

# **A possibilistic-stochastic programming approach to resilient natural gas transmission network design problem under disruption: A case study**

**Rozita Daghigh<sup>1</sup>, Mir Saman Pishvae<sup>1\*</sup>, Mohammad Saeed Jabalameli<sup>1</sup>, Saeed Pakseresht<sup>2</sup>**

1. *School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran*  
2. *Research Institute of Petroleum Industry, Tehran, Iran*

*r\_daghigh@iust.ac.ir; Pishvae@iust.ac.ir; Jabal@iust.ac.ir; s.pakseresht110@gmail.com*

## **Abstract**

Resilient natural gas production and transmission pipeline for minimum cost and minimum the maximum cumulative fraction of unsupplied demand related to the met demand before disruption) are two essential goals of natural gas transmission network design. This paper develops a multi-objective multi-period mixed possibilistic-stochastic programming model to form a trade-off between resiliency and cost. In the presented model, the uncertainty of natural gas consumptions is considered as an operational risk while disruption risks are accounted for the failure of refinery production capacity and pipeline transmission capacity. The proposed model utilizes mitigation strategy such as extra capacities in the refinery, backup and fortified pipelines before disruption event and recovery strategy for restoring lost capacities of facilities to reach normal performance after disruption event. Finally, the performance of the proposed model is validated by executing a computational analysis using the data of a real case study. Our analysis shows that the efficiency of the natural gas transmission network is highly vulnerable to failure of pipeline and refinery capacity as well as demand fluctuations. Also, results indicate that utilizing extra refinery production capacity, fortified pipeline and backup pipeline options have numerous influences in raising the resiliency of the NG network.

**Keywords:** Natural gas transmission network, resilient natural gas network, possibilistic programming, two-stage scenario-based stochastic programming, multi-objective optimization

## **1-Introduction**

Designing the resilient natural gas supply chain (R-NGSC) is an important and essential issue for industry experts and policymakers due to great economic, health, security and social losses created by relevant disruption (Liu et., 2020). Natural gas supply chain (NGSC) is comprised of upstream, midstream and downstream parts that form a complex and vast network. refinery facilities and import activities are done

---

\*Corresponding author

ISSN: 1735-8272, Copyright c 2022 JISE. All rights reserved

in upstream sector while in midstream stage, transmission and storage operations accomplished. Finally, distribution of Natural gas (NG) to end users falls in the downstream echelon. NGSC was optimized in many issues from economic (Hamedi et al., 2009; Üster and Dilaveroğlu, 2014; Liang et al., 2020; Sesini et al., 2020), environments (Azadeh et al., 2016; Kashani and Molaei, 2014; Zamanian et al., 2020), quality (Li et al., 2011), risk assessment (jo et al., 2008; Cimellaro et al., 2014), vulnerability evaluation (Omidvar and Kivi, 2016; Su et al., 2018; Tsinidis et al., 2019), and reliability assessment (Fan et al., 2017; Su et al., 2018; Yu et al., 2018; Liu et al., 2018). NGSC Decisions according to time horizons are classified into strategic, tactical and operational levels (Papageorgiou 2009). Strategic decisions are pre-operating activities that try to design the best network structure by locating of pipelines, compressor stations, city gate stations, underground gas storage (UGS) and aboveground storage. Whereas, tactical and operational decisions such as flow and pressure rate, inventory management and working capacity and recovery planning of facilities prompt the exiting network for optimal performance. When process industries like water, power, natural gas and petroleum industries are studied, the complexity of the problem is increased because it deals with the vast network due to long distances between production facilities and consumer zones. Therefore, creating and keeping flow continuity in NG network requires the mass and energy balance equations for the network nodes, the pressure-drop equations in the pipes and the gas compression equations in the compressor stations nodes which makes natural gas network design optimization an attractive but challenging topic especially under business-as-usual and disruption risks.

Disruption risks are the uncertainties with high impact but low likelihood. Various disruptions that can be divided to external and internal factors influence on the continuous performance of natural gas supply chain. External factors include natural disaster (Earthquake, landslide, liquefaction, rockfall, avalanche, storm, tsunami, flood and cold), climate change, human-made accidents (Collision with pipes and installations, Terrorist attacks, war) and pandemic that are outside control of NG workforce and industry experts. Whereas, Internal factors like technology fracture and workforce error occur in the network (Ghavamifar et al., 2018; Emenike and Falcone., 2020). On the other hands, business-as-usual events or operational risks are common uncertainties that occur in high likelihood with low effects. In the NGSC models, some parameters such as NG demand, NG supply, prices and costs can be under uncertainty. In general, the input parameter of the model can be under two kinds of uncertainty, inclusive of: (1) randomness that occurs if historical data about the input parameter is available, sufficient and reliable in which can be extracted its probability distribution. Accordingly, stochastic programming can be utilized for handling the randomness of the parameters and (2) epistemic uncertainty that arises from lack of knowledge in the input parameters in which can be estimated from expert's subjective data to express the possibility distribution of uncertain parameter. As a result, the possibilistic programming approach can be applied for modeling the epistemic uncertainty (Pishvae and Torabi, 2010). These risks cause to different kinds of challenges that can be classified into NG shortage, network pressure drop, gas pollution, pipeline fracture, explosion and fire, Leakage of toxic substances and increase of network pressure. a summary of the challenges in the NGSC, factors and the amount of importance and the location of occurrence are presented in table 1. Despite of these disruptions happens in low probability but have severe economic, environment and social impacts. One example can be pointed to the outbreak impacts of COVID-19 pandemic on the NGSC which is a rare uncertainty however have huge impacts like reduction in NG price, increase of NG demand and damage to NG trade.

**Table 1.** Different kinds of challenges in NGSC

challenges	factors	The amount of importance	The Affected area
explosion and fire	Corrosion, Collision, Terrorist attacks, the lack of safety issues.	Lead to casualties and extensive economic damage	Refineries and transmission pipeline
pipeline fracture	Corrosion, Collision	Inability to transfer NG for a long time	transmission pipeline
network pressure drops	High consumption Sudden outage of compressor stations due to power outages, workforce error earthquake.	NG consumers will be forced to choose other fuels for public use and heating	transmission pipeline distribution network
gas pollution	Defects during refining	Disruption for NG consumers	transmission pipeline
NG shortage	Reduction of production, cut-off of imports, disruption of wells and refineries due to natural disasters and human-made accidents	It Causes gas cuts to consumers or makes serious problems for gas consumption	Distribution network
Leakage of toxic substances	Damage to equipment	It Causes poisoning of several people or killing of at least one person	refineries

Each of these challenges account one of the main threats in the natural gas network that can reduce the actual capacity and limit the supply of NG to different consumers. An example of NGSC disruption is the Northridge earthquake in 1994, which burned the Balboa region by a gas pipeline explosion, and about 15,000 gas cuts were caused by leaks. Another example of disruption is security incidents in oil and gas supply chain that Karmon (2002) listed events worldwide relating to pipelines, oil and gas facilities for the period 1980-2000 in which the highest rates of sabotage and terrorist attacks are in Latin American and the lowest in East Asia.

Unlike other supply chains, NGSC requires more attention in resilience concept. The reason is that NGSC is one of the critical infrastructure networks for societies in which its infrastructure has high investment facilities. Also, it directly or indirectly employs a large number of work forces and have great impacts on the world economy. As well as, NG facilities likes NG pipelines, compressor stations and refineries are prerequisite for normal function of NG network in which the shutdown and failure of turbos and compressor stations, leaks, bursts, or rupture of NG pipeline, periodic maintenances, production and supply disruption and demand fluctuations during seasonal changes is unavoidable. Hence, the NGSC needs a resilient approach to build resilient network in order to continue, resist and recover its performance against disruptions.

The idea of Resilience is implemented as a novel approach in supply chain management in recent years. Resilience tries to sustain the network's operation continuously by emphasizing two dimensions of strength and flexibility. Various definitions about resilience supply chain (RSC) are presented by scholars in which can be seen similarities in the definitions. In general, resilience can be divided into 5 phases by reviewing the exiting definitions: (1) predicting unforeseen events (2) resisting against events, (3) responding to events, (4) restoring the network (5) going back to sustain situation and gaining knowledge from events. Many definitions emphasize that an essential factor in resilience is the ability of supply chain to recover and return to normal or even better condition after disruption (Sabouhi and Jabalameli, 2019). The UK energy research center is defined resilience in energy systems as the ability of system to reinforce its capacity and recover disrupted capacity as soon as possible as well as continue gas supply with alternative fuels when disruption occurred. Recently, some of authors such as Bringer et al. (2013) and Hosseini and

Barker (2016) introduced the resilience concept by the three capacity categories namely absorptive capacity, adaptive capacity and recoverable capacity that each of them indicates ability of system to stand prior to a disruption happening, overcome to disruption during happening and restore rapidly after disruption event, Respectively. Different strategies such as mitigation and recovery strategies are employed in various studies to build resilient supply chain. Mitigation strategies are utilized before disruption to reduce vulnerability and risk exposure. Examples of mitigation strategies consist of extra production capacity, back up routes and facilities, multiple-sourcing, emergency inventory and product substitution, etc., However recovery strategy are applied after disruption event where the most efficient actions of restoring facilities perform to reach normal performance. In general, resilience strategies in the Natural gas transmission network (NGTN) as a midstream part of NGSC can be divided into two types of redundancy and diversity that each of them increases the resistance of different parts of network, i.e., inlet (refinery), internal (pipeline and compressor stations) and output (increase in NG consumption). In the literature, redundancy strategy refers to having additional capacity and support systems in order to maintain performance in the event of challenges. Example of redundancy strategies specific to NGTN include designing of loop network using Backup pipeline, boosting compressor stations with spare turbo compressors, installing and increasing underground gas storages, extending the production capacity of refineries, connecting each refinery to at least two separate pipelines. On the other hand, diversity strategy refers to having a variety of alternatives to continue performance well. For instance, when a challenge leads to failure of pipeline near major industries and power plants, NG supply can be temporarily resumed using compressed natural gas (CNG) and liquefied natural gas (LNG). In fact, diversity strategy proposes utilizing aboveground storages for storing LNG near consumption areas especially in cases where underground gas storages (UGS) are not available due to geography.

This paper addresses a NG transmission network design problem in a three-echelon network where capacities of refineries and pipelines are vulnerable to disruption risks. Also, in order to consider consumption challenges as operational risks into the modelling, the demand parameter is formulated as imprecise data. Therefore, the proposed model attends to both operational and disruption risks at the same time. Accordingly, operational risk is handled by imprecise demand parameter which is formulated as possibility distributions in the form of fuzzy sets. Addition, the disruption risks are handled based on independent and discrete stochastic scenarios with a pre-defined probability of incident while their impacts are represented via scenario associate parameters. For this purpose, A two-stage scenario-based stochastic-possibilistic programming model is formulated to cope both disruption and operational risks. Among the major contributions of this paper is taking into account even mitigation decisions at pre-disruption and recovery strategy of lost capacities at post-disruption simultaneously. The proposed model considers additional capacities in refineries, backup pipeline, fortified pipeline and standby spare turbo compressor in compressor stations as resilience options. Moreover, this paper introduces a resilience quantitative index to minimize the maximize NG shortages based on the capacities as a result of post-disruption restorations. The Augmented  $\epsilon$ -constraint is applied to transform the bi-objective model into a single objective formulation. Finally, the proposed model is examined in Iran NGTN.

The rest of the paper is organized as follows. Section 2 reviews the related works in the resilient NGTN. the problem definition and the mathematical model is described in Section 3. In Section 4, The case study is examined besides numerical results and related sensitive analysis. Eventually, conclusions and suggestions as well as the directions for future research are presented in Section 5.

## 2-Literature review

In this section, the literature of resilient NG transmission network by five categorizations including: decision level, type of risk, vulnerable part in NGTN, strategy type and resilience is reviewed.

- **Decision level:** In general, optimization problems in NGTN are categorized into design problems and operational problems. design problems comprise strategic decisions that determine the suitable locations of pipelines and facilities to allow optimum operation. The goal of design problem includes the optimization of transmission capacity (Alves et al., 2016) and future network

expansion plans (Mikolajková et al., 2017) with minimal investment cost (Tabkhi et al., 2009). The operational problems involve tactical decisions with the aim of optimizing the operating conditions of existing network. Various objectives in natural gas transmission network operational problems such as reducing operating costs (Misra et al., 2015), increasing delivery capacity (Fasihzadeh et al., 2014), maximizing line pack (Kashani et al., 2014), reducing Environment effects (Azadeh et al., 2015) and reducing fuel consumption (Demissie et al., 2017) are considered.

- **Type of risk:** business-as-usual and disruption risks are two types of risk in NGTN. Business-as-usual or Operational risks are usual uncertainties that occur in high likelihood with low effects, such as demand (Behrooz, 2016), supply capacity (Yu et al., 2018) and cost fluctuations (Zhang et al. 2019). However, Disruption risks happen in low likelihood but severe consequences which fall into three groups: (1) natural disasters, (2) human-made threats (Urciuoli et al., 2014) and (3) technological threats (Cimellaro et al., 2015).
- **Vulnerable part in NGTN:** various studies have considered disruption risks in different parts of NGTN such as refinery, pipeline, NG storage, compressor station and consumer that can be vulnerable under disruption conditions.
- **Type of strategy:** as mentioned in the previous section, mitigation and recovery strategies are resilient actions that authors employed them in their studies. For example, line pack strategy as a mitigation strategy is utilized in Kashani and Molaei (2014) and installing backup pipeline is employed in (Mikolajková et al., 2017).
- **Resiliency:** The resiliency concept is quantitatively defined by different measurement indicators such as minimizing vulnerability (Su et al., 2019), shortage (Zamanian et al., 2020) and recovery time (Cimellaro et al., 2015) in various studies.

Tabkhi et al. (2009) formulated a mixed integer nonlinear programming model to optimize NGTN, where the model is to use supply gas and storage capacities to satisfy demand consumers. Kashani and Molaei (2014) proposed a multi-objective optimization model to find optimum operating condition of NG network. For this purpose, three conflicting objective functions namely maximum gas delivery flow and line pack, and minimum operating cost (sum of fuel consumption and carbon dioxide emission costs) are applied to increase the efficiency of network. Urciuoli et al. (2014) studied on exogenous security threats and disruption strategies of oil and gas supply chains. They introduced that some strategies like portfolio diversification, flexible contracts, and transport capacity planning and safety stock is essential to build resilient NGSC. Cimellaro et al. (2015) investigated different failure modes of pipeline in the gas distribution network in which introduce the emergency shutoff valves along pipelines as resiliency strategy in order to control disruption risk. Also, the performance of the gas distribution network is measured by formulating a new resilience index with regard to restoration phase. Azadeh et al. (2015) proposed a multi-objective fuzzy linear programming model in order to optimize NGSC under demand, cost and capacity uncertainty. They utilized NG storage as mitigation strategy to response the sudden increase in demand. Behrooz (2016) pointed that the uncertainties relevant to the demand forecast mistakes is an important factor that should be attend in order to increase the robustness of NG network daily planning. For this purpose, stochastic-chance-constrained programming technique is developed to cope with the uncertainty of the forecasted future demands. Behrooz and Boozarjomehry (2017) discussed the impact of the line-pack strategy in the robustness of NGSC under fluctuations of demand parameter. Mikolajková et al. (2017) developed a multi-period linearized MILP formulation to optimize gas distribution network design that considers the influences of other gas sources, parallel pipelines and the seasonal changes and demand fluctuations on the optimum network design. Yu et al. (2018) proposed a new methodology to evaluate the impact of both gas supply capacity and market demand uncertainties on the gas supply reliability of NGTN. Zhang et al. (2019) presented a MILP model to optimize design and operation of multi-state NGSC under uncertainty of the NG purchase price and cities' demand in which uses the seasonal storage and transportation options plane of three states of NG to resist the network against different disruptions. Yu et al. (2019) introduced a methodology to evaluate gas supply reliability of NGTN by UGS under uncertainty of gas injection/production capacity. Su et al. (2019) presented a multi-objective optimization method to

trade-off supply reliability and power demand of compressor station in the NGTN. They considered the uncertainties of supply and demand and quantified the probability of supply interruption based on the mass conservation equation. Zamanian et al. (2020) studied the resilience-sustainable NGSC in order to optimize the operations of network with a multi-objective multi-period model. Sesini et al. (2020) presented a linear programming model to design resilient NG network via LNG and NG storages under unexpected increase in demand. Liang et al. (2020) presented a two-stage approach to design the NG pipeline, in which in the first stage the throughput of the pipeline is determined by predicting the demand in the future and then in the second stage a mathematical model is proposed for designing pipeline network. Zhu et al. (2021) investigated gas supply reliability of NGTN considering the individual difference differences among users and the reparability of pipeline networks. For this purpose, they introduced a new assessment reliability index by combining gas shortage time and severity. Table 1 presents a systemic review of literature of NGTN optimization problems. It should be note that resilience column in this table shows that any reviewed studies optimized qualitatively or quantitatively the resilience in their model or not.

**Table 2.** A summary of the natural gas supply chain's literature

References	Decision level	Type of risk	Vulnerable part	Strategy type	Resilience
Tabkhi et al. (2009)	Strategic Tactical	–	–	mitigation	No
Kashani and Molaei's (2014)	Tactical			Mitigation	Yes
Urciuoli et al. (2014)	Tactical	Disruption	NG facilities	Mitigation	No
Cimellaro et al. (2015)	Tactical	Disruption	Pipelines	Mitigation Recovery	Yes
Azadeh et al. (2015)	Tactical	Operational	Demand	Mitigation	Yes
Behrooz (2016)	Tactical	Operational	Demand	Mitigation	NO
Behrooz and Boozarjomehry (2017)	Tactical	Operational	Demand	Mitigation	No
Yu et al. (2018)	Tactical	Operational	Demand/supply capacity	Mitigation	Yes
Zhang et al. (2019)	Strategic Tactical	Disruption Operational	NG purchase price and cities' demand	Mitigation	No
Yu et al. (2019)	Tactical	Operational	gas injection/production capacity	Mitigation	Yes
Su et al. (2019)	Tactical	Operational	supply and demand	Mitigation	Yes
Zamanian et al. (2020)	Tactical			Mitigation	Yes
Sesini et al. (2020)	Strategic tactical	Operational	Demand	Mitigation	Yes
Liang et al. (2020)	Strategic Tactical	Operational	Demand		No
Zhu et al. (2021)	Tactical	Disruption	Pipeline	Mitigation	Yes
This study	Strategic Tactical	Operational Disruption	Pipeline/ refinery/ Demand	Mitigation Recovery	Yes

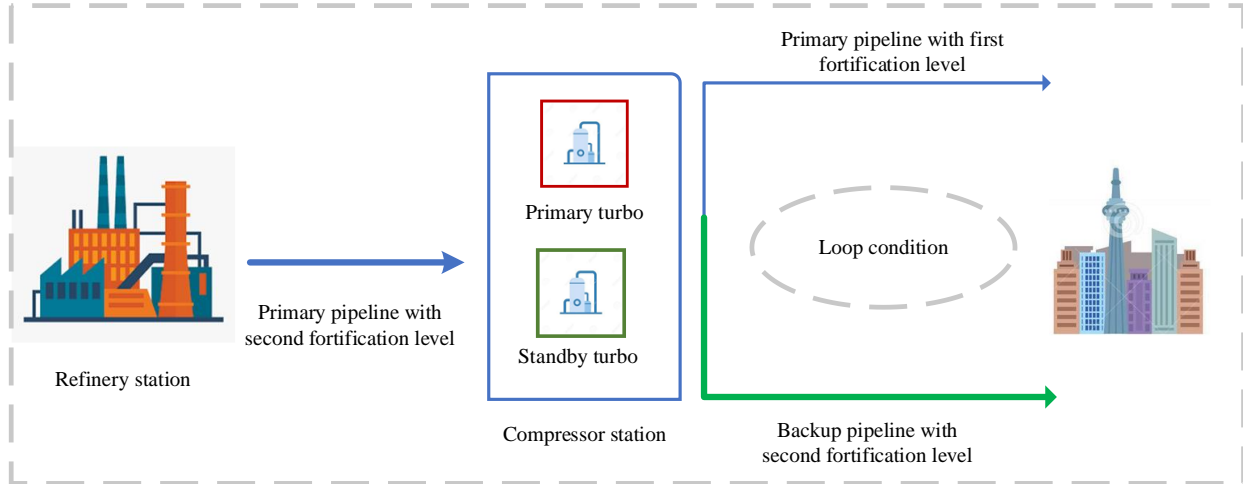
According to the reviewed articles in the table 2, it can be found that, most of these papers concentrates on tactical decisions. However, it is needed to consider resilience perspective in the NG network design as strategic decisions because of high investment costs of NG facilities. In particular, the existed researches in the literature discusses mostly operational risks such as demand fluctuational, while the disruption risk such as capacity failure at refinery, UGS and pipeline is less noticed why they need to handle with making strategic decisions such as mitigation strategy. Also, investigations show that a few papers study both disruption and operational risks concurrently. More interestingly, in spite of importance in vulnerability of

natural gas facilities (such as refinery, pipeline, compressor station and NG storage) to disruption risk, research works that addressed to this issue are so rare. Also, Reviewing the relevant literature shows that only a few papers modeled resiliency index in the NGTN design problem and measure the impact of resiliency strategies on the network resilience. It can also be seen that most of papers account mitigation strategy to build resilient NGTN, while it would be valuable to formulate resilient NGTN models accounting both mitigation and recovery strategies. Eventually, most of the papers do not address the recovery time and the time delay between the occurrence of the disruption and the recovery time. Therefore, it is needed to optimized the recovery time of facilities as an effective strategy.

To fill the literature gaps, this study presents a two-stage scenario-based stochastic-possibilistic optimization model for natural gas Transmission network design problem that some mitigation strategies are decided in the pre-disruption stage (in the first stage), and recovery decisions are determined in the post-disruption under each scenario (in the second stage). The proposed model copes with both operational and disruption risks. operational risk is seen as an uncertain demand parameter in the mathematical model that is managed with imprecise parameter and the perception about it is fuzzy triangular numbers. However, Disruption risks in the mathematical model are handled based on independent and discrete scenarios with a pre-defined probability of incident that exclusively can influence the flow capacity of pipelines and production capacity of refinery partially or completely. As a consequence, in order to build resilient NG network, some mitigation strategies such as providing extra production capacity in refineries, considering backup pipelines in the network as loop condition and fortifying of pipelines are conducted in the first stage of the model. Also, recovery strategies are done for restoring the disrupted production capacities in the refineries in the post-disruption phase. It is significant that the resilience level of NGTN is measured by minimizing the maximum cumulative fraction of unsupplied demand over the planning horizon using the chosen mitigation and recovery strategies. Also, in order to modeling the recovery strategy, two strategic and tactical time periods are considered in which there is a time delay between the occurrence of the disruption and the recovery time.

## **2-Problem definition**

This paper investigates a three-echelon, multi-objective and multi period natural gas transmission network design (figure 1) such that refineries after manufacturing the natural gas, send it to different consumer zones through compressor stations and pipelines. The output NG flow from the refineries starts with the maximum permitted value pressure in order to continues and meets some consumer zones in the acceptable pressure range until arrives one of the nearest compressor stations to boosts its pressure value because that the NG loses its pressure due to friction with the wall of pipeline. Hence, locating of pipelines and compressor stations as one of the key decisions are going to determine in this network. The flow direction in the pipelines can change from one period to another that is function of pressure difference, the NG flow rate and pipeline resistance.



**Fig 1.** Structure of natural gas transmission network under study

Refineries and pipelines capacities can be partially or completely threatened by different disruption risks that range from human-made accidents (e.g., Collision with pipes, work strikes, Terrorist attacks, war and sanction) to natural disaster (e.g., Earthquake, landslide, liquefaction, flood). To employ disruption risks in the mathematical model, a set of independent and discrete scenarios with a pre-defined probability of incident are specified that their impacts formulated by scenario-dependent parameters. To overcome disruption risks, three mitigation strategies include adding extra capacities for refineries, fortifying of pipelines and installing backup pipeline when the primary pipelines are not usable due to failure. In fact, mitigation strategies act as an absorption capacity in which help to network in order to continue its operations during disruption as well as recover lost capacities with minimal time and cost after disruption. For instance, if the primary pipeline is disrupted but the backup pipeline is undamaged; so, the flow can continue to network via backup pipeline until the primary pipeline is recovered.

Operational risk in our model is considered as an uncertain demand parameter. Because, NG demand parameter is inherently uncertain input data according to the various agents such as growth economic, electricity generation and weather conditions. Also, due to lack of the precise information and sufficient historical data about this uncertain parameter, probability distributions cannot be obtained. So, we take advantage of an expert's opinions and experiences in order to formulate the imprecise parameter based on epistemic uncertainty. Hence, this imprecise demand parameter is formed as triangular fuzzy numbers and the possibilistic chance constraint programming approach is used to deal with inaccurate demand parameter. However, disruption risk in our model is the percentage of lost capacity in pipeline and refinery that effects on the flow capacity of pipeline and production capacity of refinery, respectively. For this purpose, the disruption risks in the model are handled based on three independent and discrete scenarios, small, medium and large scale. The small-scale scenario recognizes the least severe and the large-scale scenario recognizes the most severe case. Noteworthy, each of scenario has a pre-defined probability of incident while their impacts are represented via scenario associate parameters. Hence, in order to deal with disruption risks, the scenario-based stochastic programming method is employed as a common method. Interested readers can refer to Torabi et al. (2015) and Sabouhi et al. (2018) for more information.

The purpose of this problem is concurrently minimizing the total cost and maximizing the resilience of NGTN as well as seeks to determine some decisions as follows:

- The locating of primary and backup pipelines with their fortification levels,
- The locating of compressor stations with their turbos,
- The direction of flow in the primary and backup pipelines,
- The amount of extra production capacity of refineries,
- The amount of flow transferred in each primary and backup pipeline,



- The amount of NG flow produced from refineries,
- The amount of working capacity of refineries,
- The amount of recovery capacity of refineries,
- The amount of inlet and outlet pressure in each node.

To make the mentioned decisions, a stochastic-possibilistic, multi-objective, multi-period model is proposed that includes both disruption and operational risks. The first objective is to minimize the expected entire NGTN cost in different disruption scenarios, while the second objective aims to minimize the maximum (worst case) cumulative fraction of unsupplied demand over the planning horizon.

### 3-1- mathematical model

The following assumptions are considered to formulate the problem:

- It is assumed that NGTN operates in a steady state and an isothermal situation,
- The pipeline segments are horizontal,
- The outlet pressure of compressor stations is assumed to boost the pressure at most 60% more than the inlet pressure,
- The maximum capacity expansion of the refinery is 20% of initial capacity,
- Each node should receive the flow between the minimum and maximum allowed pressure value,
- Decreased capacity of refineries should be recovered fully by the last period,
- The lost capacity of refineries is recovered after post-disruption in the recovery time period  $w_r$ ,
- It is also assumed that the occurrence of disruptions occurs in the first operational time period,
- There is a time delay between the occurrence of disruptions and the start of recovery.

In the following, the sets, parameters and decision variables used in the proposed mathematical model are presented.

---

#### Sets

$NR$	Set of refineries
$ND$	Set of demands
$NC$	Set of compressor stations
$N$	Indexes of $Nr, Nd, Nc$
$U$	Set of turbo compressor in each compressor stations
$E$	Set of Fortification levels
$W$	Set of operational time periods (month)
$T$	set of strategic time periods(year)
$S$	Set of disruption scenarios

#### Parameters

$f_{etw}^p$	Fixed cost of locating a pipeline with fortification level $e$ in period $t$ at week $w$
$fb_{etw}^p$	Fixed cost of locating a backup pipeline with fortification level $e$ in period $t$ at week $w$
$f_{tw}^c$	Fixed cost of locating one turbo compressor in a compressor station in period $t$ at week $w$
$o_{tw}^p$	Operating cost of one km of a pipeline arc in period $t$ at week $w$
$o_{tw}^c$	Operating cost of one turbo compressor in a compressor station in period $t$ at week $w$
$ob_{tw}^p$	Operating cost of one km of a backup pipeline arc in period $t$ at week $w$
$c_{tw}$	Transportation cost in period $t$ at week $w$
$ce_{itw}$	The cost for extra capacity at refinery $i \in NR$ in period $t$ at week $w$
$cp_i$	Unit cost of recovering production capacity of refinery nodes $i \in NR$
$h_{itw}$	The cost of producing natural gas by refineries $i \in NR$ in period $t$ at week $w$
$AP_{ij}$	1 if a connection is allowed between nodes $i \in N, j \in N$ , otherwise 0
$l_{ij}$	Distance between nodes $i \in N, j \in N$
$\widetilde{De}_{jtw}$	Demand of customers $j \in ND$ in period $t$ at week $w$
$D_{jtw}$	Demand of customers $j \in ND$ that is satisfied before disruption in period $t$ at week $w$

---

$cap_{ijtw}$	Capacity of the total possible flow between nodes $i \in N, j \in N$ in period $t$ at week $w$
$ca_i$	Initial Production Capacity of refinery $i \in NR$
$\vartheta_{ijes}$	Percentage of lost capacity a pipeline with fortification level $e$ between nodes $i \in N, j \in N$ under scenario $s$
$\theta_{is}$	Percentage of lost capacity refinery nodes $i \in NR$ under scenario $s$
$up_i$	Upper bound of extra capacity at refinery nodes $i \in NR$ (percentage)
$v$	Capacity of one turbo compressor in compressor station
$P_{max}$	Maximum permissible gas pressure in the network
$P_{min}$	Minimum permissible gas pressure at a demand node
$\omega$	Maximum pressure rise multiplier at a compressor
$\pi_s$	Probability of occurrence of scenario $s \in S$
$\alpha_{ijtsk}$	Lower bound of flow in interval $k$ between nodes $i \in N, j \in N$ in period $t$ under scenario $s$
$\beta_{ijtsk}$	upper bound of flow in interval $k$ between nodes $i \in N, j \in N$ in period $t$ under scenario $s$
$A_{ijtsk}$	The square of lower bound of flow in interval $k$ between nodes $i \in N, j \in N$ in period $t$ under scenario $s$
$B_{ijtsk}$	The square of upper bound of flow in interval $k$ between nodes $i \in N, j \in N$ in period $t$ under scenario $s$
Binary variables	
$Y_{ijetw}$	1 if a new pipeline is located between nodes $i \in N$ and $j \in N, i < j$ , with fortification level $e$ in period $t$ at week $w$ , 0 otherwise
$Yb_{ijetw}$	1 if a back-up pipeline is located between nodes $i \in N$ and $j \in N, i < j$ , with fortification level $e$ in period $t$ at week $w$ , 0 otherwise
$CO_{iutw}$	1 if a compressor station $i \in NC$ with type $u$ is located in period $t$ at week $W$ , 0 otherwise
$B_{ijetw}$	1 if NG flows in a pipeline with fortification level $e$ from $i \in N$ to $j \in N$ in period $t$ at week $w$ , 0 otherwise
$G_{ijretw}$	1 if NG flows in a back-up pipeline with fortification level $e$ from $i \in N$ to $j \in N$ in period $t$ at week $w$ , 0 otherwise
Continues variables	
$X_{ijstw}$	The amount of NG transferred in pipeline between nodes $i \in N$ and $j \in N$ under scenario $s$ in period $t$ at week $w$
$Xb_{ijstw}$	The amount of NG transferred in pipeline between nodes $i \in N$ and $j \in N$ under scenario $s$ in period $t$ at week $w$
$Q_{istw}$	The amount of NG produced in Refinery nodes $i \in NR$ under scenario $s$ in period $t$ at week $w$
$EP_i$	The extra production capacity for refinery nodes $i \in NR$
$Rp_{istw}$	Production capacity at refinery $i \in NR$ that is recovered under scenario $s$ in period $t$ at week $w$
$WP_{istw}$	Working capacity of refinery $i \in NR$ under scenario $s$ in period $t$ at week $w$
$P_{in-istw}$	Inlet pressure of nodes $i \in N$ under scenario $s$ in period $t$ at week $w$
$P_{out-istw}$	Outlet pressure of nodes $i \in N$ under scenario $s$ in period $t$ at week $w$

$$\begin{aligned}
\min Z_1 = & \sum_{i \in N} \sum_{j \in N} \sum_e \sum_t \sum_w (Y_{ijetw} - Y_{ijet-1w-1}) f_{etw}^p l_{ij} \\
& + \sum_{i \in N} \sum_{j \in N} \sum_e \sum_t \sum_w (Yb_{ijetw} - Yb_{ijet-1w-1}) f b_{etw}^p l_{ij} + \sum_{i \in N} \sum_{j \in N} \sum_e \sum_t \sum_w Y_{ijetw} l_{ij} o_{tw}^p \\
& + \sum_{i \in N} \sum_{j \in N} \sum_e \sum_t \sum_w Yb_{ijetw} l_{ij} o_{tw}^p + \sum_{i \in NC} \sum_u \sum_t \sum_w U(CO_{iutw} - CO_{iut-1w-1}) f_{tw}^c \\
& + \sum_{i \in NC} \sum_{u \in U} \sum_t \sum_w U CO_{iutw} o_{tw}^c \sum_{i \in NR} \sum_t \sum_w c e_{itw} EP_i \\
& + \pi_s \left( \sum_{i \in N} \sum_{j \in N} \sum_s \sum_t \sum_w (X_{ijstw} + Xb_{ijstw}) c_{tw} + \sum_{i \in NR} \sum_s \sum_t \sum_w (Q_{istw}) h_{itw} + \right. \\
& \left. + \sum_{i \in NR} \sum_s \sum_t \sum_w cp_i Rp_{itws} \right)
\end{aligned} \tag{1}$$

$$\min Z_2 = \sum_t \sum_w RS_{tw} \quad (2)$$

$$RS_{tw} \geq 1 - \frac{\sum_{i \in N} \sum_{j \in ND} \sum_s (X_{ijstw} - X_{jistw}) + \sum_{i \in N} \sum_{j \in ND} \sum_s (Xb_{ijstw} - Xb_{jistw})}{\sum_{j \in ND} (D_{jtw})} \quad \forall t, w \quad (3)$$

The objective function (1) aims to minimize the expected total expenses of NGTN design under different scenario that includes cost of installing primary and backup pipelines, cost of operating primary and backup pipelines, cost of constructing and operating compressor station, cost of extending production capacity of refineries, cost of transferring NG flow between nodes, cost of producing and refining NG at refineries and cost of recovering for restoring production capacity in refineries. Objective function (2) minimizes the maximum cumulative fraction of unsupplied demand (relative to the met demand before the disruption) that is defined in equation (3).

$$P_{out-istw} = P_{max} \quad \forall i \in NR, s \in S, t \in T, w \in W \quad (4)$$

$$P_{in-istw} \geq P_{min} \quad \forall i \in Nd, s \in S, t \in T, w \in W \quad (5)$$

$$P_{out-istw} \leq P_{max} \quad \forall i \in Nd, s \in S, t \in T, w \in W \quad (6)$$

Equations (4)-(6) define the domine of permitted pressure value in refinery and demand nodes, respectively.

$$\sum_e Y_{ijetw} \leq AP_{ij} \quad \forall i, j \in N, t \in T, w \in W \quad (7)$$

Equation (7) indicates that if a connection between two nodes is permitted, then the pipeline can be located only with one of the fortification levels.

$$Yb_{ijétw} \leq \sum_e Y_{ijetw} \quad \forall i, j \in N, i < j, e \in E, t \in T, w \in W \quad (8)$$

Equation (8) ensures that if the primary pipeline is installed then the backup pipeline can be located parallel to it.

$$Y_{ijetw} \geq Y_{ijet-1w-1} \quad \forall i, j \in N, i < j, e \in E, 1 < t \leq T, 1 < w \leq W \quad (9)$$

$$Yb_{ijetw} \geq Yb_{ijet-1w-1} \quad \forall i, j \in N, i < j, e \in E, 1 < t \leq T, 1 < w \leq W \quad (10)$$

Equations (9) and (10) enforce that if a primary or backup pipeline is located in a period, it should be remained until the end of the planning horizon, respectively.

$$B_{ijetw} + B_{jietw} \leq Y_{ijetw} \quad \forall i, j \in N, i < j, e \in E, t \in T, w \in W \quad (11)$$

$$G_{ijetw} + G_{jietw} \leq Yb_{ijetw} \quad \forall i, j \in N, i < j, e \in E, t \in T, w \in W \quad (12)$$

Equations (11) and (12) show that if a primary or backup pipeline is installed, then the flow path can occur, respectively.

$$\sum_e (B_{ijetw} + B_{jietw}) \leq 1 \quad \forall i, j \in N, i < j, t \in T, w \in W \quad (13)$$

$$\sum_e (G_{ijetw} + G_{jietw}) \leq 1 \quad \forall i, j \in N, i < j, t \in T, w \in W \quad (14)$$

Equations (13) and (14) grantee that the flow passes only in one direction in a primary and backup pipeline, respectively.

$$X_{ijstw} \leq cap_{ij} \sum_e B_{ijetw} (1 - \vartheta_{ijes}) \quad \forall i, j \in N, s \in S, t \in T, w \in W \quad (15)$$

$$Xb_{ijstw} \leq cap_{ijt} \sum_e G_{ijretw} (1 - \vartheta_{ijes}) \quad \forall i, j \in N, e \in E, s \in S, t \in T, w \in W \quad (16)$$

Equations (15) and (16) state the capacity limitations of primary and backup pipelines, respectively.

$$\left( \sum_{i \in N} X_{ijstw} - \sum_{i \in N} X_{jistw} \right) + \left( \sum_{i \in N} Xb_{ijstw} - \sum_{i \in N} Xb_{jistw} \right) \geq \bar{D}e_{jtw} \quad \forall j \in Nd, s \in S, t \in T, w \in W \quad (17)$$

Equation (17) enforces the flow balance constraint in the demand nodes.

$$Q_{istw} \geq \sum_{j \in N} X_{ijstw} + \sum_{j \in N} Xb_{ijstw} \quad \forall i \in Nr, s \in S, t \in T, w \in W \quad (18)$$

Equations (18)-(25) express the production capacity evolution of refineries over periods. Equation (18) indicates the flow balance constraint in the refinery.

$$Q_{istw} \leq WP_{istw} \quad \forall i \in Nr, s \in S, t \in T, w \in W \quad (19)$$

Equation (19) represents the upper bound of production that should not exceed the maximum available production capacity (working capacity).

$$WP_{istw} = (1 - \theta_{is})(ca_i + EP_i) \quad \forall i \in Nr, s \in S, t \in T, w = 1 \quad (20)$$

Equation (20) shows the working capacity of refinery in the first operational time period that is equal to the summation of the remaining initial capacity and extra capacity.

$$WP_{istw} \leq ca_i + EP_i \quad \forall i \in Nr, s \in S, t \in T, w \in W \quad (21)$$

Equation (21) indicates that the working capacity of refinery cannot be greater that the summation of the initial production capacity and extra capacity during the recovery stage.

$$WP_{istw} = WP_{is(t-1)(w-1)} + Rp_{istw} \quad \forall i \in Nr, s \in S, t \in T, 1 < w \leq w_n \quad (22)$$

Equation (22) expresses that the working capacity of refinery in time period  $t$  is limited by the summation of the working capacity in time period  $t-1$  and the recovered production capacity in time period  $t$ .

$$Rp_{istw} = 0 \quad \forall i \in Nr, s \in S, t \in T, 1 < w \leq w_r \quad (23)$$

Equation (23) enforces that the recovery amounts of production capacity in refinery are assumed to be zero before the start of recovery time ( $w_r$ ).

$$\sum_{w_r < w}^{w_n} WP_{istw} = ca_i + EP_i \quad \forall i \in Nr, s \in S, t \in T \quad (24)$$

Equation (24) illustrates that the final amount of working capacity in each refinery should be reach to its initial value (i.e., the summation of the initial capacity and extra capacity) in those recovery times that restoration is able.

$$EP_i \leq up_i * ca_i \quad \forall i \in Nr \quad (25)$$

Equation (25) controls the upper bound of extra production capacity.

$$(p_{out-istw}^2 - p_{in-istw}^2) - \delta_{ij}(X_{ijstw})^2 \geq M_1(\sum_e B_{ijetw} - 1) \quad \forall i, j \in N, \quad (26)$$

$$s \in S, t \in T, w \in W$$

$$(p_{out-itw}^2 - p_{in-itw}^2) - \delta_{ij}(X_{ijstw})^2 \leq M_1(\sum_e B_{ijetw} - 1) \quad \forall i, j \in N, s \quad (27)$$

$$\in S, t \in T, w \in W$$

Equations (26-27) calculate the pressure drop of the primary pipeline according to the NG flow rate and pipeline resistance, Notably, Equations (26) and (27) together calculate the pressure drop between nodes in the primary pipeline. Specifically, when there is flow from  $i$  to  $j$  ( $B_{ijet} = 1$ ), the left-hand side of these constraints must be equal to zero. However, when  $X_{ijstw}$  is zero, Equations (26) and (27) can get any value, positive or negative, and since it cannot be any more than the square of the maximum pressure difference, so, we set "M1" equal to  $(P_{max})^2$ . This issue is also valid for Equations (28) and (29).

$$(p_{out-istw}^2 - p_{in-istw}^2) - \delta_{ij}(Xb_{ijstw})^2 \geq M_1(\sum_e G_{ijetw} - 1) \quad \forall i, j \in N, \quad (28)$$

$$s \in S, t \in T, w \in W$$

$$(p_{out-itw}^2 - p_{in-itw}^2) - \delta_{ij}(Xb_{ijstw})^2 \leq M_1(\sum_e G_{ijetw} - 1) \quad \forall i, j \in N, \quad (29)$$

$$s \in S, t \in T, w \in W$$

Equations (28-29) calculate the pressure drop of the backup pipeline according to the NG flow rate and pipeline resistance,

The pipeline resistance  $\delta_{ij}$  is computed using formulation  $\delta_{ij} = (1/c_1)^2 \frac{GT_f L_{ij} Z f}{dia_{ij}^5} \left( \frac{P_b}{T_b} \right)^2$ , that depends on friction factor  $f$ , base pressure  $P_b$ , base temperature  $T_b$ , gas gravity  $G$ , average gas flowing temperature  $T_f$  and gas compressibility factor  $Z$ , pipe length  $L_{ij}$  and pipe diameter  $dia_{ij}$  (Menon 2005). The parameters  $c_1, f, P_b, T_b, G, T_f$  and  $Z$  are presumed to be set equal to  $1.1494 \times 10^{-3}$ , 0.01, 100 KPA, 288 K, 0.66, 283 K, and 0.805 in our computational study.

$$\sum_{u \in U} C_{outw} \leq 1 \quad \forall i \in NC, t \in T, w \in W \quad (30)$$

Equation (30) states that there is only one type of turbo compressor in each compressor station.

$$C_{outw} \geq C_{out-1w-1} \quad \forall i \in NC, u \in U, 1 < t \leq T, 1 < w \leq W \quad (31)$$

Equation (31) expresses that if a compressors station is located in a period, it should be remained until the end of the planning horizon.

$$p_{out-istw} \leq (1 + \omega)p_{in-istw} + M_2(1 - \sum_u C_{outw}) \quad \forall i \in NC, \quad (32)$$

$$s \in S, t \in T, w \in W$$

Equations (32)-(34) define the pressure relations in the compressor station. Equation (32) makes clear that if a compressor station is installed, the output pressure cannot be greater than  $\omega$  times the input pressure.

$$p_{out-istw} \leq p_{in-istw} + M_2(\sum_u C_{outw}) \quad \forall i \in NC, \quad (33)$$

$$s \in S, t \in T, w \in W$$

$$p_{out-istw} \geq p_{in-istw} \quad \forall i \in NC, \quad (34)$$

$$s \in S, t \in T, w \in W$$

Also, Equation (33) and (34) ensure that if the compressor station is not installed in that node, then the output pressure is equal to the input pressure.

$$\sum_{i \in N} X_{ijstw} + \sum_{i \in N} Xb_{ijstw} \leq v \sum_{u \in U} UC_{o_{jutw}} \quad \forall j \in NC, t \in T, w \in W \quad (35)$$

Equation (35) shows the flow balance constraint in the compressor station.

$$p_{in-istw}, p_{out-istw}, X_{ijstw}, Q_{istw}, EP_i, Rp_{istw}, WP_{istw} \geq 0 \quad (36)$$

$$G_{ijetw}, B_{ijetw}, Co_{iutw}, Y_{ijetw}, Yb_{ijetw} \in \{0,1\} \quad (37)$$

As it is clear, the proposed mathematical model is a mixed integer nonlinear programming model because of the presence of the squared pressure and flow variables in equations (26)-(29). Therefore, in the first phase, we partially linearize the model by eliminating the squared pressure variables via defining new variables  $ps_{in-istw}$  and  $ps_{out-istw}$  instead of  $p_{in-istw}^2$  and  $p_{out-istw}^2$ , respectively. To generalize the relevant constraints, the left-hand-side and right-hand-side of equations (4)-(6), (26) and (28), (32)-(34) should be squared as follows.

$$ps_{out-istw} = (P_{max})^2 \quad \forall i \in NR, s \in S, t \in T, w \in W \quad (38)$$

$$ps_{in-istw} \geq (P_{min})^2 \quad \forall i \in Nd, s \in S, t \in T, w \in W \quad (39)$$

$$ps_{out-istw} \leq (P_{max})^2 \quad \forall i \in Nd, s \in S, t \in T, w \in W \quad (40)$$

$$(ps_{out-istw} - ps_{in-istw}) - \delta_{ij}(X_{ijstw})^2 \geq M_1 \left( \sum_{w \in W} B_{ijetw} - 1 \right) \quad \forall i, j \in N, s \in S, t \in T, w \in W \quad (41)$$

$$(ps_{out-itw} - ps_{in-itw}) - \delta_{ij}(Xb_{ijstw})^2 \leq M_1 \left( \sum_{w \in W} G_{ijetw} - 1 \right) \quad \forall i, j \in N, s \in S, t \in T, w \in W \quad (42)$$

$$ps_{out-istw} \leq (1 + \omega)^2 ps_{in-istw} + (M_2)^2 \left( 1 - \sum_u Co_{iutw} \right) \quad \forall i \in NC, s \in S, t \in T, w \in W \quad (43)$$

$$ps_{out-istw} \leq ps_{in-istw} + (M_2)^2 \left( \sum_u Co_{iutw} \right) \quad \forall i \in NC, s \in S, t \in T, w \in W \quad (44)$$

$$ps_{out-istw} \geq ps_{in-istw} \quad \forall i \in NC, s \in S, t \in T, w \in W \quad (45)$$

At the second stage, we employ the piece-wise linear approximation in order to linearize the model completely due to the presence of the squared flow variables in the equations (41) and (42). In the following, this method is described in three stages:

- 1- Determine the variation range of flow variable (minimum and maximum value of flow variable):

$$x_{ijstw}^{min} = 0 \quad x_{ijstw}^{max} = \sum_{j \in ND} De_{jtw}$$

- 2- Divide the range of flow into some intervals. For this purpose, the lower bound and upper bound of each interval are calculated as follows:

lower bound of each interval:

$$\alpha_{ijstw} = x_{ijstw}^{min} + (k - 1) * \left[ \frac{(x_{ijstw}^{max} - x_{ijstw}^{min})}{|k|} \right]$$

upper bound of each interval:

$$B_{ijstw} = x_{ijstw}^{min} + k * \left[ \frac{(x_{ijstw}^{max} - x_{ijstw}^{min})}{|k|} \right]$$

The more intervals are made, the more accurate approximate value of flow.  $k$  is the number of intervals.

- 3- In each interval, the value of flow is equal to the linear combination of the lower bound and upper bound of the interval.

$$x_{l-ijstw} = \sum_k \lambda_{ijstwk} \alpha_{ijstwk} + \mu_{ijstwk} \beta_{ijstwk} \quad \forall i, j, s, t, w \quad (46)$$

Because the flow variable is squared in the formulation, the value of squared flow should be equal to linear combination of the square of the lower bound and upper bound of the interval. Also,  $\lambda_{ijstwk}$  and  $\mu_{ijstwk}$  get values only if the flow value falls in the interval formed by the lower and upper bounds ( $\sum_k Y_{ijstwk} = 1$ ).

$$\begin{aligned} A_{ijstwk} &= \alpha_{ijstwk}^2 \\ B_{ijstwk} &= \beta_{ijstwk}^2 \\ x_{l-ijstw}^2 &= \sum_k \lambda_{ijstwk} A_{ijstwk} + \mu_{ijstwk} B_{ijstwk} \quad \forall i, j, s, t, w \end{aligned} \quad (47)$$

$$\lambda_{ijstwk} + \mu_{ijstwk} \leq Y_{ijstwk} \quad \forall i, j, s, t, w, k \quad (48)$$

$$\sum_k Y_{ijstwk} = 1 \quad \forall i, j, s, t, w \quad (49)$$

$$Y_{ijstkw} \in \{0,1\} \quad (50)$$

$$0 \leq \lambda_{ijstwk}, \mu_{ijstwk} \leq 1$$

Finally, the linearized equation of equation (26) in the main model is equal to:

$$(ps_{out-istw} - ps_{in-istw}) - \delta_{ij} \left( \sum_k \lambda_{ijstwk} A_{ijstwk} + \mu_{ijstwk} B_{ijstwk} \right) \geq M_1 \left( \sum_e B_{ijetw} - 1 \right) \quad \forall i, j, s, t, w \quad (51)$$

This issue is valid for the  $Xb_{ijstw}$  variable.

### 3-2-The proposed possibilistic chance constrained programming approach

As mentioned before, the demand input parameter is considered as an epistemic uncertainty in the model due to lack of sufficient historical data. Therefore, in order to formulate the imprecise demand parameter, it is required to rely on domain expert's subjective data based on their contemplative opinions and professional experiences. In this regard, this uncertain parameter should be modeled via Possibility distribution in the form of trapezoidal or triangular fuzzy numbers. Here, the possibilistic chance constraint programming (PCCP) approach, one of the subsets of fuzzy mathematical programming, is applied to deal with the imprecise demand parameter in the presented model. This method relies on the expected value of fuzzy numbers and the possibility (Pos) and necessity (Nec) measures to convert the uncertain model into a crisp equivalent one. Also, this method let the Decision Maker (DM) specifies the confidence level of constraint's satisfaction. The necessity measure is used to cope with uncertain parameter because this measure demonstrates the corresponding minimum possibility level under the most pessimistic view. Since the nature of constraints is to show the mandatory limitations this kind of measure is used.

Assume that  $\tilde{\xi} = (\xi^1, \xi^2, \xi^3)$  is a triangular fuzzy number with member function  $\mu(x)$  that can be defined by the following equation:

$$\mu_{\tilde{\xi}}(x) = \left\{ \begin{array}{ll} f_{\xi}(x) = \frac{x - \xi^1}{\xi^2 - \xi^1} & \text{if } \xi^1 \leq x \leq \xi^2 \\ 1 & \text{if } x = \xi^2 \\ g_{\xi}(x) = \frac{\xi^3 - x}{\xi^3 - \xi^2} & \text{if } \xi^2 \leq x \leq \xi^3 \\ 0 & \text{if } \xi^3 \leq x \text{ or } x \leq \xi^1 \end{array} \right\}$$

suppose  $r$  be a real number and according to Babazadeh et al. (2019), the necessity measure is determined as follows:

$$Nec\{\tilde{\xi} \leq r\} = 1 - \sup\{\mu(x)_{x>r}\} \quad (52)$$

Also, the expected value of  $\tilde{\xi}$  can be defined as following based on Pishvae et al. (2012):

$$EV(\xi) = \frac{E_1^c + E_2^c}{2} = \frac{\int_0^1 f_\xi^{-1}(x)dx + \int_0^1 g_\xi^{-1}(x)dx}{2} = \frac{\frac{1}{2}(\xi^1 + \xi^2) + \frac{1}{2}(\xi^2 + \xi^3)}{2} = \frac{\xi^1 + 2\xi^2 + \xi^3}{4} \quad (53)$$

Also, the corresponding necessity measures of  $\tilde{\xi}$  is as follows:

$$Nec(\tilde{\xi} \leq r) = \left\{ \begin{array}{ll} 1 & \text{if } \xi^3 \leq r \\ \frac{r - \xi^3}{\xi^3 - \xi^2} & \text{if } \xi^2 \leq r \leq \xi^3 \\ 0 & \text{if } r \leq \xi^2 \end{array} \right\} \quad (54)$$

Therefore, based on equation (53) and Inuiguchi and Ramic (2000) we will have:

$$Nec(r \geq \tilde{\xi}) \geq \alpha \leftrightarrow r \geq (1 - \alpha)\xi^2 + \alpha\xi^3 \quad (55)$$

$\alpha$  is the confidence level of chance constraints in which determine Regarding DM's ideas in the lowest satisfaction degree of PCC.

According to the above-mentioned explanations, the compact form of the necessity-based possibilistic programming model is presented as follows. Where vectors  $C, F, D$  represent the fixed cost, variable cost and demand data. Also,  $A, B, T, L$  and  $P$  correspond to the coefficient matrices, and  $x$  and  $y$  denote the continuous and binary variables, respectively. Now, suppose that vectors  $F, D$  and  $C$  are the imprecise parameters in the proposed compact form model.

$$MinE[w_1] = E[\tilde{C}]y + E[\tilde{F}]x$$

$$MinE[w_2] = x$$

S.T.

$$Ax = 0$$

$$Bx \leq Ty$$

$$Nes\{Lx \geq \tilde{d}\} \geq \alpha$$

$$Py \leq 1$$

$$y \in \{0,1\}, x \geq 0$$

(56)

According to the above-mentioned definitions, the above model (56) can be transformed to the equivalent crisp one as follows:

$$MinE[w_1] = \left( \frac{C_{(1)} + 2C_{(2)} + C_{(3)}}{4} \right) y + \left( \frac{F_{(1)} + 2F_{(2)} + F_{(3)}}{4} \right) x$$

$$MinE[w_2] = x$$

s.t.

$$Ax = 0$$

$$Bx \leq Ty$$

$$Lx \geq (1 - \alpha)d_2 + \alpha d_3$$

$$Py \leq 1$$

$$y \in \{0,1\}, x \geq 0$$

(57)

#### 4-Case study

Energy has a crucial role in the life and economic development. Among the various types of energy, NG is widely used as the cleanest fossil fuel with the least environmental impact. This issue is significant, particularly for the countries that have the biggest NG reservoirs like Iran. Because they can access massive profits from the export of it to neighboring countries through proper management in the NG production and



consumption. On the other hand, due to Iran's location on the seismic belt of the world and the dependence of 95.6% of urban unites and 57.8 rural unite to NG network, it is essential to design resilient NGTN infrastructure so that can continue its mission in the event of a disturbance. The considered case study is related to the northern part of the country in which yearly suffers from the natural gas shortage due to far from refineries. In this case study, Hashemi Nejad refinery supplies the NG for the Razavi Khorasan, Nord Khorasan, Golestan and Mazandaran provinces. Also, four potential compressor stations including Razavi, Farooj, Neka and Noor are considered to compensate the lost pressure. The problem is considered for a 1-year strategic planning horizon and 12-month operational planning horizon. Table 3 reports the value of key parameters in the model. It is noteworthy that All information related to the case study specially the critical parameters are gathered by Tabatabaee (2016).

**Table 3.** Characteristics of the network nodes in one month.

Capacity of refineries and import ( $ca_i$ ) (million cubic meter ( $mm^3$ ))		maximum and minimum permissible gas pressure in the network	
Hashemi Nejad	1500	$P_{max}$	90 bar
<b>Demand of provinces (<math>DE_{jt}</math>)</b> (million cubic meter ( $mm^3$ ))		$P_{min}$	75 bar
		<b>Maximum pressure rise multiplier at a compressor</b>	
Razavi Khorasan	410	$\omega$	1.6
Nord Khorasan	164	<b>Diameter of pipeline</b>	
Golestan	210	$dia$	762mm
Mazandaran	716		

As mentioned earlier, the NG demand parameter in the mathematical model is under epistemic uncertainty. So, at first, the most possible quantities of demand parameters are gained by historical data. And then, the prominent points of corresponding triangular fuzzy numbers are estimated by experts' opinions as follows:

$$\widetilde{De}_{jtw} = (0.8\widetilde{De}_{jtw}, 0.95\widetilde{De}_{jtw}, 1.2\widetilde{De}_{jtw})$$

High impact of different disruption risks occurrence on the natural gas network, has forced NGTN to utilize various resilience strategies in order to reduce their consequences. Therefore, in this cases study, three potential mitigation resilience strategies including adding extra production capacity in refineries, installing backup pipelines and fortifying the pipelines were encountered. Also, it is assumed that recovery strategy is employed to restore the lost capacity of the refinery production capacity completely at the end of planning horizon. The disruption risks in the case study are handled based on three independent scenarios, small, medium and large scale. The small-scale scenario recognizes the least severe and the large-scale scenario recognizes the most severe case. As a result, each scenario has a different impact on the capacity of pipelines due to fortification levels and refinery production capacity.

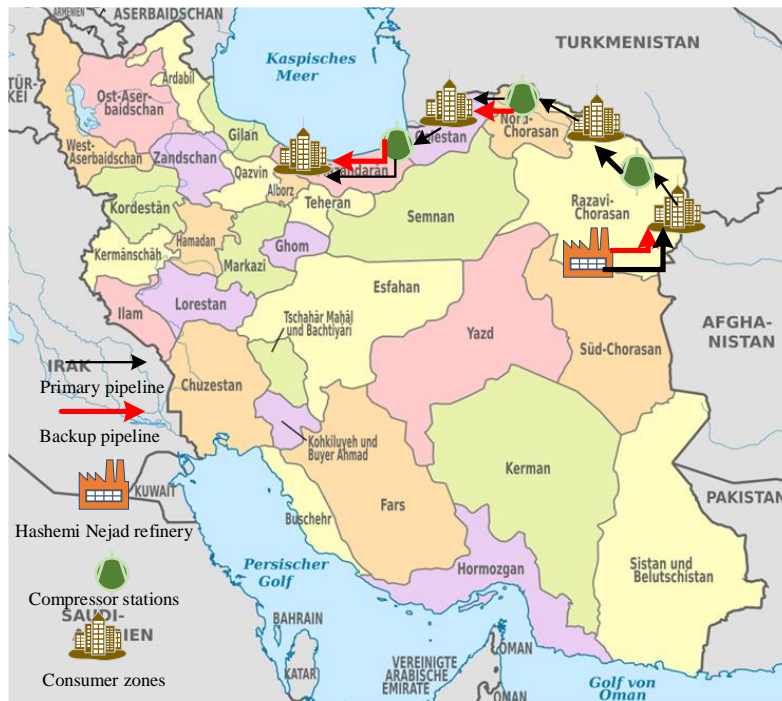
#### 4-1- Results and discussion

It should be noted that the proposed model is coded in GMAS 24.1.3 software with Cplex solver on a laptop with the Intel Core i7 processor running at 1.8GHz up to 1.99GH and with 16 GB of RAM. In addition, all the monetary data is considered in Iranian currency (i.e., *Toman*). The confidence level of chance constraints is assumed to be 0.7. Table 4 demonstrates the resulted optimal structure of NGTN in the case study at different disruption scale. From table 4, we obtain that compressor station Razavi, Farooj and Neka compensate the lost pressure in almost all situations. However, the number of turbos in each compressor station is added in larger disruptions. Another observation is that with the rise in the scale of disruptions, additive production capacity of refinery is more because the more part of working capacity is disrupted at the beginning of planning horizon. Then recovery planning should be done during next periods until the last period that the production capacity is recovered completely. Figure 3 illustrates the recovery

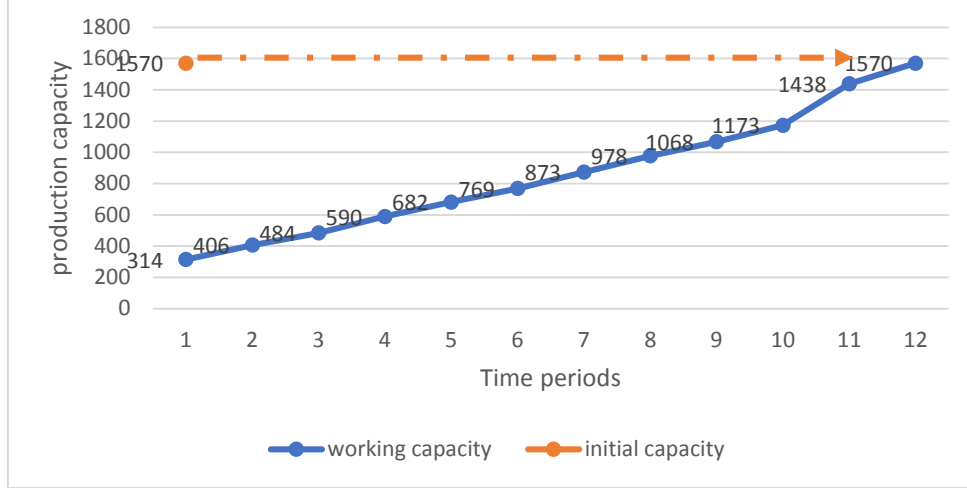
planning of production capacity in the disrupted refinery with time delay of one month. Also, the sixth and seventh columns of table 4 reports the mitigation strategies for pipelines. as the results show, the backup pipelines are installed from Hashemi Nejad refinery, Razavi stations and Farooj station to increase the flow rate, or keep flow if one of the parallel pipelines is disturbed. It is noteworthy that two pipelines must be installed from each refinery so that if one of the parallel pipelines is disrupted, the refinery can continue its supply by another pipelines. The number of fortified pipelines in order to maximize the remaining capacity against disruption risk is represented in the seventh column. Figure 3 displays the optimal structure of the given NG network in Iran.

**Table 4.** Configuration of NGTN and mitigation strategy at different disruption scale

Disruption scale	Primary pipeline	Location of compressor station and number of turbos	Working capacity of refinery	Capacity expansion	Number of backup pipeline	Number of fortified pipelines
Small	6	Razavi (1) Farooj (1) Neka (1)	1200	0	0	4
Medium	6	Razavi (1) Farooj (1) Neka (2)	765	30	1	4
Large	7	Razavi (2) Farooj (2) Neka (2) Noor (1)	314	70	3	5



**Fig 2.** The illustration of NGTN in Iran.



**Fig 3.** Restoration of production capacity of refinery in the large-scale scenario

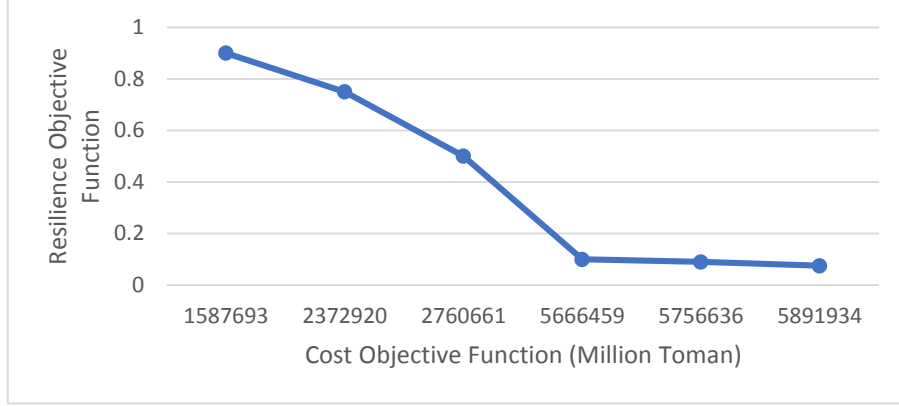
#### 4-1-1- Analysis on the trade-off between total cost and resilience

In this part, the famous Augmented  $\epsilon$ -constraint method is applied to prove the conflicting objective functions (Mavrotas, 2009). By using this method, a good approximation of the Pareto optimal could be achieved. For this purpose, each objective function of the model is first optimized separately in order to find two extreme efficient points of the Pareto frontier. Then, by adding one of the objective functions to the constraints set with a right-hand side ( $\epsilon$ parameter) step-by-step, other Pareto optimal solutions could be achieved (equation 58).

$$\begin{aligned}
 & \text{Min } f_1(x) - \delta \times (sl_2 + sl_2 + \dots + sl_p) \\
 & \text{s. t.} \\
 & f_p(x) + sl_p = \epsilon_p; \quad \forall p = 2, \dots, p \\
 & x \in X, sl_p \in R^+
 \end{aligned} \tag{58}$$

Where  $x$  is the vector of decision variables,  $f_1(x), \dots, f_p(x)$  are the  $p$  objective functions and  $X$  is the feasible region. Also,  $\delta$  is an adequately small number (usually between  $10^{-3}$  and  $10^{-6}$ ). By changing the parametrical variation in the right-hand side of constrained objective function ( $\epsilon_p; \forall p = 2, \dots, p$ ), different pareto solutions are obtained. Note that  $sl_p$  are the slack or surplus variables that ensure the model to produce only efficient solutions.

After solving the model, six Pareto-optimal solutions are generated and their results are shown in figure 4. The results approved that the considered objective functions are in contrast with each other as a decrease the disability of network leads to an increase in total costs and vice versa. Notably, the objective function of cost tends to decrease installing the pipeline and compressor stations, or to install pipeline with fewer resilience strategies. On the other hand, the second objective function for meeting all demand nodes against disruption and decreasing the risk in the network design phase requires expanding production capacity, utilizing pipelines with high fortification level, using more parallel pipelines and compressor stations with more turbo compressors. For example, when  $z_1=1587693$  and  $z_2=0.9$  (the first Pareto-optimal solution), just 6 pipelines in which consist of zero parallel pipelines, two pipelines with second fortification level and one compressor station with one turbo compressor in the station. Whereas when  $z_1 = 5891934$  and  $z_2 = 0.075$  (the last Pareto-optimal solution), 9 pipelines are installed that include 3 parallel pipelines with second fortification level and four compressor stations with two turbo compressors.



**Fig 4.** The Pareto Front found to solve conflicting objective functions

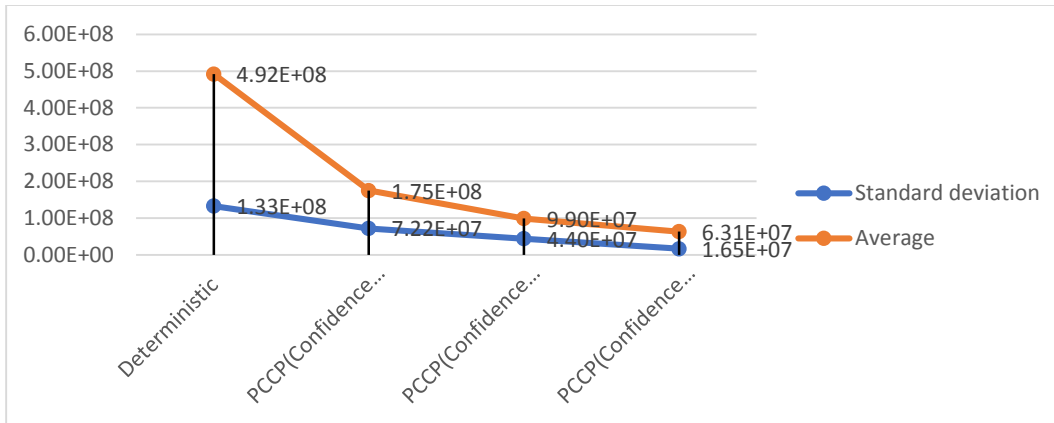
#### 4-1-2- Analysis on the efficiency of the PCCP

In this section, the validation of the obtained results from the possibilistic programming model is done via generating 10 random realizations of the problem. Each random realization is calculated with respect to the two extreme points of the relevant triangular fuzzy numbers. Then attained solutions that were gained by the PCCP model based in nominal data  $[x^*, y^*]$  will be replaced in the model. The brief form of this model is as follows:

$$\begin{aligned}
 & \text{Min } w_1 = C_{real}y^* + F_{real}x^* + \delta_1 R \\
 & \text{s.t} \\
 & w_2 \leq \varepsilon \\
 & Ax^* = 0, \\
 & Bx^* \leq Ty^*, \\
 & Lx^* + R \geq d_{real} \\
 & Py^* \leq 1, \\
 & R \geq 0.
 \end{aligned} \tag{59}$$

In this linear programming model, there are only one variable,  $R$  which are counted as the divergence from chance constraints according to different realizations and the parameters  $\delta_i$  is counted as the penalty values.

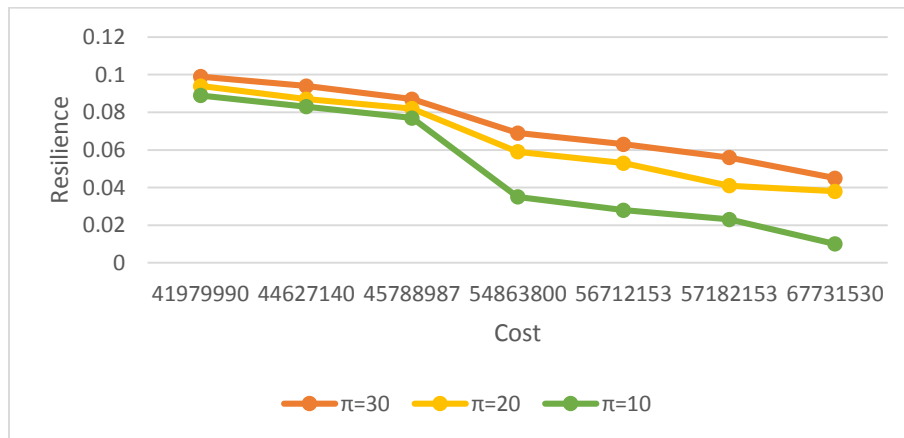
Performance of the PCCP and deterministic models has been showed in figure 5 via the corresponding values for average and standard divergence of the cost objective functions under 10 random realizations at 0.7, 0.8 and 0.9 confidence levels. As it is evident from figure 5, the average and standard deviation value of the PCCP model has been less than the deterministic model. Therefore, it can be claimed that the PCCP model has performed better than the deterministic model. Also, as it is clear, with the increase the confidence level of possibilistic chance-constrained, the standard deviation and average of objective function decrease because of the chance constraints should be satisfied in the stricter range.



**Fig 5.** The solutions of the deterministic and PCCP models under the average and standard deviation value

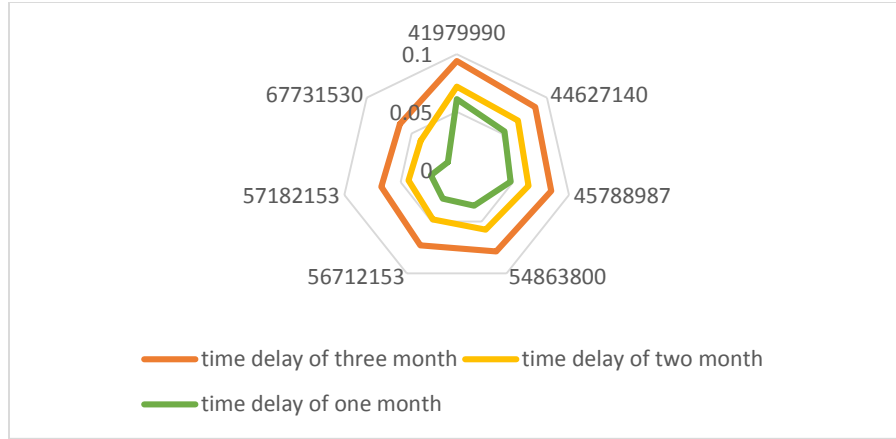
#### 4-1-3- Analysis on the trade-off between total cost and resilience under different Percentages of lost capacity and various time delay.

Figure 6 shows the Pareto curves between total cost and resilience with time delay of one month and  $\pi$  varying from 10% to 30%. The trend of the Pareto curves displays the trade-off between total cost and resilience. Also, if the total cost is fixed, the optimal disability value of network reduces with the decreasing of the lost capacity. It is noteworthy  $\pi$  reflect the severity of disruptions and a smaller  $\pi$  points that more production capacity and flow capacity are available after disruptions. on the other hand, disruptions occur with lower severity.



**Fig 6.** Pareto curves between total cost and network resilience under different lost capacity percentages.

Also, the impact of various time delay from one to three month with  $\pi = \%20$  is investigated. Due to figure 7, the result shows that time delay between the occurrence of disruptions and the start of recovery has a substantial impact on NGTN resiliency. If we assume that the total cost is fixed, longer time delay results in more NGTN disability.



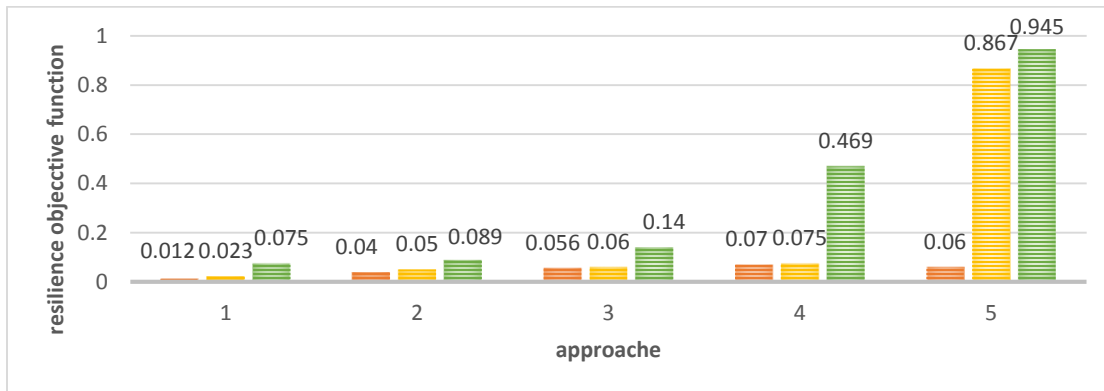
**Fig 7.** Pareto curves between total cost and network resilience under various time delay

**4-1-4- Analysis on the impact of resilience strategies.**

As mentioned in Section 3, the proposed model adopts the following resilience strategies to withstand different disruption scales: (a) adding production capacity for refineries, (b) installing backup pipelines and (3) fortifying pipelines. In this section, the effect of these strategies is evaluated on the resilience objective function as the main goal of NGTN. For this, we consider the following five approaches:

- (1) Applying all strategies.
- (2) Extending production capacity in refinery.
- (3) Applying only backup pipelines.
- (4) Applying fortifying pipelines.
- (5) Applying no strategies.

Figure 8 shows the results under different disruption scales. It is obvious that all resilience strategies have impact in the resilience of network as well as first approach imposes the highest level of resilience in comparison with other approaches. More exactly, based on the results can find that adopting the resilience strategies of extending production capacity of refinery, installing backup pipelines and fortifying pipelines can improve approximately 90%, 85% and 50%, respectively. It is noteworthy that using three resilience strategies simultaneously gains 93% resilience value. Also, the resilience enhancement is more apparent with rising the disruption scales.



**Fig 8.** The resilience performance of different approaches under different disruption scales.

#### 4-2- Managerial insights

In general, the northern regions of the natural gas transmission network face with three major challenges that need to be addressed:

- Failure of Hashemi Nejad refinery: since the Hashemi Nejad refinery is the only supplier of this network, so with the failure of this facility, all NG consumers will experience shortages. Therefore, it is suggested to strengthen the network resilience by constructing natural gas storage in this sector as a redundancy strategy.
- Failure of pipeline: One of the challenges that has the greatest impact on the network resilience is the transmission pipelines failure. Therefore, it is necessary to build two parallel pipelines for the output of each important facilities (e.g., refinery and compressor stations) so that when the main pipeline is disrupted, the backup pipeline or parallel can be used to meet consumer's demand.
- Reduction of time delay in the beginning of recovery actions: If one of the refinery equipment fails and the problem is not resolved, the entire of refinery will be affected immediately and the network performance will be stopped. So, timely recovery of refinery equipment or reduction of time delay in beginning of recovery actions is critical in maintaining its performance. In this regard, the most important action is to send the repair and recovery team to damaged section quickly.

#### 5-Conclusions

Design of resilient natural gas transmission network takes into account different types of challenges in the field of production, transmission and consumption. For this purpose, a multi-objective multi-period optimization model for designing resilient natural gas transmission network is developed while working capacity of refinery and transmission capacity of pipeline are vulnerable to disruption risks. Also, NG demand is considered as an operational risk in this model. So, a two-stage scenario-based stochastic-possibilistic programming model is used to cope with operational and disruption risks Simultaneously. Capacity expansion, backup pipeline for designing loop network and fortifying of pipeline as the mitigation strategies as well as the recovery planning of lost capacities of refinery are employed to enhance resilience in this work. a resilience index is modeled for optimizing the resilience of NGTN quantitatively based on restoration planning of lost capacity. Finally, a Necessity-based possibilistic programming model is used to convert the possibilistic programming model into its crisp counterpart.

Finally, the presented model is implemented in a real case study i.e. one of the natural gas transmission pipeline in north of Iran. The  $\epsilon$ -constraint method is applied to generate pareto-optimal solutions. This set of pareto front, authorize the DMs to manage a trade-off between maximizing the NG network resilience through more employing of mitigation and recovery strategies or minimizing the NG network cost. The result showed that using the resilience objective function as a decreasing the maximum cumulative fraction of unsupplied demand (relative to the met demand before the disruption), the NGTN has been built at a higher cost with more facilities and resilience options (i.e. more capacity expansion, more primary pipeline, more backup pipeline, more fortified pipelines and compressor stations with more number of turbos) but the least amount of unsupplied demand. The result also presented that the possibilistic chance constraint programming model has performed better than the deterministic model using standard deviation and average of cost objective function. The numerical results display that utilizing the extra production capacity of refinery, back-up pipeline and pipeline fortification at the same time can growths the resilience levels of NGTN more than 93 percent under large scale disruption scenario.

It is possible to extend the model in future, with considering underground gas storage to reinforce the resilience of NGTN especially when the refinery production capacity is disrupted. Another research topic is to consider diversity strategy such as aboveground storages for storing LNG near consumption areas especially in cases where underground gas storages (UGS) are not available due to geography. Another future study is to apply other non-deterministic programming approaches such as robust programming approaches. Also, it is suggested to use Geographic Information System (GIS) to select more suitable

candidate locations for natural gas pipelines and underground gas storage. Research can also investigate the recovery phase of disrupted pipelines to return their duty as soon as possible. Another line of future development is paying attention to solve large-scale problems by applying exact or meta-heuristic algorithms. Finally, considering other tactical decisions in modeling such as marketing, contracts and pricing are suggested for future research.

## References

Azadeh, A., Shabanpour, N., Gharibdousti, M.S. and Nasirian, B., (2016). Optimization of supply chain based on macro ergonomics criteria: A case study in gas transmission unit. *Journal of Loss Prevention in the Process Industries*, 43, pp.332-351.

Babazadeh, R., Ghaderi, H. and Pishvae, M.S., (2019). A benders-local branching algorithm for second-generation biodiesel supply chain network design under epistemic uncertainty. *Computers & Chemical Engineering*, 124, pp.364-380.

Biringer, B., Vugrin, E. and Warren, D., (2013). *Critical infrastructure system security and resiliency*. CRC press.

California. Seismic Safety Commission and ASCE-25 Task Committee on Earthquake Safety Issues for Gas Systems, (2002). *Improving Natural Gas Safety in Earthquakes* (No. 2). Seismic Safety Commission.

Cimellaro, G.P., Villa, O. and Bruneau, M., 2014. Resilience-based design of natural gas distribution networks. *Journal of Infrastructure systems*, 21(1), p.05014005.

da Silva Alves, F., de Souza, J.N.M. and Costa, A.L.H., (2016). Multi-objective design optimization of natural gas transmission networks. *Computers & Chemical Engineering*, 93, pp.212-220.

Emenike, S.N. and Falcone, G., (2020). A review on energy supply chain resilience through optimization. *Renewable and Sustainable Energy Reviews*, 134, p.110088.

Fan, M.W., Gong, J., Wu, Y. and Kong, W.H., (2017). The gas supply reliability analysis of natural gas pipeline network based on simplified topological structure. *Journal of Renewable and Sustainable Energy*, 9(4), p.045503.

Fasihzadeh, M., Sefti, M.V. and Torbati, H.M., (2014). Improving gas transmission networks operation using simulation algorithms: Case study of the National Iranian Gas Network. *Journal of Natural Gas Science and Engineering*, 20, pp.319-327.

Ghavamifar, A., Sabouhi, F. and Makui, A., (2018). An integrated model for designing a distribution network of products under facility and transportation link disruptions. *Journal of Industrial and Systems Engineering*, 11(1), pp.113-126.

Hamedi, M., Farahani, R.Z., Hussein, M.M. and Esmaeilian, G.R., (2009). A distribution-planning model for natural gas supply chain: A case study. *Energy Policy*, 37(3), pp.799-812.

Honegger, et al., "Improving Natural Gas Safety in Earthquakes", Prepared by ASCE-25 Task Committee On Earthquake Safety Issues For Gas Systems, California Seismic Safety Commission, (2002).

Hosseini, S., Barker, K. and Ramirez-Marquez, J.E., (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, 145, pp.47-61.

Jo, Y.D. and Crowl, D.A., (2008). Individual risk analysis of high-pressure natural gas pipelines. *Journal of Loss Prevention in the Process Industries*, 21(6), pp.589-595.



- Kashani, A.H.A. and Molaei, R., (2014). Techno-economical and environmental optimization of natural gas network operation. *Chemical Engineering Research and Design*, 92(11), pp.2106-2122.
- Karmon, E., (2002). The risk of terrorism against oil and gas pipelines in Central Asia. *The Oil and Gas Routed from Caspian-Caucasus Region: Geopolitics of Pipelines, Stability and International Security*.
- Li, X., Armagan, E., Tomasgard, A. and Barton, P.I., (2011). Stochastic pooling problem for natural gas production network design and operation under uncertainty. *AIChE Journal*, 57(8), pp.2120-2135.
- Liang, Y., Zheng, J., Wang, B., Zheng, T. and Xu, N., (2020). Optimization Design of Natural Gas Pipeline Based on a Hybrid Intelligent Algorithm. In *Recent Trends in Intelligent Computing, Communication and Devices* (pp. 1015-1025). Springer, Singapore.
- Liu, W., Li, Z., Song, Z. and Li, J., (2018). Seismic reliability evaluation of gas supply networks based on the probability density evolution method. *Structural safety*, 70, pp.21-34.
- Liu, W. and Song, Z., (2020). Review of studies on the resilience of urban critical infrastructure networks. *Reliability Engineering & System Safety*, 193, p.106617.
- Mavrotas, G., (2009). Effective implementation of the  $\epsilon$ -constraint method in multi-objective mathematical programming problems. *Applied mathematics and computation*, 213(2), pp.455-465.
- Misra, S., Fisher, M.W., Backhaus, S., Bent, R., Chertkov, M. and Pan, F., (2014). Optimal compression in natural gas networks: A geometric programming approach. *IEEE transactions on control of network systems*, 2(1), pp.47-56.
- Omidvar, B. and Kivi, H.K., (2016). Multi-hazard failure probability analysis of gas pipelines for earthquake shaking, ground failure and fire following earthquake. *Natural hazards*, 82(1), pp.703-720.
- Pishvaei, M.S. and Torabi, S.A., (2010). A possibilistic programming approach for closed-loop supply chain network design under uncertainty. *Fuzzy sets and systems*, 161(20), pp.2668-2683.
- Pishvaei, M.S., Razmi, J. and Torabi, S.A., (2012). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy sets and systems*, 206, pp.1-20.
- Papageorgiou, L.G., (2009). Supply chain optimisation for the process industries: Advances and opportunities. *Computers & Chemical Engineering*, 33(12), pp.1931-1938.
- Sabouhi, F. and Jabalameli, M.S., (2019). A stochastic bi-objective multi-product programming model to supply chain network design under disruption risks. *Journal of Industrial and Systems Engineering*, 12(3), pp.196-209.
- Su, H., Zio, E., Zhang, J., Li, X., Chi, L., Fan, L. and Zhang, Z., (2019). A method for the multi-objective optimization of the operation of natural gas pipeline networks considering supply reliability and operation efficiency. *Computers & Chemical Engineering*, 131, p.106584.
- Su, H., Zio, E., Zhang, J. and Li, X., (2018). A systematic framework of vulnerability analysis of a natural gas pipeline network. *Reliability Engineering & System Safety*, 175, pp.79-91.
- Sesini, M., Giarola, S. and Hawkes, A.D., (2020). The impact of liquefied natural gas and storage on the EU natural gas infrastructure resilience. *Energy*, 209, p.118367.
- Su, H., Zhang, J., Zio, E., Yang, N., Li, X. and Zhang, Z., (2018). An integrated systemic method for supply reliability assessment of natural gas pipeline networks. *Applied Energy*, 209, pp.489-501.

Tabatabaee, M., (2016). Resilience assessment of the natural gas supply system of the Country and Proposals to increase its Resiliency. *The Center for Energy Technology Development*, No. of research agreement: 193010.

Tsinidis, G., Di Sarno, L., Sextos, A. and Furtner, P., (2019). A critical review on the vulnerability assessment of natural gas pipelines subjected to seismic wave propagation. Part 1: Fragility relations and implemented seismic intensity measures. *Tunnelling and Underground Space Technology*, 86, pp.279-296.

Üster, H. and Dilaveroğlu, Ş., (2014). Optimization for design and operation of natural gas transmission networks. *Applied Energy*, 133, pp.56-69.

Yu, W., Gong, J., Song, S., Huang, W., Li, Y., Zhang, J., Hong, B., Zhang, Y., Wen, K. and Duan, X., (2019). Gas supply reliability analysis of a natural gas pipeline system considering the effects of underground gas storages. *Applied Energy*, 252, p.113418.

Zamanian, M.R., Sadeh, E., Sabegh, Z.A. and Rasi, R.E., (2020). A Multi-Objective Optimization Model for the Resilience and Sustainable Supply Chain: A Case Study. *International Journal of Supply and Operations Management*, 7(1), pp.51-75.

Zhang, H., Liang, Y., Liao, Q., Chen, J., Zhang, W., Long, Y. and Qian, C., (2019). Optimal design and operation for supply chain system of multi-state natural gas under uncertainties of demand and purchase price. *Computers & Industrial Engineering*, 131, pp.115-130.

Zhu, Y., Wang, P., Wang, Y., Tong, R., Yu, B. and Qu, Z., (2021). Assessment method for gas supply reliability of natural gas pipeline networks considering failure and repair. *Journal of Natural Gas Science and Engineering*, 88, p.103817.