A ROBUST OPTIMIZATION MODEL FOR SUSTAINABLE AND RESILIENT CLOSED-LOOP SUPPLY CHAIN NETWORK DESIGN CONSIDERING CONDITIONAL VALUE AT RISK

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Abstract. One of the challenges facing supply chain designers is designing a sustainable and resilient supply chain network. The present study considers a closed-loop supply chain by taking into account sustainability, resilience, robustness, and risk aversion for the first time. The study suggests a two-stage mixed-integer linear programming model for the problem. Further, the robust counterpart model is used to handle uncertainties. Furthermore, conditional value at risk criterion in the model is considered in order to create real-life conditions. The sustainability goals addressed in the present study include minimizing the costs, CO₂ emission, and energy, along with maximizing employment. In addition, effective environmental and social life-cycle evaluations are provided to assess the associated effects of the model on society, environment, and energy consumption. The model aims to answer the questions regarding the establishment of facilities and amount of transported goods between facilities. The model is implemented in a car assembler company in Iran. Based on the results, several managerial insights are offered to the decision-makers. Due to the complexity of the problem, a constraint relaxation is applied to produce quality upper and lower bounds in medium and large-scale models. Moreover, the LP-Metric method is used to merge the objectives to attain an optimal solution. The results revealed that the robust counterpart provides a better estimation of the total cost, pollution, energy consumption, and employment level compared to the basic model.

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1. Introduction. One of the purposes of designing a closed-loop supply chain (CLSC) is designing a network, launching and operating the material flow between the chain centers so that the economic, environmental, and social goals of the beneficiaries are simultaneously optimized. Further, creating and promoting sustainable development in the production, distribution, and recycling of the products are regarded as the other purposes of designing CLSC. Designing a supply chain, as one of the strategic decisions, includes determining network topology in order to provide services for customers in the best possible condition [30]. When both forward and reverse logistics are simultaneously noticed, a CLSC is formed which forms the CLSC of the two-way flow of goods regarding economic, environmental, and social activities. However, economic goals encompass increasing the incomes and decreasing the costs while environmental goals include decreasing the effect of environmental pollutants on water, air, and land, along with reducing energy consumption. Further, social goals refer to improving employment opportunities and the welfare of employees and people who are directly or indirectly in contact with the supply chain.

CLSC management has attracted a lot of attention in recent years. According to the governmental laws and legislation regarding environmental and social effects, customer activities and demands from supply chains are considered as the major decisive factors among competitors [46]. Therefore, the globalization of the supply chains increases the number of network units and transportation between them, leading to more greenhouse gas emission, including the emission of carbon dioxide, and energy consumption. Thus, in order to design a supply chain in the future, some necessary steps should be taken which include designing a CLSC, adopting a sustainable approach, becoming efficient in energy consumption, and being reliable and resilient against disruption conditions.

The globalization of economic activities, together with fast developments in information technologies, have led to shorter product life cycles, smaller lot sizes, and very dynamic customer behavior in terms of preferences. These changes have created a growing demand uncertainty which clearly highlights the significance of a robust and well-designed supply chain network [31].

Several researchers have investigated the field of supply chain strategic design. The initial models sought to optimize the costs by responding to customer demands while in recent research, other goals such as environmental effects, including carbon dioxide emissions and energy consumption, and social welfare are added to the literature in order to consider the sustainable problem [10, 33, 39, 18]. In this regard, considering facility reliability against disruption conditions such as flood, storm, and earthquake is among the recent developments which have been added to the supply chain by researchers [48, 20]. By taking into account the facility resilience while designing the supply chain and facility preparation for facing demand fluctuations, supply chain designers now have to deal with the issue of resilience against demand fluctuations, which makes them pay more attention to the risks and threats when designing the model [11, 29, 17].

The present study contributes to the literature by designing a robust optimization model for sustainable and resilient CLSC network design by considering conditional value at risk.

The literature review and research gaps are addressed in Section 2. In Section 3, the problem and modeling are presented and the models are compared with each other. The case study is discussed, the sensitivity analysis is performed, and the
model is solved in medium and large scales in Section 4. In Sections 5 and 6, managerial implications, practical insights, and conclusions are drawn.

2. Literature Review. The intense competition between the companies and supply chains leads to uncertainty in activity operation, resulting in high risks. The risks caused by demand uncertainty and disruption in the facility have negative effects on the activities in the supply chain and can increase the costs and reduce the competitive advantage. The supply chain management should adopt more innovative approaches in order to be capable of facing risk disruptions. Designing a supply chain which includes economic, environmental, social, and energy consumption aspects, along with considering the resilience and reliability of the facilities in risk and disruption conditions can be a new and important approach to the strategic design of a supply chain [22, 21]. A number of research regarding CLSC design conducted between 2009 and 2018 are addressed in the following.

2.1. Sustainable, reliable, and resilient CLSC. A reliable CLSC is suggested by Torabi et al. [48] which can be used where the facilities have disruption. The innovation in this model is related to using stochastic p-robust optimization approach in facing disruption in the facility. In addition, the proposed model includes both partial and complete disruption in the facility capacity and is modeled as fuzzy. The results of the study indicated that considering disruption increases the costs and optimizes the system against disturbance. Talaei et al. [46] proposed a bi-objective carbon-efficient CLSC for the copier industry. They applied robust fuzzy programming in order to assess the uncertainty in the demand and variable costs of the supply chain. The model aims to minimize the costs and carbon dioxide emissions. A reliable and resilient CLSC under supply risk is designed by Ghomi-Avili et al. [17]. In their study, the suppliers have complete disruption so that they lose all of their capacity and do not satisfy the customer’s demand at the proper time. Therefore, two resilience strategies including the use of extra inventory and lateral transshipment are employed in order to reduce the effect of disruption on supply chain performance. Further, two types of reliable and unreliable suppliers exist in the chain which have different opening costs. The results showed that using lateral transshipment and extra inventory reduces the costs. Tavakkoli-Moghaddam et al. [47] proposed a CLSC model which promotes innovations such as supplier selection at different quality levels, integration of disposal and rework facilities, considering the environmental factors including production pollution and defect in disposal, and addressing the time-windows of customer’s order, and earliness/tardiness costs. The possibilistic fuzzy approach is performed to account for the uncertainty in the parameters. Mari et al. [28] designed a sustainable and resilient forward supply chain in the textile industry. The emission of carbon dioxide is part of the sustainability aspect of the model while the probabilistic disruption in the facilities is among the resilience aspects. Carbon footprints and disruption costs are considered as the resilience criterion. In another study, Amin and Baki [1] proposed a mathematical CLSC model containing global factors such as exchange rate and customs duties in the electronics industry. Paying simultaneous attention to the global factors such as exchange rates and customs duties by domestic and international contractors, being multi-objective, and having uncertainty in the real locations of the CLSC network configuration are part of model innovations. Furthermore, Amin et al. [2] assessed the uncertainty effect on designing and optimizing CLSC network by different options for car tire marketing. Considering various tire marketing options, addressing
the uncertainty effects on closed-loop network based on the tree-based methodology, taking into account the financial flow in multi-period model with cost present values, and using Google Maps to exactly determine the distances are regarded as innovative elements of the model.

2.2. Considering risk in CLSC. Soleimani and Govindan [42] assessed the location/allocation of a two-stage scenario-based reverse supply chain, which was multi-product and single-period. In their study, the conditional value at risk index was employed as the risk evaluator in the two-stage programming. The results indicated that the profit increases by increasing the risk level while the profit decreases by increasing the risk weight In another study, Cardoso et al. [7] designed and programmed an integrated CLSC model with financial risks by embedding uncertainty in the final products. The aim of the model is to maximize the expected net present value (ENPV) while minimizing the related risk criterion. The augmented epsilon constraint method is embedded in order to solve the model for producing the Pareto front curve for each risk criterion. Further, the uncertainty in the model is addressed by the help of the scenario tree in demand. The study included variance, variability index, downside risk, and CVaR. Subulan et al. [44] modeled a multi-period, multi-product, and multi-echelon CLSC for the lead-acid battery industry. The model innovation is related to stochastic-fuzzy and possibilistic uncertainties. Moreover, Subulan et al. [44] considered the financial risks and risks associated with not collecting the products whose lives have ended. They included the indexes of VaR, CVaR, and downside risk in order to indicate the risk in the model and concluded that the downside risk index performs better than the other ones. Prakash et al. [38] designed a CLSC by modeling risk and uncertainty in demand. They employed convex robust and reliable chain in designing the chain and used the worst risk case and uncertainty in the electronics trade industry. In another study, Prakash et al. [37] assessed CLSC for the hospital beds. They embedded the risks in waiting times in modeling and showed that the system costs increase by the risks. Sahebjamnia et al. [40] designed a resilient CLSC in the tire industry. Their model is developed for economic, environmental, and social goals. They employed four hybrid methods including Red Deer Algorithm (RDA) and Simulated Annealing (SA) algorithm, Genetic Algorithm (GA) and Water Wave Optimization (WWO) algorithm, WWO and Tabu Search (TS) algorithms, and RDA and WWO algorithm for solving the model. They indicated that GA and WWO algorithm are more efficient.

A more detail classification of the literature is presented in Table 1 with respect to eight features including the kind of CLSC, resilience, disruption, uncertainty, risk, objectives, industry, and method. The features related to the problem in the present study is presented in the last row of the table.

The innovation, main contribution, and research gap of the present study are introducing a new mathematical model from a sustainable CLSC with economic, environmental, energy, and social aspects. In addition, the problem has different scenarios along with the disruption risks which generally have not been considered simultaneously in previous studies. In order to have a real-life condition, the facilities in the supply-chain network are reliable, have partial disruption, and are resilient in capacity for the facility flexibility against demand variations. Further, the deviation from demand is allowed and the problem robustness against the demand is added to the problem. In the present study, the combination of Mulvey’s
robust scenario-based approach and conditional value at risk (CVaR) is employed in all the objective functions. The effective environmental and social life-cycle assessment-based methods are applied in the model for estimating the relevant social and environmental impacts, and energy consumption.

Table 1. Survey on CLSC

| Reference | Kind of CLSC | Resilience | Disruption | Uncertainty | Risk | Objectives | Industry | Method                  |
|-----------|--------------|------------|------------|-------------|------|------------|----------|-------------------------|
| Talaei et al. [46] | Reliable     | Both partial, complete disruption | Probabilistic mixed programming | Stochastic | Robust | Economic | Numerical example | Epsilon-constraint     |
| Ghomi Avili et al. [17] | Reliable and resilient | Extra inventory, lateral transshipment, reliable and unreliable suppliers | Complete disruption | Two-stage probabilistic mixed programming | Supply risk | Economic | Numerical example *CS |
| Tavakkoli Moghadam et al. [42] | Reliable and resilient | Probabilistic disruption | Probabilistic | Probabilistic | Disruption costs | Economic | Numerical example CS |
| Mari et al. [28] | Sustainable and resilient | Probabilistic disruption | Probabilistic | Probabilistic | Disruption costs | Economic | Textile industry | CS |
| Amin and Baki [1] | Robust and reliable | Scenario | Fuzzy programming | Stochastic | CVaR | Economic | Numerical example CS |
| Brandenburg [5] | Robust, sustainable, resilient, and reliable | Scenario | Stochastic | Worst risk case | Economic | Electronics trade industry | CS |
| Brandenburg [6] | Robust, sustainable, resilient, and reliable | Simulation | VaR | Economic | Environmental, social and energy | Car manufacturing industry | CS |

*CS: Commercial Solver, AEC: Augmented epsilon constraint, MH: RDA and SA algorithm, GA and WWO algorithm, WGP: Weighted goal programming, VI: Variability index, DR: Downside risk, NA: Not Applicable.
3. Problem Statement. Various studies have been performed with regard to designing CLSC. The suggestions for future research in the studies mentioned in the literature review and new industry requirements have led us to design an integrated, sustainable and robust against demand variations, resilient, and risk-averse CLSC. This model has competitive capabilities and flexibility in any condition such as disruption. It also considers the environmental aspects and employment requirements which can reduce disruption risks in the supply chain network (SCN). The present study aims to investigate the car manufacturing industry. Considering the initiation of manufacturing old and new cars in Iran, this method of designing requires the car manufacturer of the supply chain to carefully consider the legal, environmental, energy, and employment requirements. Further, the car manufacturer is required to reduce the shareholder requirements such as costs and supply chain risks as much as possible. In addition, the method involves reliable and resilient facilities. The suggested supply chain includes suppliers, manufacturers, distribution centers, retailers, customers, collection centers, repairing centers, disposal centers, and second-hand customers (Figure. 1-(a)). In the present study, the methodology problem is presented in Figure 1-(b). Four research questions are raised which are as follows.

1. What are the important requirements of energy, sustainability, and risk-taking in reducing the costs of CLSC?
2. How is the energy efficiency, sustainability, and risk-taking effective in choosing supply chain locations?
3. What is the role of certainty and scenario-based programming in the cost of the model?
4. How should the location and flow of facilities be set in order to reduce the costs and pollutants of the environment, decrease the energy consumption in the model, and maximize the social goal?

The model aims at minimizing the costs, environmental pollutant emissions, and energy consumption as well as maximizing the employment rate, which is one of the social welfare indexes. We consider the disruption risk of each scenario and whether it is robust against demand variation. Further, this model applies cumulative energy demand (CED), guidelines for social life cycle assessment of products (GSLCAP), and ReCiPe solutions in order to evaluate the associated effects on society, environment, and energy consumption. The demands of the final customers in the proposed model have various scenarios. The facility capacity, including the manufacturers, distribution centers, retailers, and collecting and repairing centers, is flexible and resilient against different scenarios. The strategic decisions of the model encompass opening resilient centers or facilities and considering the amount of transportation between the centers. Furthermore, all the capacity and flow constraints exist between the facilities.

3.1. Problem assumptions.

1. The demand for and the returns of each product in each period is dependent on the scenario.
2. The capacity of the centers in each period depends on the scenario (resilience feature).
3. There is the probability of availability in the chain centers (reliability and resilience features).
4. The fixed costs of the facilities are independent.
5. All the constraints of the SCN models including balance and capacity are imposed on the centers.
6. The parameters of variable costs, pollutant emissions, energy consumption, and employment depend on the balance between the centers, period, scenario, and products.
7. Violating the key constraints of the demand satisfaction is also allowed, which is related to making the model robust.
8. The CVaR criterion is utilized to encounter the risk measure.
3.2. Environmental impact assessment (EIA). According to [12], life cycle assessment (LCA) is used for quantitative analysis of activities/products cycle within the environmental impact (EI) context. In order to evaluate the supply chain network of EI, several methods and tools are required to help with obtaining a sustainable and resilient CLSC. ReCiPe 2008 is one of the EIA methods selected to evaluate the EI of SCN design decisions for several reasons. First, given the end-point and mid-point impacts, the approach can determine the EI. Second, since the solution is developed recently, it is equipped with the latest advances in environmental sciences. Next, ReCiPe is regarded as one of the most comprehensive EIA methods with suitable coverage of most of the potential end-point and mid-point impacts. In addition, since ReCiPe is originated from Eco-indicator 99 and CML, it involves the benefits of both approaches. Finally, it does not require a goal setting, in contrast to the approaches such as Ecological Scarcity [36]. As the first step, ReCiPe is applied in the system for assessing the EI of various configurations of SCN. Then, the stages of the life cycle must be determined. Next, each stage should have a determined inventory. Figure 2 presents the associated inventories and life cycle of the given SMNS supply chain. The final score is determined through multiplying the inventories amounts by the associated environment indicators and adding up the results. In the present study, we applied the ReCiPe concept in an environmental objective and determined the facility emissions caused by the facilities establishment and use.

3.3. Energy impact assessment (EIA). Cumulative energy demand (CED) has been applied since the early 70s in order to evaluate the environmental impacts of the life cycle of commodity manufacture, [16]. For both of the given frameworks, the CED method is employed to assess energy consumption and has been widely used to determine the energy intakes during the service life of a unit [27]. CED is measured by adding the cumulative energy demands for the production (CEDP), cumulative energy demands for the use (CEDU), and cumulative energy demands for the disposal (CEDD) of the economic unit. Accordingly, CED allows for comparing and evaluating the services and products based on the energy criteria. We applied the CED concept for the energy objective in the present study and determined the facility energy caused by the facilities establishment and use.

3.4. Social impact assessment (SIA). Due to the complicated nature and comprehensive scope of social impacts, measuring social impact (SI) is considered a multidisciplinary and multi stakeholder issue. GSLCAP [4] was chosen as a reference for evaluating SIs in the problem of the present study. In comparison with other methods, GSLCAP has three benefits. First, GSLCAP is an SIA method with product-oriented, in contrast to organization-oriented, nature formed on the basis of LCA, and, therefore, it is consistent with the applied EIA method, namely ReCiPe, and supply chain logic and facilitates the formulation and design of the model. Second, social issues are appropriately covered in this method. However, it fails to consider the organizational issues and the environment. Therefore, its compatibility with social issues and sustainability paradigm through SC is higher. Finally, since GSLCAP is a newly developed framework, it is equipped with the recent advances in the field of SIA. GSLCAP presents five categories of stakeholders including local community, consumers, value chain actors, society, and workers (employees). Further, some socio-economic and social subcategories are associated with each category of the
stakeholders. In the present study, we applied the GSLCAP (employees) concept in a societal objective and determined the number of employees based on the facilities establishment.

3.5. **Proposed mathematical model.** The stochastic programming approach of Mulvey et al. [32] is applied in the present study in order to achieve the common business uncertainty and existing disruptions. Moreover, our approach includes minimizing the sum of the weighted average and standard deviation of an objective function, i.e. costs, environmental goal, energy, employment, and a fine related to not satisfying a key limitation, i.e. demand.

Offering flexibility and adding to the supply and production capacities are considered as the resilience strategy used to face with losing capacities of suppliers and factories resulting from disturbances [48]. Further, we involved a flexible capacity
facility depending on the scenario and we used an availability parameter to represent a reliable facility with disruption.

The CVaR criterion, designed by Rockfeller and Uryasev [42], is applied to a novel embed risk measure. CVaR, also known as the expected shortfall, is considered as a risk assessment measure which measures the amount of risk in an investment portfolio. CVaR is measured by calculating the weighted average of the “extreme” losses in the tail of the distribution of possible returns, beyond the VaR cutoff point. Conditional value at risk is embedded in the portfolio optimization for effective risk management [19, 41, 13]. In addition, CVaR is more coherent, consistent, and conservative than other risk criteria.

The method of modeling the scenario-based stochastic programming approach of Mulvey [32] is as follows.

$$\begin{align*}
\text{Min} \quad & x \in \mathbb{R}^n, y \in \mathbb{R}^n \quad c^T x + d^T y \\
\text{Subject to} \quad & Ax = b \\
& Bx + Cy = e \\
& x, y \geq 0
\end{align*}$$

Assuming that the variable $y$ is dependent on the scenario, and for each scenario $s \in \Omega$, the modeling is as follows.

The objective function is the mathematical expectation and absolute deviation from the objective function of the target function for each scenario:

$$\begin{align*}
\text{Min} \quad & \sigma(x, y_s) + \omega p(z_s) \\
\text{Subject to} \quad & \sigma(x, y_s) = \sum_{s \in \Omega} p_s \Gamma_s + \beta \sum_{s=1}^{N} p_s \left| \Gamma_s - \sum_{s=1}^{N} p_s \Gamma_s \right|, \forall s \in \Omega \\
& p(z_s) = \sum_{s \in \Omega} p_s |z_s|, \forall s \in \Omega \\
& \Gamma_s = c^T x + d^T y_s, \forall s \in \Omega \\
& Ax = b, \forall s \in \Omega \\
& B_s x + C_s y_s + z_s = e, \forall s \in \Omega \\
& x, y_s \geq 0 \quad \forall s \in \Omega
\end{align*}$$

Since CVaR has a unique feature and brilliant performance, the present study adds a risk measure to the model in the network design of the closed loop supply chain as follows [43].

$$\begin{align*}
\min_{x \in \mathbb{R}^n} \{ E(f(x, w) + \lambda CV aR(f(x, w))) \} \\
CV aR_{\alpha}(Z) = \min_{\eta \in \mathbb{R}} f(\alpha, \eta, x) \\
f(\alpha, \eta, x) = \eta + \frac{1}{1 - \alpha} E\{\max\{Z(x, \omega) - \eta, 0\}\}
\end{align*}$$

Since the solution scenario in the model is based on the scenario analysis approach, considering previous studies, the following rewrite for designing and planning the supply chain can be used [35].

$$\begin{align*}
\text{Min} \quad & \sigma(x, y_s) + \omega p(z_s) + \lambda CV aR(x, y_s) \\
\end{align*}$$
Subject to

\text{Constraints (A-6) to (A-11)}

In the following proposed mathematical model, stochastic scenario-oriented programming approach is used involving CVaR. Symbols list is presented in Appendix 1.

Model 1. A robust model by considering CVaR

\[
\min \text{obj}_1 = \sum_{s'} p_{s'} \Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'1} - \sum_{s'} p_{s'} \Gamma_{s'1} \right| + \omega \sum_{s'} p_{s'} k_{s'1} \left( \sum_r \sum_p \sum_t |z_{rpt'}| \right) + \lambda (\eta_1 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} \max(\Gamma_{s'1} - \eta_1, 0)) ,
\]

\[
\min \text{obj}_2 = \sum_{s'} p_{s'} \Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'2} - \sum_{s'} p_{s'} \Gamma_{s'2} \right| + \omega \sum_{s'} p_{s'} k_{s'2} \left( \sum_r \sum_p \sum_t |z_{rpt'}| \right) + \lambda (\eta_2 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} \max(\Gamma_{s'2} - \eta_2, 0)) ,
\]

\[
\min \text{obj}_3 = \sum_{s'} p_{s'} \Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'3} - \sum_{s'} p_{s'} \Gamma_{s'3} \right| + \omega \sum_{s'} p_{s'} k_{s'3} \left( \sum_r \sum_p \sum_t |z_{rpt'}| \right) + \lambda (\eta_3 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} \max(\Gamma_{s'3} - \eta_3, 0)) ,
\]

\[
\max \text{obj}_4 = \sum_{s'} p_{s'} \Gamma_{s'4} + \beta \sum_{s'} p_{s'} \left| \Gamma_{s'4} - \sum_{s'} p_{s'} \Gamma_{s'4} \right| + \omega \sum_{s'} p_{s'} k_{s'4} \left( \sum_r \sum_p \sum_t |z_{rpt'}| \right) + \lambda (\eta_4 + \frac{1}{1-\alpha} \sum_{s'} p_{s'} \max(\Gamma_{s'4} - \eta_4, 0)) ,
\]

\[
\Gamma_{s'1} = \text{FixCost} + \text{VariableCost}_{s'}, \forall s'
\]

\[
\text{FixCost} = \sum_s f_s x_s + \sum_m f_m x_m + \sum_d f_d x_d + \sum_r f_r x_r + \sum_c f_c x_c + \sum_k f_k x_k + \sum_e f_e x_e
\]
\[ \text{VariableCost}_{s'} = \sum_t \sum_p \sum_m \sum_s V_{smt}^{pmd} Q_{smt}^{pmd} + \]
\[ \sum_t \sum_p \sum_d \sum_m V_{md}^{mpt} Q_{md}^{mpt} + \sum_t \sum_p \sum_r \sum_d V_{dr}^{drpt} Q_{dr}^{drpt} + \]
\[ \sum_t \sum_p \sum_c \sum_r V_{rc}^{rcpts} Q_{rc}^{rcpts} + \sum_t \sum_p \sum_k \sum_c V_{ck}^{ckpts} Q_{ck}^{ckpts} + \]
\[ \sum_t \sum_p \sum_s \sum_k V_{sk}^{skpts} Q_{sk}^{skpts} + \sum_t \sum_p \sum_s \sum_k O_{sk}^{skpts} Q_{sk}^{skpts} + \forall s' \]
\[ \sum_t \sum_s \sum_m E_{sm}^{smt} Q_{sm}^{smt} + \sum_t \sum_d \sum_m E_{md}^{md} Q_{md}^{md} + \sum_t \sum_d \sum_d E_{md}^{md} Q_{md}^{md} + \sum_t \sum_r \sum_r E_{mr}^{rpts} Q_{mr}^{rpts} + \sum_t \sum_c \sum_c E_{mc}^{cpts} Q_{mc}^{cpts} + \forall s' \]
\[ \sum_t \sum_s \sum_k E_{sk}^{skpts} Q_{sk}^{skpts} + \sum_t \sum_s \sum_k E_{sk}^{skpts} Q_{sk}^{skpts} + \forall s' \]
\[ \Gamma_{s'}^2 = \text{FixEmision}_{s'} + \text{VariableEmision}_{s'} \]
\[ \text{FixEmision}_{s'} = \sum_t \sum_s E_{smt}^{spt} Q_{smt}^{spt} + \sum_t \sum_m E_{mmt}^{mmt} x_{mmt} + \]
\[ \sum_t \sum_d E_{md}^{md} x_{md} + \sum_t \sum_r E_{mr}^{mr} x_{mr} + \sum_t \sum_c E_{mc}^{mc} x_{mc} + \forall s' \]
\[ \sum_t \sum_k E_{sk}^{skpts} x_{sk} + \sum_t \sum_e E_{se}^{epts} x_{se} \]
\[ \text{VariableEmision}_{s'} = \sum_t \sum_p \sum_m \sum_s E_{smt}^{smt} Q_{smt}^{smt} + \]
\[ \sum_t \sum_p \sum_d \sum_m E_{md}^{md} Q_{md}^{md} + \sum_t \sum_p \sum_r \sum_d E_{dr}^{drpt} Q_{dr}^{drpt} + \]
\[ \sum_t \sum_p \sum_c \sum_r E_{rc}^{rcpts} Q_{rc}^{rcpts} + \sum_t \sum_p \sum_k \sum_c E_{ck}^{ckpts} Q_{ck}^{ckpts} + \forall s' \]
\[ \sum_t \sum_p \sum_s \sum_k E_{sk}^{skpts} Q_{sk}^{skpts} + \sum_t \sum_p \sum_s \sum_k E_{sk}^{skpts} Q_{sk}^{skpts} + \forall s' \]
\[ \Gamma_{s'}^3 = \text{FixEnergy}_{s'} + \text{VariableEnergy}_{s'}, \forall s' \]
\[
\text{FixEnergy}_{s'} = \sum_{t} \sum_{s} E_{sts} x_{s} + \sum_{t} \sum_{m} E_{mmts} x_{m} + \sum_{t} \sum_{d} E_{dts} x_{d} \forall s',
\]
\[
+ \sum_{t} \sum_{r} E_{rts} x_{r} + \sum_{t} \sum_{c} E_{cts} x_{c} + \sum_{t} \sum_{k} E_{kts} x_{k} + \sum_{t} \sum_{c} E_{cets} x_{c},
\]
\[(12)\]

\[
\text{VariableEnergy}_{s'} = \sum_{t} \sum_{p} \sum_{m} \sum_{s} E_{sm} x_{ms} Q_{sm} x_{ms} + \sum_{t} \sum_{p} \sum_{d} \sum_{m} E_{md} x_{md} Q_{md} x_{md} + \sum_{t} \sum_{p} \sum_{r} \sum_{d} E_{dr} x_{dr} Q_{dr} x_{dr} + \sum_{t} \sum_{p} \sum_{c} \sum_{r} E_{rc} x_{rc} Q_{rc} x_{rc} + \sum_{t} \sum_{p} \sum_{k} \sum_{c} E_{ck} x_{ck} Q_{ck} x_{ck} + \sum_{t} \sum_{p} \sum_{s} \sum_{k} E_{ks} x_{ks} Q_{ks} x_{ks},
\]
\[(13)\]

\[
\Gamma_{s'} = \text{FixOccupation}_{s'}, \forall s'
\]
\[(14)\]

\[
\text{FixOccupation}_{s'} = \sum_{t} \sum_{s} O_{sts} x_{s} + \sum_{t} \sum_{m} O_{mmts} x_{m} + \sum_{t} \sum_{d} O_{dts} x_{d} \forall s',
\]
\[
+ \sum_{t} \sum_{r} O_{rts} x_{r} + \sum_{t} \sum_{c} O_{cts} x_{c} + \sum_{t} \sum_{k} O_{kts} x_{k} + \sum_{t} \sum_{c} O_{cets} x_{c},
\]
\[(15)\]

\[
\sum_{d} Q_{dr} Q_{dr} \geq \text{dem}_{r} + \text{z}_{r} \forall r, p, t, s'
\]
\[(16)\]

\[
\sum_{s} Q_{sm} + \sum_{k} Q_{km} = \sum_{d} Q_{md} \forall m, p, t, s'
\]
\[(17)\]

\[
\sum_{s} Q_{sm} + \sum_{k} Q_{km} = \sum_{m} Q_{md} \forall s, k, p, t, s'
\]
\[(18)\]

\[
\sum_{m} Q_{md} = \sum_{d} Q_{dr} \forall d, p, t, s'
\]
\[(19)\]

\[
\sum_{r} Q_{rc} \geq \text{dem}_{r} \forall r, p, t, s'
\]
\[(20)\]

\[
\sum_{r} Q_{rc} = \sum_{k} Q_{ck} \forall c, p, t, s'
\]
\[(21)\]

\[
\rho_{1p} \sum_{c} Q_{ck} = \sum_{m} Q_{km} \forall k, p, t, s'
\]
\[(22)\]
\[ \rho_{2pt} \sum_c Q_{ckpts'} = \sum_{sc} Q_{kskscpts'}, \forall k, p, t, s' \]  
\[ \rho_{3pt} \sum_c Q_{ckpts'} = \sum_{e} Q_{kekepts'}, \forall k, p, t, s' \]  
\[ \sum_{sm} Q_{sm_smpsts'} \leq Cap_{S_smpsts'}pr_{s_smpsts'}, \forall s, m, p, t, s' \]  
\[ \sum_{k} Q_{km_{kmpts'}} \leq Cap_{M_{kmpts'}}pr_{m_{kmpts'}}x_{m_{kmpts'}}, \forall m, p, t, s' \]  
\[ \sum_{m} Q_{md_{mdpts'}} \leq Cap_{D_{mdpts'}}pr_{d_{mdpts'}}x_{d_{mdpts'}}, \forall d, p, t, s' \]  
\[ \sum_{r} Q_{rc_{rcpts'}} \leq Cap_{C_{rcpts'}}pr_{c_{rcpts'}}x_{c_{rcpts'}}, \forall c, p, t, s' \]  
\[ \sum_{k} Q_{ck_{ckpts'}} \leq Cap_{K_{ckpts'}}pr_{k_{ckpts'}}x_{k_{ckpts'}}, \forall k, p, t, s' \]  
\[ \sum_{k} Q_{ke_{kepts'}} \leq Cap_{E_{kepts'}}pr_{e_{kepts'}}x_{e_{kepts'}}, \forall e, p, t, s' \]  
\[ \sum_{c} Q_{ck_{ckpts'}} \leq Cap_{S_{ckpts'}}pr_{s_{ckpts'}}x_{s_{ckpts'}}, \forall s, m, d, r, c, k, e \]  
\[ \sum_{c} Q_{ck_{ckpts'}} \leq Cap_{E_{ckpts'}}pr_{e_{ckpts'}}x_{e_{ckpts'}}, \forall e, p, t, s' \]  
\[ xs_s, xm_m, xd_d, xr_r, xc_c, xe_e \in \{0, 1\}, \forall s, m, d, r, c, k, e \]  
\[ Q_{sm_smpsts'}, Q_{md_{mdpts'}}, Q_{dr_{drpts'}}, Q_{rc_{rcpts'}}, Q_{ck_{ckpts'}}, \forall s, m, d, r, c, k, e, t, p, s'. \]  
\[ Q_{ke_{kepts'}}, Q_{kskscpts'}, Q_{kskpts'}, \forall s, m, d, r, c, k, e, t, p, s'. \]  
\[ Q_{ke_{kepts'}}, Q_{kskscpts'}, Q_{kskpts'}, \forall s, m, d, r, c, k, e, t, p, s'. \]  
\[ \eta_1, \eta_2, \eta_3, \eta_4 \geq 0, \]  
Since the above-mentioned model is a two-stage scenario-based stochastic optimization program, the decisions in the first stage include the establishment of suppliers, manufacturers, distribution centers, retailers, final customers, collection centers (junk), disassembly/repairing, and disposal. Furthermore, the decisions in the second stage are the amount of transportation by suppliers, manufacturers, distribution centers, retailers, final customers, second-hand customers, collection centers (junk), disassembly/repairing, and transporting to disposal centers.

The objective function (1) represents the cost-economic goal which encompasses minimizing the sum of the average, standard deviation of cost, the fine related to not satisfying the demand, and a coefficient of the cost CVaR. Further, the objective function (2), indicates the environmental goal or environmental impact assessment (EIA) which includes minimizing the sum of average, the standard deviation of the produced pollutants (carbon dioxide), the fine related to not satisfying the demand, and a coefficient of the pollutant CVaR. Furthermore, the objective function (3), shows the cumulative energy demand (CED) which includes the minimization of the sum of average, the standard deviation of the consumed energy, the fine related to not satisfying the demand, and a coefficient of the pollutant CVaR. Finally, the objective function (4), represents the social impact assessment (SIA) or employment goal which includes maximizing the sum of the average, the standard deviation of the generated employment, the fine related to not satisfying the demand, and a coefficient of the pollutant CVaR.
3.6. **Linearization of the mathematical model.** In mathematical optimization, nonlinear functions or components within can be linearized in order to apply a linear solving method such as the linearization method. Since the proposed model includes the absolute value function and max type functions and it is nonlinear, the common operational research methods are used to linearize the objective function by removing the absolute value function until obtaining an optimal and global solution [15].

\[
\begin{align*}
\text{min obj}_1 &= \sum_{s'} p_{s'}\Gamma_{s'1} + \beta \sum_{s'} p_{s'}(v_{a_{s'}} + vb_{s'}) + \\
&\omega \sum_{s} p_{s'}k_{s'1}(\sum_{r} \sum_{p} \sum_{t}(vc_{rpts'} + vd_{rpts'})) + \lambda(\eta_1 + \frac{1}{1-\alpha} \sum_{s'} p_{s'}ve_{s'}), \\
\text{min obj}_2 &= \sum_{s} p_{s}\Gamma_{s'2} + \beta \sum_{s'} p_{s'}(v_{f_{s'}} + vg_{s'}) + \\
&\omega \sum_{s} p_{s'}k_{s'2}(\sum_{r} \sum_{p} \sum_{t}(vc_{rpts'} + vd_{rpts'})) + \lambda(\eta_2 + \frac{1}{1-\alpha} \sum_{s'} p_{s'}vh_{s'}), \\
\text{min obj}_3 &= \sum_{s'} p_{s'}\Gamma_{s'3} + \beta \sum_{s'} p_{s'}(vi_{s'} + vj_{s'}) + \\
&\omega \sum_{s} p_{s'}k_{s'3}(\sum_{r} \sum_{p} \sum_{t}(vc_{rpts'} + vd_{rpts'})) + \lambda(\eta_3 + \frac{1}{1-\alpha} \sum_{s'} p_{s'}vk_{s'}), \\
\text{max obj}_4 &= \sum_{s'} p_{s'}\Gamma_{s'4} + \beta \sum_{s'} p_{s'}(vl_{s'} + vm_{s'}) + \\
&\omega \sum_{s} p_{s'}k_{s'4}(\sum_{r} \sum_{p} \sum_{t}(vc_{rpts'} + vd_{rpts'})) + \lambda(\eta_4 + \frac{1}{1-\alpha} \sum_{s'} p_{s'}vo_{s'}),
\end{align*}
\]

such that

\[
\begin{align*}
\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1} &= va_{s'} - vb_{s'}, \forall s' \\
z_{rpts'} &= vc_{rpts'} - vd_{rpts'}, \forall r, p, t, s'
\end{align*}
\]
\[
\begin{align*}
ve_{s'} &\geq \Gamma_{s'1} - \eta_1, \forall s' \\
ve_{s'} &\geq 0, \forall s' \\
\Gamma_{s'2} - \sum_{s'} p_s \Gamma_{s'2} &= vf_{s'} - vg_{s'}, \forall s' \\
vh_{s'} &\geq \Gamma_{s'2} - \eta_2, \forall s' \\
vh_{s'} &\geq 0, \forall s' \\
\Gamma_{s'3} - \sum_{s'} p_s \Gamma_{s'3} &= vi_{s'} - vj_{s'}, \forall s' \\
vk_{s'} &\geq \Gamma_{s'3} - \eta_3, \forall s' \\
vk_{s'} &\geq 0, \forall s' \\
\Gamma_{s'4} - \sum_{s'} p_s \Gamma_{s'4} &= vl_{s'} - vm_{s'}, \forall s' \\
v\alpha_{s'}, vb_{s'}, vc_{rpts'}, vd_{rpts'}, vf_{s'}, vg_{s'}, vl_{s'}, vm_{s'} &\geq 0, \forall s' \\
\end{align*}
\]

Constraints (5) to (33).

We linearized objective functions (1) - (4) by defining covariates for removing absolute value function. Two positive covariates for each absolute value function appear as a summation in objective functions (34) - (37) and as a difference in constraints (38), (39), (42), (45), and (48). For linearizing the max function of CVaR in the objective functions of (1) - (4), another covariate should be defined for each objective function which is added to constraints (40) - (41), (43) - (44), (46) - (47), and (49) - (50). The constraint (51) is regarding decision covariates, which are positive for removing absolute functions from the objective functions (1) - (4).

3.7. Comparing the proposed model with the base model (without robustness, resilience, availability, and risk measure). The proposed model can be compared to the base model in order to indicate the benefits of our model. In this section, the base model is presented based on the expectation value and neglecting robustness, resilience, availability, and risk measure. The section aims to assess the proposed model and identify its strong points.

**Model 2.** Base model (without robustness, resilience, availability, and risk measure)

\[
\begin{align*}
\text{min } obj_1 &= \sum_{s'} p_s \Gamma_{s'1}, \\
\text{min } obj_2 &= \sum_{s'} p_s \Gamma_{s'2}, \\
\text{min } obj_3 &= \sum_{s'} p_s \Gamma_{s'3}, \\
\text{max } obj_4 &= \sum_{s'} p_s \Gamma_{s'4}, \\
such that
\sum_{d} Q_{d|rpts'} &\geq dem_{rpts'}, \forall r, p, t, s' \\
prm_m = prd_d = prr_r = prc_c = prk_k = pre_e = 1, \forall m, d, r, c, k, e
\end{align*}
\]




\[
\begin{align*}
\text{Cap}_{spt} & = \text{Cap}_{spt} \quad \forall s, p, t, s' \\
\text{Cap}_{mpt} & = \text{Cap}_{mpt} \quad \forall m, p, t, s' \\
\text{Cap}_{dpt} & = \text{Cap}_{dpt} \quad \forall e, p, t, s' \\
\text{Cap}_{rpt} & = \text{Cap}_{rpt} \quad \forall e, p, t, s' \\
\text{Cap}_{cpt} & = \text{Cap}_{cpt} \quad \forall k, p, t, s' \\
\text{Cap}_{kpt} & = \text{Cap}_{kpt} \quad \forall k, p, t, s' \\
\text{Cap}_{ept} & = \text{Cap}_{ept} \quad \forall e, p, t, s' \\
\end{align*}
\]

Constraints (5) - (15), (17) - (33) As can be seen, objective functions (52) - (54) include minimizing the expected value for cost, environment, and energy. Constraint (55) include maximizing the expected value for the employment. Constraint (56) is the demand satisfaction. Constraint (57) shows that there is not any resilience and reliability in the capacity of facilities. All the above terms attempt to optimize the objective functions in the average scenario case.

3.8. **Global criterion method of LP-Metric.** The global criterion method is an a priori preference articulation. It aims to minimize a function, i.e. global criterion, and is a measure of how close the decision-maker can get to the ideal vector. This method minimizes the sum of the power of the goal relative deviations from their optimal values and combines multiple objective functions into one objective. In practice, the method of LP-Metric has received more attention since it needs less information than DM and is easier to use [24]. The method of LP-Metric evaluates the nearness of a solution to its ideal. This deviation evaluation is as follows, so for the minimum objective function:

\[
\min L = \sum_{i=1}^{n} \left( \frac{z_i - \min z_i}{\max z_i - \min z_i} \right)^p
\]

Where

\[
\begin{align*}
z_i & = f_i(X_1, X_2, ..., X_n), \quad i = 1, 2, ..., n \\
g_j(X_1, X_2, ..., X_n) & \leq b_j, \quad j = 1, 2, ..., m
\end{align*}
\]

The parameter \(W_i\) denotes the importance (weight) of the \(i\)th objective. In order to eliminate the issue of objective scale differences, the ideal solution deviation of the \(i\)th objective is divided by the interval length. The value \(p\) defines the emphasis level on the deviations in a way that the larger this value gets, the more the deviation is emphasized. In addition, the objective function (58) of the LP-Metric method should be minimized to the deviation from the ideal, which is \(p = 1\) in the present study. The optimal value for the \(i\)th objective function is optimized with respect to the constraints (59) and (60) [23, 34].

4. **Case study.** The car manufacturing industry in Iran is the case study of the present study which represents the high amounts of consumption and waste, as one of the problems in this national industry. In this regard, completing the value chain of the industry and upside mines, increasing productivity, and reducing energy, material, and water consumption in the industries were among the research priorities of Iran Ministry of Industry, Mine, and Trades in 2018. The car manufacturing industry, after the petroleum industry, is one of the biggest industries in Iran. Iran was the 18th greatest car manufacturer in 2018 by manufacturing 130474 vehicles, including 123610 cars and 7137 commercial vehicles. Considering various car manufacturing companies in Iran, a suitable SCN should be designed, which includes
collection, repairing, and disassembling centers, and the steps of the reverse chain should be appropriately redesigned. The case study is based on the information of a car and manufacturing company. The company decided to manufacture a car in a car manufacturing company including suppliers, manufacturing centers, distribution centers, retailing and collection, repairing and recycling centers. The main manufacturing center of this company is in Semnan, Iran.

The values of the assignment parameters of the case study are presented in Appendix 2 (Table A2-1). The information and statistics of the present study are based on a feasibility study report, completion of a questionnaire in meetings with experts and managers, and estimating the costs.

4.1. Results of global criterion. Modeling was performed in GAMS software with CPLEX solver in a computer with a Core i5 CPU, clock speed of 2.4 GHz, and 6 GB of RAM. The results of the proposed and base models are presented in Table 2 and Figures 3 (a) - (b). The amounts of the parameters are indicated in Appendix 2 (Table A2-1), where weights are equal to 0.25. As can be seen, addressing the robust counterpart, our chosen risk measure in the proposed model leads to a better estimation of cost, pollution level, and energy consumption up to a maximum 2% increase and up to a maximum 1% reduction in the employment all compared to the base model (without resilience, availability, and risk measure). The value of the gap between the proposed and base model is 1.2% according to the objective of LP Metric, as shown in Table 2 and Figure 3-(a).

Table 2. Optimal value of the robust objective function and the value of the global criterion objective function

| Objective       | The optimal value of proposed objective function | The optimal value of base model objective function | Avg. Gap |
|-----------------|-----------------------------------------------|-----------------------------------------------|---------|
| Min Z1(Cost)    | 71470.14                                      | 71357.80                                      | 1.7%    |
| Min Z2(CO2)     | 174731.64                                      | 173265.90                                     | 1.6%    |
| Max Z4(Employ)  | 176760.32                                      | 173265.90                                     | 2.7%    |
| Min Lp          | 76688.59                                       | 76589.90                                      | 1.2%    |

* Avg. GAP = Average ((Proposed model objective - base model objective)/ base model objective)

The assembler is a car manufacturing company which manages the entire SCN in order to gain profit by dealing with the government on energy costs, environmental issues, and employment. Hence, the proposed model matches the reality of the hosting (domestic) country, i.e. Iran, and the type of business which it runs although the model is complex, due to the presence of resilience, availability, risk measure, and robustness, for SCN design. The location and flow material are illustrated in Figure 3-(b).

4.2. Sensitivity analysis. The results of the variation in the $W_i$ model’s objective weights, the parameters $\alpha$ and $\lambda$ the CVaR criterion, and the parameter $\beta$ in the robustness coefficient are presented in Table 3 and Figures 4 (a) - 8 (d). As can be seen, by increasing the importance of the cost objective, the cost decreases, the pollutants and energy increase, and employment decreases (Table 3 and Figure 4 (a)). In addition, increasing the importance of the environmental objective leads to an increase in the value of cost, energy, and employment and a decrease in the pollutants as shown in Table 3 and Figure 4 (b).

Furthermore, Table 3 and Figure 4 (c) indicate that when the importance of the energy objective increases, the cost, energy, and employment decrease and the...
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(a) Comparing the proposed model with base model

(b) Location and facility locations

Figure 3

pollutant level raises. Finally, the importance of employment objective has a direct relationship with the values of cost, pollutant level, energy, and employment level as presented in Table 3 and Figure 4 (d).
Table 3. Weight variations versus objectives

| $X_1$ | $X_2$ | $X_3$ | $X_4$ | Cost     | Pollutant (CO$_2$) | Energy     | Employment |
|-------|-------|-------|-------|----------|---------------------|------------|------------|
| 0     | 0.33  | 0.33  | 0.33  | 78143.63 | 1285793            | 1594659    | 2141.56    |
| 0.5   | 0.16  | 0.16  | 0.16  | 76688.59 | 1285770            | 1594682    | 2141.56    |
| 1     | 0     | 0     | 0     | 71470.15 | 1989597            | 2274556    | 1749.06    |
| 0.33  | 0     | 0.33  | 0.33  | 76689.36 | 1316802            | 1591633    | 2141.56    |
| 0.16  | 0.5   | 0.16  | 0.16  | 79603.18 | 1274957            | 1612078    | 2214.48    |
| 0     | 1     | 0     | 0     | 174731.6 | 1250941            | 1953758    | 4399.22    |
| 0.33  | 0.33  | 0     | 0.33  | 71470.15 | 1989597            | 2274556    | 1749.06    |
| 0.16  | 0.5   | 0     | 0.16  | 76688.97 | 1289052            | 1592359    | 2141.56    |
| 0     | 1     | 0     | 0     | 78459.12 | 1317174            | 1591575    | 2100.21    |
| 0.33  | 0.33  | 0.33  | 0     | 76688.59 | 1285770            | 1594682    | 2100.75    |
| 0.16  | 0.5   | 0.16  | 0     | 76688.59 | 1285770            | 1594682    | 2141.56    |
| 0     | 0     | 0     | 1     | 176760.3 | 1734075            | 2358202    | 4505.85    |
| 0.25  | 0.25  | 0.25  | 0.25  | 76688.59 | 1285796.68          | 1594082.21 | 2141.55    |

Figure 4

(a) Weight variations versus cost objective
(b) Weight variations versus environmental objective
(c) Weight variations versus energy objective
(d) Weight variations versus employment objective

The parameter $\lambda$, which is the importance coefficient of the CVaR index, fluctuates between 0 and 0.01. By increasing the $\lambda$ value of the cost, the amounts of pollution and energy consumption increase and the employment decreases, so more attention is paid to the risks (see Figures 5 (a)-(d)).
The parameter $\beta$ is the importance factor of the variation variance, ranging from 0 to 0.5. Increasing $\beta$ leads to an increase in the value of the cost, amounts of pollution, and energy consumption and a decrease in the employment, so risks are paid more attention to in these cases (see Figures 6 (a)-(d)).

The parameter $\alpha$ is considered as the confidence level, ranging between 0.5 and 0.95. By increasing the value of $\alpha$, the amounts of cost, pollution, and energy consumption increase up to a point and then remain constant. Further, the employment trend drops and then remains constant (Figures 7 (a)-(d)).

The value of the availability probability ($pr$), which is assumed to be identical for all the scenarios and facilities, fluctuates between 0.5 and 0.96. Figures 8 (a)-(d) illustrate that increasing the availability probability leads to a decrease in the amounts of cost, energy consumption, and employment up to a point and then they remain constant. Further, the pollution increases and then remains constant.

In Section 4.2, we discussed the results regarding the variations of the parameters $\alpha$ and $\lambda$ from CVaR criterion, parameter $\beta$ of the robustness coefficient, and availability probability parameter $pr x$ and the effects of variation of each parameter on all the objectives. Section 4.3 aims to solve the model in medium and large-scale.
(a) Variations of $\beta$ (the importance factor of variance) versus cost objective

(b) Variations of $\beta$ (the importance factor of variance) versus environmental objective

(c) Variations of $\beta$ (the importance factor of variance) versus energy objective

(d) Variations of $\beta$ (the importance factor of variance) versus employment objective

Figure 6

(a) Variations of $\alpha$ (confidence level) versus cost objective

(b) Variations of $\alpha$ (confidence level) versus environmental objective

(c) Variations of $\alpha$ (confidence level) versus energy objectives

(d) Variations of $\alpha$ (confidence level) versus employment objectives

Figure 7
4.3. **Solving the model in medium and large scales.** Various methods can solve the model in medium and large scales. Constraint relaxation, as one of the solving methods, means solving the model in the worst possible case (upper bound) and lower bound. First, some medium and large-scale problems are defined based on Table 4. Relaxing the constraint (32), which is the definition of the decision variables, means that the facility activation is transformed from binary ($X \in \{0, 1\}$) into the case between zero and one ($0 \leq X \leq 1$), the model is transformed from the mixed-integer programming into fully linear, and a lower bound is obtained for the problem [45].

Moreover, the model is solved in the worst case when all the facilities are reopened ($X = 1$) and an upper bound is obtained for the problem [45].

The above-mentioned methods reduce the solution time. The calculations of the lower bound, base model value, and upper bound or the worst case are presented in Table 5 and Figure 9 (a) along with a comparison of the distance gaps for the cost objective [25].

By increasing the scale of the model, the deviations of the main model from the lower bounds reduce to 55%, and the deviations from the upper bound increase to 300% (Table 5). As can be seen from Figure 9 (a), the difference between the lower and upper bounds and the main model can be estimated for the main model on a large scale through lower and upper bounds. The solution time trend is exponential based on Figure 9 (b), indicating that when the model size increases, the solution
Table 4. Medium and large scale problems

| Problem | \(|S| \times |M| \times |D| \times |N| \times |S_c| \times |P| \times |T| \times |S|'\) | Variable | Free Variable | Linear Variable | Constraint |
|---------|-------------------------------------------------|-----------|----------------|-----------------|-------------|
| P1      | \(3^3 \times 3^3 \times 3^3 \times 3^3 \times 3^3 \times 3^3 \times 3^3 \times 3^3\) | 2289      | 21 41          | 2227 2264       | 2264        |
| P2      | \(4^4 \times 4^4 \times 4^4 \times 4^4 \times 4^4 \times 4^4 \times 4^4 \times 4^4\) | 6829      | 28 41          | 6760 6797       | 6797        |
| P3      | \(5^5 \times 5^5 \times 5^5 \times 5^5 \times 5^5 \times 5^5 \times 5^5 \times 5^5\) | 101359    | 49 61          | 101249 121866   | 121866      |
| P4      | \(10^1 \times 10^1 \times 10^1 \times 10^1 \times 10^1 \times 10^1 \times 10^1 \times 10^1\) | 249151    | 70 41          | 249040 375077   | 375077      |
| P5      | \(10^2 \times 10^2 \times 10^2 \times 12^2 \times 12^2 \times 12^2 \times 12^2 \times 12^2\) | 577351    | 76 51          | 577284 843363   | 843363      |
| P6      | \(100^2 \times 100^2 \times 100^2 \times 100^2 \times 100^2 \times 100^2 \times 100^2 \times 100^2\) | 3245185   | 604 41         | 3244540 63107681| 63107681    |
| P7      | \(15^5 \times 15^5 \times 15^5 \times 15^5 \times 15^5 \times 15^5 \times 15^5 \times 15^5\) | 2675855   | 105 61         | 2075689 4303246 | 4303246     |

Further, the NEOS server solves the large-scale model P4-P5, which can solve and optimize the model in more than 3600 seconds, by taking into account the processor power \([8, 9, 14]\). Furthermore, meta-heuristic methods, mentioned in the Literature Review, can be used to solve the model in large scales.

Table 5. Comparison of the main model with the lower bound and worst possible case

| Problem | Lower bound | Main model | Worst-case | GAP1 | GAP2 |
|---------|-------------|------------|------------|------|------|
| P1      | 10862.19    | 2.00       | 76688.59   | 8.40 | -86% | 126% |
| P2      | 15720.97    | 3.83       | 90009.11   | 93.68| -83% | 166% |
| P3      | 21307.43    | 11.33      | 111813.32  | 1082.85| -81% | 170% |
| P4      | 44956.51    | 843.11     | *127011.40 | 38705.6| -65% | 260% |
| P5      | 74585.42    | 2967.01    | *165745.37 | 668562.73| -55% | 303% |
| P6-P8   | 15855.42    | 2967.01    | *165745.37 | 668562.73| -55% | 303% |

* Solved by NEOS-Server, \(GAP_1 = (B-A)/A\), \(GAP_2 = (C-B)/B\).

Figure 9

(a) Comparison of the main model with the lower bound and worst case
(b) Time of the main model with the lower bound and worst case
5. Managerial implications and practical insights. The proposed model can be applied to solve any practical problem in a given supply chain. In practice, the results of the model can help policymakers and investors to make synchronized decisions. Further, the proposed model can help policymakers to determine and promote an appropriate production strategy to meet the desired sustainability requirements. The investors can then invest in appropriate production strategies in order to realize long-term sustainability benefits. This type of modeling applies to both automotive supply chain and the design of other supply chain networks. Furthermore, addressing robust counterpart and risk measure in the proposed model leads to a better estimation of cost, pollution level, energy consumption, and employment compared to the base model, which is without robustness, resilience, availability, and risk measure. We should inform the supply chain network designer to design CLSC with all requirements of robustness, resilience, and risk of deviation of demand. Although the number of objectives is over one considering all the requirements, the designer ensures that everything required by the stockholders is considered in the design.

6. Conclusions. Vital and global issues such as designing the supply chains, considering environmental and social welfare, and lowering energy consumption in the chain have attracted a lot of attention in recent years. The management of the sustainable closed loop supply chain has recently gained much importance. According to the governmental laws and legislation, the issues of environmental impact, employment opportunities, and energy consumption, and customer and beneficiary expectations should be considered in the supply chain management and are regarded as major factors between competitors.

The innovation and main contribution of the present study is a global design of a resilient and sustainable supply chain, which has not been thoroughly addressed in previous research.

The present study proposes a new mathematical model for a sustainable and resilient closed loop supply chain in which all the economic, environmental, and social aspects are considered along with the risk and uses of the concepts of ReCiPe for environmental impact, CED for energy assessment, and GSLCAP for social impact. Furthermore, all the facilities in the chain have the resilience feature in the capacity and are reliable. Moreover, the model is robust against demand disruption.

We aimed to create real-life condition in order to model with the help of two-stage stochastic programming tools, scenario-based robust programming, and by considering risk indexes. The above-mentioned supply chain includes suppliers, manufacturers, distribution centers, retailers, customers, collection centers, repair centers, disposal centers, and second-hand customers. The aims of the model are minimizing the costs, environmental pollutant emission, and energy consumption as well as maximizing the employment considering disruption risks for each scenario. In addition, the model aims to be robust against demand variations. The final customer demand has different scenarios in the model. The facility capacity including suppliers, distribution centers, retailers, collection and repairing centers is resilient and flexible for different scenarios. The strategic decisions of the model are the establishment of resilient centers and amount of transportation between the centers. All the resilience capacity and flow constraints are fulfilled between facilities.

A global criterion method of LP-Metric is used to solve the model. Furthermore, a sensitivity analysis is performed for parameter importance coefficient of CVaR.
index (\(\lambda\)), confidence level (\(\alpha\)) from CVaR criterion, parameter importance factor of variance (\(\beta\)) of the robustness coefficient, and reliability probability of the model facilities. Various methods were employed to solve the model on a large scale.

The case study of the proposed model is in the car manufacturing industry of Iran, a country with high rates of consumption and waste which are major issues in Iran. The robust counterpart and risk measure in the model results in obtaining a better estimation of the cost, pollution level, and energy consumption up to a 2% increase and a 1% reduction in the employment level all compared to the base model.

The present study proposes solving the model using constraint relaxation and in the worst possible case of using objectives which causes a lower bound and an upper bound to be obtained for the model. The lower and upper bounds get near to each other by increasing the model size. Commercial solvers and the web-based server of NEOS are applied to solve the model.

Future suggestions for researchers can be summarized to using other solving techniques and evolutionary meta-heuristic algorithm [26]. Benders decomposition, column generation, Lagrange relaxation, and fix-and-optimize method for a large-scale model. Moreover, other combinations of programming levels including tactical and operational can be used in programming the model. The execution of multi-stage programming in defining the scenarios can be another suggestion. Finally, uncertainty tools including stochastic, fuzzy or grey space, robust convex counterpart, and stochastic optimal control can be the subject of future research.

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### Appendix 1. Symbols:

#### Indices:

| Index   | Description                                      |
|---------|--------------------------------------------------|
| s       | Index of suppliers                               |
| m       | Index of potential manufacturer                   |
| d       | Index of potential distribution center           |
| r       | Index of potential retailer                       |
| c       | Index of potential collection center             |
| k       | Index of potential repairing center              |
| e       | Index of potential disposal center               |
| Sc      | Index of second-hand customers                   |
| p       | Index of products                                 |
| t       | Index of time period                             |
| s′       | Index of scenarios                               |

#### Parameters:

| Parameter | Description                                      |
|-----------|--------------------------------------------------|
| dem,rp,ts | Demand at retailer r from product p in time period t under scenario s′. |

#### Fixed costs (opening):

| Parameter | Description                                      |
|-----------|--------------------------------------------------|
| fs,s     | Opening cost of supplier s                        |
| fm,m     | Opening cost of manufacturer m                    |
| fd,d     | Opening cost of distribution center d            |
| fr,r     | Opening cost of retailer r                        |
| fc,c     | Opening cost of disposal center $c$              |

#### Variable costs:

| Description | Equation                                      |
|-------------|-----------------------------------------------|
| Vsm,rp,ts   | Transportation cost from supplier s to manufacturer m for the product p in time period t under scenario s′. |
| Vmd,m,rp,ts | Transportation cost from manufacturer m to distribution center d for the product p in time period t under scenario s′. |
| Vdr,d,rp,ts | Distribution cost from distribution center d to retailer r for the product p in time period t under scenario s′. |
| Vrc,r,c,p,ts| Transportation cost from retailer r to collection center c for the product p in time period t under scenario s′. |
Variable pollution (Carbon dioxide):

$E_{sm_{sp}}$, $E_{md_{mp}}$, $E_{dr_{rp}}$, $E_{rc_{rp}}$, $E_{ck_{kp}}$, $E_{kc_{kp}}$, $E_{km_{km}}$, $E_{ksc_{ksp}}$, $E_{km_{km}}$,

Fixed pollution (opening):

$E_{ms_{st}}$, $E_{mm_{ms}}$, $E_{md_{ts}}$, $E_{mr_{rt}}$, $E_{mc_{ct}}$, $E_{mk_{kt}}$, $E_{mc_{ct}}$, $E_{mk_{kt}}$,

Fixed consumed energy (opening):

$E_{st_{st}}$, $E_{mt_{ms}}$, $E_{dt_{ts}}$, $E_{rt_{rt}}$, $E_{ct_{ct}}$, $E_{kts_{ts}}$, $E_{c_{ct}}$,

Variable consumed energy:

$E_{sm_{sp}}$, $E_{md_{mp}}$, $E_{dr_{rp}}$, $E_{rc_{rp}}$, $E_{ck_{kp}}$, $E_{kc_{kp}}$, $E_{km_{km}}$, $E_{ksc_{ksp}}$, $E_{km_{km}}$,

Transportation cost from collection center $c$ to disposal center $c$ for the product $p$ in time period $t$ under scenario $s'$.

Pollution caused by supplier $s$ in time period $t$ under scenario $s'$.

Pollution caused by manufacturer $m$ in time period $t$ under scenario $s'$.

Pollution caused by distribution center $d$ in time period $t$ under scenario $s'$.

Pollution caused by retailer $r$ in time period $t$ under scenario $s'$.

Pollution caused by collection center $c$ in time period $t$ under scenario $s'$.

Pollution caused by repairing center $k$ in time period $t$ under scenario $s'$.

Pollution caused by disposal center $e$ in time period $t$ under scenario $s'$.

Pollution caused by repairing center $k$ in time period $t$ under scenario $s'$.

Pollution caused by manufacturer $m$ in time period $t$ under scenario $s'$.

Pollution caused by repairing center $k$ to manufacturer $m$ for the product $p$ in time period $t$ under scenario $s'$.

Transportation cost from manufacturer $m$ to distribution center $d$ for the product $p$ in time period $t$ under scenario $s'$.

Pollution caused by distribution center $d$ to retailer $r$ for product $p$ in time period $t$ under scenario $s'$.

Pollution caused by retailer $r$ to collection center $c$ for product $p$ in time period $t$ under scenario $s'$.

Pollution caused by collection center $c$ to repairing center $k$ for product $p$ in time period $t$ under scenario $s'$.

Pollution caused by repairing center $k$ to disposal center $e$ for product $p$ in time period $t$ under scenario $s'$.

Energy consumed in supplier $s$ in time period $t$ under scenario $s'$.

Energy consumed in manufacturer $m$ in time period $t$ under scenario $s'$.

Energy consumed in distribution center $d$ in time period $t$ under scenario $s'$.

Energy consumed in collection center $c$ in time period $t$ under scenario $s'$.

Energy consumed in repairing center $k$ in time period $t$ under scenario $s'$.

Energy consumed in disposal center $e$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from supplier $s$ to manufacturer $m$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from manufacturer $m$ to distributor $d$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from distributor $d$ to retailer $r$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from retailer $r$ to collection center $c$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from collection center $c$ to repairing center $k$ in time period $t$ under scenario $s'$.

Energy consumed in transportation of product $p$ from repairing center $k$ to disposal center $e$ in time period $t$ under scenario $s'$.
\( E_{km}^{kpts} \)  \( E \)nergy consumed for trans-
portation of product \( p \) from re-
pairing center \( k \) to manufac-
turer \( m \) in time period \( t \) under 
scenario \( s' \).

\( \text{Amount of fixed employment} \)
(social welfare):

\( O_{sts} \)  \( O \)mployment generated in sup-
plier \( s \) in time period \( t \) under 
scenario \( s' \),

\( O_{mtr} \)  \( O \)mployment generated in 
manufacturer \( m \) in time 
period \( t \) under scenario \( s' \),

\( O_{dts} \)  \( O \)mployment generated in dis-
tributor \( d \) in timeperiod \( t \) un-
der scenario \( s' \),

\( O_{rte} \)  \( O \)mployment generated in re-
tailer \( r \) in timeperiod \( t \) under 
scenario \( s' \),

\( O_{ccs} \)  \( O \)mployment generated in col-
collection center \( c \) in 
scenario \( s' \),

\( O_{krs} \)  \( O \)mployment generated in re-
pairing center \( k \) in time period 
\( t \) under scenario \( s' \),

\( V_{ss} \)  \( V \)Salary cost in supplier \( s \) in 
time period \( t \) under scenario 
\( s' \),

\( V_{ms} \)  \( V \)Salary cost in manufacturer \( m \) in 
time period \( t \) under scenario 
\( s' \),

\( V_{md} \)  \( V \)Salary cost in distributor \( d \) in 
time period \( t \) under scenario 
\( s' \),

\( V_{rt} \)  \( V \)Salary cost in retailer \( r \) in time 
period \( t \) under scenario \( s' \),

\( V_{ce} \)  \( V \)Salary cost in collection center 
\( c \) in time period \( t \) under scena-
rio \( s' \),

\( V_{ke} \)  \( V \)Salary cost in repairing center 
\( k \) in timeperiod \( t \) under sce-
ario \( s' \),

\( V_{ce} \)  \( V \)Salary cost in disposal center \( c \) in 
timeperiod \( t \) under scenario 
\( s' \),

\( \text{Facility capacity:} \)

\( C_{sp} \)  \( C \)apacity of supplier \( s \) for 
product \( p \) in time period \( t \) un-
der scenario \( s' \),

\( C_{mp} \)  \( C \)apacity of manufacturer \( m \) for 
product \( p \) in time period \( t \) under 
scenario \( s' \),

\( C_{dp} \)  \( C \)apacity of distribution center 
\( d \) for product \( p \) in time period 
\( t \) under scenario \( s' \),

\( C_{rp} \)  \( C \)apacity of retailer \( r \) for pro-
duct \( p \) in time period 
\( t \) under scenario \( s' \),

\( C_{cp} \)  \( C \)apacity of collection center 
\( c \) for product \( p \) in time period 
\( t \) under scenario \( s' \),

\( C_{kp} \)  \( C \)apacity of repairing center 
\( k \) for product \( p \) in time period 
\( t \) under scenario \( s' \),

\( C_{pe} \)  \( C \)apacity of disposal center \( e \) for 
product \( p \) in time period \( t \) under 
scenario \( s' \),

\( \text{Availability probability (disruption)} \)

\( pr_{ss} \)  \( pr \)opability of supplier \( s \) under 
scenario \( s' \),

\( pr_{ms} \)  \( pr \)opability of manufacturer 
\( m \),

\( pr_{dd} \)  \( pr \)opability of distribution 
center \( d \),

\( pr_{re} \)  \( pr \)opability of retailer \( r \),

\( pr_{mk} \)  \( pr \)opability of collection cen-
ter \( c \),

\( pr_{ek} \)  \( pr \)opability of repairing center 
\( k \),

\( pr_{ec} \)  \( pr \)opability of disposal center 
\( e \).

\( \text{Other parameters:} \)

\( p' \)  \( p \)robability of occurrence of sce-
nario \( s' \),

\( \beta \)  \( \beta \)pctuation value weight coef-
cient,

\( \omega \)  \( \omega \)eight coefficient of deviation
from key constraints,

\( \lambda \)  \( \lambda \)pct coefficient of cvar index,

\( \alpha \)  \( \alpha \)onfidence level in cvar,

\( k_{s1} \)  \( k \)eight of deviation from de-
mand key constraints for envi-
nmental goal under scenario
\( s' \),

\( k_{s2} \)  \( k \)eight of deviation from de-
mand key constraints for envi-
nmental goal under scenario
\( s' \),

\( k_{s3} \)  \( k \)eight of deviation from de-
mand key constraints for envi-
nmental goal under scenario
\( s' \),

\( k_{s4} \)  \( k \)eight of deviation from de-
mand key constraints for em-
ployment goal under scenario
\( s' \),

\( p_{rpt} \)  \( p \)roportion of product 
\( p \) from retailer \( r \) in time period
\( t \) under scenario \( s' \),

\( p_{1pt} \)  \( p \)roportion of product 
\( p \) from retailer \( r \) in time period
\( t \) under scenario \( \{s\}' \),

\( p_{2pt} \)  \( p \)roportion of product 
\( p \) from second-hand customer in
time period \( t \) under scenario
\( s' \),

\( p_{3pt} \)  \( p \)roportion of product 
\( p \) from second-hand customer in
time period \( t \) under scenario
\( s' \),

\( \text{Decision variable:} \)

\( xs \)  \( x \) is to be estab-
lished, otherwise 0,

\( xm \)  \( x \) is to be estab-
lished, otherwise 0,

\( xd \)  \( x \) is to be estab-
lished, otherwise 0,

\( xr \)  \( x \) is to be estab-
lished, otherwise 0,

\( xc \)  \( x \) is to be estab-
lished, otherwise 0,

\( xk \)  \( x \) is to be estab-
lished, otherwise 0,

\( xe \)  \( x \) is to be estab-
lished, otherwise 0.
Flow variable:

- \( Q_{sm_{emp}},t \): Amount of transportation from supplier \( s \) to manufacturer \( m \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{md_{dpt}},t \): Amount of transportation from manufacturer \( m \) to distribution center \( d \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{dr_{dpt}},t \): Amount of transportation from distribution center \( d \) to retailer \( r \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{rc_{cpt}},t \): Amount of transportation from retailer \( r \) to collection center \( c \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{ck_{ept}},t \): Amount of transportation from collection center \( c \) to repairing center \( k \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{kc_{kpt}},t \): Amount of transportation from repairing center \( k \) to disposal center \( e \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{ks_{ept}},t \): Amount of transportation from disposal center \( e \) to second-hand customer \( Sc \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( Q_{ks_{mpt}},t \): Amount of transportation from repairing center \( k \) to manufacturer \( m \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( z_{pt},t \): Fine related to not satisfying demand at retailer \( r \) for product \( p \) in time period \( t \) under scenario \( s' \),
- \( \eta_1 \): Average of maximum shortfalls expected in conditional value-at-risk,
- \( \eta_2 \): Average of maximum pollution expected unconditional value-at-risk,
- \( \eta_3 \): Average of maximum energy expected unconditional value-at-risk,
- \( \eta_4 \): Average of maximum employment expected unconditional value-at-risk.

Covariates:

- \( v_{a,s,t}, v_{b,t} \): Covariate for linearization of economic cost objective function variance,
- \( v_{c,s,t}, v_{d,t} \): Covariate for linearization of the deviation from demand constraint,
- \( v_{e,s}, v_{f,s} \): Covariate for linearization of economic cost conditional value-at-risk,
- \( v_{g,s}, v_{h,s} \): Covariate for linearization of environmental pollution objective function variance,
- \( v_{i,s} \): Covariate for linearization of environmental pollution conditional value-at-risk,
- \( v_{j,s} \): Covariate for linearization of energy objective function variance,
- \( v_{k,s} \): Covariate for linearization of energy value-at-risk,
- \( v_{l,s}, v_{m,s} \): Covariate for linearization of employment objective function variance,
- \( v_{o,s} \): Covariate for linearization of employment value-at-risk.

\[ \Gamma_{s,t} \]: Sum of fixed and variable costs under scenario \( s' \),
\[ \text{FixCost}_{s,t} \]: Sum of fixed costs,
\[ \text{VariableCost}_{s,t} \]: Sum of variable costs under scenario \( s' \),
\[ \Gamma_{e,t} \]: Sum of fixed and variable pollution emissions under scenario \( s' \),
\[ \text{FixEmission}_{e,t} \]: Sum of fixed pollution emissions due to the establishment of facilities under scenario \( s' \),
\[ \text{VariableEmission}_{e,t} \]: Sum of variable pollution emissions due to the establishment of facilities under scenario \( s' \),
\[ \Gamma_{j,t} \]: Sum of fixed and variable energies under scenario \( s' \),
\[ \text{FixEnergy}_{j,t} \]: Sum of fixed consumed energies due to the establishment of facilities under scenario \( s' \),
\[ \text{VariableEnergy}_{j,t} \]: Sum of variable consumed energies due to the establishment of facilities between facilities under scenario \( s' \),
\[ \Gamma_{k,t} \]: Sum of employment due to the establishment of facilities under scenario \( s' \),
\[ \text{FixOccupation}_{k,t} \]: Sum of employment due to the establishment of facilities under scenario \( s' \).
## Table A2-1. Model parameters for medium and large scale problems.

| Parameters | Value | Description |
|------------|-------|-------------|
| $dem_{rt}$ | $\{\lceil s \rceil^2 \times 1000 \times uniform(1000,2000)\}$ | Demand for various scenarios |
| $fs$ | uniform(1000,2000) | Fixed costs (opening) (Thousand dollar) |
| $fm$ | uniform(3000,4000) | |
| $fr$ | uniform(1000,2000) | |
| $rd$ | uniform(1000,2000) | |
| $s$ | uniform(2000,3000) | Variable costs (Dollar) |
| $r$ | uniform(1000,2000) | |
| $e$ | uniform(1000,2000) | |
| $sm_{mps}$ | uniform(3,4) | Fixed pollution (opening) (carbon dioxide) (Centiton) |
| $sm_{dmps}$ | uniform(3,4) | |
| $dr_{mps}$ | uniform(3,4) | |
| $drc_{mps}$ | uniform(3,4) | |
| $ck_{mps}$ | uniform(3,4) | |
| $cksc_{mps}$ | uniform(3,4) | |
| $km_{mps}$ | uniform(3,4) | |
| $km_{scps}$ | uniform(3,4) | |
| $sts$ | uniform(100,200) | Variable pollution (carbon dioxide) (Centiton) |
| $st$ | uniform(100,200) | |
| $dts$ | uniform(100,200) | |
| $rcps$ | uniform(100,200) | |
| $kts$ | uniform(100,200) | |
| $ets$ | uniform(100,200) | |
| $sts$ | uniform(4000,5000) | Fixed consumed energy (opening) (MJ) |
| $st$ | uniform(4000,5000) | |
| $dts$ | uniform(4000,5000) | |
| $rcps$ | uniform(4000,5000) | |
| $kts$ | uniform(4000,5000) | |
| $ets$ | uniform(4000,5000) | |
| $sm_{mps}$ | uniform(4,5) | Variable pollution (MJ) |
| $sd_{mps}$ | uniform(4,5) | |
| $dr_{mps}$ | uniform(4,5) | |
| $drc_{mps}$ | uniform(4,5) | |
| $ck_{mps}$ | uniform(4,5) | |
| $cksc_{mps}$ | uniform(4,5) | |
| $km_{mps}$ | uniform(4,5) | |
| $km_{scps}$ | uniform(4,5) | |
| $os$ | uniform(40,50) | Fixed employment (person) |
| $om$ | uniform(300,400) | |
| $od$ | uniform(40,50) | |
| $or$ | uniform(5,10) | |
| $om$ | uniform(20,30) | |
| $ok$ | uniform(10,15) | |
| $oe$ | uniform(5,10) | |
| $vs$ | uniform(1000,1100) | Salary Cost (Dollars) |
| $vs$ | uniform(1000,1100) | |
| $vs$ | uniform(1000,1100) | |
| $vs$ | uniform(1000,1100) | |
| Variable | Distribution | Description |
|----------|--------------|-------------|
| VO_{c,t} | uniform(1000,1100) | Volume of Order in Center |
| VO_{k,t} | uniform(1000,1100) | Volume of Order in Center |
| VO_{e,t} | uniform(1000,1100) | Volume of Order in Center |
| pr_{m,t} | uniform(0.95,0.98) | Availability probability (percent) |
| pr_{d,t} | uniform(0.95,0.98) | Availability probability (percent) |
| pr_{r,t} | uniform(0.95,0.98) | Availability probability (percent) |
| pr_{e,t} | uniform(0.95,0.98) | Availability probability (percent) |
| Cap_S_{s,t} | uniform(50000,60000)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| Cap_M_{m,t} | uniform(100000,110000)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| Cap_D_{d,t} | uniform(20000,22000)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| Cap_R_{r,t} | uniform(30000,33000)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| Cap_K_{k,t} | uniform(5000,5500)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| Cap_E_{e,t} | uniform(3000,3300)*(1-{s-1\choose 0.5}+1) | Capacity (facility) |
| s | 0.33 | Scenario occurrence probability |
| β | uniform(0,0.2) | Expectation value weight |
| ω | uniform(0,0.1) | Fine associated with demand dissatisfaction |
| μ | uniform(0,0.1) | CVaR index importance |
| κ_{s,1} | 0.05 | Fine coefficient of demand dissatisfaction for quadruple objective |
| κ_{s,2} | 0.05 | Fine coefficient of demand dissatisfaction for quadruple objective |
| κ_{s,3} | 0.05 | Fine coefficient of demand dissatisfaction for quadruple objective |
| κ_{s,4} | 0.05 | Fine coefficient of demand dissatisfaction for quadruple objective |
| ρ_{1,t} | uniform(0,1) | Return percentage |
| ρ_{2,t} | uniform(0.7,0.71) | Return percentage |
| ρ_{3,t} | uniform(0.2,0.21) | Return percentage |
| ρ_{4,t} | uniform(0.1,0.11) | Return percentage |
| W | 0.25 | Objective weight |

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