible demand per a specific and constant value. Typically, these two cases are used in the supply chain, which go forward based on strategic decisions.

Vahdani and Mohammadi [20] displayed a bi-objective optimization demonstrate for planning a closed circle supply chain organize beneath vulnerability in which the overall costs and the greatest holding up times within the line of items are considered to play down. A common multi-priority and multi-server lining framework for parallel preparing execution is proposed. Too an unused cross breed arrangement approach is presented based on interim programming, stochastic programming, vigorous optimization approach, and fluffy multi-objective programming. Moreover, a meta-heuristic algorithm called self-adaptive colonialist competitive calculation is put forward for the given issue. At that point, in arrange to assess the quality of the arrangements gotten by this calculation; a lower bound method is examined. At last, different computational tests are carried out to survey the proposed demonstrate and arrangement approaches.

Ning and You [21] proposed a novel data-driven versatile strong optimization system that leverages huge information in prepare businesses is proposed. This machine-learning demonstrate is consistently coordinates with versatile vigorous optimization approach through a novel four-level optimization system. This system expressly accounts for the relationship, asymmetry and multimode of instability information, so it produces less traditionalist arrangements. Moreover, the proposed system is vigorous not as it were to parameter varieties, but moreover to bizarre estimations. Two mechanical applications on group handle planning and on prepare organize arranging are displayed to illustrate the preferences of the proposed modeling system and adequacy of the arrangement calculation.

Shang and You [22] proposed a viable distributional vigorous optimization system for arranging and planning beneath request instabilities. A novel data-driven approach is proposed to develop equivocalness sets based on foremost component investigation and first-order deviation capacities, which offer assistance

.JARIE

uncovering exact and valuable data from vulnerability information. Additionally, it leads to mixedinteger direct reformulations of arranging and planning issues. To account for the multi-stage successive decision-making structure in prepare operations, they created multi-stage distributional strong optimization models and embrace relative choice rules to address the computational issue. Applications in industrial-scale handle organize arranging and group prepare planning illustrate that, the proposed distributional vigorous optimization approach can viably use vulnerability information data, way better fence against distributional uncertainty, and abdicate more benefits.

Zhao and You [23] investigated resilient supply chain design and operations with decision-dependent uncertainty using a data-driven robust optimization approach. The decision-dependent vulnerability set guarantees that the dubious parameters (e.g., the remaining generation capacities of offices after disturbances) are subordinate on first-stage choices, counting office area choices and generation capacity choices. A data-driven strategy is utilized to build the vulnerability set to completely extricate data from chronicled information. Additionally, the proposed show takes the time delay between disturbances and recuperation into thought. To handle the computational challenge of fathoming the coming about multilevel optimization issue, two arrangement procedures are proposed. The appropriateness of the proposed approach is outlined through applications on a location-transportation issue and on a spatially-explicit biofuel supply chain optimization issue.

Hosseini-Motlagh et al. [24] investigated blood supply chain management by robust optimization, disruption risk, and blood group compatibility in a real-life case, the aim of this paper was contribution blood supply chains under uncertainty. In this respect, this paper developed a bi-objective two-stage stochastic programming model for managing a red blood cells supply chain that observes abovementioned issues. This model determines the optimum location-allocation and inventory management decisions and aims to minimize the total cost of the supply chain includes fixed costs, operating costs, inventory holding costs, wastage costs, and transportation costs along with minimizing the substitution levels to provide safer blood transfusion services. To handle the uncertainty of the blood supply chain environment, a robust optimization approach is devised to tackle the uncertainty of parameters, then, a real case study of Mashhad city in Iran, is implemented to demonstrate the model practicality as well as its solution approaches, and finally, the computational results are presented and discussed. Further, the impacts of the different parameters on the results are analyzed which help the decision makers to select the value of the parameters more accurately.

Violi et al. [25] proposed an energetic and stochastic approach for a stock directing issue in which items with a tall perishability must be conveyed from a provider to a set of clients. In arrange to viably oversee all these highlights, a rolling skyline approach based on a multistage stochastic direct program is proposed. Computational tests over medium-size occurrences outlined on the premise of the genuine information given by an agri-food company working in Southern Italy appeared the viability of the proposed approach.

Tordecilla et al. [26] checked on the papers in arrange to simulation-optimization strategies for planning and surveying strong supply chain systems beneath vulnerability scenarios. The plan of supply chain systems points at deciding the number, area, and capacity of generation offices, as well as the allotment of markets (clients) and providers to one or more of these offices. This paper reviewed the existing literature on the use of simulation-optimization methods in the design of resilient supply chain networks under uncertainty scenarios. From this review, we classify some of the many works in the topic according to factors such as their methodology, the approach they use to deal with uncertainty and risk, etc. The paper also identifies several research opportunities, such as the inclusion of multiple criteria amid the design-optimization prepare and the comfort of considering half breed approaches combining metaheuristic calculations, reenactment, and machine learning strategies to account for vulnerability and energetic conditions, individually. Goli et al. [27] investigated the prediction of dairy product demand. The main contribution of this research is to provide an integrated framework based on statistical tests, time-series neural networks with novel meta-heuristic algorithms in order to obtain the best prediction the results confirmed that the proposed hybrid methods have the ability to improve the prediction of the demand for various products.

Tirkolaee et al. [28] proposed a novel two-echelon multi-product Location-Allocation-Routing problem. The aim of this study is to minimize the total cost, which involves costs related to the establishment, shipment processes, environmental pollution, travelling, vehicle usage, and fuel consumption, in a way to cover the total demand of retailers.

Chouhan et al. [29] proposed the sugarcane industry is technologically pioneering in the area of food production. The algorithms' performance is probed using the Taguchi experiments, and the best combinations of parameters are identified. The obtained results suggest that simulation can be optimized the supply chain network by using metaheuristic method.

Tirkolaee et al. [30] simultaneously minimized the total cost, total environmental emission, maximize citizenship satisfaction and minimize the workload deviation. A hybrid multi-objective optimization algorithm, namely, MOSA-MOIWOA is designed based on Multi-Objective Simulated Annealing Algorithm (MOSA) and Multi-Objective Invasive Weed Optimization Algorithm (MOIWOA). To increase the algorithm performance, the Taguchi design technique is employed to set the parameters optimally. The results illustrated the high efficiency of the suggested model and algorithm to solve the problem.

Based on the investigations performed on the mathematical models provided for flexible supply chain and productivity of the chain network, we found that a method based on uncertainty variables is missing. In this research, we intended to combine robust optimization model using uncertainty variables to enhance flexibility and productivity of supply chain network in order to achieve productivity and flexibility in all four areas of purchase, order, production, and transportation. This research attempted to resolve weak points and strengthen the strong points of past research based on identifying their pros and cons.

3 | Theoretical Framework

In recent years, extensive research has been conducted on capturing data uncertainty in mathematical models. These studies have led to development of robust optimization methods. Uncertainty can affect the optimality and justification of problems; typically, the best data estimation is used for mathematical modeling, which is known as nominal data. The first model of robust optimization was presented by Soyster. This model dealt with creating viable solutions for a convex set. The solutions of the Soyster models were very conservative, such that optimality would be neglected against ensuring robustness of the solution. In the next step, to develop robust optimization, Ben-Tal and Nemirovski model [34] was presented. Their models had two problems: 1) it increased the computational complexity of the problem, and 2) it did not provide any probable guarantee on problem viability. The operational framework of the Ben-Tal and Nemirovski model [34] was nonlinear. Bertsimas and Sim [5] presented an approach in which there was an interaction between optimality and robustness. Their model was linear which dealt with modifying the level of conservativeness of robust solution. The features of Bertsimas and Sim [5] models included linearity, the ability of controlling the conservativeness of robust solutions through a parameter known as robustness cost, and usability in integer number problems.

According to the explanations given in the previous section regarding the modeling of objective functions and constraints, the model in its ideal form is:

JARIE

$$MinZ = \sum_{r=1}^{r} w_{r}(d_{r}^{+}, d_{r}^{-}) = w_{1}d_{1}^{+} + w_{2}d_{2}^{+} + w_{3}d_{3}^{+} + w_{4}d_{4}^{+} + w_{5}d_{5}^{-},$$
(1)
s.t.

$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} STOP_{mn} S_{mnt} + d_{1}^{-} - d_{1}^{+} = G_{1},$$
(2)

$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} PPM_{mn}S_{mnt} + d_{3}^{-} - d_{3}^{+} = G_{3}, \qquad (3)$$

$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} DP_{mn} S_{mnt} + d_{4}^{-} - d_{4}^{+} = G_{4},$$
(4)

$$\sum_{m_{M}1}^{M} \sum_{n_{N}1}^{N} \sum_{j\neq 1}^{J} \sum_{t\neq 1}^{T} CS_{mn}S_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{t=1}^{T} \tilde{C}t_{mnj}S_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{J} \sum_{t=1}^{T} Ch_{mn}IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{T} \sum_{t=1}^{T} Ch_{mn}IS_{mntj} + Z \times \Gamma_{1} - d_{5}^{+} \leq G_{5},$$
(5)

$$S_{mtj} = \sum_{n=1}^{n} S_{mntj} = \sum_{i=1}^{i} VC_{im}P_{ijt} - \sum_{n=1}^{n} IS_{mnjt-1} + \sum_{n=1}^{i} IS_{mnjt} \text{ for all } j, m, t,$$
(6)

$$\sum_{i=1}^{n} IS_{mtj} \ge VC_{im} \times X_{ijt} \times \alpha \times LT_{m} \text{ for all } j,m,t,$$
(7)

$$\sum_{i=1}^{n} IS_{mtj} \le VC_{im} \times X_{ijt} \times (1+\alpha) \times LT_{m} \text{ for all } j,m,t,$$
(8)

$$\sum_{j=1}^{J} S_{mntj} + ZZ_{mnt}\Gamma_2 + ppp_{mnt} \le \tilde{C}_{mn} \text{ for all } m, n, t,$$
⁽⁹⁾

$$\sum_{j=1}^{J} S_{mnjt} \ge \beta \times \sum_{n=1}^{n} \sum_{j=1}^{J} S_{mnjt} \text{ for all } m, n, t,$$

$$(10)$$

$$PP_{mnjt} + ZZ \ge \hat{C}t S_{mntj} \text{ for all } m, n, j, t,$$
(11)

$$PP_{mnjt} + ZZ \ge \hat{C}t S_{mntj} \text{ for all } m, n, j, t,$$
(12)

$$ZZ_{mnt} + ppp_{mnt} \ge \hat{C}_{mn} \text{ for all } m, n, t,$$
(13)

$$S_{mnit}$$
, $IS_{mtj} \ge 0$, integer for all m, n, j, t. (14)

Due to the fact that in the model designed in the previous section, there are integer variables, to convert the model to a stable counterpart, the "Bertsims and Wire" model was used. Therefore we have this model in *Eqs. (15)-(27)*:

$$MinZ = \sum_{r=1}^{r} w_{r} (d_{r}^{+}, d_{r}^{-}) = w_{1} d_{1}^{+} + w_{2} d_{2}^{+} + w_{3} d_{3}^{+} + w_{4} d_{4}^{+} + w_{5} d_{5}^{-},$$
(15)

s.t.

$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} \text{STOP}_{mn} S_{mnt} + d_{1}^{-} - d_{1}^{+} = G_{1},$$
(16)

$$\sum_{i=1}^{I} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} PPM_{mn}S_{mnt} + d_{3}^{*} - d_{3}^{*} = G_{3},$$
(17)

$$\sum_{i=1}^{L} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{t=1}^{T} DP_{mn} S_{mnt} + d_{4}^{-} - d_{4}^{+} = G_{4},$$
(18)

JARIE

$$\sum_{m=1}^{M} \sum_{n \in I}^{N} \sum_{i \neq 1}^{J} \sum_{t \neq 1}^{T} CS_{mn} S_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{T} \sum_{t=1}^{T} \tilde{C}t_{mnj} S_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{j=1}^{T} \sum_{t=1}^{T} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{M} \sum_{j=1}^{T} \sum_{t=1}^{T} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{T} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{M} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{M} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{n=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{M} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{j=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{M} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{j=1}^{M} \sum_{j=1}^{M} \sum_{t=1}^{M} Ch_{mn} IS_{mntj} + \sum_{m=1}^{M} \sum_{j=1}^{M} \sum_{j=1}^$$

$$S_{mtj} = \sum_{n=1}^{n} S_{mntj} = \sum_{i=1}^{i} VC_{im}P_{ijt} - \sum_{n=1}^{n} IS_{mnjt-1} + \sum_{n=1}^{i} IS_{mnjt}"j,m,t,$$
(20)

$$\sum_{i=1}^{n} \mathrm{IS}_{mtj} \, {}^{3}\mathrm{VC}_{im} \times X_{ijt} \times \alpha \times \mathrm{LT}_{m} \, {}^{"}j, m, t, \tag{21}$$

$$\sum_{i=1}^{n} \mathrm{IS}_{mtj} \,^{3}\mathrm{VC}_{im} \times X_{ijt} \times (1+\alpha) \times \mathrm{LT}_{m} \,''j, m, t,$$
(22)

$$\sum_{j=1}^{j} S_{mntj} + ZZ_{mnt}\Gamma_2 + ppp_{mnt} \pounds \tilde{C}_{mn} "m,n,t,$$
(23)

$$\sum_{j=1}^{J} S_{mnjt}^{3} \beta \times \sum_{n=1}^{n} \sum_{j=1}^{J} S_{mnjt}^{mnn,n,t},$$
(24)

$$PP_{mnjt} + ZZ^{3}Ct S_{mntj} m, n, j, t,$$
(25)

$$ZZ_{mnt} + ppp_{mnt} \, {}^{3}\hat{C}_{mn} \, "m,n,t, \tag{26}$$

$$S_{mnji}$$
, IS_{mtj} ³0, integer "m, n, j, t. (27)

4 | Theoretical Framework

Simulation technique is one of the most important and applicable tool for complexity of manufacturing systems. The simulation and optimization integration can maximize the performance. It can be defined as the process of finding the best input variable values from among all possibilities without explicitly evaluating each possibility [31]. The precise concept of simulation, the cases in which it can be used, its applications, advantages, disadvantages, and processes are issues to be discussed further in the section.

Unlike many technical sciences which can be ranked based on the field of their origin (such as physics or chemistry), simulation can be used in all fields. The main motivation of simulation has its roots in space programs [32]. Nevertheless, even an informal investigation of the texts related to simulation can indicate their current wide areas of application. For example, Shannon [35] in his book (science and art of system simulation) mentions the books that have been written with regards to application of simulation in the following areas including trading, economics, marketing, education, politics, social sciences, behavioral sciences, international relations, transportation, human resources, and enforcement of laws, urban studies, and global systems. Further, numerous technical papers, reports, PhD and MA theses almost in all areas of social, economic, technical, and human sciences indicate the impact and progressive growth of use of simulation in all aspects of life. Various definitions have been provided for simulation, though the most comprehensive and complete one has been presented by Shannon [35]. He defined simulation as follows: simulation refers to the process of designing a real system and conducting experiments with models to understand the behavior of the system as well as to assess different strategies within a range applied through a criterion or a set of criteria [33].

In the above definition, a real system means a system that exists or can be implemented. Before dealing with other issues, it may be better to look at a simple example to explain the concept of simulation. Consider the money cashier system of a bank. Assume that a person works in the cash retrieval counter of a bank, whereby the time of entrance of clients is distributed up to 10 min uniformly (for simplicity, the size of all times is rounded to the closest integer number). Also assume that the time required for providing services to every client is distributed on 1-6 min uniformly. We want to calculate the average time the client spends in the system including client waiting time, service time, the percentage of the time the cashier does

) .*IARIE*

not work. To simulate this system, we should create an artificial experiment that would represent the above situation. For this purpose, we should create a method to generate fabricated referral of a group of clients and the time required for providing services to each of them. In one of the methods that can be used, we begin with 10 tokens and one dice. Then, the tokens are numbered from 1 to 10, and placed in a container. By shaking the container, we mix them up. By withdrawing one token from the container and reading the number on it, the time between entrance of current and previous clients can be determined. The service time to this client can also be obtained by tossing the dice and reading the number of points on its top surface. By repeating this operation (placing the tokens inside the container and shaking it after each withdrawal), we have generated the entrance and service times of a group of imaginary clients.

In this research, to show the quality of modeling, we perform the model for a case study in the automotive industry. The details of this model are given in the form of a case study. Automotive industry is one of the most important and integral components of trade and industry in the world. The supply chain of this industry is one of the most dynamic chains. Due to this important, Iran-Khodro supply chain was selected as the largest active chain in this field in Iran. In this chain, each car contains thousands of parts. Regardless of the fact that some components are single source, many components are sourced from multiple sources. In other words, proper planning for the supply of parts by considering various criteria and also the high uncertainty of some indicators, has added to the importance of sound planning in this chain. In this study, robust planning for the supply of auto parts has been considered. The planning for the supply of these parts is based on the production plan of the Tehran factory, but the modeling has been generally developed to be applicable to several factories. Most of the research data is taken from SAPCO and Iran Khodro companies.

In order to modeling, solving and simulation the following parts are performed:

- I. Determining the model assumptions (study of theoretical literature and continuous interviews with experts and experts of the company).
- II. Mathematical modeling (defining variables, parameters, setting goals and constraints) by studying the theoretical literature, continuous interviews with experts and experts of the company.
- III. Distinguish between definite and indefinite parameters: interviews with experts.
- IV. Solid modeling (conversion of mathematical model to solid counterpart model): study of theoretical literature.
- V. Determine the values of the parameters, solve the robust model, simulate and check the quality of the answers.

5 | Results

Due to the high complexity of the model regarding the number of variables, limitations and data, the model was programmed in a space set in LINGO software (linked with Excel), so that the input data of the model would be imported from Excel, thereby enhancing the computational efficiency of the model. Given the programming, it was always attempted to use heuristic programming techniques in order to prevent useless complication of the model. After completing the programming, the robust model was solved 11 times per 11 states of protection level. After each time of solving the model, the values of the obtained variables were considered constant, while the uncertain parameters were generated and simulated within the considered range randomly in the form of a symmetric distribution function for 10000 times. At each time of simulation, it was found how many constraints were violated. In other words, once the ratio of the total number of violated constraints to the total number of constraints with uncertain parameters was clarified, the risk of every protection level was determined. The following table summarizes the results:





281

Table 1. Objective function for each of the ideals.

State	Γ_1	Γ_2	Objective Function
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 2. Percentage of deviation values from each ideal to the value of each ideal in each state.

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

Table 3. Probability of violation of restrictions in different situations and based on different indicators.

State	Α	В	С	D	Ε	F	Γ_1	Γ_2
1	0.001	0.006	0.107	0.523	0.893	0.477	0	0
2	0	0	0.097	0.436	0.903	0.564	0.1	39
3	0	0	0.086	0.388	0.914	0.612	0.2	78
4	0	0	0.075	0.339	0.925	0.661	0.3	117
5	0	0	0.065	0.291	0.935	0.709	0.4	156
6	0	0	0.055	0.246	0.945	0.754	0.5	195
7	0	0	0.044	0.196	0.956	0.804	0.6	234
8	0	0	0.033	0.149	0.967	0.851	0.7	273
9	0	0	0.023	0.099	0.977	0.901	0.8	312
10	0	0	0.011	0.049	0.989	0.951	0.9	351
11	0	0	0	0	1	1	11	387

Table 3 indicates the level of risk (probability of violating the constraints). The fifth ideal constraint as 387 uncertain parameters as well as Γ_1 protection level. Other constraints with volatile parameters (uncertain) have 387 capacity constraints which have volatile capacity parameter in them and have Γ_2 protection level. The simulation results indicated that only a number of capacity constraints (86 cases) are violable, since some capacities are beyond the demand or the model has considered under-capacity allocation for them. Thus, volatility or fluctuations in the mentioned range has no effect on them. Based on these explanations, overall two indicators were considered for calculating the risk levels:

Indicator 1: dividing the total number of violated cases by the total number of possible cases.

Indicator 2: dividing the total number of violated cases by the total number of cases dependent on constraints that can be violated.

Indicator 2 is stricter and generally, *Indicator 1* is more logical. In *Table 3*, cases 1 and 11 are the most optimistic and pessimistic cases respectively. Columns A and B represent the probability of violating the fifth ideal constraint (based on *Indicators 1* and *2*), columns c and d show the probability of violating the

capacity constraints (based on *Indicators 1* and 2), and columns e and f reveal the total confidence percentage (based on *Indicators 1* and 2).

Table 1 suggests that with reducing the risk-taking (increasing the level of protection), the objective function (of minimization type) has worsened. Indeed, as the level of protection increased, the model has chosen the values of variables in a stricter way within the allowable range, such that the probability of violating the constraints has decreased and eventually the solution of the objective function has been aggravated. This in turn can explain the accuracy of the robust modeling as well as the performance of the model.

Table 2 and slope of the relevant diagrams suggest that changing the level of risk or level of conservativeness has had a considerable impact on increasing the slope of the line of the objective function values. In other words, robustification of the model is essential and influential for reducing the decision-making risk.

Based on *Table 2*, deviation from the first goal which has the highest importance coefficient could considerably approach zero. Meanwhile, this goal has had the minimum divination percentage compared to other goals, suggesting the proper performance of the model in the presence of numerous and sometimes conflicting goals.

Based on *Table 2* and the importance coefficients of goals, although goals 1, 2, 3, 4, and 5 have had the highest importance coefficients respectively, the model has been able to reduce deviation from goals 1, 5, 3, 2, and 4 respectively. Meanwhile, percentage of reduction of deviation from goals 1, 5, and 3 compared to the value of each goal is notable.

The numbers in *Table 3* are an outcome of simulation, indicating that with increase in the level of protection, these numbers decrease. This indicates the proper performance of the robust model and simulation.

In *Table 3*, in the pessimistic state, the protection level numbers are maximum, and the probability number of violation of constraints becoming zero in this case means that no constraint is violated which coincides with the worst value of objective function. If this case does not actually occur (not all fluctuations or volatilities occur), selection of this option can compensate for the lost opportunity for decision-maker. In contrast, in the optimistic state, excessive optimism can lead to incurrence of costs and losses. Thus, the best state is the one in which the decision-maker accepts some risk based on which, they would apply the values of the variables selected by the model in practice. For example, if the decision-maker accepts risk of about 5%, based on *Table 3* and according to *Indicator 1*, the solutions obtained from case 7 guarantee 95% confidence for them, i.e. there is a balance between risk and reward.

In the model solution section, it was stated that there are 387 constraints with uncertain parameters, and only a limited number of these constraints can be violated. Thus, by observing the numbers, it can virtually be stated that 86 constraints that could be violated are of active constraint types. Presenting an algorithm for reducing these constraints before solving the solution can be the subject of future research.

Fig. 1, which is linear and has an uptrend, shows both the value of the objective function in each case and the risk or probability of breaking the constraint. In order to match the numbers of the objective function and the risk in terms of size, we have plotted the objective function on a million scales.



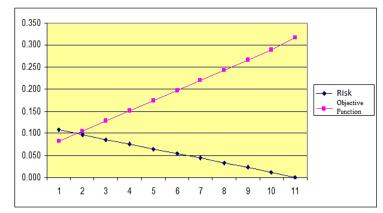


Fig. 1. Comparison of objective function trend charts and risk trend.

The diagram shows that the further we move towards mode 11, the lower the risk level and the worse the objective function.

6 | Conclusion

Given the money related bottlenecks confronting businesses in Iran and the weights on the natural angles of generation and dissemination, it is crucial to consider these issues in planning diverse measurements of commerce. In expansion to minimizing the full taken a toll, natural impacts of generation, transportation and dispersion of items were moreover minimized. Bertsimas and Sim [5] method are used to determine the uncertainty about the rate of return products. Investigation of the results of the solved model shows the positive effect of the assurance level of the model on the objective function value. Overall, the results show that increased costs are because of lower risk acceptance. Compliance with natural necessities moreover contains a coordinate effect on add up to costs. From the viable point of see, it is recommended that vital supply chain level choices be coordinates into line with natural choices. Such an approach not as it were decreases the hazard in generation and dissemination but too progresses supply chain execution both in fetched and natural terms. Also, the positive effect of observing uncertainty in the model indicates that manufacturers can improve the quality of their decisions in terms of production and distribution and design of the supply chain by considering the amount of returned goods. Moreover, the results reveal that the consideration of environmental constraints would impose additional costs on the supply chain anyway. This extra cost can be justified looking at social responsibility towards the environment and human destiny. Yet, in many developed countries because of the advancement of technology, economic efficiency is considered as much as environmental efficacy. Within the show ponder, it is appeared that the innovation utilized in reusing centers with reserve funds at the taken a toll of crude fabric supply not as it were does legitimize the natural issues but moreover has financial defense. To advance this inquire about within the future, the taking after recommendations are displayed to other analysts: the show can be amplified to a supply chain with more levels, counting discount and retail centers, central distribution centers and merchants. Natural imperatives can also be considered as an objective work instead of a confinement. For illustration, minimizing carbon emanations can be considered as one of the different destinations of the show. At long last, considering social perspectives in calculated optimization models can too be curiously.

The gathering data process is the case study limited to a small period of time. For longer periods, frequent events may be occurred and more reliable estimation could be found. So simulation base settings may be changed on necessity, although this issue does not affect the proposed method, but it can affect the accuracy of the case study results. In addition to the issues of modeling and solving the model, new indicators have also been presented regarding the concept of supplier selection such as stopping the production line in response to the performance of suppliers and the production line complaint from suppliers' pieces, which do not exist in the theoretical literature at least this explicitly. Generally, even the robustness of solutions, interview-based modeling, and consideration of different as well as important indicators according to the decision-maker opinion, it can be claimed that the model is reasonably reliable. With regard to future research, presenting new and heuristic methods is suggested for

solving models with variables as well as applying the presented model in a real study to attain real outputs, use Z-numbers calculations to examine variables and provide new and meta-innovative methods for solving models with verbal variables, and also can use senility analysis in order to compare the results under conditions of uncertainty.

Acknowledgments

The creators of this article need to thank and appreciate the close cooperation of the managers of the automotive industry to participate in this study.

Funding

No funding was received to assist with the preparation of this manuscript.

Conflicts of Interest

There is no conflict of interest in connection with this paper, and the material described here is not under publication or consideration for publication elsewhere.

References

- [1] Hoseininezhad, F., Makui, A., & Tavakkoli-Moghaddam, R. (2021). Pre-positioning of a relief chain in humanitarian logistics under uncertainty in road accidents: a real-case study. *South African journal of industrial engineering*, 32(1), 86-104.
- [2] Zhao, N., & You, F. (2021). New York State's 100% renewable electricity transition planning under uncertainty using a data-driven multistage adaptive robust optimization approach with machine-learning. *Advances in applied energy*, 2, 100019. https://doi.org/10.1016/j.adapen.2021.100019
- [3] Zhao, J., Wu, B., & Ke, G. Y. (2021). A bi-objective robust optimization approach for the management of infectious wastes with demand uncertainty during a pandemic. *Journal of cleaner production*, 314, 127922. https://doi.org/10.1016/j.jclepro.2021.127922
- [4] Janatyan, N., Zandieh, M., Alem-Tabriz, A., & Rabieh, M. (2021). A robust optimization model for sustainable pharmaceutical distribution network design: a case study. *Annals of operations research*, 1-20. https://link.springer.com/article/10.1007/s10479-020-03900-5#citeas
- [5] Bertsimas, D., & Sim, M. (2004). The price of robustness. Operations research, 52(1), 35-53.
- [6] Gong, J., & You, F. (2018). Resilient design and operations of process systems: nonlinear adaptive robust optimization model and algorithm for resilience analysis and enhancement. *Computers & chemical engineering*, 116, 231-252.
- [7] Baringo, A., & Baringo, L. (2016). A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant. *IEEE transactions on power systems*, 32(5), 3492-3504.
- [8] Bruni, M. E., Pugliese, L. D. P., Beraldi, P., & Guerriero, F. (2017). An adjustable robust optimization model for the resource-constrained project scheduling problem with uncertain activity durations. *Omega*, 71, 66-84.
- [9] Wang, L., Li, Q., Ding, R., Sun, M., & Wang, G. (2017). Integrated scheduling of energy supply and demand in microgrids under uncertainty: a robust multi-objective optimization approach. *Energy*, *130*, 1-14.
- [10] Kropat, E., Meyer-Nieberg, S., & Weber, G. W. (2019). Computational networks and systemshomogenization of variational problems on micro-architectured networks and devices. *Optimization methods and software*, 34(3), 586-611.
- [11] Yang, G. Q., Liu, Y. K., & Yang, K. (2015). Multi-objective biogeography-based optimization for supply chain network design under uncertainty. *Computers & industrial engineering*, 85, 145-156.
- [12] Apornak, A., & Hezaveh, M. A. (2019). Extension of the model of manufacturing supply chain quality management: an empirical study. *International journal of productivity and quality management*, 28(4), 417-437.
- [13] Apornak, A., Raissi, S., Keramati, A., & Khalili-Damghani, K. (2019). A simulation modelling approach to improve waiting time for outpatients of hospital emergency department. *International journal of knowledge management in tourism and hospitality*, 2(2), 160-171.

- [14] Goli, A., Khademi-Zare, H., Tavakkoli-Moghaddam, R., Sadeghieh, A., Sasanian, M., & Malekalipour Kordestanizadeh, R. (2021). An integrated approach based on artificial intelligence and novel meta-heuristic algorithms to predict demand for dairy products: a case study. *Network: computation in neural systems*, 32(1), 1-35.
- [15] Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International journal of production research*, *57*(7), 2179-2202.
- [16] Pourhassan, M. R., Raissi, S., & Apornak, A. (2021). Modeling multi-state system reliability analysis in a power station under fatal and nonfatal shocks: a simulation approach. *International journal of quality & reliability management*, 38(10), 2080-2094.
- [17] Keramati, A., Apornak, A., Abedi, H., Otrodi, F., & Roudneshin, M. (2018). The effect of service recovery on customers' satisfaction in e-banking: an empirical investigation. *International journal of business information systems*, 29(4), 459-484.
- [18] Ahmadizadeh-Tourzani, N., Keramati, A., & Apornak, A. (2018). Supplier selection model using QFD-ANP methodology under fuzzy multi-criteria environment. *International journal of productivity and quality management*, 24(1), 59-83.
- [19] Ivanov, D., Dolgui, A., Sokolov, B., & Ivanova, M. (2017). Literature review on disruption recovery in the supply chain. *International journal of production research*, 55(20), 6158-6174.
- [20] Vahdani, B., & Mohammadi, M. (2015). A bi-objective interval-stochastic robust optimization model for designing closed loop supply chain network with multi-priority queuing system. *International journal of production economics*, 170, 67-87.
- [21] Ning, C., & You, F. (2017). Data-driven adaptive nested robust optimization: general modeling framework and efficient computational algorithm for decision making under uncertainty. *AIChE journal*, 63(9), 3790-3817.
- [22] Shang, C., & You, F. (2018). Distributionally robust optimization for planning and scheduling under uncertainty. *Computers & chemical engineering*, *110*, 53-68.
- [23] Zhao, S., & You, F. (2019). Resilient supply chain design and operations with decision-dependent uncertainty using a data-driven robust optimization approach. *AIChE journal*, *65*(3), 1006-1021.
- [24] Hosseini-Motlagh, S. M., Samani, M. R. G., & Homaei, S. (2020). Blood supply chain management: robust optimization, disruption risk, and blood group compatibility (a real-life case). *Journal of ambient intelligence and humanized computing*, 11(3), 1085-1104.
- [25] Violi, A., Laganá, D., & Paradiso, R. (2020). The inventory routing problem under uncertainty with perishable products: an application in the agri-food supply chain. *Soft computing*, 24(18), 13725-13740.
- [26] Tordecilla, R. D., Juan, A. A., Montoya-Torres, J. R., Quintero-Araujo, C. L., & Panadero, J. (2021). Simulationoptimization methods for designing and assessing resilient supply chain networks under uncertainty scenarios: a review. *Simulation modelling practice and theory*, 106, 102166. https://doi.org/10.1016/j.simpat.2020.102166
- [27] Goli, A., Tirkolaee, E. B., & Aydın, N. S. (2021). Fuzzy integrated cell formation and production scheduling considering automated guided vehicles and human factors. *IEEE transactions on fuzzy systems*, 29(12), 3686-3695.
- [28] Tirkolaee, E. B., Goli, A., & Mardani, A. (2021). A novel two-echelon hierarchical location-allocation-routing optimization for green energy-efficient logistics systems. *Annals of operations research*, 1-29. https://link.springer.com/article/10.1007/s10479-021-04363-y
- [29] Chouhan, V. K., Khan, S. H., & Hajiaghaei-Keshteli, M. (2021). Metaheuristic approaches to design and address multi-echelon sugarcane closed-loop supply chain network. *Soft computing*, 25(16), 11377-11404.
- [30] Tirkolaee, E. B., Goli, A., Gütmen, S., Weber, G. W., & Szwedzka, K. (2022). A novel model for sustainable waste collection arc routing problem: pareto-based algorithms. *Annals of operations research*, 1-26. https://link.springer.com/article/10.1007/s10479-021-04486-2
- [31] Apornak, A., Raissi, S., & Pourhassan, M. R. (2021). Solving flexible flow-shop problem using a hybrid multi criteria Taguchi based computer simulation model and DEA approach. *Journal of industrial and systems engineering*, 13(2), 264-276.
- [32] Shannon, P. W., Krumwiede, K. R., & Street, J. N. (2010). Using simulation to explore lean manufacturing implementation strategies. *Journal of management education*, 34(2), 280-302.
- [33] Chen, S., Du, J., He, W., & Siponen, M. (2022). Supply chain finance platform evaluation based on acceptability analysis. *International journal of production economics*, 243, 108350. https://doi.org/10.1016/j.ijpe.2021.108350
- [34] Ben-Tal, A., & Nemirovski, A. (2002). Robust optimization-methodology and applications. Mathematical programming, 92, 453-480.
- [35] Shannon, R. E. (1998). Introduction to the art and science of simulation. 1998 winter simulation conference, proceedings (cat. no. 98ch36274) (Vol. 1, pp. 7-14). IEEE.

