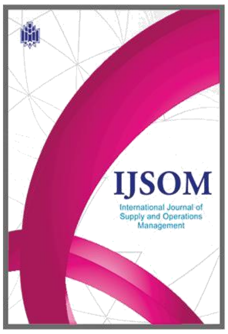
International Journal of Supply and Operations Management

IJSOM

November 2019, Volume 6, Issue 4, pp. 360-388
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



Development of a Mathematical Model for Sustainable Closed-loop Supply Chain with Efficiency and Resilience Systematic Framework

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Abstract
The design of a resilient and sustainable supply chain network is a prolific field to be studied academically, which can potentially develop and affect supply chain performance. The innovation of this research is a closed-loop supply chain network by taking the sustainability, resilience, robustness, and risk aversion approach into consideration. A two-stage, mixed-integer linear programming is used for modeling and a robust counterpart model is utilized to encounter the demand uncertainties. The Conditional Value-at-Risk criterion is considered to model risk and compared with Value-at-Risk and average absolute deviation. Sustainability goals addressed in this research include minimizing the costs, CO_2 emission, and energy, and maximizing the employment. The case study in this research is an automobile assembly company that has decided to set up a supply chain network. The LP-Metric method is applied to merge objectives and NEOS server is employed to attain an optimal solution in large scale. The constraint relaxation and fix-and-optimize are employed to produce the upper and lower bounds in medium and large scale. Results showed that the proposed model provides a better estimation of the total cost, pollution, energy consumption, and employment level compared to the basic model.

Keywords: Closed-loop supply chain; Sustainability; Resilience; Risk.

1. Introduction

A closed-loop supply chain (CLSC) network aims to design, launch, and operate the material flow between the chain centers in order to simultaneously optimize the goals of beneficiaries economically, environmentally, and socially and also to create and promote sustainable developments in the production, distribution, and recycling of the products (Moreno-Camacho, Montoya-Torres, Jaegler, & Gondran, 2019). The design of a supply chain network (SCN) is one of the strategic decisions and includes the network topology determination to provide service for customers in the best possible condition (Meixell & Gargeya, 2005). A CLSC is formed by simultaneous consideration of both forward and backward logistics and forms the CLSC of the two-way flow of goods considering economic, environmental and social activities. The economic goals, however, contain increasing the incomes and decreasing the costs, and environmental goals include decreasing the effect of environmental pollutants on water, air and land, and energy consumption. Social goals are improvements in the employment and welfare levels of employees and people who are directly and indirectly in contact with the supply chain. CLSC management has received an increasing research focus in recent years. According to the governmental laws and legislation for taking into account the environmental and social effects, the customer activity and demands from the supply chains are the main and motivating factors for competition between competitors (Talaei, Moghaddam, Pishvaee, Bozorgi-Amiri, & Gholamnejad, 2016). In other words, the internationalization of the supply chain substantially increases the number of network units and the transference between them leading to increased levels of greenhouse gas emissions (e.g., carbon dioxide) and energy consumption. Thus, the design of a CLSC with a sustainable approach, efficient energy consumption, and reliable and resilient against the disruption conditions would be an effective and necessary step in designing a SCN in the future.

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The internationalization of economic actions alongside rapid developments in information technologies has resulted in shortened product life cycles, reduced lot dimensions, and highly active customer behavior with regard to preferred items. Such facets have had contributions to rising demand uncertainty and, consequently, a strong and properly developed SCN has further gained greater importance (Melo, Nickel, & Saldanha-Da-Gama, 2009). Several studies have examined supply chain strategic planning. The initial models sought to optimize the costs by responding to customer demands. In recent researches, however, other goals such as environmental effects (carbon emission and energy consumption), and social welfare are added to the literature to consider the sustainable problem (Eskandarpour, Dejax, Miemczyk, & Péton, 2015; Kadambala, Subramanian, Tiwari, Abdulrahman, & Liu, 2017; Neto, Walther, Bloemhof, Van Nunen, & Spengler, 2009; Quariguasi Frota Neto, Walther, Bloemhof, Van Nunen, & Spengler, 2010). Recently added developments to the supply chain by researchers is the consideration of facility reliability against disruptions in the unsustainable condition of facilities such as flood, storm, and earthquake (Torabi, Namdar, Hatefi, & Jolai, 2016). Taking into account the facility resilience throughout the design of SCN and the facility preparation for facing the demand fluctuation have posed the supply chain designers the new problem of resilience against demand fluctuations making them pay more attention to risks and threats when designing a problem (Fang & Xiao, 2013; Ghomi-Avili, Tavakkoli-Moghaddam, Jalali, & Jabbarzadeh, 2017; Mari, Lee, & Memon, 2016). According to the governmental laws and legislation (environmental, energy and employment creation) as well as the customer and beneficiary expectations, it is necessary to consider resilient and sustainable in the supply chain management, which is encountered as a competitive factor between competitors. The motivation of this research is a closed-loop supply chain network by taking the sustainability, resilience, robustness, and risk aversion approach into consideration. A literature review and research gaps are addressed in Section 2. In Section 3, the problem and modeling are presented and the models are compared. A discussion on case study, an analysis of sensitivity, and the model solving in medium and large scales are presented in Section 4. Sections 5 and 6 cover managerial implications, practical insights, and conclusions.

2. Literature review

Intense competition between the firms and supply chains leads to uncertainty in the activity operation, thereby making them face high risks. Risks caused by demand uncertainty and disruption in the facility have negative effects on supply chain activities and can increase the costs and reduce the competitive advantage. The supply chain management should move towards different and innovative approaches to have more capability in facing risk disruptions. Designing a SCN by consideration of economic, environmental, energy consumption, and social aspects and also encountering the resilience and reliability of facilities in risk and disruption conditions can be a new approach for designing a SCN strategically (Kleindorfer & Saad, 2005; Klibi, Martel, & Guitouni, 2010). The important research works conducted on CLSC design between 2009 and 2018 are addressed in the following.

2.1. Survey on CLSC

Soleimani and Govindan assessed the location/allocation of a two-stage scenario oriented reverse SCN, which was multi-product and single-period (Soleimani & Govindan, 2014). The Conditional Value-at-Risk (CVaR) index was used in their research as the risk evaluator in the two-stage programming. They found increased and decreased profit by increasing the risk level and weight, respectively. Subulan et al. modeled a multi-period, multi-product, and multi-echelon CLSC for the lead-acid battery industry (Subulan, Baykasoğlu, Özsoydan, Taşan, & Selim, 2015). The model innovation is the consideration of stochastic-fuzzy and possibilistic uncertainties by paying attention to financial risks and those associated with not collecting the products with expired lifespan. They used three indexes of Value-at-Risk (VaR) and CVaR and downside risk to show the risk in the model and showed that the downside risk index performed better than other indexes. Mari et al designed a sustainable and resilient forward SCN in the textile industry (Mari, Lee, & Memon, 2014). Considering carbon dioxide emissions and probabilistic disruption in the facilities were the sustainability and resilience aspects of the model, respectively. Carbon footprints and the disruption costs were taken as resilience criteria. Tavakkoli-Moghaddam et al. proposed a CLSC model the innovation of which was the selection of suppliers at different quality levels, integration of disposal and rework facilities, considering environmental factors including the production pollution in accordance with disposal and defect, and considering time-windows of customer's order and earliness/tardiness costs (Tavakkoli-Moghaddam, Sadri, Pourmohammad-Zia, & Mohammadi, 2015). The possibilistic fuzzy approach is used to incorporate the uncertainty in the parameters. Talaei et al. introduced a bi-objective carbon-efficient CLSC in the copier industry (Talaei et al., 2016). They suggested a robust fuzzy programming to assess the uncertainty in the demand and variable costs of the supply chain. The model goals were to minimize the costs and carbon dioxide emission. Torabi et al. suggested a reliable CLSC where the facilities had disruptions (Torabi et al., 2016). The innovation of their model was that it used the p-robust approach in facing disruptions in the facility, and the proposed model could consider that both partial and complete disruptions in the facility capacity were fuzzy. They concluded that accounting for disruption increases the costs and that one could optimize the system against disturbance. Ghomi-Avili et al. designed a reliable and resilient CLSC under supply risk where suppliers had complete disruption so that they lost all their capacity and did not satisfy customer demands in a suitable time (Ghomi-Avili et al., 2017). Moreover, two resilience strategies including the utilization of extra inventory and lateral transshipment were considered to reduce the impact of disruption on the supply chain performance. Two types of reliable and unreliable suppliers with different opening costs also existed in the chain. Their results showed that using the lateral transshipment and the extra inventory reduced the costs. Amin and Baki (Amin & Baki, 2017) proposed a mathematical CLSC model through universal players such as exchange rates and customs duties in the electronics industry. The model innovations were simultaneous consideration of universal players (exchange rates and customs duties) for the domestic and international contractors, being multi-objective and uncertainty in the real localities in the CLSC network conformation. In another research, Amin et al. assessed the uncertainty effect on designing and optimizing the CLSC network by different options of car tire marketing (Amin, Zhang, & Akhtar, 2017). The model innovations were taking into account various tire marketing options, the uncertainty effects on the closed-loop network on the basis of tree-based procedure, and the financial flow in the multi-period model with cost present values, using the Google map tool to exactly determine the distances. Cardoso et al. designed and programmed an integrated CLSC model by considering financial risks through embedding uncertainty in the final products (Cardoso, Barbosa-Póvoa, & Relvas, 2016). The model aimed to maximize the expected net present value (ENPV) while minimizing the related risk criterion. The amplified epsilon constraint procedure was utilized to solve the model to produce the Pareto front curve for every risk criterion. The uncertainty in the model was addressed by the aid of the scenario tree in the demand. Four risk criteria used in their research included variance, variability index, downside risk, and CVaR. Prakash et al. designed a CLSC by modeling risk and uncertainty in the demand (Prakash, Soni, & Rathore, 2017). They used a convex robust and reliable chain to design the chain with the worst risk case and uncertainty in the electronics trade industry. In another study, Prakash et al. (Prakash, Kumar, Soni, Jain, & Rathore, 2018) assessed CLSC for the hospital beds. They embedded the risks in waiting times of the modeling and showed increased system costs by considering the risks. Sahebjamnia et al. designed a sustainable CLSC in the tire industry to be used for economic, environmental and social goals (Sahebjamnia, Fathollahi-Fard, & Hajiaghaei-Keshteli, 2018). They used four hybrid methods including RDA and SA algorithms, WWO and GA algorithms, WWO and TS algorithms, and WWO and RDA algorithms to solve the model and finally showed that WWO and GA algorithms were more efficient.

2.2. Survey on resiliency and sustainability of supply chain

The available modeling works on designing resilient and sustainable SCN are classifiable according to the resilience and sustainable procedures applied to improve strength against random disturbances. Typical resilience and procedures are as follows (Jabbarzadeh, Fahimnia, & Sabouhi, 2018):

1. Making contractions with backing suppliers/facilities to assist at times of unavailable main suppliers/facilities in disturbances (Namdar, Li, Sawhney, & Pradhan, 2018)
2. Manifold souring and assignment rather than souring and assignment alone, which is the best commonly used tactic of risk decline (Sawik, 2017; Torabi et al., 2016)
3. Fortifying suppliers/facilities to minimalize their susceptibility to disturbances (Jabbarzadeh, Fahimnia, Sheu, & Moghadam, 2016)
4. Storing extra inventories to utilize in disturbance circumstances (Ghomi-Avili et al., 2017)
5. Flexibility and addition of more supply/production capabilities to face up missing capabilities of suppliers/factories resulting from disturbances (Torabi et al., 2016)
6. Development of business stability and catastrophe retrieval policies to empower organizations for the delivery of their vital activities to satisfactory levels in facing disturbances (Torabi et al., 2016)
7. Reducing flow complexity and managing node complexity (Zahiri, Zhuang, & Mohammadi, 2017)

Common sustainability strategies include:

1. Dealing with cost/emission/social function of the forward and reverse CLSC networks design (Mari et al., 2014, 2016; Sahebjamnia et al., 2018)
2. Balancing environmental and economic factors (Brandenburg, 2015)
3. Life cycle evaluation models concentrating on the environmental issues along supply chains and minimization of their impacts (Pishvaee, Razmi, & Torabi, 2014)
4. Models for optimizing investigations on environmental policy tools including a carbon tax and transaction mode of actions (Zakeri, Dehghanian, Fahimnia, & Sarkis, 2015)

In this research, the flexibility capacity and CLSC network designing models were used to address cost/emission/social functioning of the forward and reverse networks.

Table 1. Survey on the CLSC

References	CLSC	Resilient	Disruption	Uncertainty	Risk	Objectives	Industry	Method
(Mari et al., 2014)	Sustainable and resilient		Probabilistic disruption			Economic and emission Carbon footprints Disruption costs	Textile industry	CS
(Soleimani & Govindan, 2014)				Two-stage scenario	CVaR	Economic	Numerical example	CS
(Tavakkoli-Moghaddam et al., 2015)				Possibilistic fuzzy approach		Economic	Numerical example	CS
(Subulan et al., 2015)				Stochastic-fuzzy and possibilistic	VaR, CVaR and downside risk	Economic, mean a collection of the used products	Lead-acid battery	CS
(Brandenburg, 2015)	Sustainable			Scenario		Economic Environmental	FMCG manufacturer	*WGP
(Torabi et al., 2016)	Reliable	Multiple sourcing and assignment	Both partial, complete disruption	Probabilistic mixed programming	P-robust	Economic	Numerical example	Epsilon-constraint
(Cardoso et al., 2016)				Stochastic	Variance, *VI, *DR, and CVaR	Economic (ENPV)	Numerical example	*AEC
(Ghomi-Avili et al., 2017)	Reliable and resilient	Extra inventory Lateral transshipment Reliable suppliers	Complete disruption	Two-stage probabilistic mixed programming	Supply risk	Economic	Numerical example	*CS
(Amin & Baki, 2017)				Fuzzy programming		Economic	Electronics industry	CS
(Amin et al., 2017)			Scenario	Scenario tree		Economic	Tire marketing	CS
(Prakash et al., 2017)	reliable			convex robust	Waiting times	Economic	Hospital beds	CS
(Brandenburg, 2017)	Green			Simulation	VaR	Economic Environmental	Numerical example	CS
(Sahebjamnia et al., 2018)	Sustainable					Economic, environmental and social	Tire industry	*MH
(Behzadi, O'Sullivan, Olsen, & Zhang, 2018)	Resilient	Varied demand market, backing demand market, and adaptable redirecting	Scenario	Robust optimization	Two-stage stochastic	Economic	Kiwifruit	CS
(Prakash et al., 2018)	Robust and reliable		Scenario	Stochastic	Worst risk case	Economic	Electronics trade industry	CS
(Sangaiah, Tirkolaee, Goli, & Dehnavi-Arani, 2019)				Robust optimization	--	Economic	LNG industry	CS, *COA
This Research	Robust, sustainable and resilient	Capacity based on Scenario	Partial disruption	Stochastic	CVaR	Economic, environmental and social	Car manufacturing industry	CS NEOS

*CS: Commercial Solver, AEC: Augmented epsilon constraint, MH: RDA and SA algorithms, WWO and GA algorithms, COA: cuckoo optimization algorithm, WGP: Weighted goal programming, VI: Variability index, DR: Downside risk, NA: Not Applicable.

Table (1) classifies previous researches according to the CLSC.
An innovation of this research is the presentation of a new mathematical model from a sustainable CLSC, which has economic, environmental, energy, and social aspects. The problem also has different scenarios along with disruption risks, which were less simultaneously encountered in previous researches. To approach the actual space, the facilities of the supply chain are reliable, have partial disruption, are resilient in capacity for the facility flexibility against the demand variations, have deviation from demand , and the problem robustness against the demand is added to the problem. The combination of Mulvey (Mulvey, Vanderbei, & Zenios, 1995) robust scenario-based approach and the CVaR is utilized in all the objective functions in this research. Efficacious environmental and social life cycle evaluation-based approaches are employed in the model to estimate the pertinent social and environmental influences and energy consumption.

3. Problem Statement

As mentioned in the literature review, various studies have been performed for the design of CLSC, and their recommendations for future research as well as the new industry requirements have led us to design an integrated sustainable, resilient and risk-averse CLSC that is robust against demand variations. Accordingly, it has both the competitive capabilities and flexibility against any condition and disruption and also considers the environmental and employment requirements and can reduce the disruption risks in the supply chain. The case study of our research is a car manufacturing industry. According to the initiation of a new car manufacturing in Iran, this design style causes the car manufacturer supply chain to consider the legal, environmental, energy, and employment requirements as much as possible. It also reduces the shareholder requirements, which are costs and supply chain risks as far as probable and considers reliability and resilience of the facilities. The suggested supply chain includes suppliers, manufacturers, distribution centers, retailers, customers, collection centers, repairing centers, disposal centers, and second-hand customers (Figure 1a). The methodology problem is presented in Figure 1 (b) and research questions are as the following:

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

The aims of the model are to minimize the costs, environmental pollutant emissions, and energy consumption and to maximize the employment rate as one of the social welfare indexes considering the disruption risk of each scenario being robust against the demand variation. In order to evaluate the associated impacts on society, environment, and energy consumption, this model applies CED, GSLCAP, and ReCiPe solutions. The demands of final customers have various scenarios in the proposed model. The facility capacity (manufacturers, distribution centers, retailers, collecting and repairing centers) is flexible and resilient against different scenarios. The model of strategic decisions includes opening resilient centers and also the amount of transportation between the centers. All the capacity and flow constraints also exist between facilities.

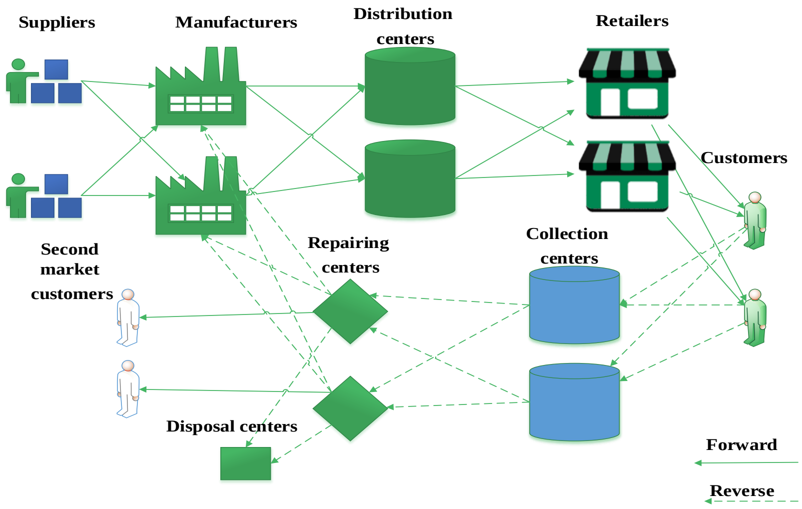


Figure 1 (a). The problem of sustainable and resilient CLSC

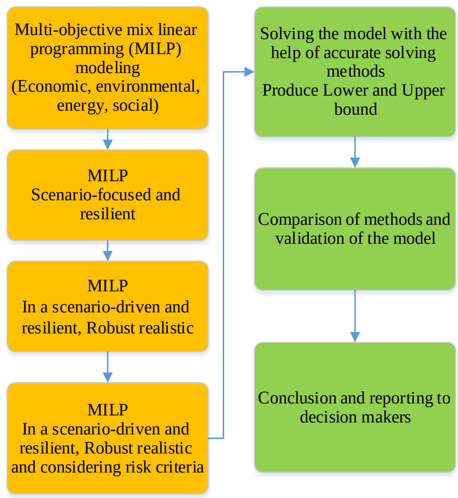


Figure 1 (b). Methodology Problem

3.1. Research assumptions

1. The demand for and return of every product at any time period is dependent on the scenario.
2. The center capacities in each time period depend on the scenario (resilience feature).
3. There is the probability of disruption in the chain centers (reliability and resilience feature).
4. The fixed costs of facilities are independent.
5. All the constraints of the supply chain models, including balance and capacity, hold between the centers.
6. The parameters of variable costs, pollutant emission, energy consumption, and employment depend on the balance between the centers, time period, scenario, and the products.
7. Violation of key constraints of the demand satisfaction is also allowed (making robust).
8. The CVaR criterion is utilized to encounter the risk measure.

3.2. Environmental impact assessment (EIA)

According to Goedkoop et al., (2009), LCA (life cycle assessment) is used for quantitative analysis of activities/products cycle within the environmental impact context. To evaluate the supply chain of environmental impact (EI), some methods and tools are required that can help to acquire a sustainable and resilient CLSC. Given the following merits, one of the investigated EIA methods, i.e. ReCiPe 2008, was chosen to evaluate the EI of SCND decisions: (1) given the end-point and mid-point impacts, the approach can determine the EI; (2) since the solution is developed, and it has recently been equipped with the latest environmental science advancements; (3) ReCiPe is the most all-inclusive EIA approach with suitable coverage of many potential end-point and mid-point influences; (4) because ReCiPe originates from Eco-indicator 99 and CML, it involves the benefits of both approaches; and (5) it does not need goal setting contrary to the approaches such as Ecological Scarcity (Pishvaee et al., 2014). ReCiPe is applied in the system to assess the EI of various configurations of SCN. Secondly, the stages of the life cycle must be determined. Thirdly, each stage should have a determined inventory. Figure 2 presents the associated inventories and life cycle of the given SMNS supply chain. By multiplying the amount of inventories by the associated environmental indicators and adding up the results, the final score was determined at the fourth step. Here, the ReCiPe concept was applied in an environmental objective to determine the facility emissions caused by facilities establishment and uses.

3.3. Energy assessment (EA)

Since the early 70s, the environmental impacts of the life cycle of commodity manufacture has been evaluated using CED (cumulative energy demand) (Huijbregts et al., 2010). For both the given frameworks, the CED (Cumulative Energy Demand) technique is utilized to determine the energy consumption because this procedure has had wide applications for determining the energy intakes during the service life of a unit (Mahmud, Huda, Farjana, & Lang, 2018). CED is determined by summing up the CED_P (cumulative energy demands for the production), CED_U (cumulative energy demands for the use), and CED_D (cumulative energy demands for the disposal) of an economic good. The comparison and evaluation of services and products according to the energy criteria become possible by CED. The CED concept in energy objective was used in this study to determine the facility energy caused by facilities establishment and uses.

3.4. Social impact assessment (SIA)

Due to the complicated nature and comprehensive scope of social impacts, SI (social impact) measurement is an interdisciplinary and multi-stakeholder subject.

GSLCAP (‘‘Guidelines for Social Life Cycle Assessment of Products’’) (Benoît et al., 2010) was chosen as a reference for SIs evaluation in a given problem. In comparison to other studied methods, GSLCAP has the following benefits: (1) GSLCAP is an SIA method with product-oriented (in contrast to organization oriented) nature formed on the basis of LCA, and thus it is consistent with the applied EIA method (ReCiPe) and the SC logic, and facilitates the model formulation and designing; (2) social issues are appropriately covered by the method. Also, it does not account for organizational subjects and the environment. Therefore, it has a high compatibility with social issues and sustainability paradigm through SC; and (3) as a newly developed framework, it is equipped with recent advances in the SIA field. GSLCAP presents five categories of stakeholders: local community, consumers, value chain actors, society, and workers (employees). Some socio-economic/social subcategories are associated with each category of stakeholders. In this study, the GSLCAP (employees) concept was applied in a societal objective to determine the number of employees due to facilities establishment.

3.5. Problem mathematical model

The stochastic scenario-based programming approach of Mulvey et al. (Mulvey et al., 1995) is used here to consider the business common uncertainty and the existing disruptions. The CVaR criterion designed by Rockfeller and Uryasev (Soleimani & Govindan, 2014) is used to embed risk measurement. CVaR, identified as the expected shortfall as well, is a risk assessment criterion for quantifying the level of risk in an investment portfolio. CVaR is obtained by taking a weighted mean of “extreme” losses in the tail of the distribution of probable returns farther than the Value-at-Risk (VaR) cutoff point. CVaR is used for optimizing portfolio to manage risk effectively (Kara, Özmen, & Weber, 2019), which is more coherent, consistent, and conservative with respect to other risk criteria. The proposed mathematical model (Model 1) uses stochastic scenario-based programming approach and a list of CVaR and relevant symbols is presented in Appendix 1.

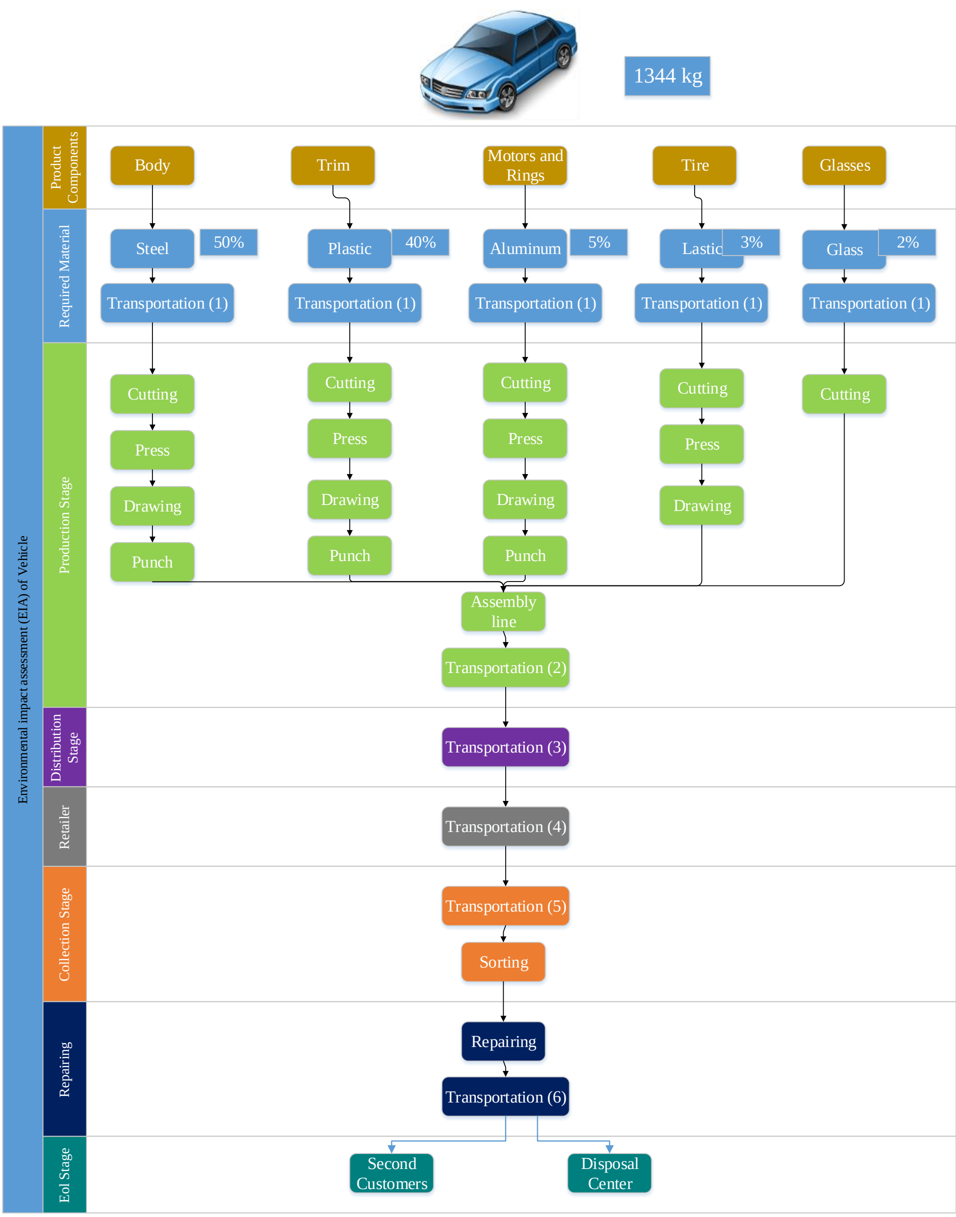


Figure 2. The life cycle steps and equivalent inventories

Model 1. A robust model considering risk

$$\min obj_1 = \sum_{s'} p_{s'}\Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1}\right| + \omega \sum_{s'} p_{s'} k_{s'1} \left(\sum_{r}\sum_{p}\sum_{t} \left|z_{rpts'}\right|\right) + \lambda\left(\eta_1 + \frac{1}{1-\alpha}\sum_{s'} p_{s'} \max(\Gamma_{s'1}-\eta_1, 0)\right), \quad (1)$$

$$\min obj_2 = \sum_{s'} p_{s'}\Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'2} - \sum_{s'} p_{s'}\Gamma_{s'2}\right| + \omega \sum_{s'} p_{s'} k_{s'2} \left(\sum_{r}\sum_{p}\sum_{t} \left|z_{rpts'}\right|\right) + \lambda\left(\eta_2 + \frac{1}{1-\alpha}\sum_{s'} p_{s'} \max(\Gamma_{s'2}-\eta_2, 0)\right), \quad (2)$$

$$\min obj_3 = \sum_{s'} p_{s'}\Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'3} - \sum_{s'} p_{s'}\Gamma_{s'3}\right| + \omega \sum_{s'} p_{s'} k_{s'3} \left(\sum_{r}\sum_{p}\sum_{t} \left|z_{rpts'}\right|\right) + \lambda\left(\eta_3 + \frac{1}{1-\alpha}\sum_{s'} p_{s'} \max(\Gamma_{s'3}-\eta_3, 0)\right), \quad (3)$$

$$\max obj_4 = \sum_{s'} p_{s'}\Gamma_{s'4} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'4} - \sum_{s'} p_{s'}\Gamma_{s'4}\right| + \omega \sum_{s'} p_{s'} k_{s'4} \left(\sum_{r}\sum_{p}\sum_{t} \left|z_{rpts'}\right|\right) + \lambda\left(\eta_4 + \frac{1}{1-\alpha}\sum_{s} p_{s'} \max(\Gamma_{s'4}-\eta_4, 0)\right), \quad (4)$$

such that:

$$\Gamma_{s'1} = FixCost + VariableCost_{s'}, \qquad \forall s' \quad (5)$$

$$FixCost = \sum_{s} fs_s xs_s + \sum_{m} fm_m xm_m + \sum_{d} fd_d xd_d + \sum_{r} fr_r xr_r + \sum_{c} fc_c xc_c + \sum_{k} fk_k xk_k + \sum_{e} fe_e xe_e, \quad (6)$$

$$VariableCost_{s'} = \sum_t\sum_p\sum_m\sum_s Vsm_{smpts'} Qsm_{smpts'} + \sum_t\sum_p\sum_d\sum_m Vmd_{mdpts'} Qmd_{mdpts'} + \sum_t\sum_p\sum_r\sum_d Vdr_{drpts'} Qdr_{drpts'}$$
$$+ \sum_t\sum_p\sum_c\sum_r Vrc_{rcpts'} Qrc_{rcpts'} + \sum_t\sum_p\sum_k\sum_c Vck_{ckpts'} Qck_{ckpts'} + \sum_t\sum_p\sum_e\sum_k Vke_{kepts'} Qke_{kepts'}$$
$$+ \sum_t\sum_p\sum_{sc}\sum_k Vksc_{kscpts'} Qksc_{kscpts'} + \sum_t\sum_p\sum_s\sum_k Vks_{kspts'} Qks_{kspts'} \qquad \forall s' \qquad (7)$$
$$+\sum_t\sum_s Os_{sts'} VOs_{st} xs_s + \sum_t\sum_m Om_{mts'} VOm_{mt} xm_m + \sum_t\sum_d Od_{dts'} VOd_{dt} xd_d + \sum_t\sum_r Or_{rts'} VOr_{rt} xr_r$$
$$+\sum_t\sum_c Oc_{cts'} VOc_{ct} xc_c + \sum_t\sum_k Ok_{kts'} VOk_{kt} xk_k + \sum_t\sum_e Oe_{ets'} VOe_{et} xe_e;$$

$$\Gamma_{s'2} = FixEmision_{s'} + VariableEmision_{s'}, \qquad (8)$$

$$FixEmision_{s'} = \sum_t\sum_s Ems_{sts'} xs_s + \sum_t\sum_m Emm_{mts'} xm_m +$$
$$\sum_t\sum_d Emd_{dts'} xd_d + \sum_t\sum_r Emr_{rts'} xr_r + \sum_t\sum_c Emc_{cts'} xc_c + \qquad \forall s' \qquad (9)$$
$$\sum_t\sum_k Emk_{kts'} xk_k + \sum_t\sum_e Eme_{ets'} xe_e,$$

$$VariableEmision_{s'} = \sum_t\sum_p\sum_m\sum_s Emsm_{smpts'} Qsm_{smpts'} + \sum_t\sum_p\sum_d\sum_m Emmd_{mdpts'} Qmd_{mdpts'}$$
$$+\sum_t\sum_p\sum_r\sum_d Emdr_{drpts'} Qdr_{drpts'} + \sum_t\sum_p\sum_c\sum_r Emrc_{rcpts'} Qrc_{rcpts'} + \sum_t\sum_p\sum_k\sum_c Emck_{ckpts'} Qck_{ckpts'} \qquad \forall s' \qquad (10)$$
$$+\sum_t\sum_p\sum_e\sum_k Emke_{kepts'} Qke_{kepts'} + \sum_t\sum_p\sum_{sc}\sum_k Emksc_{kscpts'} Qksc_{kscpts'} + \sum_t\sum_p\sum_s\sum_k Emksc_{kscpts'} Qks_{kspts'},$$

$$\Gamma_{s'3} = FixEnergy_{s'} + VariableEnergy_{s'}, \qquad \forall s' \qquad (11)$$

$$FixEnergy_{s'} = \sum_t\sum_s Es_{sts'} xs_s + \sum_t\sum_m Emm_{mts'} xm_m + \sum_t\sum_d Ed_{dts'} xd_d \qquad \forall s'$$
$$+\sum_t\sum_r Er_{rts'} xr_r + \sum_t\sum_c Ec_{cts'} xc_c + \sum_t\sum_k Ek_{kts'} xk_k + \sum_t\sum_e Ee_{ets'} xe_e, \qquad (12)$$

$$VariableEnergy_{s'} = \sum_t\sum_p\sum_m\sum_s Esm_{smpts'} Qsm_{smpts'} + \sum_t\sum_p\sum_d\sum_m Emd_{mdpts'} Qmd_{mdpts'} \qquad \forall s'$$
$$+\sum_t\sum_p\sum_r\sum_d Edr_{drpts'} Qdr_{drpts'} + \sum_t\sum_p\sum_c\sum_r Erc_{rcpts'} Qrc_{rcpts'} + \sum_t\sum_p\sum_k\sum_c Eck_{ckpts'} Qck_{ckpts'} \qquad (13)$$
$$+\sum_t\sum_p\sum_e\sum_k Eke_{kepts'} Qke_{kepts'} + \sum_t\sum_p\sum_{sc}\sum_k Eksc_{kscpts'} Qksc_{kscpts'} + \sum_t\sum_p\sum_s\sum_k Eksc_{kspts'} Qks_{kspts'},$$

$$\Gamma_{s'4} = FixOcuppation_{s'}, \qquad \forall s' \qquad (14)$$

$$FixOcuppation_{s'} = \sum_t\sum_s Os_{sts'} xs_s + \sum_t\sum_m Om_{mts'} xm_m +$$
$$\sum_t\sum_d Od_{dts'} xd_d + \sum_t\sum_r Or_{rts'} xr_r + \sum_t\sum_c Oc_{cts'} xc_c + \sum_t\sum_k Ok_{kts'} xk_k \qquad \forall s' \qquad (15)$$
$$+\sum_t\sum_e Oe_{ets'} xe_e;$$

Balance:

$$\sum_d Qdr_{drpts'} \geq dem_{rpts'} + z_{rpts'}, \qquad \forall r,p,t,s' \qquad (16)$$

$$\sum_s Qsm_{smpts'} + \sum_k Qkm_{kmpts'} = \sum_d Qmd_{mdpts'}, \qquad \forall m,p,t,s' \qquad (17)$$

$$\sum_m Qsm_{smpts'} + \sum_m Qkm_{kmpts'} = \sum_m Qmd_{mdpts'}, \qquad \forall s,k,p,t,s' \quad (18)$$

$$\sum_m Qmd_{mdpts'} = \sum_r Qdr_{drpts'}, \qquad \forall d,p,t,s' \quad (19)$$

$$\sum_c Qrc_{rcpts'} \geq \rho_{rpt} dem_{rpts'}, \qquad \forall r,p,t,s' \quad (20)$$

$$\sum_r Qrc_{rcpts'} = \sum_k Qck_{ckpts'}, \qquad \forall c,p,t,s' \quad (21)$$

$$\rho_{1pt} \sum_c Qck_{ckpts'} = \sum_m Qkm_{kmpts'}, \qquad \forall k,p,t,s' \quad (22)$$

$$\rho_{2pt} \sum_c Qck_{ckpts'} = \sum_{sc} Qks_{kscpts'}, \qquad \forall k,p,t,s' \quad (23)$$

$$\rho_{3pt} \sum_c Qck_{ckpts'} = \sum_e Qke_{kepts'}, \qquad \forall k,p,t,s' \quad (24)$$

Capacity (resilience and disruption (availability)):

$$Qsm_{smpts'} \leq CapS_{spts'} prs_s xs_s, \qquad \forall s,m,p,t,s' \quad (25)$$

$$\sum_s Qsm_{smpts'} + \sum_k Qkm_{kmpts'} \leq CapM_{mpts'} prm_m xm_m, \qquad \forall m,p,t,s' \quad (26)$$

$$\sum_m Qmd_{mdpts'} \leq CapD_{dpts'} prd_d xd_d, \qquad \forall d,p,t,s' \quad (27)$$

$$\sum_d Qdr_{drpts'} \leq CapR_{rpts'} prr_r xr_r, \qquad \forall r,p,t,s' \quad (28)$$

$$\sum_r Qrc_{rcpts'} \leq CapC_{cpts'} prc_c xc_c, \qquad \forall c,p,t,s' \quad (29)$$

$$\sum_c Qck_{ckpts'} \leq CapK_{kpts'} prk_k xk_k, \qquad \forall k,p,t,s' \quad (30)$$

$$\sum_k Qke_{kepts'} \leq CapE_{epts'} pre_e xe_e, \qquad \forall e,p,t,s' \quad (31)$$

$$xs_s, xm_m, xd_d, xr_r, xc_c, xk_k, xe_e \in \{0,1\}, \qquad \forall s,m,d,r,c,k,e$$

$$Qsm_{smpts'}, Qmd_{mdpts'}, Qdr_{drpts'}, Qrc_{rcpts'}, Qck_{ckpts'}, Qke_{kepts'}, Qksc_{kscpts'}, Qks_{kspts'}, z_{rpts'} \geq 0, \qquad \forall s,m,d,r,c,k,e,t,p,s'. \quad (32)$$

$$\eta_1, \eta_2, \eta_3, \eta_4 \geq 0,$$

Since the above model is a two-stage scenario-based stochastic optimization, decisions of the initial step include establishment of suppliers, manufacturers, distribution centers, retailers, final customers, collection centers (junk), disassembly/repairing, and disposal. The decisions of 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 including the minimization of the sum of the weighted average and cost standard deviation and the fine related to not satisfying the demand, and is a coefficient of cost CVaR. The objective function (2) represents the environmental goal or EIA, which includes the minimization of the sum of the weighted mean and the standard deviation of the produced pollutants (carbon dioxide) and the fine related to not satisfying the demand, which is a coefficient of pollutant CVaR. The objective function (3) shows the cumulative energy demand (CED), which includes the minimization of the sum of the weighted mean and the standard deviation of the consumed energy and the fine related to not satisfying the demand, which is a coefficient of pollutant CVaR. The objective function (4) shows the SIA or employment goal, which includes the maximization of the sum of the weighted average and the standard deviation of the generated employment and the fine related to not satisfying the demand, which is a coefficient of pollutant CVaR. Constraints (5) to (7) are related to the summation of costs, including constant and changeable costs, throughout the whole periods for all the products and for each scenario in all centers. Constraints (8) to (10) illustrate the sum of pollutants produced in each center and those produced due to good transportation throughout the whole periods for all products and for each scenario in all centers. Constraints (11) to (13) illustrate the sum of energies consumed in each center and those generated due to good transportation throughout the whole periods for all products and for each scenario in all centers. Constraints (14) and (15) show the employment generated for each scenario throughout the whole periods. Constraint (16) is the demand satisfaction considering excess demand, which is embedded as fine in objective functions. Constraints (17) to (19) are the balance in the forward loop of the supply chain. Constraints (20) to (24) are the balance in the reverse loop of the supply chain. Constraints (25) to (31) are the consideration of the capacity of each center while taking into account the resilience against each scenario and the reliability factor of each center. Constraint (32) are decision variables, which are binary for establishing variables and are higher than or equal to zero for good transportation variable.

3.6. Linearization of the mathematical model

Since this nonlinear model has absolute value and maximum functions, the common Research Operation methods are used to linearize the objective function by removing absolute value function:

$$\min obj_1 = \sum_{s'} p_{s'}\Gamma_{s'1} + \beta \sum_{s'} p_{s'}(va_{s'} + vb_{s'}) + \omega \sum_{s} p_{s'}k_{s'1}\left(\sum_r \sum_p \sum_t (vc_{rpts'} + vd_{rpts'})\right) + \lambda\left(\eta_1 + \frac{1}{1-\alpha}\sum_{s'} p_{s'}ve_{s'}\right), \tag{33}$$

$$\min obj_2 = \sum_{s'} p_{s'}\Gamma_{s'2} + \beta \sum_{s'} p_{s'}(vf_{s'} + vg_{s'}) + \omega \sum_{s} p_{s'}k_{s'2}\left(\sum_r \sum_p \sum_t (vc_{rpts'} + vd_{rpts'})\right) + \lambda\left(\eta_2 + \frac{1}{1-\alpha}\sum_{s'} p_{s'}vh_{s'}\right), \tag{34}$$

$$\min obj_3 = \sum_{s'} p_{s'}\Gamma_{s'3} + \beta \sum_{s'} p_{s'}(vi_{s'} + vj_{s'}) + \omega \sum_{s} p_{s'}k_{s'3}\left(\sum_r \sum_p \sum_t (vc_{rpts'} + vd_{rpts'})\right) + \lambda\left(\eta_3 + \frac{1}{1-\alpha}\sum_{s'} p_{s'}vk_{s'}\right) \tag{35}$$

$$\max obj_4 = \sum_{s'} p_{s'}\Gamma_{s'4} + \beta \sum_{s'} p_{s'}(vl_{s'} + vm_{s'}) + \omega \sum_{s} p_{s'}k_{s'4}\left(\sum_r \sum_p \sum_t (vc_{rpts'} + vd_{rpts'})\right) + \lambda\left(\eta_4 + \frac{1}{1-\alpha}\sum_{s'} p_{s'}vo_{s'}\right). \tag{36}$$

Such that:

$$\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1} = va_{s'} - vb_{s'}, \qquad \forall s' \tag{37}$$

$$z_{rpts'} = vc_{rpts'} - vd_{rpts'}, \qquad \forall r, p, t, s' \tag{38}$$

$$ve_{s'} \geq \Gamma_{s'1} - \eta_1, \qquad \forall s' \tag{39}$$

$$ve_{s'} \geq 0, \qquad \forall s' \tag{40}$$

$$\Gamma_{s'2} - \sum_{s'} p_{s'}\Gamma_{s'2} = vf_{s'} - vg_{s'}, \qquad \forall s' \tag{41}$$

$$vh_{s'} \geq \Gamma_{s'2} - \eta_2, \qquad \forall s' \tag{42}$$

$$vh_{s'} \geq 0, \qquad \forall s' \tag{43}$$

$$\Gamma_{s'3} - \sum_{s'} p_{s'}\Gamma_{s'3} = vi_{s'} - vj_{s'}, \qquad \forall s' \tag{44}$$

$$vk_{s'} \geq \Gamma_{s'3} - \eta_3, \qquad \forall s' \qquad (45)$$

$$vk_{s'} \geq 0, \qquad \forall s' \qquad (46)$$

$$\Gamma_{s'4} - \sum_{s'} p_{s'}\Gamma_{s'4} = vl_{s'} - vm_{s'}, \qquad \forall s' \qquad (47)$$

$$vo_{s'} \geq \Gamma_{s'4} - \eta_4, \qquad \forall s' \qquad (48)$$

$$vo_{s'} \geq 0, \qquad \forall s' \qquad (49)$$

$$\begin{aligned} &va_{s'}, vb_{s'}, vc_{rpts'}, vd_{rpts'}, \\ &vf_{s'}, vg_{s'}, vl_{s'}, vm_{s'} \geq 0, \end{aligned} \qquad \forall s' \qquad (50)$$

Constraints (5) to (32).

The objective functions (1)-(4) were linearized by defining covariates for removing absolute value functions. Two positive covariates for each absolute value function appear as a summation in objective functions (33)-(36) and as a difference in constraints (37), (38), (41), (44), and (47). To linearize the max function of CVaR in objective functions (1)-(4), another covariate should be defined for each objective function, which is added to constraints (39), (40), (42), (43), (45), (46), (48), and (49). Constraint (50) is also a covariate for determining the minimum shortfall resulted from risk in each objective function.

3.7. Comparison of the proposed model with the base model (without resilience, disruption, and risk measure)

The above model can also be compared to the base model aiming at showing the benefits of the proposed model. In this section, the base model is presented based on the expectation value and neglecting risk. The aim of this section is to assess the proposed model and identify its strong points.

Model 2. Base model based on the scenario expectation value and neglecting risk (51)

$$\min obj_1 = \sum_{s'} p_{s'}\Gamma_{s'1},$$

$$\min\ obj_2 = \sum_{s'} p_{s'}\Gamma_{s'2}, \qquad (52)$$

$$\min\ obj_3 = \sum_{s'} p_{s'}\Gamma_{s'3}, \qquad (53)$$

$$\max obj_4 = \sum_{s'} p_{s'}\Gamma_{s'4}, \qquad (54)$$

Such that:

$$\sum_d Qdr_{drpts'} \geq dem_{rpts'}, \qquad \forall r,p,t,s' \qquad (55)$$

$$\begin{aligned} &prm_m = prd_d = prr_r && \forall m,d,r, \\ &= prc_c = prk_k = pre_e = 1, && c,k,e \\ &CapS_{spts'} = CapS_{spt} && \forall s,p,t,s' \\ &CapM_{mpts'} = CapM_{mpt} && \forall m,p,t,s' \\ &CapD_{dpts'} = CapD_{dpt} && \forall d,p,t,s' \\ &CapR_{rpts'} = CapR_{rpt} && \forall r,p,t,s' \\ &CapC_{cpts'} = CapC_{cpt} && \forall c,p,t,s' \\ &CapK_{kpts'} = CapK_{kpt} && \forall k,p,t,s' \\ &CapE_{epts'} = CapE_{ept} && \forall e,p,t,s' \end{aligned} \qquad (56)$$

Constraint (5)-(15), (17)-(32).

As can be seen, objective functions (51) - (53) including minimization of cost, environment, and energy are defined, as the expectation value and are defined as maximizing the expected value for the employment (54). Constraint (55) is the demand satisfaction considering excess demand. Constraint (56) shows that there are no resilience and disruption (availability) in the facility. All the above terms attempt to optimize the objective functions in the average scenario case.

3.8. Comparison of the proposed model with another risk method

The proposed model can also be compared to the MAD model. Other risk models are presented here aiming at assessing the introduced model and identify its strong points.

Model 3. Risk model based on the Mean absolute deviation (MAD) (57)

$$\min obj_1 = \sum_{s'} p_{s'}\Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1}\right| + \omega \sum_{s'} p_{s'} k_{s'1} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda (\sum_{s'} p_{s'} \left|\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1}\right|),$$

$$\min obj_2 = \sum_{s'} p_{s'}\Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'2} - \sum_{s'} p_{s'}\Gamma_{s'2}\right| + \omega \sum_{s'} p_{s'} k_{s'2} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda (\sum_{s'} p_{s'} \left|\Gamma_{s'2} - \sum_{s'} p_{s'}\Gamma_{s'2}\right|), \quad (58)$$

$$\min obj_3 = \sum_{s'} p_{s'}\Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'3} - \sum_{s'} p_{s'}\Gamma_{s'3}\right| + \omega \sum_{s'} p_{s'} k_{s'3} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda (\sum_{s'} p_{s'} \left|\Gamma_{s'3} - \sum_{s'} p_{s'}\Gamma_{s'3}\right|), \quad (59)$$

$$\max obj_4 = \sum_{s'} p_{s'}\Gamma_{s'4} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'4} - \sum_{s'} p_{s'}\Gamma_{s'4}\right| + \omega \sum_{s'} p_{s'} k_{s'4} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda (\sum_{s'} p_{s'} \left|\Gamma_{s'4} - \sum_{s'} p_{s'}\Gamma_{s'4}\right|), \quad (60)$$

Such that:

Constraint (5)-(32).

As can be seen, objective functions (57)-(59), including minimization of cost, environment, and energy, are defined as the first section of objective function (1)-(3) with adding MAD therein. The objective functions (60) including maximization of employment are defined as the first section of objective function (4) with adding MAD therein.

Model 4. Risk model based on the Value-at-Risk (VaR)

$$\min obj_1 = \sum_{s'} p_{s'}\Gamma_{s'1} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'1} - \sum_{s'} p_{s'}\Gamma_{s'1}\right| + \omega \sum_{s'} p_{s'} k_{s'1} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda(\eta_1), \quad (61)$$

$$\min obj_2 = \sum_{s'} p_{s'}\Gamma_{s'2} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'2} - \sum_{s'} p_{s'}\Gamma_{s'2}\right| + \omega \sum_{s'} p_{s'} k_{s'2} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda(\eta_2), \quad (62)$$

$$\min obj_3 = \sum_{s'} p_{s'}\Gamma_{s'3} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'3} - \sum_{s'} p_{s'}\Gamma_{s'3}\right| + \omega \sum_{s'} p_{s'} k_{s'3} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda(\eta_3), \quad (63)$$

$$\max obj_4 = \sum_{s'} p_{s'}\Gamma_{s'4} + \beta \sum_{s'} p_{s'} \left|\Gamma_{s'4} - \sum_{s'} p_{s'}\Gamma_{s'4}\right| + \omega \sum_{s'} p_{s'} k_{s'4} (\sum_r \sum_p \sum_t |z_{rpts'}|) + \lambda(\eta_4), \quad (64)$$

Such that:

$$\inf \{h_u \;^3\; 0, F(G_{s \phi u})\;^3\; a\}, \qquad u \;\hat{I}\; U \{1,..,4\} \quad (65)$$

Constraint (5)-(33).

As can be seen, objective functions (61) - (63) including minimization of cost, environment, and energy are defined as the first section of objective function (1)-(3) with adding VaR to therein. The objective functions (64) including maximization of employment are defined as the first section objective function (4) with adding VaR therein. Constraint (65) shows VaR criterion.

3.9. Global criterion method of LP-Metric

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. Since the method of LP-Metric needs less information from the DM and it is easy to use in practice, it has been paid more attention (Golpîra & Tirkolaee, 2019; Lotfi, Mehrjerdi, & Mardani, 2017). The method of LP-Metric is used to evaluate the nearness of a solution to its ideal. This deviation evaluation would be as follows, so for the minimum objective function:

$$\min L = (\sum_{i=1}^{n} W_i (\frac{z_i - \text{zmin}_i}{\text{zmax}_i - \text{zmin}_i})^p)^{1/p} \quad (66)$$

$$z_i = f_i(X_1, X_2, ..., X_n), \qquad i = 1, 2, ..., n \quad (67)$$

$$g_j(X_1, X_2, ..., X_n) \le b_j. \qquad j = 1, 2, ..., m \quad (68)$$

The parameter W_i is 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 such that the greater this value the higher the emphasis on the largest deviation. The objective function (66) of the LP-Metric method should also be minimized to minimize the deviation from the ideal, which is $p = 1$ in this research. The optimum value of the *i*th objective function is optimized considering constraints (67) and (68) (Lotfi & Amin Nayeri, 2016; Nour Alsana & Kamali Ardakani, 2009).

4. Case study

The car manufacturing industry is the case study of this research, which has high consumption and waste rates in the country and is one of the problems in the national industry. Completing the value chain of the industry and upside mines, increasing the productivity, and reducing the energy, and material and water consumption in the industries are of the research priorities of Iran Ministry of Industry, Mine and Trades in 2018. After the petroleum industry, the car manufacturing industry is one of the largest industries in Iran. Iran has been the eighteenth greatest car manufacturer in 2018 by manufacturing 123,610 vehicles and 7,137 commercial vehicles, with a total of 130,474 ones. Consequently, a suitable supply chain should be designed by considering various car manufacturing companies in the country, which includes collection, repair, and disassembly centers and the reverse chain steps should be suitably redesigned. The case study of our survey is taken from the information of a car trade and manufacturing firm that currently imports cars and has decided to start a car manufacturing company considering providers, fabrication centers, distribution centers, retailing and collection, repairing and recycling centers. The main manufacturing center of this firm is in the provincial center of Semnan city, northern Iran. The values of the assignment parameters of the case study are presented in Table (1), where the above information and statistics are based on the feasibility study, feasibility study report, and completion of a questionnaire by holding meetings with experts and managers for estimating costs.

4.1. The global criterion results

Modeling is performed in GAMS software with CPLEX solver in a computer with a Core i5 CPU, a 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 Figure (3). Parameters are shown in Appendix 2, Table (A2-1) and weights are equal to 0.25. As can be seen, consideration of robust counterpart and risk measurement in the model (proposed model) result in a better estimation of cost, pollution level, and energy consumption up to maxima of 2 percent increase and 1 percent reduction in the employment with respect to the base model. Gap amount of robust objective function and base model objective is 1.2% without considering risk and those of robust objective function, MAD, and VaR model objective are 0.05%, 0.1% in LP-Metric objective with considering risk (see Table 2 and Figure 3a).

Table 2. Comparison of proposed model with the base model and another risk model

Objective		Min Z_1	Min Z_2	Min Z_3	Max Z_4	Min Lp
Optimal values of the proposed objective function	Cost	71470.14	174731.64	78459.12	176760.32	76688.59
	Pollutant (CO_2)	1989597.2	1250941	1317174.2	1734074.6	1285769.7
	Energy	2274555.6	1953758.2	1591575.2	2358201.8	1594682.2
	Employ.	1749	4399	2100	4505	2141
The optimal value of base model (Model 2)	Cost	71357.8	171286.39	76899.32	173265.9	76589.9
	Pollutant (CO_2)	1901777.2	1217249.6	1258753.3	1650207.1	1251038.2
	Energy	2181635.3	1882470.3	1556561	2263490.8	1559701.1
	Employ.	1788	4499	2150	4520	2151
Avg. Gap		1.7%	1.6%	1.6%	2.7%	1.2%
Optimal values of MAD model (Model 3)	Cost	71398.586	171306.116	76921.354	173295.300	76611.968
	Pollutant (CO_2)	1952035.871	1249601.765	1292331.566	1701579.045	1284397.488
	Energy	2231425.590	1916445.179	1589903.064	2313426.428	1593005.739
	Employ.	1784.791	4489.099	2143.154	4510.370	2143.704
Avg. Gap		0.5%	0.5%	0.5%	1.4%	0.05%
The optimal value of VaR model (Model 4)	Cost	71470.057	171477.457	76998.314	173468.648	76688.619
	Pollutant (CO_2)	1954075.592	1250908.704	1293683.407	1703371.669	1285741.007
	Energy	2233745.832	1918421.837	1591552.059	2315828.354	1594657.770
	Employ.	1786.569	4493.571	2145.284	4514.862	2145.834
Avg. Gap		0.4%	0.4%	0.4%	1.3%	0.1%

* Avg. GAP = average (proposed obj_k- obj_k model)/obj_k.

The car assembler is a car manufacturing that manages the entire supply chain to gain profit by dealing with the government on energy costs, environmental issues, and employment. Hence, although the proposed model is complex, it matches the reality of our country and the type of business running here. After decision making in location and flow material, suppliers are some of supply chain actors. Location and flow material are shown in Figure 3 (b).

4.1. Sensitivity analysis

The results of variation in the W_i model objective weights, parameters a and l of CVaR criterion, parameter b of robustness coefficient and availability probability parameter prx_s are also presented in Table 3 and Figure 4- 8. Obviously, Table 3 and Figure 4 (a) represent that by rising the importance of the cost objective, cost has been decreased, pollutants and energy have been increased, and employment has been decreased.

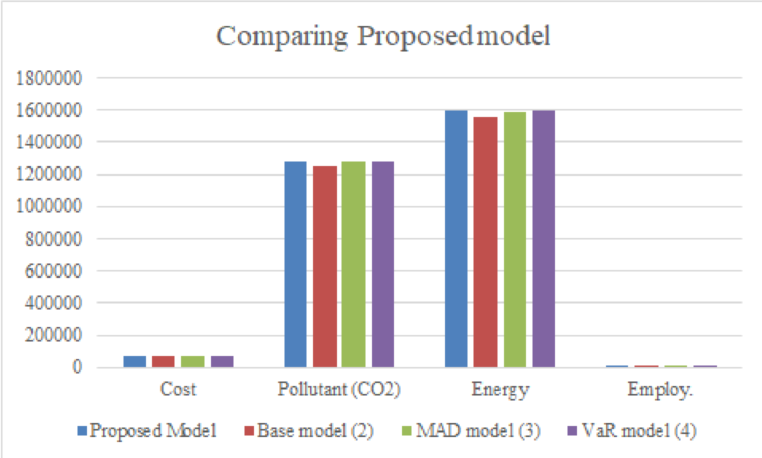


Figure 3 (a). Comparison of proposed model with the base model

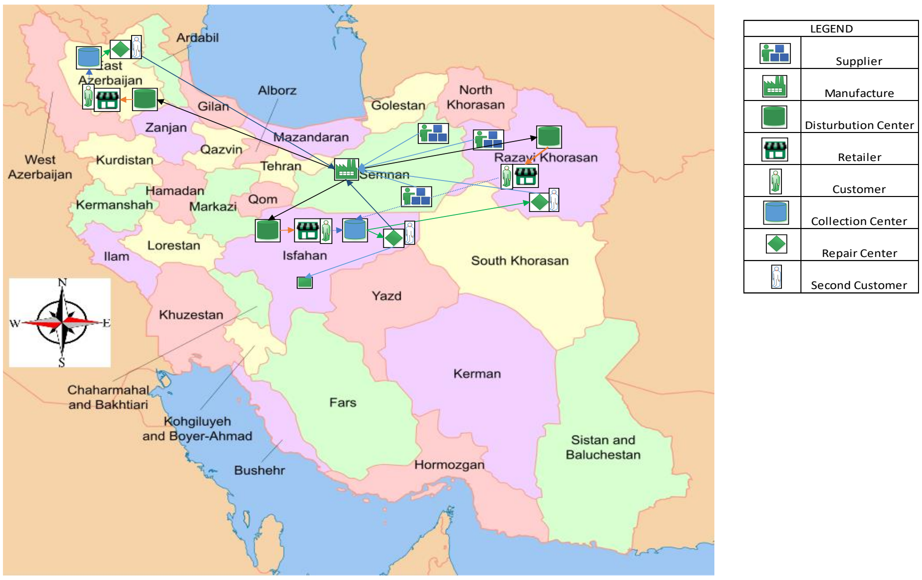


Figure 3 (b). Location and facility locations

Raising the importance of the environmental objective led to increased energy, employment, and value of cost, and decreased pollutants (Table 3, Figure 4b). According to Table 3 and Figure 4 (c), increasing the importance of the energy objective resulted in decreased cost, energy, employment, and pollutant levels. As shown in Table 3 and Figure 4 (d), increasing the employment objective importance elevated the values of cost, pollutant, energy, and employment.

Table 3. Weight variations versus objectives

W_1	W_2	W_3	W_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	81873.39	1270004	1672336	2340.66
0.16	0.16	0.5	0.16	76688.97	1289052	1592359	2141.56
0	0	1	0	78459.12	1317174	1591575	2100.21

0.33	0.33	0.33	0	76688.59	1285770	1594682	2100.75
0.16	0.16	0.16	0.5	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	1285769.68	1594682	2141.55

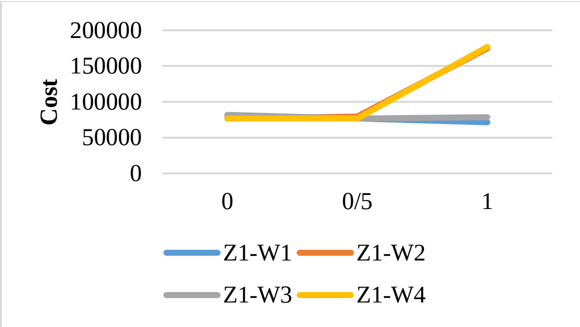


Figure 4 (a). Weight variations versus cost objective

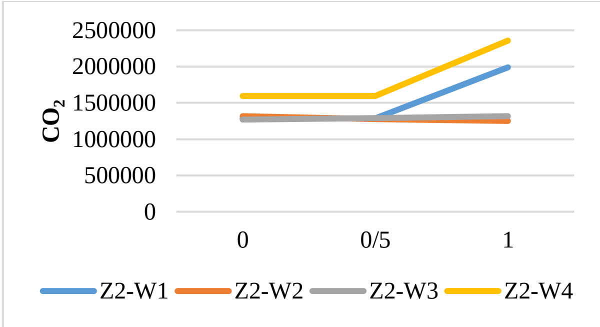


Figure 4 (b). Weight variations versus environmental objective

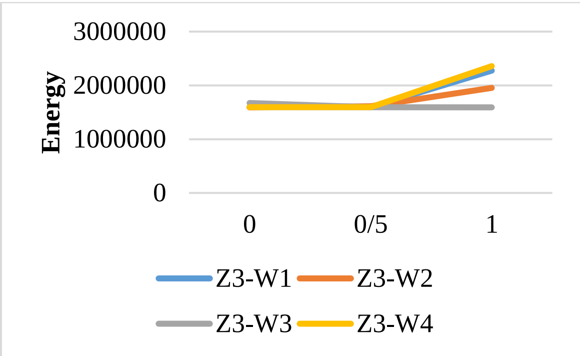


Figure 4 (c). Weight variations versus energy objective

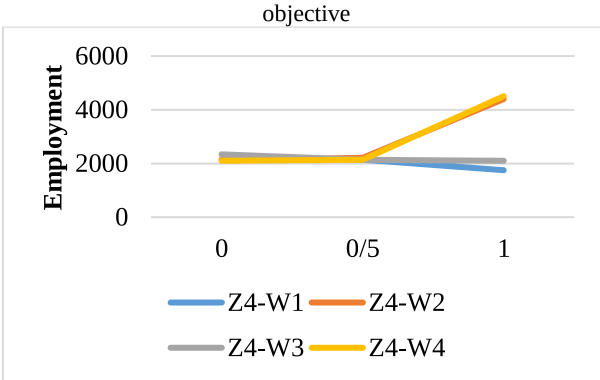


Figure 4 (d). Weight variations versus energy objective

The parameter l , which is the importance coefficient of the CVaR index, varied in the (0-0.01) range. Values of the cost, the amount of pollution, and energy consumption increased and employment decreased by increasing the l where there was more detailed attention to risks (Figure 5 (a)-(d)). Parameter β is the important factor of the variation variance and varied in the (0-0.5) range. Value of the cost, the amount of pollution, and energy consumption increased and employment decreased by increasing β where there was more elaborate attention to risks (Figure 6 (a)-(d)).

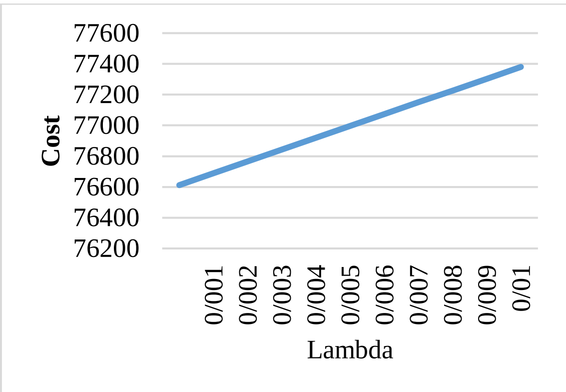


Figure 5 (a). Variation of l (importance coefficient of CVaR index) versus cost objective

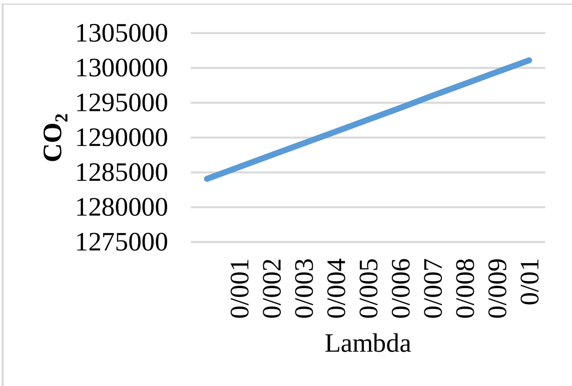


Figure 5 (b). Variation of l (importance coefficient of CVaR index) versus environmental objective

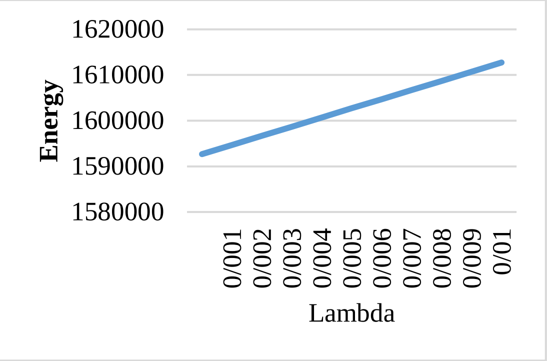


Figure 5 (c). Variation of l (importance coefficient of CVaR index) versus energy objective

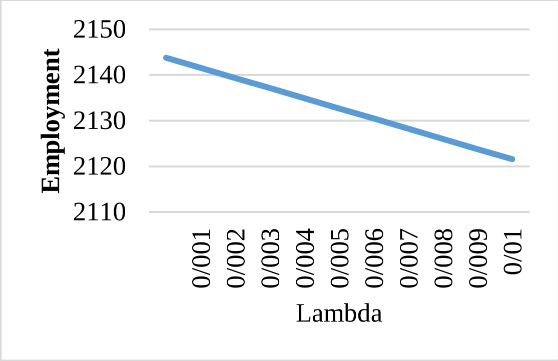


Figure 5 (d). Variation of l (importance coefficient of CVaR index) versus employment objective

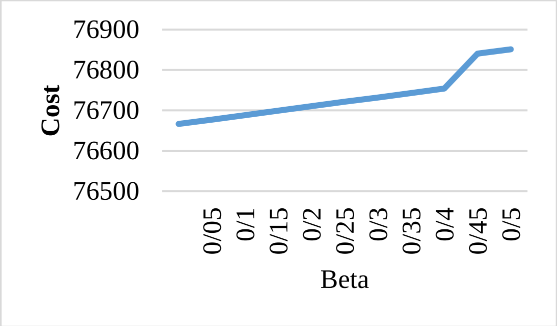


Figure 6 (a). Variations of β (importance factor of variance) versus cost objective

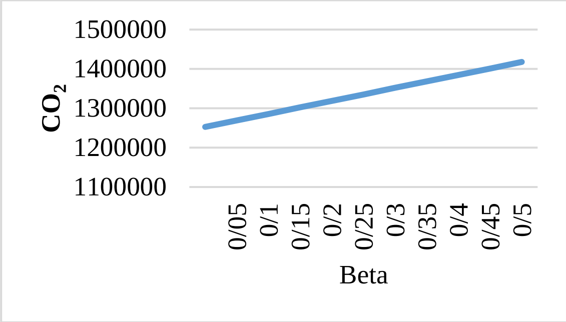


Figure 6 (b). Variations of β (importance factor of variance) versus environmental objective

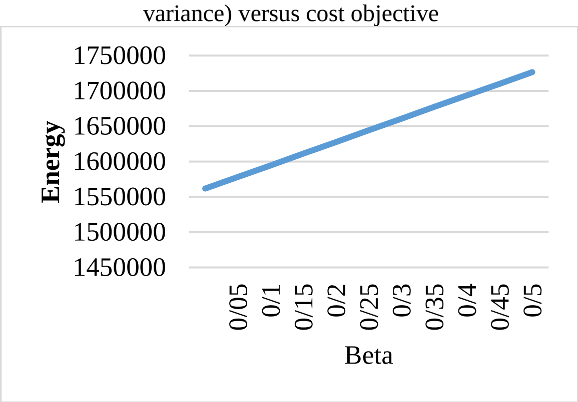


Figure 6 (c). Variations of β (importance factor of variance) versus energy objective

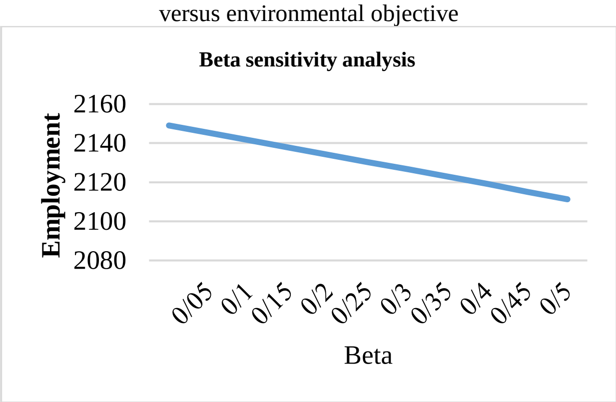
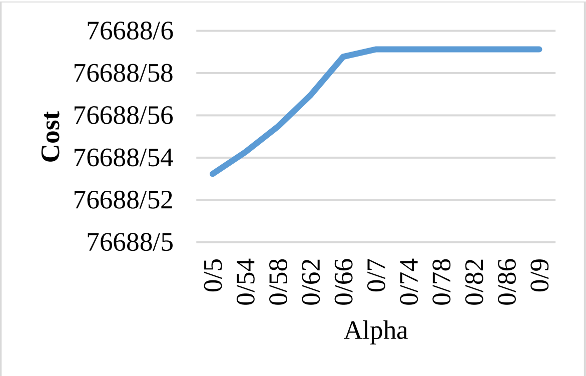


Figure 6 (d). Variations of β (importance factor of variance) versus employment objective

The parameter α is the confidence level, which varied in (0.5-0.9) range: by increasing the value of α the amount of cost, pollution, and energy consumption increased up to a point and then remained constant and the employment trend dropped and then remained constant (Figure 7 (a)-(d)).



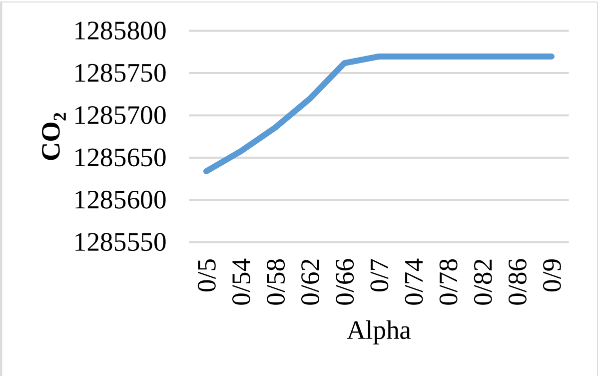
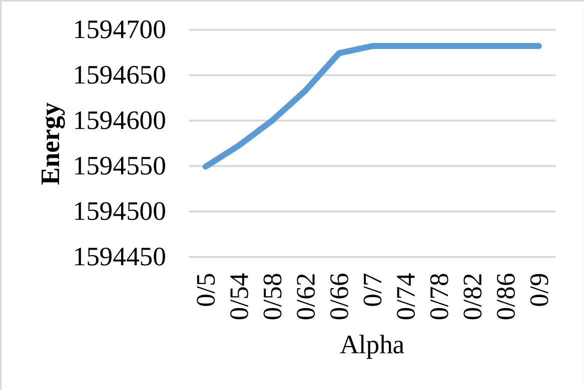


Figure 7 (a). Variations of α (confidence level) versus cost objective

Figure 7 (b). Variations of α (confidence level) versus environmental objective



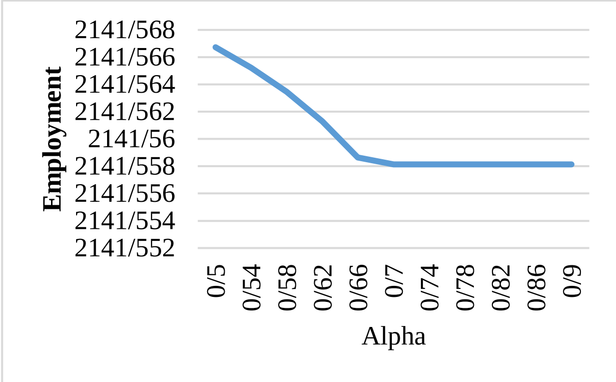
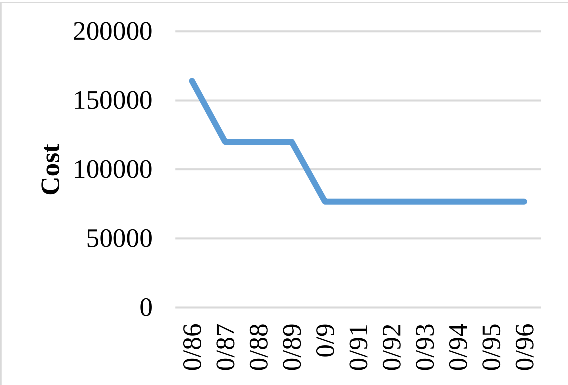


Figure 7 (c). Variations of α (confidence level) versus energy objectives

Figure 7 (d). Variations of α (confidence level) versus employment objectives



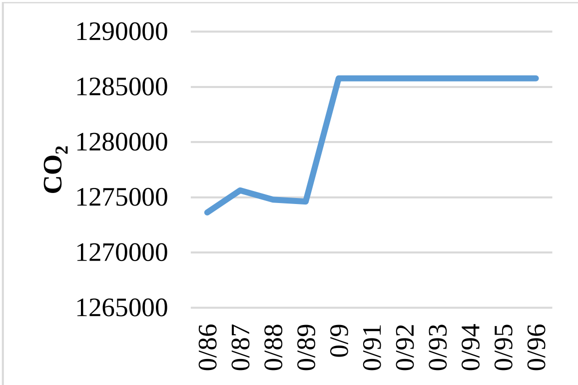
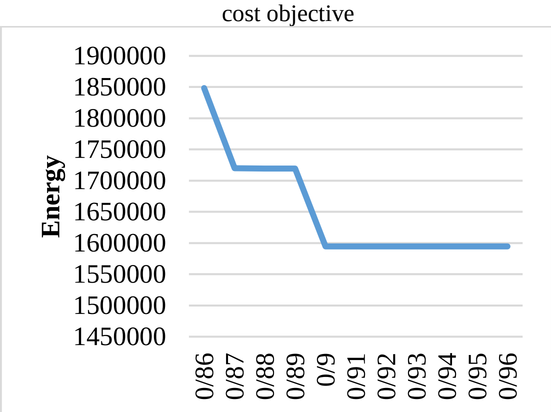


Figure 8 (a). Variations of availability probability versus cost objective

Figure 8 (b). Variations of availability probability versus environmental objective



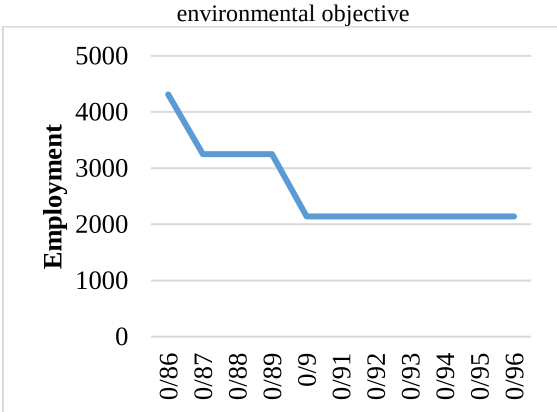


Figure 8 (c). Variations of availability probability versus energy objective

Figure 8 (d). Variations of availability probability versus employment objective

The value of the availability probability pr which is assumed to be identical for all the scenarios and facilities varied in the (0.5-0.96) range: by increasing the availability probability, the amount of cost, energy consumption and the employment decreased to a point and then they remained constant and the pollution increased and then remain constant (Figure 8 (a)-(d)).

The results of variations of parameters α and l from the CVaR criterion, parameter b of the robustness coefficient, and the availability probability parameter prx_s which are described above are discussions for the effects of variation of each parameter on all the objectives.

2.1. Solving the model in medium and large scales

Various methods can be used to solve the model in medium and large scales. One of the solving methods is constraint relaxation and solving the model in the worst possible case. First, some medium scale and large scale problems are defined based on Table 4. Amounts of parameters are shown in Appendix 2, Table A2-1 for large scale problems.

Table 4. Large scale problems

Problem	$\lvert S\rvert*\lvert M\rvert*\lvert D\rvert*\lvert R\rvert*\lvert C\rvert*\lvert K\rvert*\lvert E\rvert*\lvert Sc\rvert*\lvert P\rvert*\lvert T\rvert*\lvert S'\rvert$	Main model Variable	Binary Variable	Free Variable	Linear Variable	Constraint	Fix-and-opt Variable
P1	3*3*3*3*3*3*3*3*3*3*3	2289	21	41	2227	2264	2268
P2	4*4*4*4*4*4*4*4*4*4*3	6829	28	41	6760	6797	6801
P3	5*5*5*5*5*5*5*5*5*5*3	16241	35	41	16165	16952	16206
P4	7*7*7*7*7*7*7*7*7*7*5	101359	49	61	101249	121886	101310
P5	10*10*10*10*10*10*10*10*10*10*3	249151	70	41	249040	375077	249081

By relaxing constraint (32), which is the definition of decision variables and means that the facility activation is transformed from the binary ($X \in\{0,1\}$) into the case of between zero and one ($0\leq X \leq1$), the model is transformed from the mixed-integer state into fully linear and a lower bound is obtained for the problem. The upper bound was defined through fix-and-optimize heuristic offered individually by Gintner et al. (2005) and Pochet and Wolsey (2006). Fix-and-optimize is a meta-heuristic with the ability of iterative decomposition of a problem into smaller sub-problems. A decomposition procedure is applied in each iteration of the algorithm aiming at fixing the majority of the decision variables at their value in the existing solution (Figure 9a). The above methods reduce the solution time. The calculations of the lower bound, base model value, and the upper bound are presented in Table 5 along with the comparison of the distance gaps for the cost objective (Lotfi, Zare Mehrjerdi, Pishvaee, & Sadeghieh, 2019).

By increasing the scale of the model, deviations of the main model from the lower and upper bounds were reduced to 55 percent (GAP_1) and 21 percent (GAP_2), respectively. As shown in Figure 9 (b), the differences between the lower and upper bounds and the main model can be estimated for the main model on a large scale through the above bounds. The solution time trend is exponential based on Figure 9 (c) and the solution time is exponentially increased by increasing the model size. Moreover, the NEOS server is used to solve the large scale model P4-P5, which could solve and optimize the model in time in more than 3600 seconds considering the processor power (Czyzyk, Mesnier, & Moré, 1998; Dolan, 2001; Gropp & Moré, 1997). However, the 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 to the lower bound and the fix-and-optimize

Prob.	**Lower bound**		**Main model**		**Upper bound**		**GAP_1**	**GAP_2**
	(A) LP-Relax $0\leq X \leq1$	Time GAMS	(B) Main model $X \in\{0,1\}$	Time	(C) Fix-and-Optimize	Time		
P1	10862.2	2.0	76688.9	8.40	81881.7	39.6	-86%	7%
P2	15720.9	3.8	90009.1	93.7	97274.24	186.9	-83%	8%
P3	21307.4	11.3	111813.3	1082.9	113892.4	224.7	-81%	2%
P4	44956.5	843.1	*127011.4	*3705.6	156705.77	5678.3	-65%	23%
P5	74585.4	2967.0	*165745.4	*28810	200551.9	23220.3	-55%	21%

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

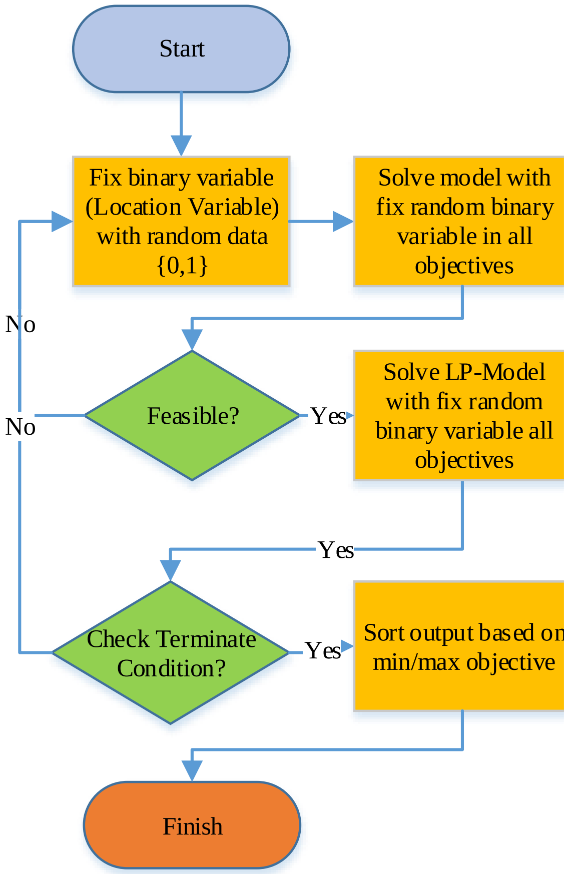


Figure 9 (a). Fix and optimize algorithm

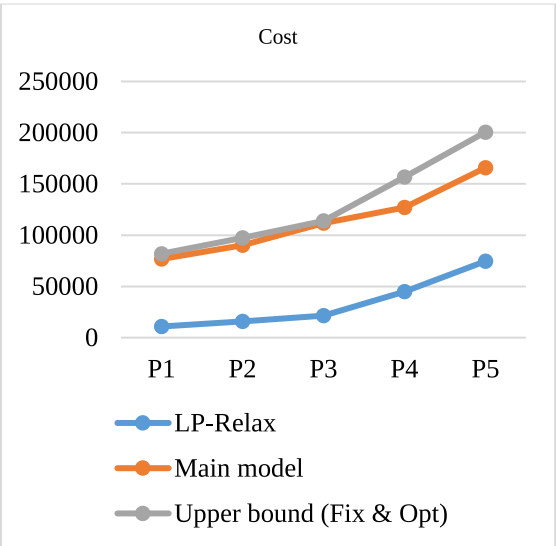


Figure 9 (b). Comparison of the main model to lower and upper bounds

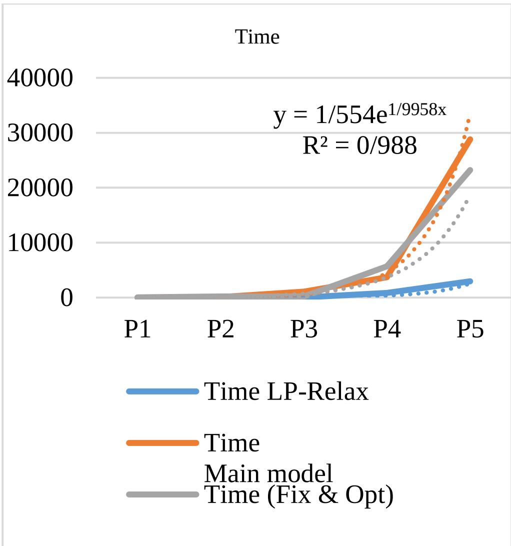


Figure 9 (c). The main model time with the lower and upper bounds

5. Managerial implications and practical insights

The introduced model is applicable for solving all practical problems in a certain SCN. Practically, the introduced model outcomes could assist policymakers and stakeholders in making coordinated decisions and in determining and promoting a suitable production policy to meet the targeted sustainability necessities. The stakeholders are then capable of investing in suitable production policies for realizing long-run sustainability profits. This type of modeling is applicable not only to the automotive supply chain but also to the design of other SCNs. 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. The SCN designer should be informed to design CLSC with all requirements of robustness, resilience, and risk of deviation of demand. Although the number of objectives is over one by considering all the requirements, the designer ensures that everything required by the stockholders is considered in the design.

6. Conclusion

The importance of the supply chain and consideration of the environment, social welfare, and the saving on the energy consumption in the chain have changed into vital and global issues in recent century. The management of sustainable CLSC has received an increasing research focus in recent years. According to the governmental laws and legislation (environmental, energy and employment creation) as well as the customer and beneficiary expectations, it is necessary to consider this issue in the supply chain management, which is encountered as a competitive factor between competitors. This research proposes a new mathematical model for the sustainable and resilient CLSC in which all the economic, environmental, and social facets are taken into account along with risk and uses the concept of ReCiPe for environmental impact and CED for an energy assessment and GSLCAP for social impact. Furthermore, all the facilities in the chain have the resilience feature in the capacity and are reliable; the above model is also robust against the demand disruption. The innovation of this research is a global designation of a resilient and sustainable supply chain, which was not comprehensively addressed in previous researches.

The modeling in this research tried to reflect the real world using two-stage stochastic programming tools, scenario-based robust programming, and considering risk indexes. The above supply chain contains suppliers, manufacturers, distribution centers, retailers, customers, collection centers, repair centers, disposal centers, and second-hand customers. The aims of the model are the minimization of costs, environmental pollutant emissions, and energy consumption, and the maximization of the employment considering disruption risks for each scenario; the model is also robust against demand variations. The final customer demand has different scenarios in the model. The facility capacity (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 the amount of transportation between the centers. All the resilience capacity and flow constraints are fulfilled between facilities. The case study of this model is a car manufacturing industry in Iran, which has high consumption and waste rates being one of the country difficulties.

The global criterion (Lp-Metric) is used to solve the model. The sensitivity analysis is also performed for parameters l and a from the CVaR criterion, parameter b of the robustness coefficient, and reliability probability of the model facilities. To solve the model on a large scale, various methods were used in this research, of which constraint relaxation is proposed to be used in the worst possible case of the utilization for objectives, resulting in obtaining lower and upper bounds for the model. The lower and upper bounds approached each other by increasing the model size. Commercial solvers and the web-based server of NEOS were used to solve the model. Obviously, the robust counterpart and the risk measure in the model led to a better estimation of the cost, pollution level, and energy consumption up to a 2-percent increase with respect to the base model and a 1-percent reduction in the employment level in terms of the base model. By increasing the scale of the model, the deviations of the main model from the lower and upper bounds reduced up to 55 and 21 percent, respectively.

Future suggestions for researchers can be summarized as the use of other solving techniques and evolutionary meta-heuristic algorithm (Lotfi, Weber, Sajadifar, & Mardani, 2018), Benders decomposition, column generation, and Lagrange relaxation method for a large scale model. Moreover, another combination of tactical and operational programming levels and the execution of multi-stage programming in defining the scenarios can be used in programming the model. Considering other uncertainty tools, including stochastic, fuzzy or grey space, and convex robust counterpart (Babaee Tirkolaee, Goli, Pahlevan, & Malekalipour Kordestanizadeh, 2019; Babaee Tirkolaee, Mahdavi, Seyyed Esfahani, & Weber, 2019; Tirkolaee, Mahdavi, Seyyed Esfahani, & Weber, 2020) can also be the subjects of future investigations.

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Appendix 1.

Indices:

s	Index of suppliers,	e	Index of potential disposal center,
m	Index of potential manufacturer,	Sc	Index of second-hand customers,
d	Index of potential distribution center,	p	Index of products,
r	Index of potential retailer,	t	Index of time period,
c	Index of potential collection center,	s'	Index of scenarios.
k	Index of potential repairing center,	i	Objective function i

Parameters:

$dem_{rpts'}$ Demand at retailer r from product p in time t under scenario s'.

Fixed costs (opening) :

fs_s	Opening cost of supplier s ,	fc_c	Opening cost of collection center c ,
fm_m	Opening cost of manufacturer m ,	fk_k	Opening cost of repairing center k ,
fd_d	Opening cost of distribution center d ,	fe_e	Opening cost of disposal center e .
fr_r	Opening cost of retailer r ,		

Variable costs:

$Vsm_{smpts'}$	Transportation cost from supplier s to manufacturer m for the product p in time period t under scenario s',	$Vrc_{rcpts'}$	Transportation cost from retailer r to collection center c for the product p in time period t under scenario s',
$Vmd_{mdpts'}$	Transportation cost from manufacturer m to distribution center d for the product p in time period t under scenario s',	$Vck_{ckpts'}$	Transportation cost from collection center c to repairing center k for the product p in time period t under scenario s',
$Vdr_{drpts'}$	Transportation cost from distribution center d to retailer r for the product p in time period t under scenario s' ,	$Vke_{kepts'}$	Transportation cost from repairing center k to disposal center e for the product p in time period t under scenario s',
$Vksc_{ksc pts'}$	Transportation cost from repairing center k to the second-hand customer Sc for the product p in time period t under scenario s',	$Vkm_{kmpts'}$	Transportation cost from repairing center k to manufacturer m for the product p in time t under scenario s'.

Fixed pollution (opening):

$Ems_{sts'}$	Pollution caused by supplier s in time period t under scenario s',	$Emc_{cts'}$	Pollution caused by collection center c in time period t under scenario s',
$Emm_{mts'}$	Pollution caused by manufacturer m in time period t under scenario s',	$Emk_{kts'}$	Pollution caused by repairing center k in time period t under scenario s',
$Emd_{dts'}$	Pollution caused by distribution center d in time period t under scenario s',	$Eme_{ets'}$	Pollution caused by disposal center e in time t under scenario s'.
$Emr_{rts'}$	Pollution caused by retailer r in time period t under scenario s',		

Variable pollution (Carbon dioxide):

$Emsm_{smpts'}$	Pollution of transportation from supplier s to manufacturer m for product p in time period t under scenario s',	$Emck_{ckpts'}$	Pollution of transportation from collection center c to repairing center k for product p in time period t under scenario s',
$Emmd_{mdpts'}$	Pollution of transportation from manufacturer m to distribution center d for product p in time period t under scenario s',	$Emke_{kepts'}$	Pollution of transportation from repairing center k to disposal center e for product p in time period t under scenario s',
$Emdr_{drpts'}$	Pollution of transportation from distribution center d to retailer r	$Emksc_{ksc pts'}$	Pollution of transportation from repairing center k to second-hand customer Sc for

for product p in time period t under scenario s',

$Emrc_{rcpts'}$ Pollution of transportation from retailer r to collection center c for product p in time period t under scenario s',

product p in time period t under scenario s',

$Emkm_{kmpts'}$ Pollution of transportation from repairing center k to manufacturer m for product P in time t under scenario s'.

Fixed consumed energy (opening):

$Es_{sts'}$ Energy consumed in supplier s in time period t under scenario s',

$Em_{mts'}$ Energy consumed in manufacturer m in time period t under scenario s',

$Ed_{dts'}$ Energy consumed in distribution center d in time period t under scenario s',

$Er_{rts'}$ Energy consumed in retailer r in time period t under scenario s',

$Ec_{cts'}$ Energy consumed in collection center c in time period t under scenario s',

$Ek_{kts'}$ Energy consumed in repairing center k in time period t under scenario s',

$Ee_{ets'}$ Energy consumed in disposal center e in time t under scenario s'.

Variable consumed energy:

$Esm_{smpts'}$ Energy consumed for transportation of product p from supplier s to manufacturer m in time period t under scenario s',

$Eemd_{mdpts'}$ Energy consumed for transportation of product p from manufacturer m to distributor d in time period t under scenario s',

$Edr_{drpts'}$ Energy consumed for transportation of product p from distributor d to retailer r in time period t under scenario s',

$Erc_{rcpts'}$ Energy consumed for transportation of product p from retailer r to collection center c in time period t under scenario s',

$Eck_{ckpts'}$ Energy consumed for transportation of product p from collection center c to repairing center k in time period t under scenario s',

$Eke_{kepts'}$ Energy consumed for transportation of product p from repairing center k to disposal center e in time period t under scenario s',

$Eksc_{ks_cpts'}$ Energy consumed for transportation of product p from repairing center k to second-hand customer Sc in time period t under scenario s',

$Ekm_{kmpts'}$ Energy consumed for transportation of product p from repairing center k to manufacturer m in time t under scenario s'.

Amount of fixed employment (social welfare):

$Os_{sts'}$ Employment generated in supplier s in time period t under scenario s',

$Om_{mts'}$ Employment generated in manufacturer m in time period t under scenario s',

$Od_{dts'}$ Employment generated in distributor d in time period t under scenario s',

$Or_{rts'}$ Employment generated in retailer r in time period t under scenario s',

$Oc_{cts'}$ Employment generated in collection center c in time period t under scenario s',

$Ok_{kts'}$ Employment generated in repairing center k in time period t under scenario s',

$Oe_{ets'}$ Employment generated in disposal center e in time t under scenario s'.

VOs_{st} Salary cost in supplier s in time period t under scenario s',

VOm_{mt} Salary cost in manufacturer m in time period t under scenario s',

VOd_{dt} Salary cost in distributor d in time period t under scenario s',

VOr_{rt} Salary cost in retailer r in time period t under scenario s',

VOc_{ct} Salary cost in collection center c in time period t under scenario s',

VOk_{kt} Salary cost in repairing center k in time period t under scenario s',

VOe_{et} Salary cost in disposal center e in time period t under scenario s'.

Facility capacity:

$CapS_{spts'}$ Capacity of supplier s for product p in time period t under scenario s',

$CapM_{mpts'}$ Capacity of manufacturer m for product p in time period t under scenario s',

$CapC_{cpts'}$ Capacity of collection center c for product p in time period t under scenario s',

$CapK_{kpts'}$ Capacity of repairing center k for product p in time period t under scenario s',

$CapD_{dpts'}$ Capacity of distribution center d for product p in time period t under scenario s',

$CapR_{rpts'}$ Capacity of retailer r for product p in time period t under scenario s',

$CapE_{epts'}$ Capacity of disposal center e for product p in time t under scenario s'.

Availability probability (disruption)

prs_s Availability of supplier s ,

prm_m Availability of manufacturer m ,

prd_d Availability of distribution center d ,

prr_r Availability of retailer r ,

prm_m Availability of collection center c ,

prk_k Availability of repairing center k ,

pre_e Availability of disposal center e .

Other parameters:

$p_{s'}$ Occurrence probability of scenario s',

β Expectation value weight coefficient,

ω Weight coefficient of deviation from key constraints,

λ Weight coefficient of CVaR index,

α Confidence level in CVaR,

$k_{s'1}$ Weight of deviation from demand key constraints for cost goal under scenario s',

$k_{s'2}$ Weight of deviation from demand key constraints for environmental goal under scenario s',

$k_{s'3}$ Weight of deviation from demand key constraints for energy goal under scenario s',

$k_{s'4}$ Weight of deviation from demand key constraints for employment goal under scenario s',

$\rho_{rpts'}$ Return percentage of product p from retailer r in time period t under scenario s'

$\rho_{1pts'}$ Repairable percentage of product p in time period t under scenario s',

$\rho_{2pts'}$ Salable percentage of product p to second-hand customer in time period t under scenario s',

$\rho_{3pts'}$ Disposal percentage of product p in time period t under scenario s'.

Decision variable:

Location variable:

xs_s 1 if supplier s is to be established, otherwise 0,

xm_m 1 if manufacturer m is to be established, otherwise 0,

xd_d 1 if distribution center d is to be established, otherwise 0,

xr_r 1 if retailer r is to be established, otherwise 0,

xc_c 1 if collection center c is to be established, otherwise 0,

xk_k 1 if repairing center k is to be established, otherwise 0,

xe_e 1 if disposal center e is to be established, otherwise 0.

Flow variable:

$Qsm_{smpts'}$ Amount of transportation from supplier s to manufacturer m for product p in time period t under scenario s',

$Qmd_{mdpts'}$ Amount of transportation from manufacturer m to distribution center d for product p in time period t under scenario s',

$Qdr_{drpts'}$ Amount of transportation from distribution center d to retailer r for product p in time period t under scenario s',

$Qrc_{rcpts'}$ Amount of transportation from retailer r to collection center c for product p in time period t under scenario s',

$Qks_{kmpts'}$ Amount of transportation from repairing center k to manufacturer m for product p in time period t under scenario s',

$z_{rpts'}$ Fine related to not satisfying demand at retailer r from product p in time period t under scenario s'

η_1 Average of maximum shortfalls expected in CVaR,

η_2 Average of maximum pollution expected in CVaR,

$Qck_{ckpts'}$	Amount of transportation from collection center c to repairing center k for product p in time period t under scenario s',	η_3	Average of maximum energy expected in CVaR,
$Qke_{kepts'}$	Amount of transportation from repairing center k to disposal center e for product p in time period t under scenario s',	η_4	Average of maximum employment expected in CVaR.
$Qksc_{kscpts'}$	Amount of transportation from repairing center k to second-hand customer Sc for product p in time period t under scenario s',		

Covariates:

$va_{s'}, vb_{s'}$	Covariate for linearization of economic cost objective function variance,	$FixCost$	Sum of fixed costs,
$vc_{rpts'}, vd_{rpts'}$	Covariate for linearization of the deviation from demand constraint,	$VariableCost_{s'}$	Sum of variable costs under scenario s',
$ve_{s'}$	Covariate for linearization of economic cost CVaR,	$\Gamma_{s'2}$	Sum of fixed and variable pollution emissions under scenario s',
$vf_{s'}, vg_{s'}$	Covariate for linearization of environmental pollution objective function variance,	$FixEmision_{s'}$	Sum of fixed pollution emissions due to the establishment of facilities under scenario s',
$vh_{s'}$	Covariate for linearization of environmental pollution CVaR,	$Variable\ Emision_{s'}$	Sum of variable pollution emissions due to the transportation between facilities under scenario s',
$vi_{s'}, vj_{s'}$	Covariate for linearization of energy objective function variance,	$\Gamma_{s'3}$	Sum of fixed and variable energies under scenario s',
$vk_{s'}$	Covariate for linearization of energy CVaR	$FixEnergy_{s'}$	Sum of fixed consumed energies due to the establishment of facilities under scenario s',
$vl_{s'}, vm_{s'}$	Covariate for linearization of employment objective function variance,	$Variable\ Energy_{s'}$	Sum of variable consumed energies due to the transportation between facilities under scenario s',
$vo_{s'}$	Covariate for linearization of employment CVaR	$\Gamma_{s'4}$	Sum of employment due to the establishment of facilities under scenario s',
$\Gamma_{s'1}$	Sum of fixed and variable costs under scenario s',	$FixOcuppation_{s'}$	Sum of employment due to the establishment of facilities under scenario s'.

Appendix 2.

Table A2-1. Model parameters for medium- and large-scale problems.

Parameters	Value	Description	Parameters	Value	Description
$dem_{rpts'}$	$(\lvert s' \rvert$-1)*1000+ uniform (1000,2000)	Demand for various scenarios			
fs_s	uniform (1000,2000)	Fixed costs (opening) (Thousand dollar)	fc_c	uniform(2000,3000)	Fixed costs (opening) (Thousand dollar)
fm_m	uniform(40000,50000)		fk_k	uniform(2000,3000)	
fd_d	uniform(3000,4000		fe_e	uniform(1000,2000)	
fr_r	uniform(1000,2000)				
$Vsm_{smpts'}$	uniform(3,4)	Variable costs (Dollar)	$Vck_{ckpts'}$	uniform(3,4)	Variable costs (Dollar)
$Vmd_{mdpts'}$	uniform(3,4)		$Vke_{kepts'}$	uniform(3,4)	
$Vdr_{drpts'}$	uniform(3,4)		$Vksc_{kscpts'}$	uniform(3,4)	
$Vrc_{rcpts'}$	uniform(3,4)		$Vkm_{kmpts'}$	uniform(3,4)	
$Ems_{sts'}$	uniform(100,200)	Fixed pollution (opening) (carbon dioxide) (Ton)	$Emc_{cts'}$	uniform(100,200)	Fixed pollution (opening) (carbon dioxide) (Ton)
$Emm_{mts'}$	uniform(1000,2000)		$Emk_{kts'}$	uniform(100,200)	
$Emd_{dts'}$	uniform(100,200)		$Eme_{ets'}$	uniform(100,200)	
$Emr_{rts'}$	uniform(100,200)				
$Emsm_{smpts'}$	uniform(4,5)	Variable pollution (carbon dioxide) (Ton)	$Emck_{ckpts'}$	uniform(4,5)	Variable pollution (carbon dioxide) (Ton)
$Emmd_{mdpts'}$	uniform(4,5)		$Emke_{kepts'}$	uniform(4,5)	
$Emdr_{drpts'}$	uniform(4,5)		$Emksc_{kscpts'}$	uniform(4,5)	
$Emrc_{rcpts'}$	uniform(4,5)		$Emkm_{kmpts'}$	uniform(4,5)	
$Es_{sts'}$	uniform(4000,5000)	Fixed consumed energy (opening) (MJ)	$Ec_{mts'}$	uniform(4000,5000)	Fixed consumed energy (opening) (MJ)
$Em_{mts'}$	uniform(40000,50000)		$Ek_{kts'}$	uniform(4000,5000)	
$Ed_{dts'}$	uniform(4000,5000)		$Ee_{ets'}$	uniform(4000,5000)	
$Er_{rts'}$	uniform(4000,5000)				
$Esm_{smpts'}$	uniform(4,5)	Variable pollution (MJ)	$Eck_{ckpts'}$	uniform(4,5)	Variable pollution (MJ)
$Eemd_{mdpts'}$	uniform(4,5)		$Eke_{kepts'}$	uniform(4,5)	
$Edr_{drpts'}$	uniform(4,5)		$Eksc_{kscpts'}$	uniform(4,5)	
$Erc_{rcpts'}$	uniform(4,5)		$Ekm_{kmpts'}$	uniform(4,5)	
$Os_{sts'}$	uniform(40,50)	Fixed employment (person)	$Om_{mts'}$	uniform(20,30)	Fixed employment (person)
$Om_{mts'}$	uniform(300,400)		$Ok_{kts'}$	uniform(10,15)	
$Od_{dts'}$	uniform(40,50)		$Oe_{ets'}$	uniform(5,10)	
$Or_{rts'}$	uniform(5,10)				
VOs_{st}	uniform(1000,1100)	Salary Cost (Dollars)	VOc_{ct}	uniform(1000,1100)	Salary Cost (Dollars)
VOm_{mt}	uniform(1000,1100)		VOk_{kt}	uniform(1000,1100)	
VOd_{dt}	uniform(1000,1100)		VOe_{et}	uniform(1000,1100)	
VOr_{rt}	uniform(1000,1100)				
prs_s	uniform(0.95,0.98)	Availability probability (percent)	prd_d	uniform(0.95,0.98)	Availability probability (percent)
prm_m	uniform(0.95,0.98)		prr_r	uniform(0.95,0.98)	

prm_m	uniform(0.95,0.98)		pre_e	uniform(0.95,0.98)	
prk_k	uniform(0.95,0.98)				
$CapS_{spts'}$	uniform(50000,60000)*(($\lvert s' \rvert$ -1)*0.5+1)	Capacity (facility)	$CapC_{cpts'}$	uniform(20000,22000)*(($\lvert s' \rvert$ -1)*0.5+1)	Capacity (facility)
$CapM_{mpts'}$	uniform(100000,110000)*(($\lvert s' \rvert$ -1)*0.5+1)		$CapK_{kpts'}$	uniform(5000,5500)*(($\lvert s' \rvert$ -1)*0.5+1)	
$CapD_{dpts'}$	uniform(20000,22000)*(($\lvert s' \rvert$ -1)*0.5+1)		$CapE_{epts'}$	uniform(3000,3300)*(($\lvert s' \rvert$ -1)*0.5+1)	
$CapR_{rpts'}$	uniform(3000,3300)*(($\lvert s' \rvert$ -1)*0.5+1)				
$p_{s'}$	0.33	Scenario occurrence probability	$k_{s'3}$	0.05	Fine coefficient of demand dissatisfaction for quadruple objective
β	uniform(0,0.2)	Expectation value weight	$k_{s'4}$	0.05	
ω	uniform(0,0.1)	Fine associated with demand dissatisfaction	$\rho_{rpts'}$	uniform (0,1)	Return percentage
λ	uniform(0,0.1)	CVaR index importance	$\rho_{1pts'}$	uniform(0.7,0.71)	
α	uniform(0,0.05) 95%	Confidence level in CVaR	$\rho_{2pts'}$	uniform(0.2,0.21)	
$k_{s'1}$	0.05	Fine coefficient of demand dissatisfaction for quadruple objective	$\rho_{3pts'}$	uniform(0.1,0.11)	
$k_{s'2}$	0.05		W_i	0.25	Objective weight