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RESEARCH PAPER

A Multi-Objective Supply Chain Configuration for the Oil Industry under Uncertainty

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Abstract

In recent years, supply chains have become an attractive topic for managers and industrialists, and the life and death of organizations and businesses somehow depend on the activity of intertwined chains. In this study, transferring petroleum products from supply points to consumption areas is examined through a supply chain. Also, in today's competitive environment, the high speed of change and evolution has raised the uncertainty and ambiguity of decisions, that makes it difficult to predict future conditions in supply chains. Hence, a mathematical model is used with two objectives including the reduction of shipping costs and the reduction of the number of loads. Then, by means of some sensitivity analysis, sensitive parameters of the model are recognized. For coping with the uncertainty, reliable planning should be done in uncertain and ambiguous conditions for better and more accurate planning. One of the new and reliable techniques is the robust optimization approach. Therefore, due to the high volume of calculations and the problem data as well as the lack of ability to use exact solution methods, especially on a large scale, PSO and MOGA-II meta-heuristic algorithms are applied to resolve the proposed model. The outcomes show that the model has the required efficiency in large dimensions and the proposed solution methods provide appropriate answers. To be precise, the new bi-objective model had several advantages and the most important one is related to the objectives of reducing the shipping costs and the number of loads.

Keywords:
Oil Supply Chain;
Robust Optimization;
Multi-Objective Optimization;
Meta-Heuristic Algorithm

Introduction

In our competitive world, supply chain management is a fundamental issue that affects the activities of organizations and businesses to generate products and provide services needed by customers [7]. Hence, considering the chances and threats in the field of business and evaluating the capability of organizations to cope with uncertainty in this area is of undeniable importance. In this regard, the amount of production, kind of transfer, and the rate and scope of the supply process are very crucial. The main factor for survival in today's environment is the decline in shipping, maintenance, and costs in this cycle. Also, the optimal rate of receipt from suppliers can exponentially decrease purchasing costs and enhance competitiveness [43]. A supply chain entails all the activities regarding the flow and conversion of merchandise from the step of raw material extraction to the step of delivery to the final consumer. This also involves the corresponding data flow.

In addition, uncertainty is a critical issue in a supply chain. According to Galbraith's theory [15], uncertainty refers to the variance between the quantity of the data needed to achieve a task

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and the quantity of the data actually available. In the decision-making process of a supply chain, uncertainty is a factor affecting the effectiveness of the chain configuration and coordination [2]. Many experts have cited uncertainty as an open topic in designing supply chains. Suler [38] states that most of the techniques used to design supply chains deal with such issues as demand, costs, waiting time, and other input parameters. In contrast, supply chain scenarios in the real world are probably characterized by random data affected by demand variations, absent data, and so on. Such problems need sophisticated optimization techniques that consider random data to look more realistically at real-world production and distribution network issues and, thus, to make more effective decisions.

Previously, many have claimed that the oil and gas industry may have experienced an era of very rare resources. Yet, the resources are not the reason for supply constraints, given the huge potential still accessible including, additional potential findings, and the new border of massive oil sands and oil shale reserves that are in the money at today's charges [50]. Fundamentally, regarding the good popularity of the industry's research, we have enough resources left to sustain present generation levels for at least the next 50 years. Then, the foremost challenge fronting the oil and gas industry is not the accessibility of oil and gas resources, but putting these reserves into generation and delivering the final goods to clients at the minimum cost. Therefore, a solid supply-chain management program will improve this purpose.

It has been a long debate whether the oil supply chain is divided into two or three sections, being the allocation of refinery operations at the center of the conversation. As defined by Sahebishahemabadi [54], the oil supply chain can be classified into three different classification structures. The first considers the oil supply chain divided between upstream and downstream parts. However, the second divides the network into upstream, midstream and downstream segments. Lastly, the third also reflects the oil supply chain divided into three parts, but the midstream part refers to crude oil transportation to terminal and storage facilities. For the objectives of this literature review, the second classification scheme is more acceptable [55]. At that time, the upstream segment comprises all functions from petroleum exploration, production, and transportation to the refineries. The midstream concerns about the conversion of petroleum into refined products at refineries and petrochemicals. Finally, the downstream part includes storage, primary and secondary distributions, and marketing of refined products. In each segment, there are petroleum companies that depend on physical infrastructures across the network to progress these functions [56].

In this research, a new model is designed for a supply chain of petroleum products and the corresponding transportation and distribution problem is investigated. The problem is defined by the main petroleum products including gasoline, kerosene, gas-oil, and fuel oil. It also considers their production and consumption cycle including supply points, intermediate warehouses, and consumption areas. The consumption areas are the final layer of the chain and the centers for delivering the products to the customers. Considering four different transportation modes is another feature of the suggested model. These modes are road transportation by refueling tankers, rail transportation, pipeline transportation, and transportation by refueling ships, each with its own costs and capacities. Fig. 1 depicts the general stages of producing and transporting petroleum products.

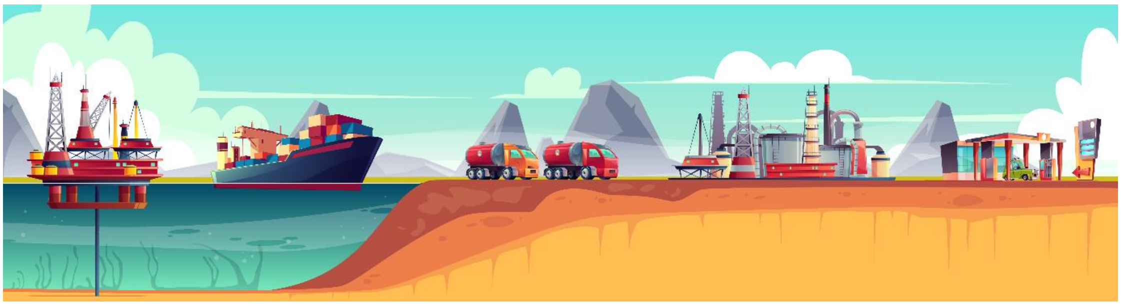

Fig. 1. The process of oil production

The first objective of the model is minimizing the transportation cost of petroleum products. Another one is to enable the direct distribution of products with the least number of loads so as to have more safety in them by maintaining the defined health and environmental principles. Considering the robustness of the structure, the proposed model seeks to resolve a problem with enormous dimensions, which, of course, exact methods such as branch and bound are unable to solve [3]. Therefore, PSO and MOGA-II, as two meta-heuristic algorithms, are utilized to solve the model. Thus, the problem of transporting petroleum products is solved given the variability of demand and the possibility of incorrect estimation concerning the available data.

Because of the high costs of refining and distributing petroleum goods and the increasing requirement to decrease the macro costs of governments and maximize the usage of resources, a comprehensive plan is undeniably required for the refueling procedure, considering all the variables that may be of significance in the future. Also, owing to the robustness of the suggested model, if one of the refineries in use fails to function for some time, petroleum products distribution companies can plan to carry the products and meet the fuel needs with the least possible loss. Accordingly, all the elements and components involved in a product sales cycle, or the components of a supply chain, must be dealt with in practical ways and appropriate mechanisms must be applied to reduce costs and increase transportation speed by considering safety issues. The aim of this paper is to achieve an inclusive model for the process of fueling with the objectives of reducing the costs and creating the flexibility to withstand any external stimuli under uncertain data.

Based on the above discussion, the chief contribution of this study is to determine how much of every product is relocated from each supply source to each warehouse by each transportation mode. The contribution is also to determine how much of every product is moved from each warehouse to another warehouse and from each warehouse to every consumption area by any transportation mode. To the best of our knowledge, no study has examined the oil industry completely so far; therefore, in this paper, we try to consider the oil industry utilizing the supply chain context comprehensively.

With regard to the uncertain conditions and the robustness of the model and to minimize the bio-objective mathematical model, the objectives of this article are generally as follows:

- Designing a comprehensive model for the oil industry to minimize the transportation cost of products along the chain and use fuel tankers to create greater safety;
- Involving uncertainty in the proposed model and providing a proper method to engage with it;
- Solving the suggested model on a very large scale with appropriate methods and by considering the robustness of the structure.

Moreover, the research questions that will be answered at the end are as follows:

- How does uncertainty affect the supply chain outcomes? How should it be dealt with?
- Can the proposed model be implemented on a large scale? What is a suitable solution for it?

- Is the proposed model appropriate for an oil supply chain, and can it cover the existing problems?
- What are the benefits of the proposed model for the oil industry?

The rest of this study is prepared in several segments. The second section is dedicated to the review of the literature on oil supply chains. In the third section, the suggested mathematical model is shown and defined. The fourth section is given to the mathematical modeling of the problem in deterministic and uncertain modes. Model linearization and sensitivity analysis are also accessible in this section. The fifth section presents the methods and algorithms proposed for the mathematical model. After the computational results are provided in the sixth section, the model is resolved by the GAMS and MATLAB software programs and the PSO and MOGA-II algorithms in both single-objective and multi-objective modes. Section seven is devoted to managerial insights. The paper is closed up in the eighth section with the conclusion and recommendations for future study.

Literature review

In this part, some of the most critical research works in the field are reviewed. For convenience, the review is divided into four subsections.

Supply Chain and Oil Supply Chain Design

To provide insight into supply chain network designs, Fleischmann et al. [14] carried out a complete evaluation of modeling in backward logistics management. Their study is viewed as one of the main works in backward supply chain network design. Barros et al. [8] suggested a mixed linear integer modeling model for a sand recycling network. Jayaraman et al., [20] established a mixed-integer linear programming model (MILP) to design a backward logistics network under a traction-based system for customer demand and product improvement. Krikke et al. [22] also developed a model for a two-stage reverse supply chain network for a copier manufacturer. Min et al. [27] recommended a mixed-integer nonlinear programming (MINLP) model and a genetic algorithm for the multi-level reverse supply chain network problem that measured the temporal and spatial composition of the return products. Abdolazimi and Abraham [9] presented a single-layer location model for a certain period and a network design model in the form of two main problems. Ambrosino and Scutella [6] also presented a dynamic model for a multi-layer network taking into account the product flow. The proposed model included factories, central and local distribution centers, and customers or demand points. Govindan et al. [17] comprehensively studied the articles on reverse and closed-loop supply chains. A paper by Stanworth et al. [39] reported a probable optimization model for a multi-period and multi-objective stable blood supply chain. The data were uncertain due to uncertain conditions during and after a disaster. Larimi et al. [24] introduced a robust, multi-objective, stochastic linear programming model for an integrated platelet supply chain with unidirectional lateral transshipment between hospitals and clinics.

The oil industry is one of the main industries covering a wide variety of actions across the globe. All the actions and procedures included in the oil industry are known as oil supply chain activities [19]. In the oil and gas supply chain, as in other industries, minor suppliers incline to have inadequate effects on their supply chains. Wisner [57] opposes that, in greatest cases, SCM is not feasible in conditions such as "when the focal organization is not in a location of power or structural dominance". It is vital hence for the chief operators in the industry to cause the growth of SCM. This is progressively being recognized, as main oil corporations, for instance, feel that an agile supply chain instead of interior operations will become the core basis of performance development. Indeed, SCM practices are now seen as contribution occasions to upscale performance when the latitude for cutting interior costs and re-engineering business procedures has been beaten or does not exist [58]. This follows the tendency previously set in other areas [59]. Despite the necessity for more SCM practices in the oil and gas industry, evidence proposes that a noteworthy quantity of oil corporations have worries about the efficiency of their supply chains and less than half think they have the necessary tools and skills to optimize their supply chains [59]. As oil corporations move from the practices of retaining all required capacity in-house to a higher level of outsourcing, more combination and SCM competence have become deeply imperative [60]. In some interviews by Yusuf et al. [61], some industry managers have recommended that up to 40% of oil and gas actions will be outsourced from the supply chain over the next five years. This underscores the requirement for a better understanding of the connections across oil and gas supply chains, the nascent complexity, operations management challenges, and the request for larger agility.

Polycyclic aromatic hydrocarbons (PAHs) are the standard components of crude oil that form a collection of persistent organic contaminants. Hidalgo et al. (ibid) dealt with PAH biodegradation at various steps of the oil supply chain, which affects varied environments (e.g., groundwater, seawater, oil reservoir), concentrating on genes and trails as well as the key actors entailed in this progression. An in-depth understanding of the biodegradation procedure provides the knowledge to optimize and monitor bioremediation in an oil spill and/or damage to reservoirs and prevent the deterioration of crude oil quality. In the research by Zhou et al. [45], a multi-objective MILP model was recommended to simultaneously minimize the total economic costs and the CO2 emissions in an oil supply chain. Actual processes and various technical constraints such as pipeline construction, pump station design, and the hydraulic configuration of the pipeline and pumps were also considered in the model. In the research by Piya et al. [34], the essential factors that drive agile supply chain management were identified, mainly in the oil and gas industry. For this purpose, an extensive literature review and research work through questionnaires were conducted in the oil and gas industry supply chain (OGSC) to recognize critical factors. In addition, some brainstorming sessions were held with specialists of the OGSC to be aware of the contextual relationships among the identified factors. Sakib et al. [36] presented a Bayesian network (BN) model for disaster forecasting and assessment in the OGSC according to seven foremost factors including technical, economic, social, political, safety, environmental, and legal factors. Bayesian belief network (BBN) is a graphical model of probability mainly applied in risk examination to evaluate the possible relationships among different variables. The results showed that the technical factors had the greatest impact on OGSC disasters, but legal and political aspects had the least impact. Abdel-Basset et al. [1] assessed a set of measures to finance a sustainable supply chain in the gas industry under uncertainty. Expert evaluations showed that financial characteristics and product (service) management are the most important criteria for improving a company's performance and achieving sustainable finance in the supply chain. In addition, obtaining price and cost information, considering the product level, technology management and demand management emerged to be significant for the sustainable supply chain management.

The study by Aslam et al. [51] recognized the supply-chain practices of the oil industry in Pakistan. It depicted that the supply chain management (SCM) practices positively influence operational performance. On the other hand, with the aid of literature, the study known diverse Blockchain features and their impact on various supply chain practices. The paper of ALNAQBI et al. [52] defines a mathematical programming method to discourse possible synergistic gains after horizontal mergers in the upstream Crude Oil Supply Chain (COSC). A supply chain optimization model has been employed to assess the extent to which economies of scope and economies of scale positively affect possible mergers. The problem determined the investment level and effective execution of operational plans at communal services, as well as the production and processing of oil and gas. Finally, another study by Ara et al. [53] aimed to recommend a new blockchain system design to progress engineering, procurement, and construction (EPC) companies' supply chain for making oil and gas infrastructure, by modifying cost and time inadequacies.

Uncertainty and Approaches to Deal with It

Due to their importance and attraction, supply chains have established substantial attention from investigators in recent years. The flow of information in a supply chain is of great significance, and the lack of information can lead to uncertainties. Uncertainty, as emphasized in the literature, can make chain planning difficult. To overwhelm this problem, robust programming or the concept of a robust supply chain can essentially be of use. Although uncertainty cannot be completely eliminated, it is largely controllable. The first step in this regard is to identify the sources of uncertainty or, in other words, the uncertainty and risk parameters of the problem. Zhang et al. [42] used a robust programming approach based on Monte Carlo simulation as a new pattern in demand chain planning. In that study, they strongly emphasized the importance of uncertainty in the supply chain and its management. They stated that the models and methods presented in definite conditions for supply chain planning no longer meet the prevailing uncertainty. So, chain planning must be done with uncertainty taken into account. They also made comprehensive references to sources of uncertainty. Reiner and Trcka [35] presented a model to upgrade a supply chain. They showed an ideal robust supply chain environment based on the demand situation (smooth or unstable). According to them, while reducing uncertainty is possible by helping to share information and reduce the supply time, it is impossible to completely avoid uncertainty. In this regard, they referred to Van Landeghem and Vanmaele [42] and stated that robust programming is essential to manage supply chain uncertainty. They also held that, in the recent theoretical literature, the necessity for robust supply chain programming at the tactical level is emphasized to cope with uncertain customer demands.

Tang [40], in a review study, examined different quantitative models for supply chain risk management (SCRM). Based on the theoretical literature, he also reported the applications of various SCRM strategies. In this regard, he comprehensively discussed different uncertainties (e.g., uncertain demand, uncertain supply time, uncertain supply capacity, uncertain supply cost) and robust strategies (e.g., the characteristics of robust strategies, robust supply management strategies, robust demand management strategies, robust production management strategies, robust information management strategies). Leung et al. [25] dealt with the robust optimization of planning for production in a supply chain. They conducted this investigation for a multi-national company in Hong Kong. A robust optimization model was established to unravel the problem of multi-location generation planning with uncertain data. In this model, the fine parameters were tuned and the production management could determine a medium-term production strategy which included the production load program and the level of the labor force based on different economic growth scenarios. Klibi et al. [21] discussed a supply chain network (SCN) design under uncertainty. They provide an inclusive and serious overview of the optimization models presented in the theoretical literature. In this research, some of the flaws and weaknesses in the literature were addressed, and an incentive to develop a comprehensive SCN design methodology was discussed. In addition, the sources of uncertainty and risk in the supply chain were analyzed. The study also introduced the bases of uncertainty in the SCN in three main categories including internal (endogenous) assets, supply chain partners, and exogenous geographical factors. Abdolazimi et al. [2] considered a supply chain for the tire industry under deterministic and uncertain conditions. They used the two approaches of Soyster and Mulvey (scenario-based) to deal with uncertainty and then compared them. In the research of Fathollahi-Fard et al. [13], an integrated water supply and wastewater collection system (WSWCS) was proposed under uncertainty. Peng et al. [33] reviewed the study on the uncertainties intrinsic in closed-loop supply chains and offered helpful prospects for future research. For these goals, they took 302 articles done in the main web of science database from 2004 to 2018. Then they analyzed the reasons of uncertainties and identified suitable approaches for quantifying the effects of uncertainties on production processes. Finally, an article by Mondal and Roy [29] considered a two-stage, multi-stage, multi-objective, closed-loop multi-product supply chain to preserve supplies between production centers and hospitals during the COVID-19 pandemic. With uncertain random parameters in the suggested model, they applied a mixed uncertain environment to show the ambiguity in real-life data. Then, a robust optimization approach was developed for the uncertain random parameters to deal with uncertainty in various scenarios. Salehi et al. [48] proposed an optimization model for designing blood supply chain network in case of an earthquake disaster. The recommended two-stage stochastic model is programmed regarding scenarios for earthquakes in an occupied mega-city. In the suggested two-stage stochastic optimization model, decisions of locating permanent collection facilities and the amount of every blood type pre-inventory are created in the first step and operation decisions that have reliant on probable scenarios are created in the second step.

Solution Methods

Various solution approaches are utilized to solve supply chain network problems. In recent years, researchers have benefited from many methods of enhancing CSC performance efficiency. For example, the Lean concept to improve CSC collaboration was adopted by Eriksson [10]. In their research, Kumar et al. [23] used the NSGA-II algorithm to unravel the problem of multi-objective supply chain network design by considering the social relations, carbon emissions, and supply chain dangers. Fahimnia et al. [11] presented a mixed nonlinear integer model for the tactical planning of a green supply chain. To solve the model, they compared the performance of three algorithms, genetic algorithm (GA), simulated annealing (SA), and Cross-Entropy, according to which the SA algorithm could generate better outcomes in a limited time. In a study, Tsao et al. [41] offered a multi-objective planning model for designing a sustainable supply chain network. They did possible fuzzy multi-objective programming to resolve the model. Ghahremani-Nahr et al. [16] introduced a robust fuzzy mathematical programming model to design a closed-loop supply chain network. They proposed a new algorithm based on the whale optimization algorithm (WOA) to unravel the model. In their research, Hamdan and Diabat [18] stated the problem of two-stage planning in their supply chain network. To unravel the problem using the ε-constraint method, they turned the three-objective problem into a single-objective mixed integer programming (MIP) problem. Obreque et al. [31] devised a solution algorithm for a hierarchical network design problem to reduce the cost in a multi-level space. To solve the model, a three-step solution algorithm was proposed in accordance with the branch and cut algorithm. Zheng et al. [44] examined production planning for a sustainable supply chain, taking into account such factors as CO_2 emission constraints, random demand, service level, and inventory capacity. Therefore, a MIP model was advanced, and a heuristic Lagrange algorithm was suggested to cost-effectively unravel the problem of large-scale production planning. In their paper, Shoja et al. [37] provided a MILP model for a multi-product four-stage flexible supply chain network problem in a solid transportation environment. Because the problem was NP-hard, meta-heuristic algorithms had to be employed to resolve it. For this purpose, ten classical and adaptive meta-heuristic algorithms were established. Abdolazimi et al. [2] proposed a supply chain in which the inventory was controlled based on an ABC analysis. They used exact LP-metric and ε-constraint approaches for their small-size model and two meta-heuristic algorithms, MOPSO and NSGA-II, for their large-size model. The results exposed the effectiveness of the recommended methods and algorithms. In another study, Abdolazimi et al. [3] developed a two-objective MILP model and evaluated exact, heuristic, and meta-heuristic approaches to solve the proposed model in small and large sizes. In small dimensions, there were TH and ε-constraint to use as comprehensive benchmark methods. In large dimensions, the Lagrange relaxation method, MOPSO, NSGA-II, SPEA-II, and MOEA/D were used. In still another work, Abdolazimi et al. [5] introduced a multi-objective closed-loop supply chain network consisting of several levels, several periods, and several products and uncertainties in some parameters of the proposed model. Because of the multi-objective feature of the problem, four exact approaches including LP-metric, sequential linear goal programming (SLGP), TH approach, and simple additive weighting (SAW), were applied to unravel the objective functions. Arabi and Gholamian [47] presented a three-objective multi-period multi-product mixed-integer quadratic programming problem to optimize a sustainable stone supply chain network design. An ε-constraint method was employed to unravel the multi-objective model and achieved the non-dominated solutions. Eventually, in the paper by Seifbarghy et al. [49] a three-layer multi-product supply chain entailing manufacturers, distribution centers (DCs), and customers was taken into account. A two-objective model was established to detect the positions of DCs and the flows of merchandise in the entire supply chain considering a pre-determined quantity of DCs. Because the accessible problem was NP-hard in nature, three metaheuristic algorithms of NSGA-II, NRGA, and MOPSO were established to discover the Pareto-optimal solutions and were compared using some standard indexes for multi-objective algorithms.

Research Gaps

Conceptual competition is well known in today's complex world. Reducing the cost, increasing the level of customer service, and quickly meeting the customers' needs are necessary for every product and service to stay in the competition. Therefore, when there is a competition to reduce the final cost of the most strategic consumer goods in a country, the issue becomes especially important and economically justified to pay attention to. Owing to the high costs of refining and distributing petroleum goods, the need to continue this process as one of the primary necessities for the development of a country, the emphasis of state officials to achieve self-sufficiency in this strategic industry, as well as the growing need to reduce government expenditures and maximize the use of resources, a comprehensive plan with all the corresponding variables for future is essential in the process of refueling a country. At times, there might be a period when one of the refineries fails to function or one or more warehouses cannot be used. In such cases, the robustness of the proposed model makes it possible for the petroleum products distribution company to meet the fuel needs of the country by delivering the products with the least possible loss.

Accordingly, it is essential that all the elements and components involved in a product sales cycle or a supply chain be seen in effective ways, and appropriate mechanisms be used to reduce costs and speed up transmission, taking safety issues into account. Given the issues ever discussed in the literature, no research has considered these cases so far. So, the goal of the present research is to achieve a comprehensive model for refueling processes, reduce costs and gain flexibility to withstand any external stimuli under data uncertainty.

Model description

Fig. 2 illustrates the source of product supply on the left. This *R* source comprises crude oil refineries and import terminals. Warehouse *W* is taken into account in the center of the chain, which consists of strategic and non-strategic warehouses. The product first enters one of the warehouses from a production base, and then it is moved to another warehouse or goes straight to a consumption zone. Areas *A* applied for fuel are also shown on the right of Fig. 2. Despite the uncertainty, each area has a particular demand for the product. Transfers between centers are done in various modes; every product can use only one transportation mode in each stage of transfer.

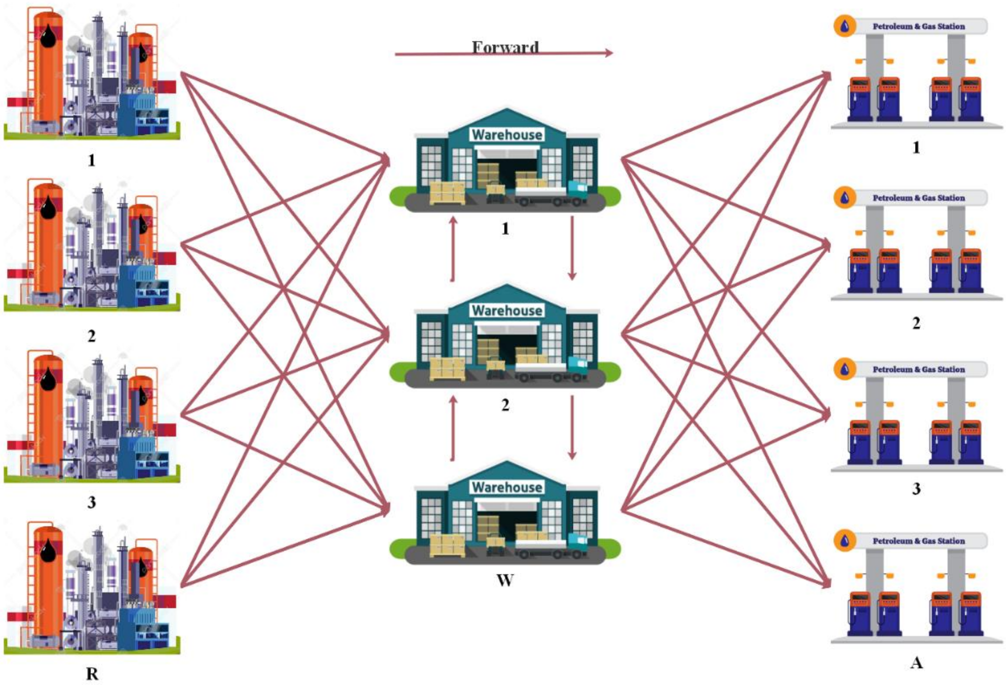

Fig. 2. The proposed oil supply chain network

The aim is to formulate the problem and delineate the optimal quantity of every product moved from any production source to any warehouse and from any other warehouse or the shipping zone. In addition, the optimal mode of transportation at every phase of transfer along the chain must be stated. The quantity of every product kept in every warehouse in every period to be employed in later periods has to be specified too.

Mathematical model

Based on the earlier part, a mathematical model of the MINLP type is showed. It is as follows:

Sets

P	Products types
R	Product supply bases (refineries and import terminals)
W, W'	Warehouses
A	Consumption zones
K	Transportation modes

Parameters

d_{pa}	The demand of area a for product p
f_{pr}	Maximum production capacity of product supply base r for product p
p^1_{rw}	Maximum capacity of the pipeline in transporting products from product supply base r to warehouse w
$p^2_{ww'}$	Maximum capacity of the pipeline in transporting products from warehouse w to warehouse w'

p_{wa}^{3}	Maximum capacity of the pipeline in transporting products from warehouse w to consumption area a
ca_{pw}	Maximum storage capacity w for storage product p
h_{w}	Holding cost of warehouse w for each unit of the kept product in a period
co_{krw}^{1}	Transportation cost of every bunch of products by transportation mode k for each unit route from product supply base r to warehouse w
$co_{kww'}^{2}$	Transportation cost of every bunch of products by transportation mode k for each unit of route from warehouse w to warehouse w'
co_{kwa}^{3}	Transportation cost of every bunch of products by transportation mode k for each unit of route from warehouse w to consumption area a
di_{krw}^{1}	Distance between product supply base r to warehouse w by transportation mode k
$di_{kww'}^{2}$	Distance between warehouse w to warehouse w' by transportation mode k
di_{kwa}^{3}	Distance between warehouse w to consumption area a by transportation mode k
b_{pk}	Minimal rate of carrying product p per transfer time by transportation mode k
BN	Big positive number

Decision Variables

X_{krw}^{1}	1, if the product transfer from product supply base r to warehouse w by transportation mode k; otherwise, 0.
$X_{kww'}^{2}$	1, if the product transfer from warehouse w to warehouse w' by transportation mode k; otherwise, 0.
X_{kwa}^{3}	1, if the product transfer from warehouse w to consumption area a by transportation mode k; otherwise, 0.
M_{pkrw}^{1}	1, if product p is carried from product supply base r to warehouse w by transportation mode k; otherwise, 0.
$M_{pkww'}^{2}$	1, if product p is carried from warehouse w to warehouse w' by transportation mode k; otherwise, 0.
M_{pkwa}^{3}	1, if product p is carried from warehouse w consumption area a by transportation mode k; otherwise, 0.
Y_{pkrw}^{1}	The volume of product p that is moved from product supply base r to warehouse w by transportation mode k
$Y_{pkww'}^{2}$	The volume of product p that is transferred from warehouse w to warehouse w' by transportation mode k
Y_{pkwa}^{3}	The volume of product p that is transferred from warehouse w to consumption area a by transportation mode k
IN_{pw}^{0}	Inventory of warehouse w for product p at the beginning of the period
IN_{pw}^{1}	Inventory of warehouse *w* for product *p* at the end of the period

Objective Functions

$$\text{Min } Z_1 = \sum_p \sum_k \sum_r \sum_w \left(\left(\frac{Y_{pkrw}^{1} X_{pkrw}^{1}}{b_{pk}}\right) di_{krw}^{1} co_{krw}^{1}\right) + \sum_p \sum_k \sum_w \sum_{w'} \left(\left(\frac{Y_{pkww'}^{2} . X_{pkww'}^{2}}{b_{pk}}\right) di_{kww'}^{2} . co_{kww'}^{2}\right)$$
$$+ \sum_p \sum_k \sum_w \sum_a \left(\left(\frac{Y_{pkwa}^{3} X_{pkwa}^{3}}{b_{pk}}\right) di_{kwa}^{3} co_{kwa}^{3}\right) + \sum_p \sum_w (h_w IN_{pw}) \tag{1}$$

$$\text{Min } Z_2 = \sum_p \sum_k \sum_r \sum_w \sum_{w'} \sum_a M_{pkrw}^{1} + M_{pkww'}^{2} + M_{pkwa}^{3} \tag{2}$$

Objective function (1) pursues to minimize the product transfer costs along the supply chain. It regards four distinct costs including the transfer cost from production centers to warehouses, the transfer cost from one warehouse to another, the transfer cost from one warehouse to the customer zone, and the holding cost of products in warehouses at the end period. It is worth noting that b_{pk} is only measured for the mode of transportation by fuel trucks to estimate the transportation cost of every truck nevertheless of the quantity of the product put in it. For the other transportation modes, this parameter is set to be 1.

The second objective function (Eq. 2) minimizes the entire quantity of the transfers by a specific transportation mode. For example, if fuel trucks are assumed as the second transportation mode ($k = 2$), the objective function, which consists of a set of three M_{p2rw} binary variables, minimizes the number of truck refueling in the three layers of the supply chain. The second objective function is to diminish road transport as much as possible to rise safety in the transport of products and decrease the dangers created by fuel tankers each time they are loaded and unloaded. According to the prices of different transportation modes, it may conflict with the first objective function.

Constraints

$$IN^{0}_{pw} + \sum_{k}\sum_{r} Y^{1}_{pkrw} X^{1}_{pkrw} + \sum_{k}\sum_{w'} Y^{2}_{pkww'} X^{2}_{pkww'} = \sum_{k}\sum_{w'} Y^{2}_{pkww'} X^{2}_{pkww'} + \sum_{k}\sum_{a} Y^{3}_{pkwa} X^{3}_{pkwa} + IN^{1}_{pw} \quad \forall p,w \quad (3)$$

$$\sum_{k}\sum_{w} Y^{3}_{pkwa} X^{3}_{pkwa} \geq d_{pa} \quad \forall p,a \quad (4)$$

$$\sum_{k}\sum_{w} Y^{1}_{pkrw} X^{1}_{pkrw} \leq f^{max}_{pr} \quad \forall p,r \quad (5)$$

$$\sum_{k=2}^{K}\sum_{r}^{R} Y^{1}_{pkrw} X^{1}_{pkrw} + \sum_{k=2}^{K}\sum_{w'}^{W'} Y^{2}_{pkww'} X^{2}_{pkww'} \leq ca_{pw} \quad \forall p,w \quad (6)$$

$$\sum_{p} Y^{1}_{pkrw} X^{1}_{pkrw} \leq p^{1}_{rw} \quad \forall r,w \quad (7)$$

$$\sum_{p} Y^{2}_{pkww'} X^{2}_{pkww'} \leq p^{2}_{ww'} \quad \forall w,w' \quad (8)$$

$$\sum_{p} Y^{3}_{pkwa} X^{3}_{pkwa} \leq p^{3}_{wa} \quad \forall w,a \quad (9)$$

$$Y^{1}_{pkrw} X^{1}_{pkrw} \geq M^{1}_{pkrw} \quad \forall p,k,r,w \quad (10)$$

$$Y^{1}_{pkrw} X^{1}_{pkrw} \leq BN \times M^{1}_{pkrw} \quad \forall p,k,r,w \quad (11)$$

$$Y^{2}_{pkww'} X^{2}_{pkww'} \geq M^{2}_{pkww'} \quad \forall p,k,w,w' \quad (12)$$

$$Y^{2}_{pkww'} X^{2}_{pkww'} \leq BN \times M^{2}_{pkww'} \quad \forall p,k,w,w' \quad (13)$$

$$Y^{3}_{pkwa} X^{3}_{pkwa} \geq M^{3}_{pkwa} \quad \forall p,k,w,a \quad (14)$$

$$Y^{3}_{pkwa} X^{3}_{pkwa} \leq BN \times M^{3}_{pkwa} \quad \forall p,k,w,a \quad (15)$$

$$\sum_{k} M^{1}_{1krw} \times \sum_{k} M^{1}_{2krw} \leq \sum_{k} M^{1}_{3krw} \quad \forall r,w \quad (16)$$

$$\sum_{k} M^{2}_{1kww'} \times \sum_{k} M^{2}_{2kww'} \leq \sum_{k} M^{2}_{3kww'} \quad \forall w,w' \quad (17)$$

$$\sum_{k} M^{3}_{1kwa} \times \sum_{k} M^{3}_{2kwa} \leq \sum_{k} M^{3}_{3kwa} \quad \forall w,a \quad (18)$$

$$\sum_{k} Y^{1}_{4krw} = 0 \quad \forall r,w \quad (19)$$

$$\sum_{k} Y^{2}_{4kww'} = 0 \quad \forall w,w' \quad (20)$$

$$\sum_{k} Y^{3}_{4kwa} = 0 \quad \forall w,a \quad (21)$$

$$X^{1}_{pkrw}, X^{2}_{pkww'}, X^{3}_{pkwa}, M^{1}_{pkrw}, M^{2}_{pkww'}, M^{3}_{pkwa} \in \{0,1\} \quad \forall p,k,r,w,w',a \quad (22)$$

$$Y^{1}_{pkrw}, Y^{2}_{pkww'}, Y^{3}_{pkwa}, IN^{0}_{pw}, IN^{1}_{pw} \geq 0 \qquad \forall p,k,r,w,w',a \qquad (23)$$

Constraint (3) logically indicates that, for every product in every warehouse, the quantity of the inventory at the beginning of the period plus the quantity of the product transferred to it from the supply bases and the quantity of the product transferred to it from the other warehouses should be equal to the quantity of the product transferred from the mentioned warehouse to the buyer zones, plus the quantity of the product moved to other warehouses, plus the inventory at the end of the period. Constraint (4) states that the minimum number of every product that must reach every buyer is equal to that customer's demand. Constraint (5) means that the maximum quantity of every product generated at each supply base is equal to the capacity of that center. Constraint (6) suggests that, for every warehouse and every product type, the sum of the values that enter that warehouse from the supply bases and the other warehouses should not surpass the capacity of the mentioned warehouse for the mentioned product. It should be noted that the pipelines that connect the warehouses only branch to each warehouse and pass through it. To calculate the warehouse, the capacity is not calculated by the pipeline. In addition, the pipeline is assumed as the first transportation mode. Constraints (7), (8), and (9) are connected to the capacity of pipelines. The entirety of all the amounts of the product types moved through the first transportation mode (by pipeline) should not surpass the maximum transport capacity by that pipeline in that way. Constraints (10) and (11) pertain to the value of the variable M^{1}_{pkrw}. According to these two constraints, when $Y^{1}_{pkrw}X^{1}_{pkrw}$ takes a non-zero value, it assigns 1 to M^{1}_{pkrw}, which is a binary variable. However, when $Y^{1}_{pkrw}X^{1}_{pkrw}$ takes a zero value, it assigns 0 to M^{1}_{pkrw}. Constraints (12) and (13) are to obtain the value of the variable $M^{2}_{pkww'}$. Similarly, Constraints (14) and (15) suggest how to obtain the value of the variable M^{3}_{pkwa}.

Constraints (16), (17), and (18) pose technical limitations to pipeline mode of transportation. As these constraints postulate, in a period with the first transportation mode (pipeline), if products p1 (e.g., gasoline) and p2 (e.g., kerosene) are transferred from one base to a destination, product p3 (gas-oil) must be placed between the first two and transported by pipeline in that route. These constraints are designed for the pipeline transportation mode where the mixing of products is limited due to technical limitations. For example, fuel oil is not able to be loaded on the line quickly after gasoline product; a minimum volume of another product including gas-oil, needs to be loaded on the line followed by kerosene. Constraints (19), (20), and (21) show that, in the first transportation mode (i.e., pipeline mode), the fourth product (furnace oil) cannot be transported. Finally, Constraints (22) and (23) apply to the decision variables of the suggested model.

Model Linearization

Instead of multiplying the binary variable of *X* and the positive variable of *Y* that make the model non-linear, Constraints (24), (25), and (26) are used as follows:

$$Y^{1}_{pkrw}X^{1}_{pkrw} \geq BN\,(X^{1}_{pkrw} - 1) + Y^{1}_{pkrw} \qquad \forall p,k,r,w \qquad (24)$$

$$Y^{2}_{pkww'}X^{2}_{pkww'} \geq BN\,(X^{2}_{pkww'} - 1) + Y^{2}_{pkww'} \qquad \forall p,k,w,w' \qquad (25)$$

$$Y^{3}_{pkwa}X^{3}_{pkwa} \geq BN\,(X^{3}_{pkwa} - 1) + Y^{3}_{pkwa} \qquad \forall p,k,w,a \qquad (26)$$

Where *BN* represents a significant positive number and converts *Y* to *YX* without multiplication. Similarly, Constraints (27), (28) and (29) are used instead of Constraints (14), (15) and (16).

$$(\sum_k M^{1}_{1krw} + \sum_k M^{1}_{2krw} - 1) \le \sum_k M^{1}_{3krw} \qquad \forall r, w \qquad (27)$$

$$(\sum_k M^{2}_{1kww'} + \sum_k M^{2}_{2kww'} - 1) \le \sum_k M^{2}_{3kww'} \qquad \forall w, w' \qquad (28)$$

$$(\sum_k M^{3}_{1kwa} + \sum_k M^{3}_{2kwa} - 1) \le \sum_k M^{3}_{3kwa} \qquad \forall w, a \qquad (29)$$

Sensitivity Analysis

To assess the effect of making changes in the main parameters of the model on the results of objective functions and determine the appropriate parameters for uncertainty, sensitivity analysis has been used in this section. Sensitivity analysis was executed on the mathematical model using the modified weighted Chebyshev method (defined in the next section). The outcomes of this sensitivity analysis are depicted in Fig. 3.

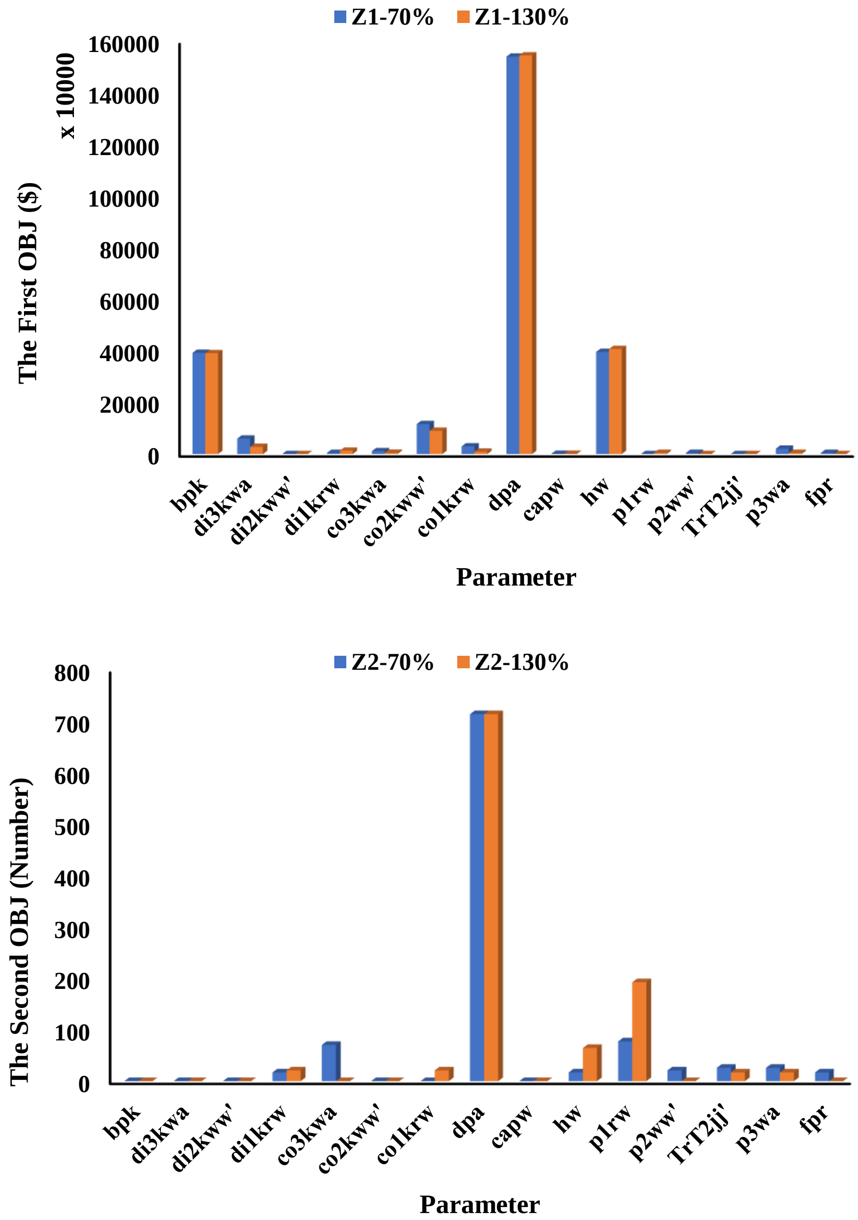

Fig. 3. The consequence of sensitive parameters on the OBJs

By means of doing sensitivity analysis, the effect of transmute in objective functions by making alterations in all model parameters, i.e., d_{pa}, f_{pr}, p^1_{rw}, $p^2_{ww'}$, p^3_{wa}, ca_{pw}, h_w, co^1_{krw}, $co^2_{kww'}$, co^3_{kwa}, di^1_{krw}, $di^2_{kww'}$, di^3_{kwa}, and b_{pk} are examined. Based on Fig. 3, the growth in the amount of the stated parameters causes variations in the objective functions, but the parameter d_{pa} has the most important influence on all objective functions. Thus, in this study, this parameter is taken into consideration uncertainly. The following part defines the variations produced by the uncertainty in the recommended model.

Robust Model

The first objective function of the problem is stabilized at this stage. Presumptuous that the demand for a fuel product is not reliable and is taken into account as an oscillating parameter, the outcome of the objective function is based on the alterations in this parameter. Accordingly, various scenarios are taken into account for the demand, and then the robust model proposed by Mulvey et al. [30] is used. First, it is essential to add a new set to the category of indices.

New Set

S Number of scenarios

Also, several new parameters and decision variables are added to the model.

New Parameters

p_s Probability of occurrence of any scenario

d_{pas} The demand of area *a* for product *p* under scenario *s*

λ The balanced weight between mathematical hope and variance in the robustness of the answer

ω The balanced weight and exchange between response stability and model stability

New Decision Variables

δ_{pas} The unsatisfied demand of product *p* for consumption area *a* under scenario *s*

θ_s The linearization parameter of the objective function under scenario *s*

The first objective function is measured as Eq. 30, and the second objective function remains unchanged.

$$\begin{aligned}
Z_{1s} &= \sum_p \sum_k \sum_r \sum_w \sum_s \left(\left(\frac{Y^1_{pkrws} X^1_{pkrws}}{b_{pk}}\right) di^1_{krw} co^1_{krw}\right) + \sum_p \sum_k \sum_w \sum_{w'} \sum_s \left(\left(\frac{Y^2_{pkww's} X^2_{pkww's}}{b_{pk}}\right) di^2_{kww'} co^2_{kww'}\right) \\
&+ \sum_p \sum_k \sum_w \sum_a \sum_s \left(\left(\frac{Y^3_{pkwas} X^3_{pkwas}}{b_{pk}}\right) di^3_{kwa} co^3_{kwa}\right) + \sum_p \sum_w \sum_s (h_w IN_{pws}) \qquad (30) \\
\text{Min } Z_1 &= \sum_s p_s Z_{1s} + \lambda \sum_s p_s \left((Z_{1s} - \sum_s p_s Z_{1s}) + 2\theta_s \right) + \omega \sum_p \sum_a \sum_s p_s \delta_{pas}
\end{aligned}$$

Linearization Eq. 31 must also be added to the set of the model constraints:

$$Z_{1s} - \sum_s p_s Z_{1s} + \theta_s \geq 0 \qquad \forall s \qquad (31)$$

The constraints of the model also change as Eqs. 32-52:

$$IN^{0}_{pws} + \sum_{k}\sum_{r} Y^{1}_{pkrws} X^{1}_{pkrws} + \sum_{k}\sum_{w'} Y^{2}_{pkww's} X^{2}_{pkww's} = \sum_{k}\sum_{w'} Y^{2}_{pkww's} X^{2}_{pkww's} + \sum_{k}\sum_{a} Y^{3}_{pkwas} X^{3}_{pkwas} + IN^{1}_{pws} \qquad \forall p,w,s \qquad (32)$$

$$\sum_{k}\sum_{w} Y^{3}_{pkwas} X^{3}_{pkwas} + \delta_{pas} = d_{pas} \qquad \forall p,a,s \qquad (33)$$

$$\sum_{k}\sum_{w} Y^{1}_{pkrws} X^{1}_{pkrws} \le f^{max}_{pr} \qquad \forall p,r,s \qquad (34)$$

$$\sum_{k=2}^{K}\sum_{r}^{R} Y^{1}_{pkrws} X^{1}_{pkrws} + \sum_{k=2}^{K}\sum_{w'}^{W'} Y^{2}_{pkww's} X^{2}_{pkww's} \le ca_{pw} \qquad \forall p,w,s \qquad (35)$$

$$\sum_{p} Y^{1}_{pkrws} X^{1}_{pkrws} \le p^{1}_{rw} \qquad \forall r,w,s \qquad (36)$$

$$\sum_{p} Y^{2}_{pkww's} X^{2}_{pkww's} \le p^{2}_{ww'} \qquad \forall w,w',s \qquad (37)$$

$$\sum_{p} Y^{3}_{pkwas} X^{3}_{pkwas} \le p^{3}_{wa} \qquad \forall w,a,s \qquad (38)$$

$$Y^{1}_{pkrws} X^{1}_{pkrws} \ge M^{1}_{pkrw} \qquad \forall p,k,r,w,s \qquad (39)$$

$$Y^{1}_{pkrws} X^{1}_{pkrws} \le BN \times M^{1}_{pkrw} \qquad \forall p,k,r,w,s \qquad (40)$$

$$Y^{2}_{pkww's} X^{2}_{pkww's} \ge M^{2}_{pkww'} \qquad \forall p,k,w,w',s \qquad (41)$$

$$Y^{2}_{pkww's} X^{2}_{pkww's} \le BN \times M^{2}_{pkww'} \qquad \forall p,k,w,w',s \qquad (42)$$

$$Y^{3}_{pkwas} X^{3}_{pkwas} \ge M^{3}_{pkwa} \qquad \forall p,k,w,a,s \qquad (43)$$

$$Y^{3}_{pkwas} X^{3}_{pkwas} \le BN \times M^{3}_{pkwa} \qquad \forall p,k,w,a,s \qquad (44)$$

$$\sum_{k} M^{1}_{1krw} \times \sum_{k} M^{1}_{2krw} \le \sum_{k} M^{1}_{3krw} \qquad \forall r,w \qquad (45)$$

$$\sum_{k} M^{2}_{1kww'} \times \sum_{k} M^{2}_{2kww'} \le \sum_{k} M^{2}_{3kww'} \qquad \forall w,w' \qquad (46)$$

$$\sum_{k} M^{3}_{1kwa} \times \sum_{k} M^{3}_{2kwa} \le \sum_{k} M^{3}_{3kwa} \qquad \forall w,a \qquad (47)$$

$$\sum_{k} Y^{1}_{4krws} = 0 \qquad \forall r,w,s \qquad (48)$$

$$\sum_{k} Y^{2}_{4kww's} = 0 \qquad \forall w,w',s \qquad (49)$$

$$\sum_{k} Y^{3}_{4kwas} = 0 \qquad \forall w,a,s \qquad (50)$$

$$X^{1}_{pkrws}, X^{2}_{pkww's}, X^{3}_{pkwas}, M^{1}_{pkrw}, M^{2}_{pkww'}, M^{3}_{pkwa} \in \{0,1\} \qquad \forall p,k,r,w,w',a,s \qquad (51)$$

$$Y^{1}_{pkrws}, Y^{2}_{pkww's}, Y^{3}_{pkwas}, IN^{0}_{pws}, IN^{1}_{pws}, \delta_{pas}, \theta_{s} \ge 0 \qquad \forall p,k,r,w,w',a,s \qquad (52)$$

Solution method

Because of the computational complication of the problem and the high number of variables and parameters in the suggested model, particularly in the robust state, an absolute optimal solution cannot be found through a linear optimization software program and exact solution approaches [4]. In this research, the PSO and MOGA-II meta-heuristic algorithms are used to resolve the model and cope with the problem. The PSO algorithm is utilized to resolve the model with a single target, and the MOGA-II algorithm serves that purpose in a multi-objective mood.

Particle Swarm Optimization (PSO) Algorithm

A PSO system begins with the random initialization of a population (swarm) of particles in the search area. It works on the social behavior in the swarm [26]. The position and the velocity of the i^{th} particle in the d-dimensional search area can be signified as $X_i = (x_{i,1}, x_{i,2}, ..., x_{i,d})$ and $V_i = (v_{i,1}, v_{i,2}, ..., v_{i,d})$, each. Every particle has its own best position (pbest) $P_i = (p_{i,1}, p_{i,2}, ..., p_{i,d})$ corresponding to the personal best objective value gained so far at time t. The global best particle (gbest) is represented by P_g, representing the best particle found at time t in the whole swarm. The new velocity of every particle is calculated as follows:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1 r_1 (p_{i,j} - x_{i,j}(t)) + c_2 r_2 (p_{g,j} + x_{i,j}(t)) \qquad j = 1,2,...,d \tag{53}$$

Where c_1 and c_2 are the acceleration constants, w is the inertia factor, and r_1 and r_2 are two independent random numbers uniformly spread in the range of [0, 1]. Hence, the position of every particle is updated in every generation in accordance with the Eq. 54:

$$x_{i,j}(t+1) = x_{i,j}(t) + \mu\, v_{i,j}(t+1) \qquad j = 1,2,...,d \tag{54}$$

Normally, the value of every module in V_i can be clamped to the range $[-v_{\max}, v_{\max}]$ to control the excessive roaming of the particles outside the search area. Next, the particles fly toward a new position regarding Eq. 54. This procedure is recurrent until a user-defined stopping touchstone is got. The pseudocode of standard PSO is abridged as Fig. 4.

Multi-Objective Genetic Algorithm-II (MOGA-II)

MOGA-II is a multi-objective genetic algorithm employed to search for optimizations. It is an effective algorithm that applies smart multi-search elitism [28]. This new elitism operator can maintain some outstanding solutions without creating premature convergence at local-optimal frontiers. The elitism is applied in MOGA-II according to the following steps:

Step 1. MOGA-II begins with an initial population P of size N and the elite set $E = \varnothing$.
Step 2. $P' = P \cup E$ is calculated for each generation.
Step 3. If the cardinality of P' is greater than P, P is randomly subtracted from the exceeding points.
Step 4. The evolution from P to P' is calculated using all the MOGA operators.
Step 5. The fitness is calculated for population P'.
Step 6. All the P' non-dominated designs are copied to E.
Step 7. E is updated by the removal of replicated or dominated designs.
Step 8. If the size of elite set E is larger than the size of the N generation, it will change due to the accidental removal of the excess points.
Step 9. Eventually, there is a return to step 2, and P' is considered a new P.

For simplicity, MOGA-II needs only a small number of user-defined parameters. Some other parameters are internally established to create the power and competence of the optimizer. This algorithm performs all the evaluations, which are as many as the points in the DOE (the design of experiments) table (initial population) multiplied by the number of generations more details are provided in Optimization (2014) [32]. Fig. 5 reveals the pseudocode of the MOGA-II algorithm.

- Initialize each particle $\vec{x} \in \mathbb{R}^n$ with a random position in the search-space:

$$\vec{x} \sim U(\vec{b}_{lo}, \vec{b}_{up})$$

where $\vec{b}_{lo}$ and $\vec{b}_{up}$ are the lower and upper boundaries of the search-space.

- Set each particle's best known position to its initial position:

$$\vec{p} \leftarrow \vec{x}$$

- Initialize each particle's velocity $\vec{v} \in \mathbb{R}^n$ to random values:

$$\vec{v} \sim U(-\vec{d}, \vec{d})$$

where $\vec{d} = |\vec{b}_{up} - \vec{b}_{lo}|$

- Initialize the swarm's best known position $\vec{g}$ to the $\vec{x}$ for which $f(\vec{x})$ is lowest.
- Until a termination criterion is met, repeat the following:
  - For each particle $\vec{x}$ in the swarm do the following:
    * Pick two random numbers: r_p, $r_g \sim U(0, 1)$
    * Update the particle's velocity $\vec{v}$ as follows:

$$\vec{v} \leftarrow \omega\vec{v} + \phi_p r_p(\vec{p} - \vec{x}) + \phi_g r_g(\vec{g} - \vec{x})$$

where ω, ϕ_p, and ϕ_g are user-defined behavioural parameters.

    * Bound the velocity, that is, for all dimensions i update v_i:

$$v_i \leftarrow \text{Bound}(v_i, -d_i, d_i)$$

See figure 2 for the definition of Bound()

    * Move the particle to its new position by adding its velocity:

$$\vec{x} \leftarrow \vec{x} + \vec{v}$$

    * Bound the position, that is, for all dimensions i update x_i:

$$x_i \leftarrow \text{Bound}(x_i, b_{lo_i}, b_{up_i})$$

    * If $(f(\vec{x}) < f(\vec{p}))$ then update the particle's best known position:

$$\vec{p} \leftarrow \vec{x}$$

    * If $(f(\vec{x}) < f(\vec{g}))$ then update the swarm's best known position:

$$\vec{g} \leftarrow \vec{x}$$

- Now $\vec{g}$ holds the best found position in the search-space.

Fig. 4. The PSO pseudocode

Initialize population

(a) Generate random population of size N and elite set $E = \varnothing$.

Evaluate objective values.

Assign rank based on Pareto dominance - 'Sort'.

Generate offspring population:

(a) Combine both population and elite sets $P' = P \cup E$.
(b) If the cardinality of P' is greater than the cardinality of P reduces P' removing randomly the exceeding points.
(c) Compute the evolution from P' to P'' applying MOGA operators.
  i. Randomly assign one operator (local tournament selection, directional crossover, one point crossover or bit flip mutation) based upon probability of invocation.

Evaluate objective values of population P''.

Assign rank to P'' individuals based on Pareto dominance - 'Sort'.

Copy all non-dominated designs of P'' to E - 'Sort'.

Update E by removing duplicated or dominated designs.

Resize the elite set E if it is bigger than the generation size N removing randomly the exceeding individuals.

Return to step 2 considering P'' as the new P until termination.

Fig. 5. The MOGA-II pseudocode [12]

Computational results

This part aims to authorize the suggested solution methods to resolve the proposed model. As mentioned before, this article presents a mathematical model for the oil and gas industry. Two meta-heuristic algorithms, counting PSO and MOGA-II, are proposed. These algorithms are applied to resolve the model. To validate these two proposed approaches and compare them in the productive solutions, the mathematical model has been implemented for each method in several numerical examples and different dimensions. It should be noted that this study is a development-applied type, and research data have been produced experimentally. As for the values of the sets, as shown in Tables 4 and 5, their values are presented in different dimensions. Besides, the parameter values utilized in the numerical examples are illustrated in Table 1, all of which are according to a uniform distribution.

Table 1. The values of the parameters employed in the numerical examples

Parameter	Value	Parameter	Value
d_{pa}	~U (50000,70000)	co^{1}_{krw}	~U (10000,15000)
f_{pr}	~U (1000000,4000000)	$co^{2}_{kww'}$	~U (20000,25000)
p^{1}_{rw}	~U (200000,500000)	co^{3}_{kwa}	~U (10000,15000)
$p^{2}_{ww'}$	~U (200000,500000)	di^{1}_{krw}	~U (1000,1500)
p^{3}_{wa}	~U (200000,500000)	$di^{2}_{kww'}$	~U (2000,3000)
ca_{pw}	~U (300000,450000)	di^{3}_{kwa}	~U (1200,2400)
h_{w}	~U (15000,20000)	b_{pk}	~U (0.50,0.65)

Initially, the PSO algorithm is applied to solve the problem in a single-objective mood for deterministic and robust states. The results are then matched on a small size with exact solution approaches by the GAMS software. Afterward, the model is resolved in a multi-objective mode by the MOGA-II algorithm, and an optimal Pareto frontier is attained. In this section, after the parameters of the recommended algorithms are introduced, their performance is discussed with an example presented in a small size. Then, the proposed model will be solved in larger dimensions. Finally, the solutions of the original model are compared in deterministic and robust states and on small and large scales. A computer with a Core i7 7700 HQ processor and 12GB of RAM has been employed to run the sample issues. The GAMS software serves to measure the nearness of the gained solutions to reality. For a maximum solving time, a time limit of three hours is taken into account. If an optimal solution is not gained for the favorite sample at the end of this period, exact solution methods recognize the model as infeasible. Because both algorithms (i.e., single-objective and multi-objective ones) are random, every sample problem is implemented 10 times by the MATLAB R2017b software. The values of the parameters used for this algorithm are given in Table 2. Also, the corresponding values for the robust mode can be depicted in Table 3.

Table 2. The parameters of the suggested algorithms

PSO parameters	Value	MOGA-II parameters	Value
Max iteration	100	*Max iteration*	100
Population Size	150	*Population Size*	150
Inertia weight	0.50	*Crossover percentage*	0.50
Damping rate	0.75	*Inertia weight*	0.50
Personal learning coefficient	2	*Mutation percentage*	0.20
Global learning coefficient	2	*Mutation Rate*	0.20

Table 3. The parameters for the robust mood

Parameters	Value
S	3
p_1	0.20
p_2	0.50
p_3	0.30
d_{pas}	1000000
λ	1
ω	225

In the following, the numerical values calculated for the suggested model are specified in a single-objective mode for the first objective function in deterministic and robust states.

The outcomes of the algorithm implementation in a deterministic single-objective mode

Size: It shows the quantity of products (p), the number of transportation modes (k), the quantity of supply bases (r), the quantity of warehouses (w), and the number of customer zones (a).

$Z_{optimal}^{\text{deterministic}}$: It is the value of the first optimal objective function of the linear problem in the deterministic mode calculated by the GAMS software.

$Z_{best}^{\text{deterministic}}$: It represents the best value of the first objective function in the deterministic mode, which is obtained by 10 times implementing the algorithm.

$Gap_{optimal-best}^{\text{deterministic}}$: It indicates the percentage difference between the value of the optimal objective function and the best value of the objective function obtained in the deterministic mode by each of the algorithms. According to Eq. 55, it is equal to:

$$Gap_{optimal-Best}^{deterministic} = \frac{(Z_{best}^{deterministic} - Z_{optimal}^{deterministic})}{Z_{optimal}^{deterministic}} \times 100 \tag{55}$$

$NFE^{deterministic}$: It is the quantity of times the objective function is named best in the deterministic mode.

$t_{optimal}^{deterministic}$: It is the solving time in seconds in the deterministic mode by the GAMS software.

Regarding the above, the outcomes are indicated in Table 4.

Table 4. Numerical values obtained for the deterministic mode

	Small size (P×K×R×W×A)			**Large-size model**
	3×1×2×3×4	**3×4×5×6×8**	**4×5×6×8×11**	**5×5×12×87×228**
$Z_{optimal}^{deterministic}$	635744	8575550	68543897	38102906330
$Z_{best}^{deterministic}$	664772	8603667	70757599	41336806221
$Z_{average}^{deterministic}$	662431	8811121	73232567	42468767927
$Gap_{optimal-best}^{deterministic}$	2.3245	1.3756	3.3756	3.1758
$NFE^{deterministic}$	1034	4238	32548	16254389
$t_{optimal}^{deterministic}$	1.43	3.24	25.30	12873

The outcomes of the algorithm implementation in the robust single-objective mode

Size: It shows the quantity of products (p), the quantity of transportation modes (k), the quantity of supply bases (r), the quantity of warehouses (w), and the number of customer zones (a).

$Z_{optimal}^{robust}$: It is the value of the first optimal objective function of the linear problem in the robust mode utilizing the GAMS software.

Z_{best}^{robust}: It represents the best value of the first objective function in the robust mode, which is obtained in 10 implementations of the algorithm.

$Gap_{optimal-best}^{robust}$: It indicates the percentage difference between the value of the optimal objective function and the best value of that function obtained in the robust mode by each of the algorithms. According to Eq. 56, it is equal to:

$$Gap_{optimal-Best}^{robust} = \frac{(Z_{best}^{robust} - Z_{optimal}^{robust})}{Z_{optimal}^{robust}} \times 100 \tag{56}$$

NFE^{robust}: It is the quantity of times the objective function is named best in the robust mode.

$t_{optimal}^{robust}$: It is the solving time in seconds in the robust mode by the GAMS software.

According to the above, the outcomes are depicted in Table 5.

Solve the model in the multi-objective mode

In this part, the recommended model is solved in the multi-objective mode by the suggested algorithm.

To assess the effectiveness of the algorithm by combining diverse parameters, the following two competence scales have been applied:

Table 5. Numerical values gained for the robust mode

	Small size (P×K×R×W×A)			Large-size model
	3×1×2×3×4	3×4×5×6×8	4×5×6×8×11	5×5×12×87×228
$Z_{optimal}^{robust}$	845457	12009346	90112340	-
Z_{best}^{robust}	856926	12488171	93154082	50765234347
$Z_{average}^{robust}$	89768	13543009	964576651	55385098322
$Gap_{optimal-best}^{robust}$	1.35	3.98	3.37	-
$NFE^{deterministic}$	3625	15828	88243	45654904
$t_{optimal}^{robust}$	5.30	12.50	110.30	35987

Number of Pareto Solutions (NPS)

This index calculates the quantity of the non-dominated solutions gained every time by utilizing the algorithm. The algorithm does well enough when NPS is higher.

Mean Ideal Distance (MID)

The value of this index equals the distance of the Pareto points from the ideal point and can be calculated according to Eq. 57, where n is the quantity of Pareto points and (f_1^{best}, f_2^{best}) is the coordinates of the ideal point. In Addition, $f_{i,total}^{max}$ and $f_{i,total}^{min}$ are the highest and the lowest objective function values compared to the other objective functions. A lower value of MID shows a better performance of the algorithm.

$$c_i = \sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{max} - f_{1,total}^{min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,total}^{max} - f_{2,total}^{min}}\right)^2}$$
$$MID = \frac{\sum_{i=1}^{n} c_i}{n} \tag{57}$$

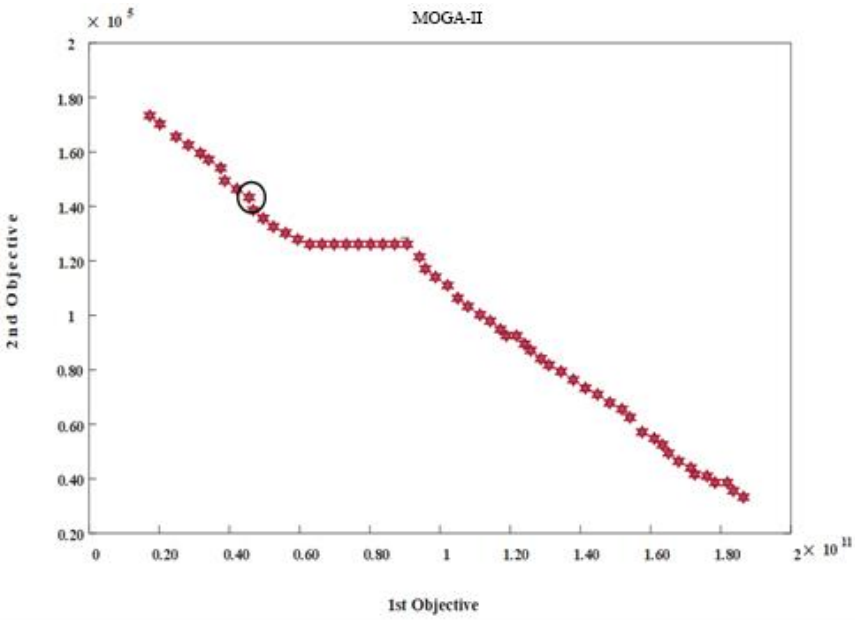

Fig. 6. The outcomes of the MOGA-II

After the model is solved for each of the objective functions in a single-objective mode by the PSO algorithm, it is solved in a two-objective mode with the MOGA-II algorithm and the same parameters. In this case, there are 59non-repetitive non-dominated solutions (NPS) obtained. In each of these solutions, the value of each of the two objective functions is specified. The maximum Zitzler distance scale [46] is found to be 0.8645. As depicted in Fig. 6, the value of the first robust-mode objective function attained by the PSO algorithm is a portion of the set of Pareto frontier solutions, which illustrates the reliability of the Pareto frontier. Some costs of the network are depicted in Table 6.

Table 6. Costs for the highlighted point regarding different transportation modes

Mode of Transportation	Cost (MU)
The entire moving cost by rail in the robust mode for the emphasized point from the Pareto level	101458789
The entire moving cost by ship in the robust mode for the emphasized point from the Pareto level	2154586458
The entire moving cost through pipelines in the robust mode for the emphasized point from the Pareto level	16526145365

Managerial Insights

In this section, proper insights are exploited from the analyses to help managers and decision-makers act preparedly in the face of real-world challenges.

First, the suggested model sufficiently covers all the operational limitations, entailing holding costs. It could be very helpful for the related managers. Second, despite the facts that planning is inherently a process to occur over time and numerous expenses are ignored in planning for distinct periods, the recommended model is accomplished with multi-period programming. The third benefit, as the most important one, is the robustness of the model to deal with which a scenario-based method has been employed. Given the very high costs of refueling processes, the output data of the model based on which decisions are made gain significance. Without a model designed in the form of a supply chain, a slight error when entering information into the model or an incorrect or somewhat unrealistic approximation of the demand of various regions for diverse types of petroleum products would make the total calculations go wrong. In addition, there will be no other decision if the estimates are made properly but, for technical reasons, a refinery or a warehouse fails to do its tasks. In the suggested model, however, with the cost initially paid as a fixed cost, which is much less than the stated significance, the gained program is insured over time. Managers can confidently use the proposed model and trust the results because applying uncertainty in the model reduces the amount of error in the calculations. The fourth advantage is related to the objectives of reducing the shipping costs and the number of loads. As everybody acknowledges, human lives are superior to any additional asset. In this model, therefore, it is not enough to reduce costs; the use of fuel tankers, which pose a high risk to people on the road, has been reduced as much as probable. This risk decrease is very valuable, although it rises costs somewhat. The solution algorithms used in this model make it advantageous too. The PSO algorithm is applied to resolve the model in a single target, and the MOGA-II algorithm is utilized to solve it in a multi-objective mode. With these algorithms, the calculations are easy to deal with, no matter how high the amount of information is or how many calculations are involved. It is, thus, possible to alternatively make plans for different periods. The high computational volume of the robust mode is also simply managed, and near-optimal solutions can be achieved within a reasonable time. All in all, considering the management insights provided, relevant managers can not only increase the safety and lives of people involved in the supply chain but also monitor all aspects of the oil industry in the type of a supply chain.

Conclusion and future outlooks

Owing to the high costs of refining and distributing petroleum products as well as the increasing requirments to decrease the macro-costs of governments and maximize the usage of resources, there is an undeniable and urgent need to comprehensively plan refueling processes with all the variables for future periods taken into account. In this paper, product transfer operations from supply points to consumption areas are considered a bi-objective supply chain. Considering different transportation modes is another feature of the proposed model. There are four different transportation modes, including road transportation by refueling tankers, transportation by rail, transportation through pipelines, and transportation by refueling ships. The mentioned methods can be applied with various capacities and costs. The ultimate objective of the proposed model is to minimize the cost of transporting petroleum products. Another goal is to enable the direct distribution of products with the least number of loads in order to have more security in these loads and maintain the principles defined in health, safety, and environmental systems. In addition, one of the most serious issues in the supply chain is uncertainty. To do this, using sensitivity analysis, the sensitive parameters of the model were identified (demand parameter) to allow uncertainty in the suggested model. Then, using the scenario-based robust programming technique, uncertainty is dealt with. Considering the robustness of the structure, the proposed model tries to solve a problem with large dimensions, which certainly fails to solve exact methods. To cope with this problem, meta-heuristic algorithms have been used to resolve the model. First, the proposed model was solved as a single-objective (considering the first objective function) and using the PSO algorithm in large and small dimensions in two modes of deterministic and uncertainty, and the results were examined. Next, the proposed multi-objective model (with the addition of the second objective function) was solved using the MOGA-II algorithm in the uncertainty mode, and the results were compared to the single-objective mode. In this case, the number of NPS was 59, and in each of these solutions, the values of every target function were specified. For the maximum Zitzler distance scale, 0.8645 was obtained, the value calculated for the first robust mode objective function gained by the PSO algorithm, which was also part of the Pareto solution. Thus, it indicated the reliability of the Pareto frontier was obtained. Finally, considering one of the Pareto frontier solutions, the entire cost of moving in the robust mode for the specified point was calculated based on four transportation modes.

Based on the issues discussed in this research, there are several recommendations to make for future studies as follows: a) pipeline planning can be completed on a daily basis to control variations because of operational reasons; b) planning can be done periodically; c) the suggested model can be provided as software within the internal network; d) if the algorithm is optimized, it will take less time to reach a solution; e) some insight may be provided by the comparison of bi-objective algorithms and similar algorithms in terms of performance; f) the production of refineries and the size of products in tanks may be measured with uncertainty.; and, g) the economic possibility of adding pipelines in certain places makes a good subject for research.

References

[1] Abdel-Basset, M., Mohamed, R., Sallam, K., & Elhoseny, M. (2020). A novel decision-making model for sustainable supply chain finance under uncertainty environment. *Journal of Cleaner Production, 269*, 122324.

[2] Abdolazimi, O., Esfandarani, M. S., Salehi, M., & Shishebori, D. (2020a). Robust design of a multi-objective closed-loop supply chain by integrating on-time delivery, cost, and environmental aspects, case study of a Tire Factory. *Journal of Cleaner Production*, *264*, 121566.

[3] Abdolazimi, O., Salehi Esfandarani, M., Salehi, M., & Shishebori, D. (2020b). A Comparison of Solution Methods for the Multi-Objective Closed Loop Supply Chains. *Advances in Industrial Engineering*, *54*(1), 75-98.

[4] Abdolazimi, O., Esfandarani, M. S., & Shishebori, D. (2021a). Design of a supply chain network for determining the optimal number of items at the inventory groups based on ABC analysis: a comparison of exact and meta-heuristic methods. *Neural Computing and Applications*, *33*(12), 6641-6656.

[5] Abdolazimi, O., Bahrami, F., Shishebori, D., & Ardakani, M. A. (2021b). A multi-objective closed-loop supply chain network design problem under parameter uncertainty: comparison of exact methods. *Environment, Development and Sustainability*, 1-35.

[6] Ambrosino, D., & Scutella, M. G. (2005). Distribution network design: New problems and related models. *European journal of operational research*, *165*(3), 610-624.

[7] Asamoah, D., Agyei-Owusu, B., Andoh-Baidoo, F. K., & Ayaburi, E. (2021). Inter-organizational systems use and supply chain performance: Mediating role of supply chain management capabilities. *International journal of information management*, *58*, 102195.

[8] Barros, A. I., Dekker, R., & Scholten, V. (1998). A two-level network for recycling sand: a case study. *European journal of operational research*, *110*(2), 199-214.

[9] Abdolazimi, O., & Abraham, A. (2020c, December). Meta-heuristic Based Multi Objective Supply Chain Model for the Oil Industry in Conditions of Uncertainty. In *International Conference on Innovations in Bio-Inspired Computing and Applications* (pp. 141-153). Springer, Cham.

[10] Eriksson, P. E. (2010). Improving construction supply chain collaboration and performance: a lean construction pilot project. *Supply Chain Management: An International Journal*.

[11] Fahimnia, B., Davarzani, H., & Eshragh, A. (2018). Planning of complex supply chains: A performance comparison of three meta-heuristic algorithms. *Computers & Operations Research*, *89*, 241-252.

[12] Farnsworth, M., Benkhelifa, E., Tiwari, A., Zhu, M., & Moniri, M. (2011). An efficient evolutionary multi-objective framework for MEMS design optimisation: validation, comparison and analysis. *Memetic Computing*, *3*(3), 175-197.

[13] Fathollahi-Fard, A. M., Ahmadi, A., & Al-e-Hashem, S. M. (2020). Sustainable closed-loop supply chain network for an integrated water supply and wastewater collection system under uncertainty. *Journal of Environmental Management*, *275*, 111277.

[14] Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., Van der Laan, E., Van Nunen, J. A., & Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European journal of operational research*, *103*(1), 1-17.

[15] Galbraith, J. (1973). Designing complex organizations. *Reading, Mass*.

[16] Ghahremani-Nahr, J., Kian, R., & Sabet, E. (2019). A robust fuzzy mathematical programming model for the closed-loop supply chain network design and a whale optimization solution algorithm. *Expert systems with applications*, *116*, 454-471.

[17] Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European journal of operational research*, *240*(3), 603-626.

[18] Hamdan, B., & Diabat, A. (2019). A two-stage multi-echelon stochastic blood supply chain problem. *Computers & Operations Research*, *101*, 130-143.

[19] Hidalgo, K. J., Sierra-Garcia, I. N., Dellagnezze, B. M., & de Oliveira, V. M. (2020). Metagenomic insights into the mechanisms for biodegradation of polycyclic aromatic hydrocarbons in the oil supply chain. *Frontiers in Microbiology*, *11*.

[20] Jayaraman, V., Guide Jr, V. D. R., & Srivastava, R. (1999). A closed-loop logistics model for remanufacturing. *Journal of the operational research society*, *50*(5), 497-508.

[21] Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: a critical review. *European Journal of Operational Research*, *203*(2), 283-293.

[22] Krikke, H. R., van Harten, A., & Schuur, P. C. (1999). Business case Oce: reverse logistic network re-design for copiers. *Or-Spektrum*, *21*(3), 381-409.

[23] Kumar, R. S., Choudhary, A., Babu, S. A. I., Kumar, S. K., Goswami, A., & Tiwari, M. K. (2017). Designing multi-period supply chain network considering risk and emission: A multi-objective approach. *Annals of Operations Research*, *250*(2), 427-461.

[24] Larimi, N. G., Yaghoubi, S., & Hosseini-Motlagh, S. M. (2019). Itemized platelet supply chain with lateral transshipment under uncertainty evaluating inappropriate output in laboratories. *Socio-Economic Planning Sciences*, *68*, 100697.

[25] Leung, S. C., Tsang, S. O., Ng, W. L., & Wu, Y. (2007). A robust optimization model for multi-site production planning problem in an uncertain environment. *European journal of operational research*, *181*(1), 224-238.

[26] Liu, B., Wang, L., & Jin, Y. H. (2007). An effective PSO-based memetic algorithm for flow shop scheduling. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *37*(1), 18-27.

[27] Min, H., Ko, C. S., & Ko, H. J. (2006). The spatial and temporal consolidation of returned products in a closed-loop supply chain network. *Computers & Industrial Engineering*, *51*(2), 309-320.

[28] Mohammed, M. K., Umer, U., & Al-Ahmari, A. (2017). Optimization of laser micro milling of alumina ceramic using radial basis functions and MOGA-II. *The International Journal of Advanced Manufacturing Technology*, *91*(5).

[29] Mondal, A., & Roy, S. K. (2021). Multi-objective sustainable opened-and closed-loop supply chain under mixed uncertainty during COVID-19 pandemic situation. *Computers & Industrial Engineering*, *159*, 107453.

[30] Mulvey, J. M., Vanderbei, R. J., & Zenios, S. A. (1995). Robust optimization of large-scale systems. *Operations research*, *43*(2), 264-281.

[31] Obreque, C., Donoso, M., Gutiérrez, G., & Marianov, V. (2010). A branch and cut algorithm for the hierarchical network design problem. *European Journal of Operational Research*, *200*(1), 28-35.

[32] Optimization, M. I. (2014). Mode Frontier Version 4.0. *User Manual, Esteco, SPA*.

[33] Peng, H., Shen, N., Liao, H., Xue, H., & Wang, Q. (2020). Uncertainty factors, methods, and solutions of closed-loop supply chain—A review for current situation and future prospects. *Journal of Cleaner Production*, *254*, 120032.

[34] Piya, S., Shamsuzzoha, A., Khadem, M., & Al-Hinai, N. (2020). Identification of critical factors and their interrelationships to design agile supply chain: special focus to oil and gas industries. *Global Journal of Flexible Systems Management*, *21*(3), 263-281.

[35] Reiner, G., & Trcka, M. (2004). Customized supply chain design: Problems and alternatives for a production company in the food industry. A simulation based analysis. *International Journal of Production Economics*, *89*(2), 217-229.

[36] Sakib, N., Hossain, N. U. I., Nur, F., Talluri, S., Jaradat, R., & Lawrence, J. M. (2021). An assessment of probabilistic disaster in the oil and gas supply chain leveraging Bayesian belief network. *International Journal of Production Economics*, 108107.

[37] Shoja, A., Molla-Alizadeh-Zavardehi, S., & Niroomand, S. (2019). Adaptive meta-heuristic algorithms for flexible supply chain network design problem with different delivery modes. *Computers & Industrial Engineering*, *138*, 106107.

[38] Suler, J. (2009). The psychotherapeutics of online photosharing. *International Journal of Applied Psychoanalytic Studies*, *6*(4), 339-344.

[39] Stanworth, S. J., New, H. V., Apelseth, T. O., Brunskill, S., Cardigan, R., Doree, C., ... & Thachil, J. (2020). Effects of the COVID-19 pandemic on supply and use of blood for transfusion. *The Lancet Haematology*.

[40] Tang, C. S. (2006). Perspectives in supply chain risk management. *International journal of production economics*, *103*(2), 451-488.

[41] Tsao, Y. C., Thanh, V. V., Lu, J. C., & Yu, V. (2018). Designing sustainable supply chain networks under uncertain environments: Fuzzy multi-objective programming. *Journal of Cleaner Production*, *174*, 1550-1565.

[42] Zhang, S., Lei, Q., Wu, L., Wang, Y., Zheng, L., & Chen, X. (2021). Supply chain design and integration for the Co-Processing of bio-oil and vacuum gas oil in a refinery. *Energy*, 122912.

[43] Zhang, J., Yalcin, M. G., & Hales, D. N. (2021). Elements of paradoxes in supply chain management literature: a systematic literature review. *International Journal of Production Economics*, *232*, 107928.

[44] Zheng, M., Li, W., Liu, Y., & Liu, X. (2020). A Lagrangian heuristic algorithm for sustainable supply chain network considering CO2 emission. *Journal of Cleaner Production*, *270*, 122409.

[45] Zhou, X., Zhang, H., Xin, S., Yan, Y., Long, Y., Yuan, M., & Liang, Y. (2020). Future scenario of China’s downstream oil supply chain: Low carbon-oriented optimization for the design of planned multi-product pipelines. *Journal of Cleaner Production*, *244*, 118866.

[46] Zitzler, E., Laumanns, M., & Thiele, L. (2001). SPEA2: Improving the strength Pareto evolutionary algorithm. *TIK-report*, *103*.

[47] Arabi, M., & Gholamian, M. R. (2021). Sustainable Supply Chain Network Design with Price-Based Demand Considering Sound and Dust Pollutions: A Case Study. *Advances in Industrial Engineering*, *55*(3), 285-306.

[48] Salehi, F., Allahyari Emamzadeh, Y., Mirzapour, A. E., Hashem, S. M. J., & Shafiei Aghdam, R. (2021). An L-Shaped Method to Solve a Stochastic Blood Supply Chain Network Design Problem in a Natural Disaster. *Advances in Industrial Engineering*, *55*(1), 47-68.

[49] Seifbarghy, M. S., Soleimani, M., & Jabbari, M. (2020). Comparing Multi-Objective Meta-Heuristics for Multi-Commodity Supply Chain Design Problem with Partial Coverage. *Advances in Industrial Engineering*, *54*(4), 365-379.

[50] Chima, C. M. (2007). Supply-chain management issues in the oil and gas industry. *Journal of Business & Economics Research (JBER)*, *5*(6).

[51] Aslam, J., Saleem, A., Khan, N. T., & Kim, Y. B. (2021). Factors influencing blockchain adoption in supply chain management practices: A study based on the oil industry. *Journal of Innovation & Knowledge*, *6*(2), 124-134.

[52] ALNAQBI, A., DWEIRI, F., & CHAABANE, A. (2022). Impact of Horizontal Mergers on Supply Chain Performance: The Case of the Upstream Oil and Gas Industry. *Computers & Chemical Engineering*, 107659.

[53] Ara, R. A., Paardenkooper, K., & van Duin, R. (2021). A new blockchain system design to improve the supply chain of engineering, procurement and construction (EPC) companies–a case study in the oil and gas sector. *Journal of Engineering, Design and Technology*.

[54] Sahebishahemabadi, H. (2013). Strategic and Tactical Crude Oil Supply Chain: Mathematical Programming Models.

[55] Lima, C., Relvas, S., & Barbosa-Póvoa, A. P. F. (2016). Downstream oil supply chain management: A critical review and future directions. *Computers & Chemical Engineering*, *92*, 78-92.

[56] Fernandes, L. J., Relvas, S., & Barbosa-Póvoa, A. P. (2014). Collaborative design and tactical planning of downstream petroleum supply chains. *Industrial & Engineering Chemistry Research*, *53*(44), 17155-17181.

[57] Wisner, J. D. (2003). A structural equation model of supply chain management strategies and firm performance. *Journal of Business logistics*, *24*(1), 1-26.

[58] Ernst, D., & Steinhubl, A. M. (1997). Alliances in upstream oil and gas. *McKinsey Quarterly*, 144-155.

[59] Ramdas, K., & Spekman, R. E. (2000). Chain or shackles: understanding what drives supply-chain performance. *Interfaces*, *30*(4), 3-21.

[60] Zhou, Y. C., Wang, X. N., Liu, X. P., Xue, L., Liang, S., & Sun, C. H. (2010, July). Enabling integrated information framework as cloud services for chemical and petroleum industry. In *2010 6th World Congress on Services* (pp. 1-7). IEEE.

[61] Yusuf, Y. Y., Gunasekaran, A., Musa, A., Dauda, M., El-Berishy, N. M., & Cang, S. (2014). A relational study of supply chain agility, competitiveness and business performance in the oil and gas industry. *International Journal of Production Economics*, *147*, 531-543.