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RESEARCH PAPER

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Abstract

The hydrocarbon supply chain (HCSC) is integral to the world economy. This chain includes petroleum products extraction, refinement, distribution, and consumption. Considering the importance of planning HCSC for the chain's activities, it is necessary to simultaneously review and optimize these activities by incorporating important and influential factors. The problem considered in this research has three objectives: 1) maximizing profits, 2) minimizing withdrawal from reservoirs, and 3) minimizing greenhouse gas emissions. The results demonstrated that the profit level in a specific time (10 periods) improved by 18% compared to the current point. In addition, a numerical example was used to simulate distribution, refinement, and extraction locations as a supply chain for petroleum products. Finally, the sensitivity analysis revealed that the optimization results are robust to parameter changes and can further improve the optimization of the oil and gas supply chain by maintaining different balances (e.g., natural resources) and reducing environmental effects. Interactive fuzzy programming based on credibility criteria was applied to address the parameter uncertainty. Further, to reduce the problem's computational complexity and produce valid and reliable optimal Pareto cuts, the Benders decomposition method has been employed, which has led to the production of efficient solutions.

Keywords:
Fuzzy Programming; Uncertainty; Benders Decomposition.

Introduction

Petroleum products are among the strategic tools of countries such that some changes in their supply and price can lead to significant political, social, and economic consequences (Rahimi et al., 2019). The change in the supply and demand of these products, in addition to the local and regional effects, will lead to some global issues. In this respect, national and global policies directly impact each other, causing political and military confrontation (Ghaithan et al., 2017). Hence, macro policies are established in specific periods by adding specific technical, spatial, and time constraints to these policies. Extraction, refinement, distribution, and consumption planning of petroleum products in supply chain management is a critical issue among researchers concerning oil demand and selling price. Many factors involved in these supply chains can influence their optimization. The present research investigates a planning model of extraction, refinement, distribution, and consumption for a four-level supply chain with several extractors, producers, distributors, and consumers. To this end, we need a model that can incorporate national laws and policies in the supply chain of petroleum products and technical issues, maximize the profit from petroleum resources, and make it feasible to implement them

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realistically. Highly agitating business competition is among the significant challenges of modern supply chains (Kumar et al., 2023). One of the goals under such circumstances is to create an efficient supply chain structure that can be robust against upcoming risks. Failure to create an efficient supply chain leads to severe consequences such as low product quality, loss of property and machinery, delay in delivery, and conflict between different shareholders (Wang et al., 2023). In addition, it may adversely affect the firm's reputation and lead to a severe drop in its stock price (Rahimi et al., 2019).

Activities related to the oil industry are divided into upstream and downstream sectors. The upstream activities include exploration and drilling of oil reservoirs, crude oil extraction, and oil supply to domestic refineries and export terminals. On the other hand, in the downstream section of the oil industry, crude oil is refined, and oil derivatives are produced in refineries. In this respect, the output of upstream activities is the production of crude oil, which is transferred to the downstream sector (i.e., refineries and oil export terminals). Crude oil refining processes occur in refineries, producing petroleum products, and distributing these products to consumers in the downstream sector of the petroleum industry. Therefore, the strategic decisions from the upstream section have a significant effect on the operational issues of the hydrocarbon supply chain (HCSC) (Attia, 2021).

Strategic and medium-term decisions (e.g., distribution planning, transportation planning, and operational and short-term decisions) are made in this field. An example of these decisions is managing the flow of goods between facilities after establishing and implementing strategic decisions and designing the structure of the supply chain network. This issue plays a critical role in making the best decisions. As a result, these decisions are considered in the integrated planning of the supply chain network to avoid sub-optimization caused by individual decision-making at strategic, tactical, and operational levels (Alnaqbi et al., 2023).

The present research is conducted through network design, production planning, distribution, and transportation. In this respect, a significant challenge in developing the HCSC network and oil fields is the presence of environmental and systemic uncertainty. Its environmental type is caused by continuous and severe changes in the energy industry and market. However, a significant part of the system type is caused by strategic decisions related to network design, distribution structure, and strategic plans for selling oil and gas and oil derivatives. In this respect, even a tiny deviation from the expected value imposes increasing uncertainty on the system, thereby degrading the network achievements (e.g., profitability) (Najafi et al., 2024). In the present study, we face various uncertainties such as demand, selling price, production cost, crude oil price, transportation costs, and capacity of oil tanks. Thus, it is necessary to determine the risk aversion limits of the network to control other vital parameters. Having an emphasis on environmental laws caused by the strict government laws, this study incorporates the modern aspect of the sustainability of oil tanks. Making a balance between the rate of emptying oil tanks and the oil selling profitability, this approach prolongs the life of the tanks and the share of Iran's market. In addition, due to the increasing uncertainty in oil demand and selling price, the effective approach of credit fuzzy planning was employed to determine the level of flexible confidence to face these destructive changes.

Over time, energy planners have faced several issues in the energy field, such as the depletion and non-renewability of fossil energy resources. Climate and weather changes caused by global warming and the increasing trend of greenhouse gas emissions are among other issues contributing to establishing a new energy planning concept (Attia et al., 2019). In addition to focusing on profit maximization of extraction and refinement, energy planning also requires a commitment to reducing harmful environmental effects. The literature shows no multi-objective model for the HCSC with more than three levels. The present study proposes multi-objective mathematical programming to integrate the decisions concerning the HCSC network. Besides, it incorporates the balance of products and strategy planning for modeling the petroleum supply chain. This research designs and optimizes a multi-objective planning model to enhance the optimal performance of these products' extraction, refinement, and distribution chains. This model has three objective functions: 1) maximizing profit from selling crude petroleum products, 2) minimizing extraction from underground hydrocarbon resources, and 3) minimizing greenhouse gas emissions. This function solves the problem using deterministic methods and optimizes it using fuzzy techniques (due to the price and demand uncertainty). Finally, Benders decomposition is applied to divide and solve the problem against size and uncertainty optimally. This comprehensive approach allows for solving the desired complex problem concerning maintaining different objectives and managing uncertainty. The proposed model aims to achieve several goals, such as reducing costs, increasing productivity, and minimizing environmental pollutants and impacts. To this end, it simultaneously optimizes different parameters, including extraction, refinement, transportation, warehousing, and energy consumption. Eventually, this model can help oil and gas extraction, improve refining companies' performance, and lower their costs.

The remainder of this is organized as follows. In Section 2, the literature on the subject is reviewed. Section 3 introduces the problem and states the assumptions. Section 4 describes the case study, and Section 5 presents the results. Finally, Section 6 provides the conclusions.

Literature Review

Several studies have modeled different parts of the HCSC as a whole or separately. The literature concerning HCSC modeling can be classified based on objectives such as modeling, mathematical programming, extraction, refinement, distribution of hydrocarbon products, reducing underground resources, and lowering greenhouse gas emissions. Some papers have examined modeling and planning for HCSC. For instance, Aizemberg et al. (2014) presented a decision optimization model based on interval linear programming. These researchers selected and implemented the best policy by modeling and optimizing this model in the HCSC cases.

Motahari et al. (2022) proposed a multi-objective linear programming model (MOLP) to optimize completion time, transportation cost, and machine idle time for a multi-product system. Next, they compared the results using three meta-heuristic algorithms and chose the optimum method. Vafadarnikjoo et al. (2023) developed a multi-objective binary linear programming model to minimize risk, cost, and time. This research aimed to mitigate the effects of skilled labor shortage, non-standard leadership, failure in information technology systems, and insufficient capacity to produce quality and poor products. Based on modeling outputs, continuous training, development, and vulnerability analysis of information technology systems were identified as the most effective risk reduction strategies to mitigate these factors.

The second group of studies explores the HCSC of oil-based upstream industries. In this respect, Gupta and Grossmann (2012) modeled and formulated the non-linearity of oil field behavior as a third-degree polynomial. Next, they compared their method with traditional methods and proved its superior performance. Aizmberg et al. (2014) prepared a crude oil transportation planning problem from offshore facilities to processing units and solved it using commercial software based on the branch-and-bound algorithm. In addition, they solved the problem using a heuristic algorithm based on column production. Nasab and Amin-Naseri (2016) investigated the installation and development of the capacity of pipeline routes and crude oil production facilities. In this research, the dependence between crude oil and natural gas was ignored, the optimal method was presented, and the results were compared based on their interdependence. Rocha et al. (2017) proposed a decomposition algorithm based on the cascade backpack structure for solving large-scale models of the oil supply chain. Finally, they presented the numerical results of their model. Alnaqbi et al. (2022) described horizontal mathematical planning in the upstream crude oil supply chain using a supply chain model.

These authors assessed the favorable impact of economies of scope and economies of scale on potential mergers and formulated a MILP model. This model determines the level of investment and efficient implementation of operational strategies in shared services and petroleum production and processing.

One group of papers about HCSC discusses the modeling of oil-based downstream industries. Komesker et al. (2022) proposed a network-based strategy to enhance the resilience of integrated gas systems. The objective of this work was to provide a clear representation of network components that should be protected by recovery prioritization of components, taking into account power interdependencies .

Another group of papers deals with the depletion of underground hydrocarbon resources from storage reservoirs. In this respect, Li et al. (2021) reviewed the methods for lowering heavy oil and bitumen viscosity by underground catalytic cracking. Considering the peak production and compensation of the future rising demand, they recommended upgrading to improve the mobility of heavy oil underground. In this respect, catalytic cracking catalysts are produced and used through in situ upgrading technology by injecting ultra-dispersed nanocatalysts at a low cost, high activity, high selectivity, and wide adaptability. These catalysts are compatible with a wide range of heavy oils and have different properties, especially ultra-dispersed nanocatalysts. Overall, this method was reported to be promising for improving the quality of lower-grade heavy oil components and enhancing the recovery of heavy oil reservoirs.

Some relevant studies have dealt with greenhouse gas reduction. For example, Buslaev et al. (2021) studied the greenhouse gas reduction for heavy oil extraction in the Arctic, where heavy oil has a high viscosity and requires significant energy. Spending the energy required in this process increases the emission of greenhouse gases. Hence, they proposed a model to reduce the carbon footprint related to hydrocarbon extraction in the Arctic area. Applying this structure revealed a 24% reduction in carbon footprint in the proposed process compared to the results obtained at the present oil fields in the Arctic region. Patterson et al. (2022) applied an innovative bio-oil co-production method to lower greenhouse gas emissions in combined heat and power plants. These efforts allowed plant operators to obtain an extra heat sink and produce primary renewable transportation fuels. Reducing greenhouse gas emissions in manufacturing through substitution effects in the transport sector is vital to ensure coherence with climate ambitions. In this respect, research has shown a yearly reduction in greenhouse gas emissions of up to 8%. This reduction is mainly attributed to the substituting of fossil fuels in the transportation sector. Estimating the yearly production rate revealed that European countries are transitioning to a fossil-free energy system at different stages. Consequently, according to the IF-based calculations, the commercialization of hybrid heat, power, and bio-oil technology allows for avoiding greenhouse gas emissions in various sectors.

To our knowledge, there is a research gap in optimizing the four-level vertical oil and gas supply chain (i.e., planning extraction, refining, distribution, and consumption of oil and gas) considering the reduction rate of underground hydrocarbon resources, the environmental impacts of greenhouse gases, and uncertainty of supply and demand. The present paper considers these three modeling objectives to extract an optimal solution. Table 1 presents the summary of the previous studies concerning HCSC.

Table 1. Research literature

Papers	Objective functions	Model type	Uncertainty	Planning strategy	Transportation	Solution Method	activity area

	Income/cost	environment	social	certain	fuzzy		Single period	Multi-period	One mode	multi-mode	certain	fuzzy	Exact solution	heuristic	upstream of oil and gas	Middle oil and gas	downstream of oil and gas	other
Susarla & Karimi (2012)	✓			✓			✓		✓		✓							✓
Gupta & Grossmann (2012)	✓			✓			✓		✓		✓				✓			
Aizemberg et al. (2014)	✓			✓				✓		✓					✓			
Nasab & Amin-Naseri (2016)	✓			✓			✓		✓					✓	✓			
Liang et al. (2016)	✓		✓	✓				✓	✓		✓						✓	
Rocha et al. (2017)	✓		✓		✓			✓	✓			✓					✓	
Ghaithan et al. (2017)	✓		✓	✓	✓		✓			✓	✓						✓	
Rahimi et al. (2019)	✓	✓		✓		✓	✓		✓		✓				✓			
Attia et al. (2019)	✓	✓	✓	✓				✓		✓	✓		✓		✓			
Kumar et al. (2021)	✓		✓		✓	✓	✓			✓	✓					✓		
Li et al. (2021)	✓			✓			✓		✓		✓					✓		
Ge & Yuan (2021)	✓		✓	✓				✓		✓			✓			✓		
Sahoo et al. (2022)	✓				✓	✓	✓			✓	✓	✓				✓		
Zhao et al. (2021)	✓	✓		✓				✓		✓	✓		✓					✓
Buslaev et al. (2021)	✓		✓	✓			✓			✓	✓		✓		✓			
Pettersson et al. (2022)	✓		✓		✓	✓	✓			✓				✓		✓		
Scrimieri et al. (2022)	✓		✓	✓				✓	✓					✓	✓	✓		
Alnaqbi et al. (2022)	✓	✓			✓			✓	✓		✓					✓		
Motahari et al. (2022)	✓	✓	✓		✓		✓		✓			✓				✓	✓	
Sang et al. (2022)	✓				✓	✓		✓	✓			✓			✓	✓		
Vafadarnikjoo et al. (2023)	✓	✓			✓		✓				✓					✓		
AlEdan & Erfani (2023)	✓				✓	✓	✓		✓		✓						✓	
Kumar et al. (2023)	✓	✓		✓		✓	✓				✓					✓		
Wang et al. (2023)	✓	✓		✓		✓	✓				✓					✓	✓	
Ratner et al. (2024)	✓	✓		✓					✓		✓							✓
Avellaneda et al. (2024)		✓		✓					✓		✓							✓
Najafi et al (2024)	✓			✓		✓			✓			✓						✓
The present research	✓	✓	✓	✓	✓	✓		✓		✓	✓	✓	✓		✓	✓	✓	

Reviewing the research conducted in the field of HCSC network, the innovations of the present research are summarized as follows:

- ✓ Integrating strategic and operational decisions for demand fulfillment
- ✓ Multi-objective, multi-period, and multi-state mathematical modeling in the range of upstream, intermediate, and downstream areas of the oil and gas supply chain

- ✓ Developing a sustainable approach in the HCSC products while focusing on economic goals and increasing the life cycle of reservoirs and the environment; and
- ✓ Focusing on demand uncertainties and domestic and international oil and gas selling prices.
- ✓ Offering a hybrid approach including fuzzy mathematical programming, financial limits, and Benders decomposition algorithm

This research models the four levels of the supply chain by combining the Benders decomposition and epsilon constraint. Next, it extracts the optimal state with other objectives. Afterward, it optimizes the supply chain, which significantly improves the supply chain performance and guarantees the quality of products and services offered to customers. Finally, it determines the best mode by optimizing and extracting all three objectives by integrating the goals.

Mathematical Modeling

Description of the Problem

HCSC covers a large part of Iran’s energy economy. Applying strict environmental laws by the government and the commitment of the oil industry authorities to control the carbon effect and ensure the stability of oil fields have led to prioritizing sustainable approaches in developing HCSC for petroleum products. The present study covers the upstream and downstream levels of the supply chain of petroleum products for exploration and production activities, processing, and distribution to the final customer. The developed mathematical model maximizes the profit from selling crude oil and petroleum products while lowering the amount of extraction from oil and gas reserves. This approach guarantees the life cycle of oil and gas resources in future periods. In addition, much attention has been paid to the issue of reducing greenhouse gas emissions caused by gas injection during oil and gas extraction.

This section investigates the research problem and expresses its mathematical model. The model deals with the long-term time horizon with a sustainable development approach. Besides, it provides solutions to determine the optimal combination of the production chain and the supply of hydrocarbon resources. This solution is based on the depletion rate of underground hydrocarbon reserves and lowering the effects of greenhouse gases. Fig. 1 illustrates the optimization process of the supply chain of hydrocarbon products for gasoline, diesel, oil gas, LNG, LPG, etc. All stages have constraints on extraction, transportation, processing, and storage. Also, this research considers that the quality of products extracted from underground hydrocarbon reservoirs is different considering the difference in the separation rate of crude oil and gross gas and their sellings. Moreover, the initial transportation cost from the extraction site to oil storage reservoirs of crude and impure gases is assumed to be the same due to constant pipeline transmission. The storage cost of crude oil and gross gases is directly related to time because of the tank retention time. Due to the double transfer from the primary storage reservoirs to the refineries, each method’s transfer and transportation costs are considered different. Processing and storage costs of refineries vary according to the feed type and the percentage of processed products of each refinery. The maintenance cost of each product in refineries is directly related to the shelf life. The ultimate transfer cost is considered different according to various methods. Finally, it aims to determine the optimal policy, extraction, transfer, processing, and consumption of hydrocarbon products concerning global, national, and regional constraints. The assumptions applied in the extended model are defined as follows:

- The site of product-selling terminals, refineries, and extraction poles is clear.
- Products from refineries to selling terminals are transported by three modes, namely pipeline, road, and rail.
- The amount of crude oil export quota is fixed.
- The quota of the Organization of the Petroleum Exporting Countries (OPEC) is known.

- The volume and selling price of exported crude oil has a normal distribution with upper and lower constraints.
- The time of non-service of terminals and refineries is known.
- The amount of greenhouse gas emission is known.
- If the storage limit of any product, crude oil, or gas is reached, the entire production of the complex will be stopped.
- The two extractors' crude oil and crude gas extraction rates are different.
- The costs of secondary and final transportation by carriers are not the same.
- The percentage of loss of crude oil and gas volume of extractors is considered zero.
- The storage volume of crude oil and gross gas is constant.
- The processing capacity of oil and gas refineries can change over time.
- The composition percentage of processed products of crude oil and crude gas of extractors are different.
- The selling prices of crude oil and gross gas vary for different local and international customers.
- Selling prices of processed products vary for different local and international customers.
- Since the OPEC quota limit has been considered, uncertainties arise due to oil demand fluctuations and other macroeconomic factors (possible uncertainty). Hence, the operational risk is considered.

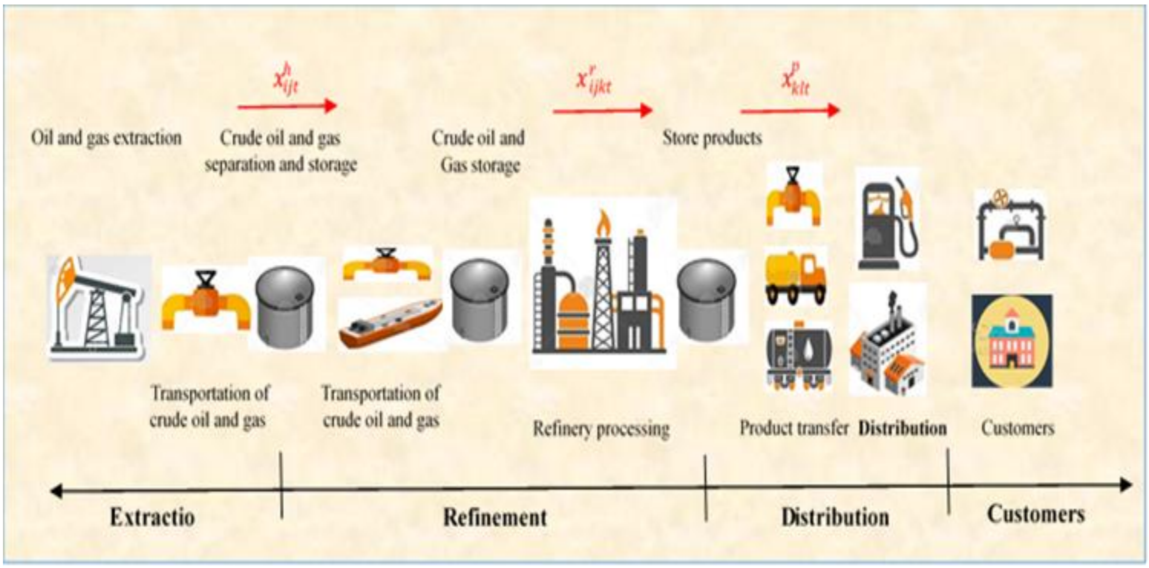

Fig. 1. Hydrocarbon supply

Indices

i=1…I	Hydrocarbon extraction poles
j=1…J	Products extracted from the poles
k=1…K	Refineries
l=1...L	Processed products of refineries
m=1…M	Distribution centers for processed products
n=1…N	The product transportation mode
t=1…T	Periods
h	Hydrocarbon products (i.e., oil and gas)
r	Types of refined product
EXP	Type of export products
p	Type of manufactured products (i.e., gas and oil)
u	The ultimate transfer

Parameters	
Ph_{ij}^{h}	The yield rate of hydrocarbon products h for extracted products j from extraction pole i
H_{ijt}^{h}	The transfer capacity of hydrocarbon products h for extraction j from extraction pole i in the period t
Pr_{ijkl}^{r}	The extraction efficiency rate of products j for processed product l from refining products r in extraction pole i in refinery k
Cr_{kjt}^{r}	The capacity of refined products r from the extraction pole in refinery k in the period t
SC_{kl}^{p}	The capacity of production products reservoirs p for processing l in refinery k
dr_{ijkt}^{r}	The amount of demand for refined products r from extracted products j in refinery k to extraction pole i in period t
dp_{klmt}^{p}	The amount of demand for manufactured products p from processed products l in refinery k by distribution centers m in period t
$OPECQ$	OPEC quota
Cm_{max}	The maximum allowable CO2 emission
Pp_{klmn}^{p}	Transfer rate of manufactured product p for processed product l from refinery k to distributor m by method n
TC_{lm}^{u}	Final transportation transfer capacity for processed products l to distribution centers m
SoC_{jk}^{r}	The capacity of the reservoirs of refined products r from the extraction pole j in the refinery k
Ch_{ij}^{h}	Storage capacity of products h for product j from extraction pole i
HC_{i}	Extraction capacity from pole i
Pi_{j}^{h}	Domestic selling price per unit of extracted materials xn_{ijt}^{h} in the extraction poles
Pe_{j}^{h}	Global selling price per unit of extracted materials xn_{ijt}^{h} in the extraction poles
Pri_{l}^{r}	Domestic selling price per unit of processed product xr_{ijkt}^{r} in the refineries
Pre_{l}^{r}	Global selling price per unit of processed product xr_{ijkt}^{r} in refineries
Pdi_{l}^{r}	Domestic selling price per unit of processed product xr_{ijkt}^{r} in the distribution centers
Ce_{ij}^{h}	The cost of extracting each unit of material xn_{ijt}^{h} in the extraction poles
Crp_{kl}^{r}	Processing cost per unit of product xr_{ijkt}^{r} in refineries
Cc_{jn}^{h}	The cost of transporting each unit of products h extracted j in terms of the unit distance of the route from the poles to the bases by method n
Cl_{ln}^{r}	The transportation cost of each unit of processed refined product l according to the distance of the routing unit from the poles to the distribution centers by method n
TD_{ik}^{h}	Path distances of n products h from extraction pole i
TDr_{km}^{r}	Distances of the route of the refined product r from the refinery k to the distribution center m
$Chm_{ij(t-1)}^{h+}$	The cost of maintaining the remaining extracted materials $xt_{ij(t-1)}^{h+}$ in period t-1
Chc_{ijt}^{h-}	Cost of lost sellings of extracted residual material xsp_{ijt}^{h-} in period t
$Ccp_{kl(t-1)}^{p+}$	The cost of storing processed products $xrp_{kl(t-1)}^{p+}$ in period t -1
Ccs_{klt}^{p-}	Cost of lost sellings of processed products xs_{lmt}^{p-} in period t
$Cmp_{lm(t-1)}^{p+}$	The cost of maintaining processed products $xrc_{lm(t-1)}^{p+}$ in the period t-1
OCC_{j}^{Exp}	The maximum export of product Exp from extraction poles j
P_{ijkn}^{h}	Transfer rate of product h extracted j from pole i by method n to refinery k
MC_{jk}^{r}	The maximum amount of transfer of refined products r extracted j to refinery k
Decision variables	

xe_{it}^{h}	The amount of extracted products h from extraction pole i in period t
xn_{ijt}^{h}	The amount of products extracted i from the hydrocarbon products h from pole i during period t
$xt_{ij(t-1)}^{h+}$	The total extracted product j available from hydrocarbon products h in extraction reservoir i in period t-1
xr_{ijkt}^{r}	The amount of demand for extracted products j from refined products r in refinery k from extraction pole i in period t
xe_{ijt}^{Exp}	The type of export products, the extracted product j from pole i in period t
$xf_{kj(t-1)}^{r+}$	The total extracted products i from refined products r in refinery k by distributor m in period t-1
xp_{klt}^{p}	The amount of production products p from processed products l in refinery k in period t
xdp_{klmt}^{p}	The amount of demand for manufactured products p from processed products l in refinery k by distributor m in period t
$xrp_{kl(t-1)}^{p+}$	Inventory of manufactured products p from processed products l in refinery k in period t-1
xsp_{ijt}^{h-}	The amount of shortage of extracted products j from hydrocarbon products h in extraction pole i in period t
xpp_{klt}^{p-}	The amount of shortage of manufactured products p from processed products l in refinery k in period t
xex_{klt}^{Exp}	Export amount of products from processed products l in refinery k in period t
$xrc_{lm(t-1)}^{p+}$	Inventory of manufactured products p from processed products l in distribution center m in period t-1
xs_{lmt}^{p-}	The amount of shortage of manufactured products p from processed products l in distribution center m in period t
$ghgh_{it}^{h}$	The amount of injection of products h to extract products i in period t
$ghgr_{jt}^{r}$	The amount of greenhouse gas emissions of refining products r to extract products j in period t
$ghgf_{nt}$	Fossil fuel consumption of vehicles n and hydrocarbon products in period t

Model Formulation

The first objective of this research is to maximize the total profit in a planning horizon in the extraction, refinement, distribution, and selling chain. This objective is mathematically expressed by Eq. (1):

$$
\begin{aligned}
Max\ benefit = & \sum_{h}\sum_{Exp}\sum_{i}\sum_{j}\sum_{t}((Pi_{j}^{h} \times (xn_{ijt}^{h} - xe_{ijt}^{Exp})) + (Pe_{j}^{h} \times xe_{ijt}^{Exp})) \\
& + \sum_{r}\sum_{Exp}\sum_{l}\sum_{k}\sum_{t} Pre_{l}^{r} \times xex_{klt}^{Exp} \\
& + \sum_{k}\sum_{l}\sum_{m}\sum_{t}(Pdi_{l}^{r} \times xdp_{klmt}^{p}) - \sum_{i}\sum_{j}\sum_{t}(Ch_{ij}^{h} \times xn_{ijt}^{h}) \\
& - \sum_{k}\sum_{l}\sum_{t}\sum_{r}\sum_{i}\sum_{j}(Crp_{kl}^{r} \times xr_{ijkt}^{r}) \\
& - \sum_{j}\sum_{n}\sum_{i}\sum_{k}\sum_{h}(Cc_{jn}^{h} \times TD_{ik}^{h}) \\
& - \sum_{l}\sum_{n}\sum_{k}\sum_{m}\sum_{r}(Cl_{ln}^{r} \times TDr_{km}^{r}) - \sum_{i}\sum_{j}\sum_{t}\sum_{h}(Chm_{ij(t-1)}^{h+} \times xt_{ij(t-1)}^{h+}) \\
& - \sum_{i}\sum_{j}\sum_{t}\sum_{h}(Chc_{ijt}^{h-} \times xsp_{ijt}^{h-}) \\
& - \sum_{k}\sum_{l}\sum_{t}\sum_{p}(Ccp_{kl(t-1)}^{p+} \times xrp_{kl(t-1)}^{p+})) - \sum_{k}\sum_{l}\sum_{t}\sum_{p}(Ccs_{klt}^{p-} \times xpp_{klt}^{p-}) \\
& - \sum_{l}\sum_{m}\sum_{t}\sum_{p}(Cmp_{lm(t-1)}^{p+} \times xrc_{lm(t-1)}^{p+}) - \sum_{k}\sum_{l}\sum_{t}\sum_{p}(Ccs_{klt}^{p-} \times xs_{lmt}^{p-})
\end{aligned}
\tag{1}
$$

The second objective is to minimize the discharge rate of underground hydrocarbon resources according to national policies and short-term strategic planning. This goal is mathematically displayed by Eq. (2).

$$Minmize\ Discharge = \sum_i \sum_j \sum_h \sum_k \sum_l \sum_t \sum_p ph_{ij}^{h}\, xp_{klt}^{p} + \sum_i \sum_j \sum_k \sum_l \sum_t \sum_r pr_{ijkl}^{r}\, xr_{ijkt}^{r} \tag{2}$$

The third objective is to minimize the emission of greenhouse gases (i.e., the total emission of environmentally harmful gases) when injecting gas to extract oil and gas from underground reservoirs, processing and refining hydrocarbon products and transporting hydrocarbon products. This goal is expressed by Eq. (3), as follows:

$$Minmize\ RGHG = \sum_i \sum_t \sum_h ghgh_{it}^{h} + \sum_j \sum_t \sum_r ghgr_{jt}^{r} + \sum_n \sum_t ghgf_{nt} \tag{3}$$

A set of linear constraints is proposed to determine the feasible space of the model. These constraints are divided into the following parts: balance of materials in extraction centers, capacity of refineries and reservoirs, capacity of transmission routes, OPEC quota in international terminals, CO2 emissions in refineries, and stability of oil and gas fields.

The constraint of material balance:

Eq. (4) denotes the total extraction and separate delivery of crude oil and crude gas and the amount of loss of non-extractable gases according to the rate of their combination in oil and gas extracted in pole i in a given period (i.e., the principle of mass conservation in the network).

$$\sum_h \sum_t Ph_{ij}^{h} xe_{it}^{h} = \sum_h \sum_t xn_{ijt}^{h} \quad \forall\, i, j \tag{4}$$

Since the oil and gas extracted from pole i are separated into crude oil and gross gas by a simple initial process, each is transferred to the respective storage reservoirs with pipelines. The transfer constraint of this process is expressed by Eq. (5).

$$\sum_h \sum_j xn_{ijt}^{h} \le \sum_h H_{ijt}^{h} \quad \forall\, i, t \tag{5}$$

The storage volume of the extracted material from pole i is specified by Constraint (6).

$$\sum_t \sum_h (xn_{ijt}^{h} + xt_{ij(t-1)}^{h+}) - \sum_k \sum_t \sum_r xr_{ijkt}^{r} - \sum_t \sum_{Exp} xe_{ijt}^{Exp} \le Ce_{ij}^{h} \quad \forall\, i, j \tag{6}$$

Despite estimating the volume of underground oil and gas reservoirs, the extraction limit of pole i in Constraint (7) is as follows.

$$\sum_t \sum_h xe_{it}^{h} \le HC_i \ \forall\, i \tag{7}$$

The volume of extracted materials from the poles and the consumption of all domestic refineries according to macro policies are displayed by Constraint (8).

$$\sum_i \sum_k \sum_t \sum_r xr_{ijkt}^{r} + \sum_i \sum_{Exp} \sum_t xe_{ijt}^{Exp} \le OCC_j^{Exp} \quad \forall\, j \tag{8}$$

The maximum demand for the extracted materials of each extractor is the result of extraction in the period and the reserve of the previous period of each minus the export from that pole. This demand is shown by Constraint (9).

$$\sum_{k}\sum_{t}\sum_{r} xr^{r}_{ijkt} \leq \sum_{t}\sum_{h} xn^{h}_{ijt} + \sum_{h} xt^{h+}_{ij(t-1)} - \sum_{t}\sum_{Exp} xe^{Exp}_{ijt} \ \forall\, i,j \tag{9}$$

The extracted materials are transported from the extraction poles by different modes. This transportation is specified by Constraint (10).

$$\sum_{i}\sum_{j}\sum_{n}\sum_{t}\sum_{h}\sum_{r} P^{h}_{ijkn} xr^{r}_{ijkt} \leq \sum_{r} MC^{r}_{jk} \ \forall\, k \tag{10}$$

The storage of feed received by refineries involves some limitations given by Constraint (11).

$$\sum_{i}\sum_{t}\sum_{r} xr^{r}_{ikjt} + \sum_{p} xf^{r+}_{kj(t-1)} - \sum_{l}\sum_{t}\sum_{p} xp^{p}_{klt} \leq \sum_{r} SoC^{r}_{jk} \ \forall\, j,k,l \tag{11}$$

The materials extracted in different poles have different product rates, leading to different refinement of products in refineries. This issue is specified in Constraint (12).

$$\sum_{i}\sum_{j}\sum_{l}\sum_{r}\sum_{t} Pr^{r}_{ijkl} xr^{r}_{ijkt} \leq \sum_{i}\sum_{j}\sum_{r}\sum_{t} xr^{r}_{ijkt} \tag{12}$$

Each refinery has specific production limitations expressed by Constraint (13).

$$\sum_{i}\sum_{l}\sum_{t}\sum_{r}\sum_{k} Pr^{r}_{ijkl} xr^{r}_{ijkt} \leq \sum_{k}\sum_{r}\sum_{t} Cr^{r}_{kjt} \ \forall\, j \tag{13}$$

Each product processed in refineries has independent reservoirs with storage limits. These limitations are specified in Constraints (14) and (15).

$$\sum_{t}\sum_{p} xp^{p}_{klt} + \sum_{p}\sum_{t} xrp^{p+}_{kl(t-1)} - \sum_{m}\sum_{t}\sum_{p} xdp^{p}_{klmt} \leq \sum_{p} SC^{p}_{kl} \ \forall\, k,l \tag{14}$$

$$\sum_{t}\sum_{p} xp^{p}_{klt} \leq \sum_{i}\sum_{j}\sum_{t}\sum_{r} Pr^{r}_{ijkl} xr^{r}_{ijt} \ \forall\, t,k,l \tag{15}$$

Constraint (16) shows how refinery products are transported to distribution centers.

$$\sum_{k}\sum_{n}\sum_{t}\sum_{p} Pp^{p}_{klmn} xp^{p}_{klt} \leq \sum_{u} TC^{u}_{lm} \ \forall\, m,k,l \tag{16}$$

Constraints of demand from extractors:

Eq. (17) specifies the constraint of the extraction amount of poles and the demand for refineries in the given period.

$$\sum_{i}\sum_{h}\sum_{j}\Big(\sum_{t} xn^{h}_{ijt} + xt^{h+}_{ij(t-1)}\Big) = \sum_{i}\sum_{r}\sum_{h}\sum_{j}\Big(\sum_{k}\sum_{t} dr^{r}_{ijkt} + xt^{h+}_{ij(t-1)}\Big) \tag{17}$$

Constraints of demand from refineries: The constraint of demand from refineries is expressed by Eq. (18).

$$\sum_{k}\sum_{p}\sum_{l}(\sum_{t} xp_{klt}^{p} + xrp_{kl(t-1)}^{p+}) = \sum_{p}\sum_{k}\sum_{l}\sum_{m}(\sum_{t} dp_{klmt}^{p} + xrp_{kl(t-1)}^{p-}) \tag{18}$$

The OPEC quota is represented by Eq. (19). According to this constraint, the total amount of crude oil of different types in international terminals should not exceed the OPEC quota or the market share.

$$\sum_{i}\sum_{t}\sum_{Exp} xe_{ijt}^{Exp} \leq OPECQ \;\; \forall j = 1(oil\ crude) \tag{19}$$

Constraint (20) specifies CO2 emissions.

$$\sum_{i}\sum_{t}\sum_{j} xn_{ijt}^{h} \leq Cm_{max} \;\; \forall j = 3(Flare\ Gas) \tag{20}$$

Case Study

The production and distribution chain of actual flexible petroleum products from Iran was selected for the proposed model, followed by an analysis of the obtained numerical results. Afterward, sensitivity analysis is performed to check the model's critical parameters on the decisions. Fig. 2 presents the map of hydrocarbon materials' extraction and production poles and the location of the existing oil and gas refineries in Iran. As can be seen, the distribution centers in the country are extensive and cover the entire country.

A network for this purpose includes production hubs, oil and gas refineries, and main distribution centers in the country (Fig. 3).

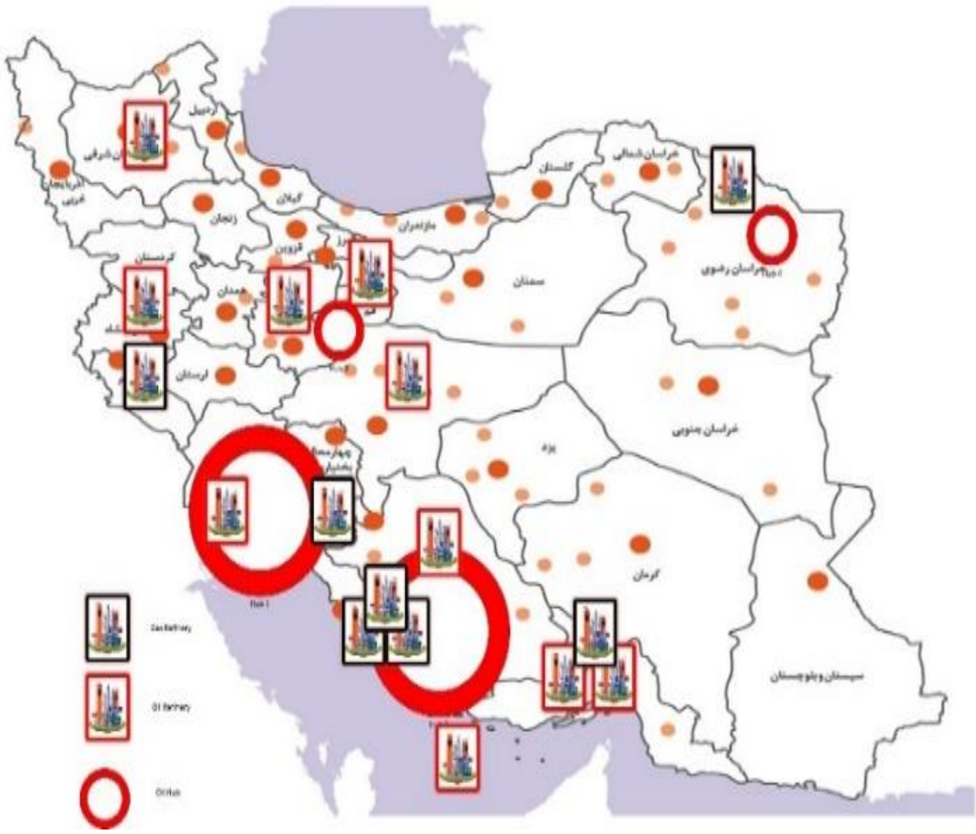

Fig. 2. Hydrocarbon reservoirs of Iran

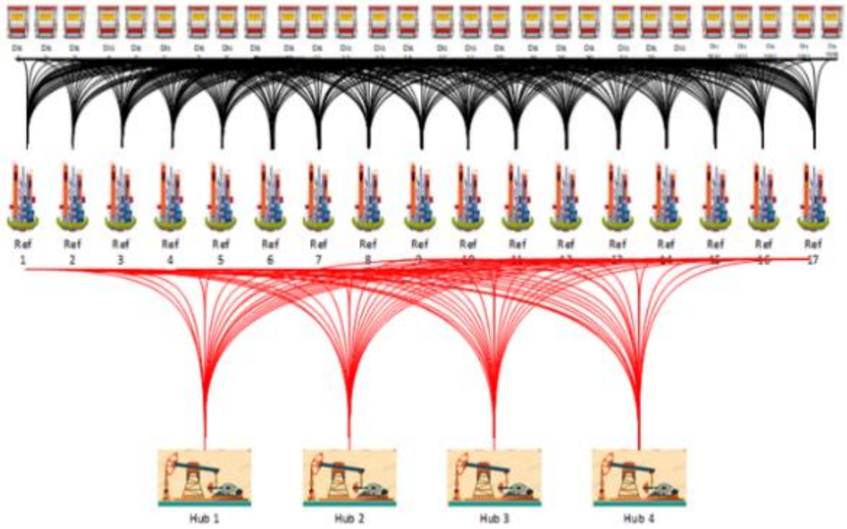

Fig. 3. Hydrocarbon production and distribution network

Augmented Epsilon Constraint Approach

The linear programming model developed in the present study is the augmented epsilon (ε)-constrained (AEC) method to maximize chain profit and reservoir discharge rate, as well as mitigate the greenhouse effects. Accordingly, one of the high-priority objective functions is optimized by transferring the other objective functions to constraints. In this respect, one of the existing objective functions is selected as the primary objective function, and other objective functions are converted into upper-bound constraints. This method generates a set of Pareto optimal solutions for the decision-maker. However, due to the unreliable recognition of the range of suitable changes, the lack of guaranteeing the efficiency of the generated solutions, and prolonged problem-solving time, the generalized ε-constrained method is developed such that the constraint related to the sub-objective functions is converted into equality by adding additional variables. Meanwhile, the normalized values of the excess variables are considered the second term in the objective function, forcing the problem to produce an efficient solution. Uncertainty is controlled using a fuzzy mathematical programming approach based on the credibility index. The credibility criteria is the average of the possibility and obligation indicators. Equipped with characteristics such as the probability index, this index plays the role of the probability size in the random space. Accordingly, non-deterministic parameters are assumed to be triangular fuzzy numbers. Here, non-deterministic parameters include the demand and selling price of oil. In this research, the expected value and limited chance programming method were integrated to develop a fuzzy mathematical programming approach based on the credibility index. This hybrid approach not only does not increase constraints but also does not require components such as confidence level or ideal solution.

When there is a gap between the exact answer and the obtained answer, the penalty due to the model execution raises the risk of deviation from the optimal results of the decisions. Therefore, the Benders decomposition algorithm was developed as an accurate method to decrease the problem's complexity. This algorithm converges to the optimal solution during fewer iterations. Fig. 4 presents the steps for implementing this research.

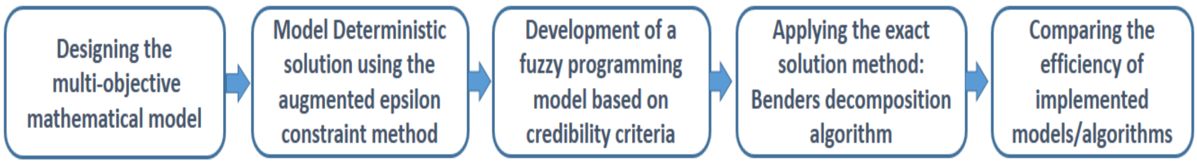

Fig. 4. Research implementation process

Fuzzy Credibility-Constrained Programming (FCCP)

The AEC method was applied to calculate the efficient solutions to the multi-objective problem. These solutions include only those in the Pareto optimal area.

$$\begin{aligned}&min f_1(x)\\&min f_2(x)\\&\text{s.t}\\&x \epsilon \tilde{s}\end{aligned} \tag{21}$$

where x is the vector of the decision variable, f_1 and f_2 are the objectives of the problem and $\tilde{s}$ is the feasible region of the problem.

The relevant balance table is prepared using the single objective optimization method to apply this method effectively. Next, the range of each target is divided into equal distances (e_f), which creates a guide point $e_f + 1$. Based on this, model (22) is built as follows:

$$\begin{aligned}&min f_1(x)\\&\text{s.t}\\&f_1(x) \leq e_{f_2}\\&x \in \tilde{s}\end{aligned} \tag{22}$$

where e_{f_2} is calculated as follows:

$$e_f = \frac{l_f + (j_f + v_f)}{s_f} \tag{23}$$

where l_f is the lower boundary of the second objective function, v_f is the range of the second objective function, s_f is the number of guide points, and j_f is the counter of the function from 0 to a number as large as the generation of efficient solutions. Model (23) provides an efficient answer only if the constraints related to the objective function are mandatory. Otherwise, the obtained answer is inefficient. Therefore, the model is rearranged in the following simple way to provide an efficient answer:

$$\begin{aligned}&min\left(f_1(x) + \varepsilon\left(-\frac{\varphi f_2}{v f_2}\right)\right)\\&\text{s.t}\\&f_2(x) + \varphi f_2 = e\\&x \in \tilde{s}\\&\varphi f_2 \in R^+\end{aligned} \tag{24}$$

where ε is a very small number in this model

Fuzzy Credibility-Constrained Programming (FCCP)

In this research, fuzzy multi-objective programming was used to address the problems of parametric uncertainty. The changes in each objective function are expressed as a fuzzy membership function. Then, one of the membership functions is included in the constraints, and the other is included in the target function to control the value of the constraints and calculate the best value. The proposed solution method is presented based on the AEC method, except that fuzzy utility values are used instead of objective function values. This method works based on two concepts: α_{nadir} and $\alpha_{optimal}$. Here, $\alpha_{optimal}$ is the best optimal solution for each objective function and the corresponding decision variables (Pishvaee et al., 2012). In addition, α_{nadir} is the worst value allowed for each objective function, which is defined according to Eq. (25):

$$F_1^{\alpha_{optimal}} = Max\{F_1 | x \in E(x)\}$$
$$F_2^{\alpha_{optimal}} = Max\{F_2 | x \in E(x)\} \tag{25}$$

where E(x) is the set of reasonable solutions to the problem. When the following objective function has an optimal solution, it is calculated using Eq. (26):

$$F_1^{\alpha_{nadir}} = Max\{F_1 \middle| F_2 \le F_2^{\alpha_{nadir}} and\ x \in E(x)\}$$
$$F_2^{\alpha_{nadir}} = Max\{F_2 \middle| F_1 \ge F_1^{\alpha_{nadir}} and\ x \in E(x)\} \tag{26}$$

The linear fuzzy utility function for each objective function is defined as follows:

$$\mu_1(F_1) = \begin{cases} 1 & F_1 > F_1^{\alpha_{optimal}} \\ 0 & F_1 < F_1^{\alpha_{nadir}} \\ \dfrac{F_1 - F_1^{\alpha_{nadir}}}{F_1^{\alpha_{optimal}} - F_1^{\alpha_{nadir}}} & otherwise \end{cases} \tag{27}$$

$$\mu_2(F_2) = \begin{cases} 1 & F_2 > F_2^{\alpha_{optimal}} \\ 0 & F_2 < F_2^{\alpha_{nadir}} \\ \dfrac{F_2^{\alpha_{nadir}} - F_2}{F_2^{\alpha_{nadir}} - F_2^{\alpha_{optimal}}} & otherwise \end{cases} \tag{28}$$

where $\mu_1(x)$ and $\mu_2(x)$ are the degree of fuzzy membership for the first and second objective functions, respectively.

Eq. (29) is used to estimate the multi-objective problem based on the single-objective model using the AEC method:

$$max\{\mu_1(x) | \mu_2(x) \ge \varepsilon, x \in F(x), 0 \le \varepsilon \le 1\} \tag{29}$$

where the satisfaction degree with the performance of the first objective is used in the maintenance objective function. Meanwhile, the satisfaction degree with the second objective function is used as an additional constraint. Also, the epsilon value is systematically determined in the range of 0 and 1.

The general configuration of the present problem according to constraints (30-34) is as follows:

$$\begin{aligned} & Min\ z = (\widetilde{fi})y + (\widetilde{Vc})x \\ & s.t\ \ Ax \ge \widetilde{dm} \\ & Bx = 0 \\ & Sy \le (\widetilde{H})x \\ & x \in \{0,1\}, y \ge 0 \end{aligned} \tag{30}$$

In this research, fi, $\widetilde{Vc}$, and dm are the parameters vector, and A, B, S, and H express the matrix of parameters for the technical coefficients of the model. In this respect, A, B, and S are estimated deterministically. Moreover, fi, Vc, dm, and H are fuzzy variables related to investment cost, other costs, customer demand, and capacity, respectively. The first and third constraints of the problem are fuzzy-chance constrained. In this study, these constraints are controlled using the credibility index presented in the above constraints as follows:

$$\begin{aligned} & Min\ \bar{M}[\widetilde{fi}]x + \bar{M}[\widetilde{Vc}]y \\ & s.t\ Cr(\tilde{A}y \ge \widetilde{dm}) \ge \rho \\ & Bx = 0 \\ & Cr(Sy \le \tilde{H}x) \ge \omega \\ & x \in \{0,1\}, y \ge 0 \end{aligned} \tag{31}$$

Regarding the mentioned points, in this section, only some parts of the objective function and constraints are developed as a deterministic model:

$$
\begin{aligned}
Max\ benefit = & \sum_i \sum_j \sum_t \left(\frac{Pi_{j(1)}^h + 2Pi_{j(2)}^h + Pi_{j(3)}^h}{3}\right).x_{ijt}^h \\
& - \sum_i \sum_j \sum_t \left(\frac{Pi_{j(1)}^h + 2Pi_{j(2)}^h + Pi_{j(3)}^h}{3}\right).x_{ijt}^{Exp} \\
& + \sum_j \sum_i \sum_t \left(\frac{Pe_{j(1)}^h + 2pe_{j(2)}^h + pe_{j(3)}^h}{3}\right).x_{ijt}^{Exp} \\
& + \sum_k \sum_l \sum_t \left(\frac{Pri_{l(1)}^r + 2Pri_{l(2)}^r + Pri_{l(3)}^r}{3}\right).x_{klt}^r \\
& - \sum_l \sum_k \sum_t \left(\frac{Pri_{l(1)}^r + 2Pri_{l(2)}^r + Pri_{l(3)}^r}{3}\right).x_{klt}^{Exp})) \\
& + \sum_l \sum_k \sum_t \left(\frac{Pre_{l(1)}^r + 2Pre_{l(2)}^r + Pre_{l(3)}^r}{3}\right).x_{klt}^{Exp} \\
& + \sum_k \sum_l \sum_m \sum_t \left(\frac{Pdi_{l(1)}^r + 2Pdi_{l(2)}^r + Pdi_{l(3)}^r}{3}\right).x_{klmt}^p \\
& - \sum_i \sum_j \sum_t \left(\frac{C_{ij(1)}^h + 2C_{ij(2)}^h + C_{ij(3)}^h}{3}\right).x_{ijt}^h \\
& - \sum_k \sum_l \sum_t \left(\frac{Cr_{kl(1)}^r + 2Cr_{kl(2)}^r + Cr_{kl(3)}^r}{3}\right).x_{klt}^r) \\
& - \sum_j \sum_n \sum_i \sum_k \left(\frac{C_{jn(1)}^h + 2C_{jn(2)}^h + C_{jn(3)}^h}{3}\right).TD_{ik}^h \\
& - \sum_l \sum_n \sum_k \sum_m \left(\frac{C_{ln(1)}^r + 2C_{ln(2)}^r + C_{ln(3)}^r}{3}\right).TD_{km}^r \\
& - \sum_i \sum_j \sum_t \left(\frac{C_{ij(t-1)}^{h+} + 2C_{ij(t-1)}^{h+} + C_{ij(t-1)}^{h+}}{3}\right).x_{ij(t-1)}^{h+} \\
& - \sum_i \sum_j \sum_t \left(\frac{C_{ijt(1)}^{h-} + 2C_{ijt(2)}^{h-} + C_{ijt(3)}^{h-}}{3}\right).x_{ijt}^{h-} \\
& - \sum_k \sum_l \sum_t \left(\frac{C_{kl(t-1)(1)}^{p+} + 2C_{kl(t-1)(2)}^{p+} + C_{kl(t-1)(3)}^{p+}}{3}\right).x_{kl(t-1)}^{p+} \\
& - \sum_k \sum_l \sum_t \left(\frac{C_{klt(1)}^{p-} + 2C_{klt(2)}^{p-} + C_{klt(3)}^{p-}}{3}\right).x_{klt}^{p-} \\
& - \sum_l \sum_m \sum_t \left(\frac{C_{lm(t-1)(1)}^{p+} + 2C_{lm(t-1)(2)}^{p+} + C_{lm(t-1)(3)}^{p+}}{3}\right).x_{lm(t-1)}^{p+} \\
& - \sum_k \sum_l \sum_t \left(\frac{C_{lmt(1)}^{p-} + 2C_{lmt(2)}^{p-} + C_{lmt(3)}^{p-}}{3}\right).x_{lmt}^{p-}
\end{aligned} \tag{32}
$$

$$\sum_t ([(2-2\varepsilon)P_{ij}^h + (2\varepsilon - 1)P_{ij}^h]x_{it}^h) = \sum_t x_{ijt}^h \ \forall\, i,j,t \tag{33}$$

$$\sum_i \sum_j \sum_n \sum_t ([(2-2\varepsilon)P_{ijkn}^h + (2\varepsilon - 1)P_{ijkn}^h]x_{ijkt}^r) \le MC_{jk}^r \ \forall\, i,j,t,k \tag{34}$$

$$\sum_i \sum_j \sum_l \sum_t ([(2-2\varepsilon)P_{ijkl}^r + (2\alpha - 1)P_{ijkl}^r]x_{ijkt}^r) \le \sum_i \sum_j \sum_t x_{ijkt}^r \ \forall\, i,j,t,k,l \tag{35}$$

$$\sum_i \sum_l \sum_t ([(2-2\varepsilon)P^r_{ijkl} + (2\varepsilon-1)P^r_{ijkl}]x^r_{ijkt}) \le ([(2\varepsilon-1)C^r_{kjt} + (2-2\varepsilon)C^r_{kjt}])\ \forall\, i,j,t,k,l \tag{36}$$

$$\sum_t x^p_{klt} \le \sum_i \sum_j \sum_t ([(2\varepsilon-1)P^r_{ijkl} + (2-2\varepsilon)P^r_{ijkl}]x^r_{ijt})\ \forall\, i,j,t,k,l \tag{37}$$

$$\sum_k \sum_n \sum_t ([(2-2\varepsilon)P^p_{klmn} + (2\varepsilon-1)P^p_{klmn}]x^p_{klt}) \le TC^u_{lm}\ \ \forall\, i,j,t,k,l \tag{38}$$

$$\sum_i \sum_j (\sum_t x^h_{ijt} + x^{h+}_{ij(t-1)}) = \sum_i \sum_j (\sum_k \sum_t ([(2\varepsilon-1)d^r_{ijkt} + (2-2\varepsilon)d^r_{ijkt}]) + x^{h-}_{ij(t-1)})\ \ \forall\, i,j,t,k,l \tag{39}$$

$$\sum_k \sum_l (\sum_t x^p_{klt} + x^{p+}_{kl(t-1)}) = \sum_k \sum_l \sum_m (\sum_t ([(2\alpha-1)d^p_{klmt} + (2-2\alpha)d^p_{klmt}]) + x^{p-}_{kl(t-1)})\ \forall\, i,j,t,k,l \tag{40}$$

$$\sum_i \sum_t x^h_{ijt} \le [(2\varepsilon-1)C_{max} + (2-2\varepsilon)C_{max}]\ \forall\, i,j,t,\forall j = 3(Flare\ Gas) \tag{41}$$

$$\varepsilon \in [0,1] \tag{42}$$

Benders Decomposition Algorithm

This research offers two efficient problem-solving processes. Then, better quality solutions are generated using the fuzzy validity limit planning approach. Next, the solution space is limited by defining the fuzzy credibility or inequality constraints and assigning them to the problem. Finally, more efficient answers are generated. These inequalities are defined according to the conditions and assumptions of the problem. Therefore, several valid optimal cuts with different strengths associated with a set of optimal solutions are generated. In this case, among the possible answers, we look for a cut that generates a more robust cut. It is of note that the Benders decomposition method reaches the optimal solution in finite iterations and at an appropriate convergence rate.

Benders decomposition algorithm has been developed as an exact solution for optimization problems. In this respect, when there is a gap between the exact solution and the obtained solution, a significant penalty is imposed on the problem. Thus, the Benders algorithm is applied to decrease the complexity of the master problem. The above problem converges to the optimal solution in fewer iterations.

In Benders decomposition, the main optimization problem is a function of a master problem, and sub-problems are solved iteratively based on each other's solutions. The master problem optimizes the decision variables. Besides, based on the decisions made in the master problem, the Benders problem iteratively creates new constraints until the overall optimal solution is formed. In this research, discrete and binary variables were considered for complex variables to determine the DSP model. Afterward, the Benders decomposition algorithm was used to solve the proposed model. If the vectors q and y are binary variables of the problem, then DSP is deemed a lower bound for the objective function. The master problem in each iteration is formulated as follows:

$$DSP\!: min \sum_i \sum_j \sum_t ((Pi^h_j \times (xn^h_{ijt} - xe^{Exp}_{ijt})) + (Pe^h_j \times xe^{Exp}_{ijt}))y + \sum_k \sum_l \sum_t ((Pri^r_l \times xex^{Exp}_{klt}))y + (Pre^r_l \times x^{Exp}_{klt})) \tag{43}$$

s.t

$$\sum_t ph^h_{ij} xe^h_{it}\, q = -\sum_t xn^h_{ijt}\ \ \forall\, i,j,t \tag{44}$$

$$\sum_t xn^h_{ijt}\, q \ge -H^h_{ij}\ \forall\, i,j,t \tag{45}$$

$$\sum_{t} xn_{ijt}^{h} + xt_{ij(t-1)}^{h+} - \sum_{k}\sum_{t} xr_{ijkt}^{r} - \sum_{t} xe_{ijt}^{Exp}\, q \geq -Ce_{ij}^{h} \quad \forall\, i,j,t,k \tag{46}$$

$$\sum_{t} xe_{it}^{h}\, q \;\geq HC_i \;\forall\, i,t \tag{47}$$

$$\sum_{i}\sum_{k}\sum_{t} xr_{ijkt}^{r}\, q + \sum_{i}\sum_{t} xe_{ijt}^{Exp}\, q \geq OCC_{j}^{Export} \quad \forall\, i,j,t,k \tag{48}$$

$$\sum_{k}\sum_{t} xr_{ijkt}^{r} \;\geq \sum_{t} xn_{ijt}^{h} + xt_{ij(t-1)}^{h+} q - \sum_{t} xe_{ijt}^{Exp}\, q \;\forall\, i,j,t \tag{49}$$

$$\sum_{i}\sum_{j}\sum_{n}\sum_{t} P_{ijkn}^{h} xr_{ijkt}^{r}\, q \;\geq MC_{jk}^{r} \;\forall\, i,j,t,k \tag{50}$$

$$q, y \geq 0 \tag{51}$$

According to DSP and MP models, the upper bound for the primary objective function of the model in each iteration is as follows:

$$\begin{aligned} MP\colon Max^{MP} = {} & \sum_{i}\sum_{j}\sum_{t}((Pi_{j}^{h} \times (xn_{ijt}^{h} - xe_{ijt}^{Exp})) + (Pe_{j}^{h} \times xe_{ijt}^{Exp})) + \sum_{k}\sum_{l}\sum_{t}((Pri_{l}^{r}\; xex_{klt}^{Exp})) \\ & + (Pre_{l}^{r} \times xex_{klt}^{Exp})) \\ & + \sum_{k}\sum_{l}\sum_{m}\sum_{t}(Pdi_{l}^{r} \times xdp_{klmt}^{p}) - \sum_{i}\sum_{j}\sum_{t}(Ch_{ij}^{h} \times xn_{ijt}^{h}) \\ & - \sum_{k}\sum_{l}\sum_{t}(Crp_{kl}^{r} \times xr_{klt}^{r}) \\ & - \sum_{j}\sum_{n}\sum_{i}\sum_{k}\left(Cc_{jn}^{h} \times TD_{ik}^{h}\right) \\ & - \sum_{l}\sum_{n}\sum_{k}\sum_{m}(Cl_{ln}^{r} \times TDr_{km}^{r}) - \sum_{i}\sum_{j}\sum_{t}(Chm_{ij(t-1)}^{h+} \times xt_{ij(t-1)}^{h+}) \\ & - \sum_{i}\sum_{j}\sum_{t}(Chc_{ijt}^{h-} \times xsp_{ijt}^{h-}) \\ & - \sum_{k}\sum_{l}\sum_{t}(Ccp_{kl(t-1)}^{p+} \times xrp_{kl(t-1)}^{p+})\,) - \sum_{k}\sum_{l}\sum_{t}(Ccs_{klt}^{p-} \times xpp_{klt}^{p-}) \\ & - \sum_{l}\sum_{m}\sum_{t}(Cmp_{lm(t-1)}^{p+} \times xrc_{lm(t-1)}^{p+}) - \sum_{k}\sum_{l}\sum_{t}(Ccs_{klt}^{p-} \times xs_{lmt}^{p-}) \end{aligned} \tag{52}$$

s.t

Cuttable:

$$\begin{aligned} \theta \leq {} & \sum_{i}\sum_{j}\sum_{t}((Pi_{j}^{h} \times (xn_{ijt}^{h} - xe_{ijt}^{Exp})) + (Pe_{j}^{h} \times xe_{ijt}^{Exp}))y + \sum_{k}\sum_{l}\sum_{t}((Pri_{l}^{r} \times xex_{klt}^{Exp}))y \\ & + (Pre_{l}^{r} \times xex_{klt}^{Exp})) - \sum_{i}\sum_{j}\sum_{t}[(\Delta Pi_{j}^{h} \times \Delta xn_{ijt}^{h} - \Delta xe_{ijt}^{Exp}) + (\Delta Pe_{j}^{h} \times \Delta xe_{ijt}^{Exp})] \end{aligned} \tag{53}$$

Optimality cut:

$$\begin{aligned} & \sum_{i}\sum_{j}\sum_{t}((Pi_{j}^{h} \times (xn_{ijt}^{h} - xe_{ijt}^{Exp})) + (Pe_{j}^{h} \times xe_{ijt}^{Exp}))y + \sum_{k}\sum_{l}\sum_{t}((Pri_{l}^{r} \times xex_{klt}^{Exp}))y \\ & \quad + (Pre_{l}^{r} \times xex_{klt}^{Exp})) - \sum_{i}\sum_{j}\sum_{t}[(\Delta Pi_{j}^{h} \times \Delta xn_{ijt}^{h} - \Delta xe_{ijt}^{Exp}) + (\Delta Pe_{j}^{h} \times \Delta xe_{ijt}^{Exp})] \\ & \quad \geq 0 \end{aligned} \tag{54}$$

The low quality of the solutions obtained from MP Pareto optimal cut is among the factors leading to the low convergence speed of the classic Benders decomposition algorithm. This inefficiency can be prevented by setting valid inequalities (constraints). Next, the problem's solution space is constrained by adding these constraints to the MP problem, and more quality solutions are produced. The DSP model may have multiple optimal solutions in some iterations. Therefore, several valid optimal cuts with different strengths associated with a set of optimal solutions are generated. In this case, among the possible solutions, a cut that can generate a stronger cut is selected. Thus, the master problem and the sub-problem are solved iteratively until reaching a termination condition; i.e., when the distance between the upper bound and the lower bound is less than a certain value.

Accordingly, the flow of different levels of the supply chain, demand, and price of valid unequal products are added to the MP.

$$\sum_{i,j,t} C_{ij}^{h} X_{ijt}^{p} \leq \sum_{j} HC_{j} \tag{55}$$

$$\sum_{k,l,t} C_{kl}^{r} X_{klt}^{h} \leq \sum_{j,k} SC_{jk}^{r} \tag{56}$$

$$\sum_{i,j,t} X_{ijt}^{p} \leq \sum_{i,j.k.t} d_{ijkt}^{r} \tag{57}$$

Computational Results

This practical development research was conducted to solve the design and planning problem of the HCSC. The proposed approach is aimed at assisting in the optimal planning of crude oil supply chain management and the sustainability of oil reservoirs. These efforts are made to maximize the profit from selling hydrocarbon products in the chain of extraction, refining, distribution, and selling crude oil in the planning horizon. The sustainability approach is followed to minimize the effect of greenhouse gases and reduce the extraction rate of oil reservoirs. To this end, a multi-period mixed integer linear programming (MILP) was presented. Afterward, the model is applied to determine the key decision variables (e.g., the amount of crude oil extraction and demand, the amount of shortage, and the inventory of manufactured products). The fuzzy credit limit programming approach controls the uncertainty of the problem. Hence, the decision maker can satisfy the chance constraints at some confidence level. The demand and price of crude oil and the stability of oil reservoirs are critical parameters in oil field development and operations and significantly affect decisions. Besides, since oil field development is planned in the medium and long terms, the uncertainty of the data increases.

In this section, a numerical example is solved to check the model’s performance. For this purpose, 4 sites for extraction poles, 7 sites for oil and gas refineries, 25 main distribution sites, and 380 consumers are considered. This research was conducted in 10 time periods, and model parameters were extracted from a specific period. The model was solved using GAMS software and using the AEC method. The problem solutions with deterministic, fuzzy approaches and the Benders decomposition algorithm are presented in Table 2.

Due to the uncertainty involved in selling prices and demand values, the problem is solved through fuzzy programming. In this approach, instead of defining fixed values for these parameters, random variables and probabilistic functions are used to represent uncertainty. The fuzzy set for the selling price of crude oil is determined as a fuzzy set with “low”, “medium”, and “high” values. These values are based on the deterministic data. In this problem, the values corresponding to “low”, “medium”, and “high” are equal to \$68, \$76, and \$81, respectively. The fuzzy set for demand is determined in the same way. The values of “low”, “medium”, and “high” demand are equal to 300,000, 800,000, and 1200,000 barrels per day, respectively. However, due to the lack of full use of extraction poles and refining companies, 15% of these values are considered. According to the values obtained in the deterministic approach, we solved only the profit that was subject to the first objective and was affected by the two uncertainties of prices and demand. In addition, the deterministic solution was applied to extract the dependent values of greenhouse gas emissions and the consumption of underground hydrocarbon resources based on the extracted values that lead to profit.

compares profit values based on the dependence of extraction and refining values on underground resource extraction and greenhouse gas emissions. Considering the stability of the second and third objectives, the profit obtained in these three methods varies from 39 $MM to 42 $MM. The best profit was obtained in the Benders decomposition method, marked with green dots in the Pareto diagrams of all three solutions.

Table 2. The outputs of solution approaches

	Deterministic solution			Fuzzy solution			Benders solution		
Period	Obj1	Obj2	Obj3	Obj1	Obj2	Obj3	Obj1	Obj2	Obj3
1	34.2	0.261	0.181	36.49	0.261	0.181	39.29	0.261	0.181
2	38.9	0.53	0.331	41.32	0.53	0.331	42.2	0.53	0.331
3	31.7	0.095	0.122	34.08	0.095	0.122	35.18	0.095	0.122
4	42.3	0.832	0.606	44.79	0.832	0.606	44.99	0.832	0.606
5	36.8	0.405	0.272	38.12	0.405	0.272	41.33	0.405	0.272
6	30.5	0.048	0.082	33.06	0.048	0.082	34.65	0.048	0.082
7	44.2	1.015	0.818	46.76	1.015	0.818	47.16	1.015	0.818
8	41.6	0.741	0.499	42.61	0.741	0.499	44.23	0.741	0.499
9	39.1	0.641	0.406	41.61	0.641	0.406	43.53	0.641	0.406
10	33.8	0.182	0.165	41.32	0.53	0.331	37.47	0.182	0.165

Fig. 5 illustrates the problem solution through the deterministic approach. As can be seen, for-profit values of about 34 $MM for the extraction, the amount of underground resources used has grown abnormally. Meanwhile, the amount of profit and the greenhouse gas emissions follow the same trend from the beginning, and this trend continues until the amount of extraction leads to a profit of 39 $MM. At this stage, after passing the constant profit trend, both the use of underground reservoirs and the greenhouse gas emissions have grown significantly. This trend has continued up to the amount of mining that leads to a profit of slightly more than 42 $MM. Afterward, their growth rate slows down, but they go through an upward trend. This trend suggests that after the amount of mining that leads to a profit of 39 $MM, the greenhouse gas emissions and the use of underground resources have increased due to the lack of extraction and proper processing. As can be noticed, the optimal point in this type of deterministic solution is a profit of 39 $MM. This profit is obtained from selling crude petroleum products in a specific period, according to the policies of determining the extraction and greenhouse gas emission limitations.

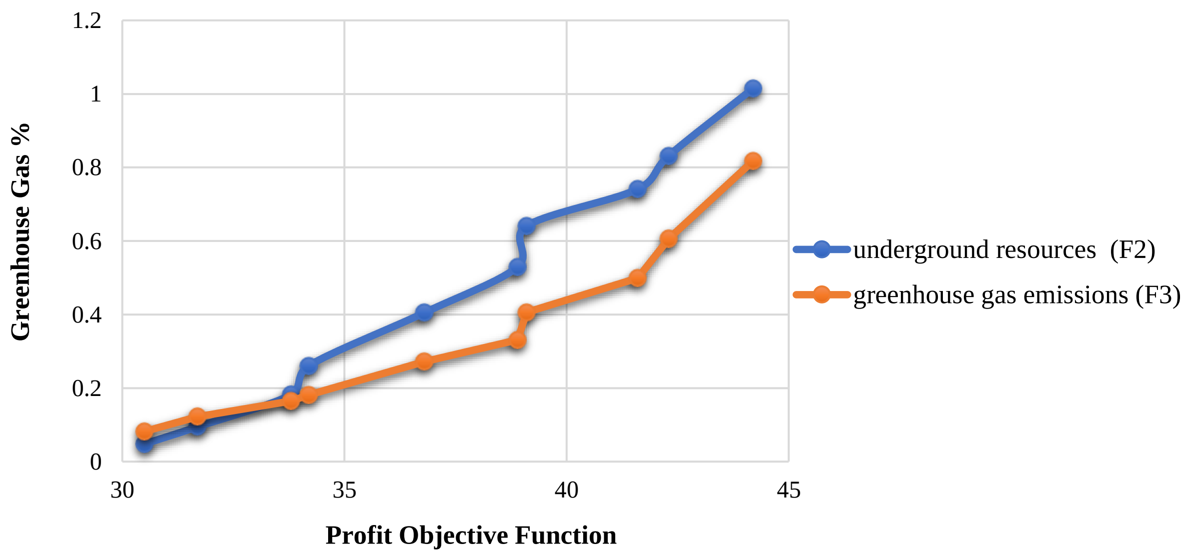

Fig 5. Performance graph of objective functions

The above process is examined using the fuzzy solution approach in Fig. 6. As can be seen, the underground resources have grown normally for the extraction amount, for which the profit was 36 $MM. Nevertheless, from 36 million to 38 $MM, there is some acceleration until the extraction time, leading to about 41 $MM of less growth. Afterward, the growth rate of using underground resources and the greenhouse gas emissions increases such that the best Pareto point in this type of fuzzy solution is the profit level of 41 $MM. This profit is attributed to selling crude petroleum products in a specific period according to the policies of extraction and green gas emission constraints.

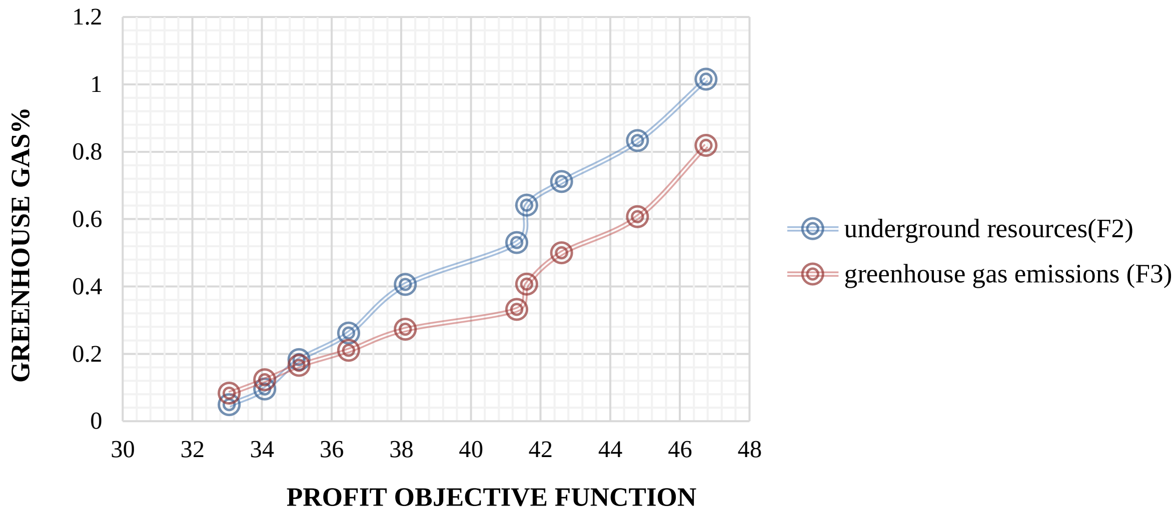

Fig 6. Performance diagram of objective functions relative to each other in the fuzzy solution

Fig. 7 exhibits the answer obtained from the Benders decomposition method. According to this figure, the use of underground resources has grown normally for the extraction amount where the profit was 37 $MM. However, from a profit of 37 to 39 $MM, this use has accelerated slightly until the extraction time, which leads to about 42 $MM of lower growth. After that, the growth rate of using underground resources and greenhouse gas emissions increases abnormally. In this situation, the best Pareto point for this profit is 42 $MM, which is derived from selling crude petroleum products in a certain period according to the policies of extraction and greenhouse gas emission limits.

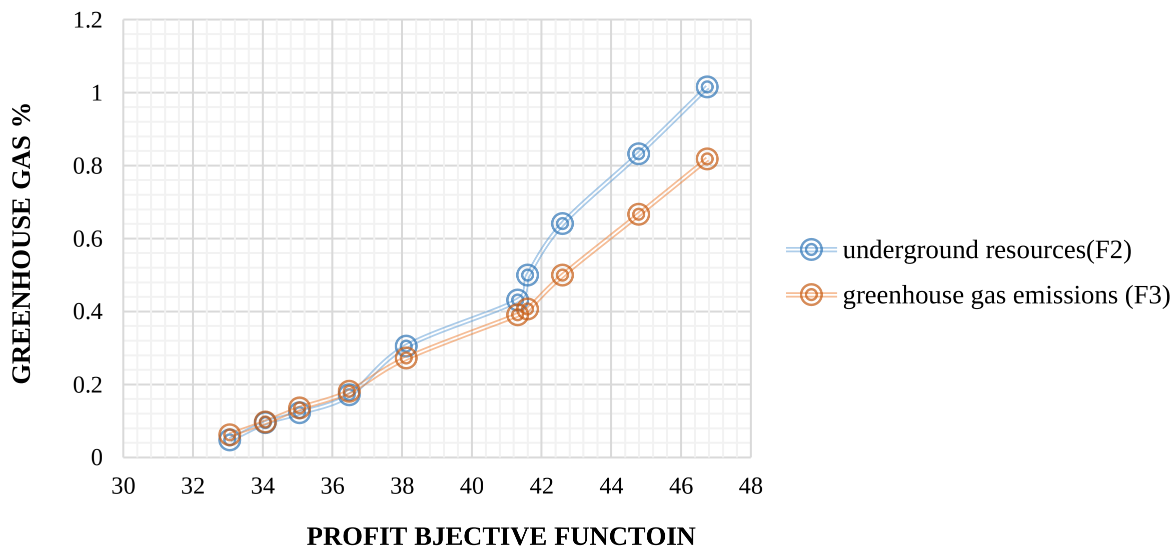

Fig. 7. Performance diagram of objective functions relative to each other in Benders decomposition method

Fig. 8 demonstrates the convergence process of the upper bound and the lower bound of the decomposition Benders algorithm. As can be seen, by increasing the number of iterations, the objective function value takes an upward trend. The lower bound of this method is always upward, and its upper bound fluctuates. The validation results show that the hydrocarbon products supply chain network model algorithm proposed in this research efficiently solves large-scale problems.

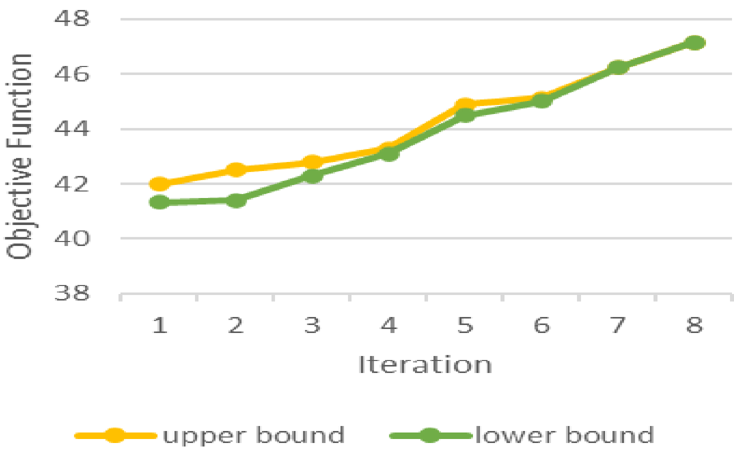

Fig 8. Convergence of the BD algorithm

With the fluctuations in the crude oil price, important parameters also change and increase some costs (e.g., insurance costs and the cost of using energy for processing). As a result, 80 dollars per barrel of crude oil is obtained by keeping the demand constant and extracting the highest profit. In three methods proposed for solving the problem, sensitivity to price change and the main function without sensitivity to price change are obtained based on Table 3.

Table. 3. Profit sensitivity to price fluctuations

Sale price ($)	Profit: Deterministic ($MM)-deterministic	Profit: Fuzzy ($MM)-Fuzzy	Profit: Second deterministic ($MM)-Benders decomposition
Solving the problem without changing the crude oil price	38.9	41.32	42.2
Price change to 70$	40	42	41.2
Price change to 75$	43	45.6	44.6
Price change to 80$	41.5	43.8	42.9

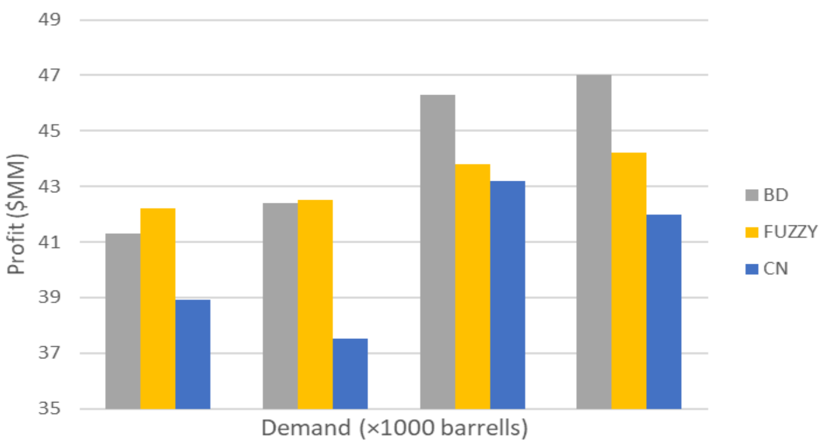

Fig 9. Sensitivity analysis of demand change

According to Fig. 9, with a temporary production increase from 500,000 to 650,000 barrels, the relative profit decreased in all three methods. However, it increased significantly and reached higher than the initial oil. Therefore, with the increase in demand, the profit increases and reaches its highest level in a certain period. According to the convergence analysis in this study, no changes occurred in the direction of improving one objective without decreasing at least one of the other objectives. In this regard, seeking advice from industry experts and presenting new approaches and solutions can be beneficial to enhance performance and achieve more effective development. These approaches may encompass process optimization, the use of advanced and cutting-edge technologies, reduction in the consumption of limited resources and raw materials, improvements in production processes, and enhancing the efficiency of human resources.

Table 4 compares computing time, the number of Benders cuts, and the convergence of the lower bound. As can be seen, CPLEX computing time for 7 iterations is lower than the number of higher iterations, and it cannot be solved from experiment 3 onward. However, in more experiments, the Benders algorithm performs better, and the biggest gap is in iteration 7. One of the characteristics of the Benders algorithm is that its lower limit always ascends and fluctuates. Based on the upper and lower boundaries, the optimal gap is obtained from the following formula

$$Optimality\ Gap = \frac{UB - LB}{LB} \times 100 \tag{58}$$

Table4. Lower bounds, optimal gap, number of iterations, and computational time (BD)

No.	BD				CPLEX		
	Time (s)	**Iteration**	**Optimal Gap**	**Profit Objective Function**	**Time (s)**	**Time**	**Profit Objective Function**
1	10	5	0.25	3929	12	8	4012
2	24	10	0.35	4220	34	20	4250
3	38	30	0.99	4290	45	30	4280
4	59	18	0.86	4320	69	-	4315
5	68	10	0.68	4456	78	-	4410
6	88	20	0.81	4512	90	-	4502
7	94	30	0.95	4623	98	-	4623
8	100	30	1.12	4716	110.66	-	4716

Conclusion

The present research aims to solve the problem of the supply chain network of hydrocarbon products and to identify the optimal value of strategic and operational variables. For this purpose, a multi-objective, multi-period, and multi-state mixed linear programming (MILP) model was developed to maximize the conditional profit. In this respect, there are some constraints (e.g., balance and transfer of materials, limited extraction capacity, refinery production, domestic and international supply, stability of oil reservoirs, and fulfilling the requirements of oil supply based on the domestic, foreign, and OPEC basket. The main objective of this research is to determine the optimal exploitation of oil fields. Overall, a huge investment is required to control the discharge rate of oil tanks with a serious look at the lost selling and supply the flow of oil and its derivatives to domestic refineries and export terminals to respond to the selling obligations of the above chain mission. Hence, deciding on these conditions is an important management challenge for countries and companies of crude oil production and supply. The optimal answer to such a problem is to maximize the profit from the production and selling of crude oil. This paper employs a multi-objective optimization model for strategic planning of crude oil and natural gas by-product supply chains with three objectives: 1) maximizing profit, 2) minimizing withdrawal from reservoirs, and 3) minimizing greenhouse gas emissions. The problem was solved with three methods, namely deterministic, fuzzy programming, and Benders decomposition, and the outputs were compared. The results of sensitivity analysis showed the higher efficiency of the fuzzy programming method for these problems. Also, the objective functions varied slightly, suggesting that the optimization results are robust and not sensitive to small parameter changes. The ultimate optimization results show an 18% improvement in the best profit value in the specific time (period 10) compared to the ideal point. These results show that the three mentioned goals have improved and approached the ideal point in the 10 studied periods. In other words, optimization with these methods, especially with the fuzzy planning method, has led to the withdrawal reduction from reservoirs and greenhouse gas emissions and a profit increase in a certain period. These results demonstrate the desired progress in optimizing the problem with three objectives and approaching the desired objectives. This research can be a basis for planning oil and gas supply chains. For future research, it is suggested that a stochastic programming model be used to calculate the uncertainty of other parameters instead of examining the model's sensitivity to the variations of some parameters. Moreover, further improvements are expected to model the non-linear behavior of some plants and processing units. In general, this research can be considered a practical and successful proposal for optimizing oil and gas supply chains and provides more possibilities to improve the performance of supply chain systems.

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