Redesign of a sustainable and resilient closed-loop supply chain network under uncertainty and disruption caused by sanctions and COVID-19

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Abstract
Due to the increased levels of uncertainty in the world today and the expansion of supply chain boundaries, companies have been observed trying to enhance supply chain resilience to deal with disruptions caused by severe disasters. There is, however, a new stimulus for the disorder, something quite similar to what has been witnessed recently. It is a new phenomenon called pandemics such as SARS, Ebola, and Coronaviruses. On the other hand, as a result of the imposition of economic sanctions, there is uncertainty in the decision-making parameters of the supply chains, creating difficulties for them. Iron is a raw material that affects both the industry and economy of a nation and can be turned into a closed-loop network. In the current research, using a multi-objective mathematical model, a closed-loop supply chain of steel is presented under the circumstances of the COVID-19 embargo and pandemic. Existing uncertainties are modelled with a robust optimization approach in an uncertain environment. As part of the analysis, appropriate strategies to increase chain resilience will be identified and evaluated. A case study of an active steel supply chain in Iran has been examined for model validation. This model optimizes final net profit, water, and energy use, emissions, and control of coronavirus emissions. In the present study, a three-objective mathematical model is determined and solved in small dimensions based on modified LP-metric and ε-constraint approaches. Further, based on MOPSO and NSGA-II meta-heuristic methods, the best solution was selected in large dimensions.

Keywords Closed-loop supply chain · Sustainability · Resilience · Sanctions · COVID-19 · Steel industry

1 Introduction
In nature, iron is a non-renewable resource and its products can be used by a wide range of industries. Steel manufacturer has destructive environmental aspects like water consumption, energy use, and greenhouse gas emissions (Gu et al. 2015). Therefore, Steel production must be optimized to minimize its environmental aspects. Additionally, as a primary and strategic industry, optimizing its economic effects is essential. Studies indicate that the steel sector has significant potential in reproduction and recycling processes, hence, more attention should be paid to the utilization of the closed-loop supply chains in steel. On the other hand, the business environment of this industry is accompanied by a wide range of uncertainties, so the essential preparedness to deal with the risk and disruption induced by these uncertainties will be present in all supply chain management decisions. Consequently, a closed-loop and stable steel supply chain design is necessary. Based on the World Steel Association, Iran produced 29 million tons of crude steel in 2020, an increase of 13.4% compared to 2019, It was ranked among the top 10 crude steel producing countries in the world, as illustrated in Fig. 1 (Oxford Economics 2019).

Greenhouse gas emissions, water scarcity crisis, climate change, and rising industrial unemployment rates are forcing governments to create a balance among three pillars of
sustainable supply chain (SSC), namely social, economic, and environmental aspects. The SSC obliges organizations to reutilize products at the end of their life cycle, and it is noted that the process of collecting and reusing these products not only has remarkable economic value but also results in a reduction in adverse environmental impacts, and a reduction in the unemployment rate in society. The iron and steel plants have the potential to perform as a closed-loop supply chain (CLSC), meaning that products at the end of their life cycle can be reused again as scrap. A CLSC is made when reverse logistics tries to revert the gathered returned products to its network, and through it, the collected waste is utilized again to produce new billets. Furthermore, to deal with greenhouse gas emissions reduction, the use of clean and efficient renewable energy can be considered the preferred source of energy for low carbon and sustainable development in this industry (Xu et al. 2020).

One of the most obvious environmental aspects of the steel industry is the adverse impacts on energy, water, and greenhouse gas emissions from manufacturing activities. The biggest environmental crises in Iran, namely water shortage and significant water consumption in this sector have made it the main part of the environmental aspects of this research. Opportunities from recycling waste, technology modifications, and converting retailers to hybrid facilities, as well as sanctions imposed on the industry, are economic aspects of this study. The involvement of the world with the COVID-19 pandemic and the crisis that threatens most businesses and human societies are other notable subjects in this research that are among the social considerations.

The global water crisis is a serious and great threat to the sustainable development of countries, particularly those located in dry areas. Iran, which is facing frequent droughts, is placed in one of the arid regions. Steel industries consume a lot of water, which is an integral part of it, so it has recently engrossed researchers. Additionally, natural disasters, whether artificial or man-made, have negative adverse impacts on supply chains, which undoubtedly have the sustainability of health in society due to high demand fluctuations, creating ripple effects on the supply chain. Due to the coronavirus epidemic, the integration of demand-dependent factors to manage the risk of uncertainty during this epidemic has been a challenge to achieve significant and sustainable benefits for other partners (Alkahtani et al. 2021). The combination of sustainable development with closed-loop supply chain management results in a new concept called sustainable closed-loop supply chain management (SCLSC).

2 Literature review

2.1 Closed-loop supply chain

In the literature, many researchers have investigated a variety of closed-loop supply chains under uncertainty and disruption. Pan et al. (2021) concluded that enterprises should make a balance between societal development and environmental protection to reach sustainable goals. In the CLSC, this balance is made by incorporating supply chain and reverse logistics with conventional approaches. A new two-stage mixed-integer linear model was introduced by Zeballos et al. (2018) in order to optimize a CLSC problem. They formulated this model by incorporating uncertain quality and quantity for returned products. Ullah et al. (2021) to investigate the optimal regeneration strategy and reusable capacity under stochastic demand and the rate of return, conducted studies on single closed-loop supply chain problems and some retailers.

Fu et al. (2021) developed a CLSC network model with heterogeneous products that meet different market demands.
In their work, the waste product is collected and recycled from the supply chain at the end of its life cycle to finally produce another type of product as input raw material in the form of a reverse supply chain. Abdi et al. (2021) developed a new stochastic optimization model in their study using two-stage stochastic programming for the closed-loop supply chain network design problem. They used financial risk as a distinct objective function to find a robust solution to control the uncertainty of product production, customer demand, product prices, and rates of return. In another work, Zahedi et al. (2021) investigated real-life problems that use various modes of transportation and rely on sales representatives. They formulated a novel CLSC model with the addition of sales representatives and customers, employing a mixed-line programming model.

### 2.2 Sustainable supply chain

The concept of sustainability because of the supply chain globalization, market validation, demand uncertainty, and economic daries, and on the other hand, the importance of examining sustainability, has attracted increasing attention of researchers (Arabsheybani et al. 2018). Sustainability in the supply chain indicates that achieving sustainable competitive advantages in the market is not possible only by improving the economic approaches of the supply chain (Nourmohamadi Shalke et al. 2018). One of the challenges facing supply chain designers is designing a sustainable and resilient supply chain network (Lotfi et al. 2021).

To attain a sustainable supply chain, Khan et al. (2021a) surveyed 364 small and medium enterprises’ supply chain networks to find out the relationships between blockchain technology effects and organizational performance improvement. For testing the hypotheses, they employed partial least squares structural equation modeling. The findings indicated that there is a positive relationship between a sustainable supply chain and operational, environmental, and economic aspects. Moreover, Zhou et al. (2022) believed that for creating a sustainable supply chain platform, it is necessary to provide lower transaction costs and higher trust when a transaction is made on platforms over traditional supply chains. It should be mentioned that the driving variables to achieve a transparent road map for sustainable development are energy consumption, economic growth, and environmental aspects (Yu et al. 2022). Moreover, the findings reveal nexus between renewable energy consumption and health growth (Khan et al. 2021b). One of the most significant environmental aspects of the sustainability concept is carbon emission which can affect the economic and social variables simultaneously. The path to carbon zero begins with energy reduction or substituting with renewable energy (Khan et al. 2022). On the other hand, by considering the role of consumer identification with psychological ownership and hometown geographical, businesses can mitigate the risk of environmental aspects including carbon emissions and enhance the economic effects (Zhang et al. 2022).

Hajiaghaei-Kesheti and Fathollahi Fard (2019) in the study of the supply chain of the glass industry tried to maximize the total profit of the supply chain, environmental benefits, and social benefits with the aim of using the sustainability approach. They employed various meta-heuristic algorithms for solving the SSC program model and compared the results. Another study in the travertine ore industry for multi-period SSC design was conducted by Soleimani (2018). He employed the ε-constraint method to solve the model to maximize the profit of the whole chain and minimize the energy consumption criterion.

Mehrjerdi and Shafiee (2020) considered different dimensions of sustainability by reducing total cost, energy use, and pollution, and creating job vacancies. Accordingly, they formulated a multi-objective mixed-integer programming mathematical model for optimizing the CLSC in the rubber industry. Lotfi et al. (2021) designed a two-stage mixed-integer linear programming model to solve the problem of optimally establishing the facilities and the number of goods transported among facilities. The sustainability goals discussed in this study included minimizing costs, CO₂ emission, energy, and employment maximization.

Khan et al. (2021d) studied long-term factors of carbon emissions regarding the Paris Climate Conference in 19 European countries to examine real challenges in the way of achieving environmental sustainability. They used Moments' Quantile Regression method to investigate the conditional distribution of carbon emission effects in different locations and scales. The results showed that the use of environmental tax and clean technology as a policy can aim for carbon offset achievement. In the work of Khan et al. (2021e), the economic, social, and environmental indicators of green supply chain management in European Union (EU) member states were examined. They used advanced statistical methods for testing the hypotheses. The obtained results revealed that to achieve sustainability goals, it is necessary to mitigate the risk of carbon emissions in supply chain networks.

### 2.3 Sustainable closed-loop supply chain

In recent years, deep concerns about the environmental and social criteria of enterprise operations have risen rapidly. Although the concept of the closed-loop supply chain is added to rebuild sustainable networks, there is still a gap in the comprehensive modeling of the sustainable closed-loop supply chain. In the literature, a few researchers have studied the SCLSC. The SCLSCs are formed in order to maximize the value of previously rejected products in the value chain (Khalili Nasr et al. 2021). Salehi-Amiri et al. (2021) presented a new
mixed-integral linear programming for a sustainable closed-loop supply chain network in the agricultural industry. They took into consideration both forward and reverse flow for demands and returned rate.

Tavana et al. (2022) introduced a proper solution for designing a new SCLSC network by using an integrated multi-objective mixed-integer linear programming under uncertainty. They utilized the solution for eight facilities to examine the performance of each network. The findings demonstrated the effectiveness of their presented model. In the work of Tirkolaee et al. (2022), a multi-product multi-period multi-echelon sustainable CLSC model during the COVID-19 Pandemic for producing masks was designed. The proposed model focused on mitigating human risk and minimizing the total pollution and network costs. Mohab-Alizadeh et al. (2021) presented an effective SCLSC network by developing a stochastic model to deal with scarce resources of facilities in the electronics industry. In their model, two dimensions of network efficiency including resource consumption and outcomes were considered. A hybrid three-step was developed for solving the suggested SCLSC network. The trade-offs between economic and social aspects were finally observed to balance efficiency and sustainability simultaneously.

2.4 Resilient supply chain

While crises provide opportunities for sustainability, they can also lead to frustration. From this crisis, the transition to greater supply chain sustainability can be predicted, although uncertainties and concerns remain. Organizations often take an easier path in the face of sustainability challenges, given the win–win opportunities (Nikolaou et al. 2019). Dubey et al. (2021) examined the ability to analyze data as a tool to improve information processing capacity. They also studied supply chain flexibility as a means of reducing ripple effects in the supply chain or rapid recovery after supply chain disruption. Accordingly, they based their theoretical model on organizational information processing theory (OIPT). They then solved their model using an analysis of variance-based structural equations, known as PLS-SEM. Local disturbances can spread from one company to another in the supply network and ultimately affect the entire supply network.

In this regard, Shi et al. (2021) in their study proposed a ripple effect with collaboration (REC) to consider the above phenomenon and proposed three new criteria for supply network resilience to assess its resilience. Then, employing generated supply networks and real supply networks, they simulated resilience concerning REC under stochastic and targeted disturbances. The results show that the effectiveness of collaboration can be influenced by supply network structures and other parameters, and the collaboration can even in some cases negatively affect the resilience of the supply network.

In an in-depth study, Azadegan and Dooley (2021) examined supply chain resilience strategies from a network-level perspective, including types of collaboration within and among supply networks. Examining a new dimension in addition to the micro and macro levels, as the intermediate level, which is also a missing link in previous studies, they found that flexibility emerges at this level when multiple supply networks collaborate in short- and medium-term supply risks. These collaborations are more opportunistic and temporary than micro or macro collaborations, and therefore they can be considered complex adaptive systems, which show self-organization and dynamism.

Khan et al. (2021c) investigated the impact of industry 4.0 on the environmental aspects by using the circular economy concept to achieve net-zero goals. They proposed the COVID-19 outbreak in their study by designing a questionnaire to collect the related information. They conducted this survey in 214 facilities. The achieved results demonstrated that there is no direct relationship between COVID-19 and the circular economy.

2.5 Uncertainty in the supply chain

On the other hand, uncertainty is often expressed as a combination of exogenous turmoil that is not under the control of an organization and internal cognitive constraints due to a lack of information, awareness, or decision clarity. The processes of the supply chain are affected by different types of uncertainty, which are classified into two major sorts, namely environmental and system. In the literature, for creating resilience in a supply chain to deal with disruptions, the uncertainty of the supply chain mostly focuses on reconfiguring tangible resources, such as supply chain assets and inventories. For example, Gholizadeh and Fazlollahtabar (2020) examined the supply of green closed loops for different grades extracted from a melting process under uncertainty. To deal with the uncertainty in the model, they used scenario-based demand programming and used a robust optimization approach to investigate various cases in this area, which leads to increased profitability of the whole chain.

Different methods have been suggested for deterministic decisions under uncertainty. The most commonly used approaches are robust, stochastic, and fuzzy programming. To cope with uncertainty robust programming is applied when there is insufficient information for forecasting the probability distribution with respect to unknown parameters (Ben-Tal et al. 2009). Stochastic programming is utilized when there is a certain probability distribution and there is some data about the way of acting past parameters. Finally, fuzzy programming is employed for unknown parameters.
with fuzzy number properties (Mirzapour Al-E-Hashem et al. 2011).

### 2.6 COVID-19 pandemic disorder in supply chain

In recent years, the impact of COVID-19 on supply chains has been undeniable so most enterprises had to face new challenges. The social, political, and economic developments caused by COVID-19 are tangible (Shahed et al. 2021). Given that the coronavirus crisis as a major shock has recently taken the world by surprise, no systematic and structured studies have been carried out in this regard so far, but some case studies that have been conducted are described below. (Alkahtani et al. 2021) developed a nonlinear supply chain management model with a controllable production rate to optimize the total cost, which has economic benefits for the manufacturing company to cope with different conditions under variable demand. The model costs for dealing with the uncertain conditions caused by the COVID-19 epidemic are determined using fuzzy programming. In the work of Liu et al. (2022), the multi-criteria group decision-making method was combined with intuitionistic fuzzy sets to design reverse supply chains for COVID-19 medical waste recycling channels. The results showed that a more efficient COVID-19 medical waste reverse supply chain is needed for defining the reverse supply chain strategy of hospitals.

Akintokunbo and Victor (2020) conceptually examined the impact of COVID-19 on supply chain disruption and the strategies adopted. This study demonstrates how online data, along with other datasets, can be utilized for real-time policymaking. The results indicate that supply chains during COVID-19 are more fragile and sensitive to products that travel long distances before reaching their final point of sale. In another study, Hu et al. (2021) re-examined the important components of global supply chain management (GSCM) during the COVID-19 pandemic with the aim of establishing an intelligent system to properly address and control this complex issue. They introduced a combination of data envelopment analysis (DEA), rough set theory (RST), and Multi-Criteria Decision-Making (MCDM) to make the real-ity of the analysis problem faster and better understood.

Karmaker et al. (2021) examined sustainable supply chain stimulators (SSCs) to address supply chain disruptions during the Coronavirus epidemic in the context of the emerging economy in Bangladesh. The findings also indicate that government funding and supply chain partners are needed to deal with the immediate SCS shock caused by COVID-19. In another study related to the identification of supply chain sustainability and resilience strategies during the COVID-19 epidemic, Baveja et al. (2020) introduced a plan to stop the transmission of the epidemic. By proposing principles of the Theory of Constraints, this proposal significantly curbs the epidemic, reduces its economic outcomes, and increases social trust.

### 2.7 Research gap

As expected, with a comprehensive analysis of the literature review, there is no study in the field of the sustainable closed-loop supply chain under covid and sanction disruptions, simultaneously. Moreover, as can be observed from Table 1, industry researchers have selected a specific product and proposed models for case studies. However, the contribution of the steel industry, which has significant impacts on the economy, environment, and society, seems to have a small contribution among these studies (Oxford Economics 2019). For these reasons, in the present research, three main elements of sustainability are proposed, which leads to the expression of three specific objective functions.

The economic aspect of SCLSC is the first goal that maximizes the profitability of the entire network and the second goal is the environmental aspect. The aim is to minimize water and energy use, CO2 emissions in the crude steel process and other air pollutants including NO, CO, SO2, NO2, and PM2.5 which are emitted through industrial emissions, mechanical processes, transportation, car exhaust, fuel burning, and exhaust gases. Another topic that has received a lot of attention recently is COVID-19. The post-epidemic disease has not only affected many industries, including the steel industry but has also raised concerns as a social problem.

Therefore, in the proposed model of this paper, this disease has been considered and added to the proposed mathematical model as a third objective function. The purpose of this function is to minimize the spread of coronavirus within the closed environments of the proposed supply chain centers. Besides, utilizing the robust optimization approach, the uncertainty in the uncertain environment is modeled and the designed multi-objective model is extended. Appropriate strategies to increase chain resilience will also be identified and evaluated. This model optimizes total net profit, water, and energy use, emissions, and control of coronavirus emissions.

### 3 Material and methods

#### 3.1 Problem definition

The problem consists of internal and external suppliers, billet manufacturers, manufacturers, retailers, customers, and collection centers. In some production technologies, almost all raw materials are purchased from suppliers, and in other technologies, most raw materials are purchased from customers (as scrap). Scrap can be purchased...
from customers of ordered products and general products. Therefore, manufacturing technologies can change the importance of reverse logistics in this SCLSC. After purchasing raw materials, steel billets are produced by several technologies in separate furnaces. They are then transferred from the billet production centers to the main production centers. There, the billets produced are divided into two parts: The ordered products and general products. The ordered products are sold directly to the customers, but the general products are sent to the retailers and then sold to the customers. The collection centers collect the scrap, as well. In Fig. 2, the proposed network framework and the flow of elements involved are shown.

Three principles of sustainability are examined in the suggested model, in which three objective functions are determined. The first goal is to maximize the total profit of the supply chain with respect to the economic aspect of sustainability and the environmental effect is taken into consideration in the second goal, in which water and energy use and CO2 emissions in the manufacturing process are minimized. High water consumption in the steel industry regarding the severe water crisis has become an important part of the second goal. In the third goal, the social perspective includes minimizing the spread of coronavirus within the closed environments of supply chain centers. The research method is illustrated in Fig. 3.

### 3.2 Mathematical model

The following indices, parameters, and decision variables are used to formulate the problem:

Notations:

| Method | Case Study | Disturbance | Uncertainty | Resilience | Sustainability | Object | Model | Authors |
|--------|------------|-------------|-------------|------------|----------------|--------|-------|---------|
| Exact  | Steel      | -           | Yes         | -          | -              | One    | MINLP & MILP | Sabzevari Zadeh et al. 2014 |
| Metaheuristic (Memetic Algorithm) | Medical | -           | Yes         | Yes        | -              | Multi  | MILP | Hasani et al. 2015 |
| Exact & Metaheuristic | Gold | -           | Yes         | -          | -              | Multi  | ILP | Zohal & Soleiman 2016 |
| Metaheuristic | Tire | -           | Yes         | -          | Yes            | One    | MILP | Sahebjamnia et al. 2018 |
| Exact | Goods      | -           | Yes         | -          | Yes            | One    | MILP | Zeballos et al. 2018 |
| Exact (CPLEX) | Logistic | Yes         | -          | -          | -              | One    | MINLP | Büyüktahtakım et al. 2018 |
| Exact (Benders) | Wire | -           | -          | -          | -              | Multi  | MILP | Mardan et al. 2019 |
| Exact | Casting    | -           | Yes         | -          | -              | Multi  | MILP | Gholipoor et al. 2019 |
| Exact | -           | -           | Yes         | -          | Yes            | Multi  | MINLP | Zhen et al. 2019 |
| Exact | Cable      | -           | Yes         | -          | Yes            | Multi  | MILP | Sherafati et al. 2019 |
| Exact | -           | -           | Yes         | -          | -              | One    | MILP | Ruiz-Torres et al. 2019 |
| Exact & Metaheuristic | Health | -           | Yes         | -          | Yes            | Multi  | MILP | Fathollahi-Fard et al. 2019 |
| Stochastic Programming | Conditioning | Yes | - | - | - | - | One | MINLP | Mehrotra et al. 2020 |
| Exact | Food       | -           | -          | -          | -              | One    | MILP | Accorsi et al. 2020 |
| Exact | Recycle    | -           | Yes         | -          | Yes            | One    | MILP | Samuel et al. 2020 |
| Metaheuristic | Manufacture | -           | -          | -          | -              | One    | MILP | Zahedi et al. 2021 |
| Exact | Automobile | -           | Yes         | Yes        | Yes            | Multi  | MILP | Lotfi et al. 2021 |
| Exact & Metaheuristic | Manufacture | Yes       | -          | Yes        | Yes            | Multi  | MILP | Alkahtani et al. 2021 |
| Exact & Metaheuristic | Steel | Yes         | Yes        | Yes        | Yes            | Multi  | MILP | current study |

Mixed Integer Nonlinear Programming (MINLP), Mixed Integer Linear Programming (MILP), Integer Linear Programming (ILP), Fuzzy linear programming (FLP), Fuzzy stochastic programming (FSP), Nonlinear programming (NLP)
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Fig. 2 Designed network and flow of elements

Parameters:

- \( D E K_{eks} \) Customer demand \( k \) for the ordered product \( e \) in scenario \( s \)
- \( D E L_{fls} \) Customer demand \( l \) for the general product \( f \) in scenario \( s \)
- \( C I l_{in} \) Cost of purchasing raw material \( i \) per kg from internal supplier \( n \)
- \( C I l_{en} \) The purchase cost of raw material \( i \) per kg from external supplier \( e \)
- \( C S K_k \) Cost of purchasing each ton of scrap from the customer \( k \) for ordered products
- \( C S L_l \) Cost of purchasing each ton of scrap from the customer \( l \) for general products
- \( P C B_{jm} \) Cost of billet production per ton in the billet production center \( m \) using technology \( j \)
- \( P C E_e \) The production cost of the ordered product \( e \) per unit
- \( P C F_f \) The production cost of general product \( f \) per unit
- \( P F_f \) The purchase cost of product \( f \) per unit
- \( D S 1_{np} \) Distance between internal supplier \( n \) and producer \( p \)
- \( D S 2_{enp} \) Distance between external supplier \( en \) and manufacturer \( p \)
- \( D K_{kp} \) Distance between the customer of ordered products \( k \) and manufacturer \( p \)
- \( D P_{pq} \) The distance between the ordered products \( k \) and the collection center \( q \)
- \( D P R_{pr} \) Distance between production center \( p \) and retailer \( r \)
- \( D R L_{rl} \) Distance between retailer \( r \) and customer of general products \( l \)
- \( D L Q_{rq} \) Distance between the customer of general products \( l \) and collection center \( q \)
- \( D Q_{qm} \) Distance between collection center \( q \) and billet production center \( m \)
- \( D R_{rp} \) Distance between retailer center \( r \) and manufacturer \( p \)
The cost of transporting general products per kilometre

\( BI_{ij} \) The amount of raw material required \( i \) to produce one ton of billet using \( j \) technology

\( BS_j \) The amount of scrap required to produce one ton of billet using \( j \) technology

\( CAN_{1in} \) Internal supplier capacity \( n \) to supply raw material \( i \)

\( CAN_{2en} \) External supplier capacity \( en \) to supply raw material \( i \)

\( CAB_{jm} \) Billet production capacity in the billet production center \( m \) using \( j \) technology

\( CAE_{ep} \) Production capacity of production center \( p \) for the ordered product \( e \)

\( CAP_{fp} \) Production capacity of production center \( p \) for general product \( f \)

\( CARF_{rf} \) Retail storage capacity \( r \) for general product \( f \)

\( CAQ_q \) Maintenance capacity of collection center \( q \) for scrap

\( FCT_{jm} \) Fixed cost of technology change, to technology \( j \) in the billet production center \( m \)

\( RSP \) Percentage of operating costs of the collection center per ton of scrap purchased

\( RSS \) Percentage of retailer operating costs per unit of product sold

\( M \) Massive number

\( DR_{1kqs} \) The customer disposal rate of the ordered product \( e \) of the customer ordered product \( k \) for the collection center \( q \) in scenario \( s \)

\( DR_{2lqs} \) General product disposal rate \( f \) by the general product customer \( l \) for the collection center \( q \) in scenario \( s \)

Decision variables:

\( XI_{1ins} \) Kg of raw material \( i \) purchased in scenario \( s \) from internal supplier \( n \)

\( XI_{2iens} \) Kg of raw material \( i \) purchased in scenario \( s \) from an external supplier \( en \)

\( XSK_{kqs} \) Scrap tonnage purchased from the customer of ordered products \( k \) by collection center \( q \) in scenario \( s \)

\( XSQ_{lqs} \) Scrap tonnage purchased from a customer of general products \( l \) by the \( q \) collection center in scenario \( s \)

\( XB_{jms} \) Billet tonnage produced using \( j \) technology at the billet production center \( m \) in scenario \( s \)

\( XEK_{epks} \) The unit of ordered product \( e \) from the production center \( p \) sold to customer \( k \) in scenario \( s \)

\( XFL_{frs} \) General product unit \( f \), sold in scenario \( s \) from retailer \( r \) to customer \( l \)

\( XPR_{frps} \) General product unit \( f \) transferred from production center \( p \) to retailer \( r \) in scenario \( s \)

\( ZSQ_{qms} \) Scrap tonnage transferred from collection center \( q \) to billet production center \( m \) in scenario \( s \)

\( YJ_{jm} \) 1 if the billet production center \( m \) produces billet production technology \( j \); Otherwise, 0

Objective functions and constraints:

Considering the above-mentioned definitions, the objective functions and limitations of the proposed mathematical model are described below.
\[
\text{Max}Z_1 = \sum_j \left( \sum_{i} \sum_{p} \sum_{f} PE_c \times XE_K_{eps} + (1 - RSS) \sum_{f} \sum_{i} \sum_{p} PF_j \times XFL_{fibs} \right) \\
- \sum_{i} \sum_{p} CI_{1w} \times XI_{1ins} + \sum_{i} \sum_{p} CI_{2\text{ens}} \times XI_{2\text{ens}} + \sum_{i} \sum_{q} CSK_{q} \times XSK_{kqs} + \sum_{i} \sum_{q} CSL_{q} \times XSQ_{lqs} \\
- \sum_{j} \sum_{m} PCB_{jms} \times XB_{jms} + \sum_{i} \sum_{p} \sum_{k} PC_{e} \times XE_K_{eps} + \sum_{i} \sum_{p} \sum_{r} PCF_{f} \times XPR_{fprs} \\
- \sum_{i} \sum_{q} CSL_{q} \times XSQ_{lqs} + \sum_{j} \sum_{m} FCT_{jm} \times YJ_{jm} \\
\right)
\]

\[
\text{Min} Z_2 = \sum_s \left( \frac{WE \times \sum_{s} \sum_{n} EU_{ns} \times XB_{jms}}{\text{MAXEU}_s} + \frac{WW \times \sum_{s} \sum_{m} GE_{ms} \times XB_{jms}}{\text{MAXWU}} \right) \\
\]

\[
\text{Min} Z_3 = \sum_s \left( \sum_{n} YN_{1ns} + \sum_{en} YN_{2ens} + \sum_{p} YP_{pjs} + \sum_{q} YQ_{qps} \right) \frac{\sum_{p} \sum_{q} \sum_{e} (1 - DR_{1kpe}) \times XE_K_{eps} \geq \sum_{q} XSK_{kqs} \forall k, s}{\frac{\sum_{p} \sum_{q} (1 - DR_{1kpe}) \times XE_K_{eps} \geq \sum_{q} XSK_{kqs} \forall k, s}{\sum_{p} XSK_{kqs} \geq DEK_{eks} \forall e, k, s} \text{subject to:}} \right)
\]

\[
\sum_{m} XB_{jms} = \sum_{i} \sum_{n} BI_{ij} \times (XI_{1\text{ins}} + XI_{2\text{ens}}) + \sum_{q} \sum_{i} BS_{js} \times ZS_{qms} \forall V_s = 0, j, s \quad (4)
\]

\[
\sum_{m} XB_{jms} = \sum_{i} \sum_{n} BI_{ij} \times XI_{1\text{ins}} + \sum_{q} \sum_{m} BS_{js} \times ZS_{qms} \forall V_s = 1, j, s + \sum_{m} XB_{jms} = \sum_{f} \sum_{r} XPR_{fprs} = \sum_{f} \sum_{r} XFL_{fibs} \forall r, s \quad (5)
\]

\[
\sum_{j} \sum_{m} XB_{jms} = \sum_{f} \sum_{r} XPR_{fprs} + \sum_{q} \sum_{m} XE_K_{eps} \forall s \quad (6)
\]

\[
\sum_{f} \sum_{q} (1 - DR_{2kqs}) \times XFL_{fibs} \geq \sum_{q} XSQ_{lqs} \forall l, s \quad (10)
\]
\[
\sum_r XFL_{fls} \geq DEL_{fls} \quad \forall f, l, s 
\] (11)

\[
\sum_m ZSQ_{qms} = \sum_l XSQ_{lqs} + \sum_k XSK_{kqs} \quad \forall q, s
\] (12)

\[
XI_{ins} \leq CAN_{ins} \times YN1_{ns} \quad \forall V_s = 0, i, n, s
\] (13)

\[
XI_{iens} \leq CAN_{iens} \times YN2_{ens} \quad \forall V_s = 0, i, en, s
\] (14)

\[
XI_{ins} \leq CAN_{ins} \times YN1_{ns} \quad \forall V_s = 1, i, n, s
\] (15)

\[
XB_{jms} \leq CAB_{jm} \times YJ_{jm} \quad \forall j, m, s
\] (16)

\[
\sum_k XEK_{epks} \leq CAE_{eps} \times YP_{ps} \quad \forall p, e, s
\] (17)

\[
\sum_r XPR_{jps} \leq CAP_{jps} \times YP_{ps} \quad \forall f, p, s
\] (18)

\[
\sum_p XPR_{jps} \leq CARF_{rf} \quad \forall f, r, s
\] (19)

\[
\sum_l XSQ_{lqs} + \sum_k XSK_{kqs} \leq CAQ_{qs} \times YQ_{qs} \quad \forall q, s
\] (20)

\[
\sum_n YN1_{ns} \leq 1 \quad \forall V_s = 0, s
\] (21)

\[
\sum_en YN2_{ens} \leq 1 \quad \forall V_s = 0, s
\] (22)

\[
\sum_n YN1_{ns} \leq 1 \quad \forall V_s = 1, s
\] (23)

\[
\sum_p YP_{ps} \leq 1 \quad \forall s
\] (24)

\[
\sum_q YQ_{qs} \leq 1 \quad \forall s
\] (25)

\[
XI_{ins}, XSK_{kqs}, XSQ_{lqs}, XB_{jms}, XEK_{epks}, XFL_{fls}, XPR_{jps}, ZSQ_{qms} \geq 0
\] (26)

\[
YJ_{jm}, YN_{ns}, YP_{ps}, YQ_{qs} \in \{0, 1\}
\] (27)

The first goal, which maximizes profits, reflects the supply chain economic aspect. The first part calculates the income from various parts of the network, which includes sales of ordered and public products. Retailers' operating expenses are part of the income from the sale of public products. Thus, the relevant income is determined as a percentage of the revenue from the sale of public products in the second part of the first segment. The second part calculates the cost of purchasing several materials, consisting of raw materials from internal and external suppliers, and also scrap from customers. The third part includes the calculation of the production costs, such as billet production costs, ordered and general products. The fourth part calculates operating costs, including the cost of retailers and collection centers. This is an operation that is equivalent to a percentage of the cost of purchasing scrap metal. In the next section, the costs of transporting among different facilities are obtained. Finally, the sixth part calculates the cost of changing technology from the old to the new one.

The second objective reflects the environmental aspects of the supply chain in which the environmental impact of the billet production process is minimized. Equation (2) shows the normalized number of environmental aspects multiplied by their given weight. In the first part, the effects of energy consumption are determined; The second part calculates the impact of water consumption; The third part calculates the effect of CO2 emissions in the production process by different technologies in each center; And finally, the fourth part, the effect of other air pollutants are calculated in this objective function for the proposed supply chain of this paper including NO, C\(_6\)H\(_6\), CO, SO\(_2\), NO\(_2\), and PM\(_{2.5}\) which are emitted through industrial emissions, mechanical processes, transportation, car exhaust, fuel burning, and exhaust gases.

The third objective function calculates the transmission rate of coronavirus in closed environments. In this objective function, the β parameter is employed, which indicates the percentage of coronavirus transmission from a person with COVID19 in a closed environment to healthy individuals. This parameter calculates the percentage of disease transmission within the centers of production, supplier, and collection. To estimate the percentage used for the β parameter, the paper of Abdolazimi et al. (2021b) has been used. Constraint (4) ensures the equality of raw materials purchased from internal and external suppliers in the absence of sanctions. Moreover, it includes the equality of scrap purchased from collection centers and the extent to which they are used in produced billets. Constraint (5) plays the role of constraint (4) but in the case of sanctions because it is not possible to buy from external suppliers. Constraint (6) guarantees equality of the number of billets produced with the number of ordered products and the number of general products produced. Restriction (7) indicates that the number of ordered products produced for customers of ordered products is more than the amount of scrap returned from customers of ordered products. Constraints (8) and (11) indicate that billets sold to larger customers are bigger than or equal to each customer's demand for each product. Limit (9) makes sure equality of input and output of general products for each retailer and each product. Constraint (10) shows that the number of general products produced for customers of these products is more than the amount of scrap returned from customers. Constraint (12) confirms the equality of the amount of scrap input and output.
for each collection center. Constraint (13) ensures that the raw materials procured are less than or equal to the capacity of each supplier to procure each raw material if the supplier is selected and sanctions are not imposed. Constraint (14) also works as a constraint (13) for external suppliers in the absence of sanctions. Constraint (15) plays exactly the role of constraint (13) in the presence of sanctions. Constraint (16) ensures that the billets produced are less than or equal to the production capacity of each technology in each billet production center. With constraint (17), the products ordered are ensured to be produced less than or equal to their production capacity for each product if the production center is chosen. Constraint (18) ensures that the general products produced are less than or equal to the production capacity of the general products for each production center and product. Constraint (19) guarantees that the input of general products to a retailer is less than or equal to the retailer’s capacity. With constraint (20), its scrap input to a collection center is guaranteed to be less than or equal to its capacity for each center. Limitations (21) to (25) indicate that in each scenario no more than one supplier (internal or external depending on the presence or absence of sanctions), producer, and collector should be selected. Finally, constraints (26) and (27) determine the characteristics of decision variables.

### 3.3 Proposed uncertainty model

The goal programming concept is performed in the proposed model, which is less sensitive to the variation of parameters (Abdolazimi et al. 2020). The Mulvey model includes two main parts, namely the control part and structural part for unspecified and specific data, respectively. Thus, a variable and parameter sets are defined as control variables and scenario parameters, in turn. In the following, uncertain parameters and decision variables of the model are also defined.

**Parameters:**

- $p_s$ Probability of scenario $s$
- $\lambda$ Constant value
- $\omega$ Cost of fine for each unit that is not met

**Decision variables:**

- $\delta_{1_{ek}}$ Unsatisfied demand of customer $k$ for ordered product $e$ in scenario $s$
- $\delta_{2_{fk}}$ Unsatisfied demand of customer $l$ for general product $f$ in scenario $s$
- $\theta_s$ Linear factor under scenario $s$

**Control variables:**

- $\delta_{1_{ci}}$ Unsatisfied demand customer $c$ for component $i$ under scenario $u$
- $\theta_{1u}$ Linear factor under scenario $u$ for the first objective function.
- $\theta_{2u}$ Linear factor under scenario $u$ for the second objective function.

Based on the above, Eqs. (1) and (2) are altered as follows:

\[
Z = \sum_{f} \left[ \sum_{p} \sum_{r} \sum_{j} P_{r} \times X_{EK_{p}f} \times X_{F_{j}p} + (1 - RSS) \sum_{f} \sum_{r} P_{r} \times X_{F_{j}p} \right]
\]

\[
- \sum_{f} \sum_{p} \sum_{r} C_{1_{fpr}} \times X_{I_{fpr}} + \sum_{f} \sum_{p} C_{1_{fpr}} \times X_{I_{fpr}} + \sum_{f} \sum_{p} CS_{K_{fpr}} \times X_{S_{K_{fpr}}} + \sum_{f} \sum_{p} CS_{L_{fpr}} \times X_{S_{Q_{fpr}}}
\]

\[
- \sum_{f} \sum_{p} PCB_{fpr} \times X_{B_{fpr}} + \sum_{f} \sum_{p} PC_{E_{fpr}} \times X_{EK_{p}f} + \sum_{f} \sum_{p} P_{f} \times X_{P_{fpr}}
\]

\[
- RSP \times \left( \sum_{f} \sum_{p} CS_{L_{fpr}} \times X_{S_{Q_{fpr}}} \right) + RSS \times \left( \sum_{f} \sum_{p} PF_{f} \times X_{F_{j}p} \right)
\]

\[
Z = \sum_{f} \left[ \sum_{r} \sum_{p} \sum_{f} DS_{1_{fpr}} \times T_{CG_{fpr}} \times X_{I_{fpr}} + \sum_{f} \sum_{p} DS_{2_{fpr}} \times T_{CG_{fpr}} \times X_{I_{fpr}} + \sum_{f} \sum_{p} DK_{fpr} \times T_{CE_{fpr}} \times X_{EK_{p}f} \right]
\]

\[
+ \sum_{f} \sum_{p} D_{P_{fpr}} \times T_{CF_{fpr}} \times X_{P_{fpr}} + \sum_{f} \sum_{p} D_{R_{fpr}} \times T_{CF_{fpr}} \times X_{F_{j}p} \right]
\]

\[
+ \sum_{f} \sum_{p} D_{Q_{fpr}} \times T_{CT_{fpr}} \times X_{S_{Q_{fpr}}} + \sum_{f} \sum_{p} D_{Q_{fpr}} \times T_{CT_{fpr}} \times X_{S_{Q_{fpr}}} \right]
\]

\[
+ \sum_{f} \sum_{p} D_{Q_{fpr}} \times T_{CT_{fpr}} \times X_{S_{Q_{fpr}}} \right]
\]

\[
- \sum_{f} \sum_{p} F_{C_{fpr}} \times X_{I_{fpr}}
\]

\[
\begin{align*}
\min Z & = \sum_{f} p_{f} Z_{f} + \lambda \sum_{f} (Z_{f} - \sum_{p} p_{f} Z_{f}) + 2\theta \left( \sum_{f} \sum_{p} p_{f} \delta_{1_{f}} + \sum_{f} \sum_{p} p_{f} \delta_{2_{f}} \right) \\
& + \omega \left( \sum_{f} \sum_{p} p_{f} \delta_{1_{f}} + \sum_{f} \sum_{p} p_{f} \delta_{2_{f}} \right)
\end{align*}
\]
The first term maximizes the average profit or minimizes the average costs for each scenario in Eq. (28). The variance of the objective function minimizes in the second term. For model robustness, penalty functions are considered in other terms. Also, all of the model constraints are modified. It should be mentioned that constraints (8) and (11) convert into new constraints (29) and (30) by incorporating the control variables. Moreover, the new constraint (31) optimizes the robustness of the objective function.

\[
\sum_p X_{EK_{e+k}} + \delta_{1_{e+k}} = DEK_{e+k} \quad \forall e,k,s
\]  

(29)

\[
\sum_r X_{FL_{f+l}} + \delta_{2_{f+l}} = DEL_{f+l} \quad \forall f,l,s
\]  

(30)

\[
Z_{1s} - \sum_s p_s Z_{1s} + \theta_s \geq 0 \quad \forall s
\]  

(31)

### 3.4 Solving methods

#### 3.4.1 LP-metric method

LP-metric is a technique in which the variance of target functions in a multi-objective decision-making (MODM) model is minimized. (Shakhsi-Niaei and Esfandarani 2019). To put it simply, this method is utilized for measuring the proximity of the achieved and ideal solution on the basis of Eq. (32):

\[
\min \left[ \sum_i \left( w_i \left( \frac{f_i^u - f_i^*}{f_i^u} \right) \right)^p \right]^{\frac{1}{p}}
\]  

(32)

where \(w_i\) denotes the importance degree of the \(i\)-th objective and \(p\) presents the degree of emphasis on deviations (1 < \(p\) < \(\infty\)). In this research, the value of \(p\) and the summation of \(w_i\) is 1.

#### 3.4.2 AUGMECON2

Most of the real cases need to optimize many conflicting objectives together (Abdolazimi et al. 2021a). There are various techniques to solve the multi-objective models, for instance, the weighted sum method which is extensively applied to change the multi-objective functions into a single objective and determine a Pareto optimal solution set (Mehrjerdi and Shafiee 2020). AUGMECON2 is the improved version of augmented \(\epsilon\)-constraint for solving the multi-objective function which was introduced by Mavrotas and Florios (2013). This effective method concentrates on making a balance among objective functions, providing non-dominated solutions, and decreasing the computational time of Eq. (33) (Mavrotas 2009; Mavrotas and Florios 2013):

\[
\text{Max} \left( Z_i(x) + e \times (S_{f_2} + 10^{-1} \times S_{f_3} + ... + 10^{-p-1} \times S_{f_P}) \right)
\]

Subject to:

\[
Z_k(x) - S_k = \epsilon_k, \forall k \in \{2, ..., P\}
\]  

(33)

where \(Z_k(x)\) denotes the objective function to be optimized, \(e\) is a small number between \(10^{-6}\) and \(10^{-3}\), \(\epsilon_k\) shows the right-hand side of each objective function, \(S_k\) depicts the surplus variable, and \(r_1, r_2, ..., r_P\) are the set of parameters for objective functions.

### 4 Results and discussion

#### 4.1 Description of the case

A steel company in Iran that sends its billets to the market on a custom and public basis is considered a case study for the validation of the proposed model. Some of the raw materials utilized in the company are provided by three main suppliers and the rest are scrap goods, which consist of custom customers and customers of general products purchased through waste collection centers. The ordered products are delivered directly to the customized customers and the general billets are delivered to the general customers through the retail centers. The company also is capable of reusing the scrap as a raw material along with direct reduced iron (DRI) due to its production technology. Additive materials such as silicon dioxide, copper, graphite, and manganese are also utilized in the production process. Figure 4 shows the location of this manufacturing company.

#### 4.2 Results of the model

In this section, the validation of the proposed solution methods to solve the mathematical model is reviewed. In the first part, the LP-metric and AUGMECON2 methods, which are used for small dimensions, are shown. To validate and compare their answers, 15 numerical examples are solved for each. The results of the solution are compared using a t-test. Finally, with the determination of the superior solution method, the optimal solutions are determined by that method. In the second part, the mathematical model is solved in a larger dimension. To do this, algorithms have been used. In the second part, multi-objective particle swarm optimization (MOPSO) and non-dominant sorting genetics (NSGA-II) algorithms are used to solve the model on a larger scale. As in the first part, validation and comparison of results are done by solving 15 numerical examples and using a t-test. Algorithms are implemented. Finally, with the determination of the superior algorithm, by it, the near-optimal solutions are determined.
4.3 Numerical examples for the exact methods in small scale

To evaluate the proposed mathematical model four criteria, namely first to third objective functions and the CPU time are determined. Afterward, 15 numerical examples on a small scale which are presented in Table 2 are implemented to present the solutions.

Other parameters utilized in this numerical example are based on uniform distribution. These parameters are demonstrated in Table 3.

The solver CPLEX of GMAS software version 24.1.3 is applied to solve the mathematical model on small scale. Table 4 shows the results of LP- metric and $\varepsilon$-constraint methods.

| Numerical Examples | $n$ | $en$ | $i$ | $j$ | $e$ | $p$ | $f$ | $k$ | $l$ | $r$ | $q$ | $m$ | $s$ |
|-------------------|-----|------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1                 | 20  | 5    | 13  | 20  | 10  | 2   | 16  | 13  | 4   | 16  | 13  | 8   | 18  |
| 2                 | 15  | 7    | 11  | 17  | 17  | 2   | 12  | 18  | 12  | 3   | 14  | 6   | 1   |
| 3                 | 16  | 14   | 4   | 7   | 11  | 8   | 18  | 6   | 20  | 2   | 14  | 15  | 14  |
| 4                 | 13  | 17   | 10  | 7   | 9   | 11  | 9   | 19  | 12  | 17  | 16  | 6   | 13  |
| 5                 | 17  | 6    | 7   | 5   | 19  | 2   | 12  | 13  | 17  | 15  | 17  | 16  | 20  |
| 6                 | 10  | 8    | 19  | 8   | 19  | 11  | 9   | 16  | 9   | 9   | 1   | 17  | 12  |
| 7                 | 15  | 9    | 7   | 20  | 2   | 19  | 11  | 7   | 8   | 3   | 11  | 7   | 17  |
| 8                 | 4   | 19   | 2   | 11  | 5   | 1   | 10  | 8   | 19  | 6   | 12  | 5   | 4   |
| 9                 | 18  | 16   | 4   | 1   | 3   | 13  | 17  | 3   | 15  | 9   | 5   | 15  | 13  |
| 10                | 13  | 2    | 6   | 1   | 7   | 9   | 9   | 17  | 2   | 19  | 14  | 7   | 3   |
| 11                | 1   | 14   | 6   | 8   | 20  | 13  | 19  | 18  | 1   | 5   | 16  | 4   | 1   |
| 12                | 3   | 16   | 12  | 13  | 5   | 9   | 6   | 13  | 1   | 9   | 19  | 2   | 17  |
| 13                | 1   | 8    | 11  | 14  | 19  | 8   | 20  | 19  | 4   | 1   | 3   | 3   | 4   |
| 14                | 5   | 14   | 6   | 13  | 16  | 4   | 5   | 16  | 20  | 2   | 17  | 15  | 14  |
| 15                | 1   | 10   | 17  | 12  | 4   | 19  | 10  | 19  | 8   | 9   | 3   | 7   | 10  |
4.4 Statistical analysis

The t-test is used for analyzing and comparing the two proposed methods with each other. To run a statistical comparison test of the results, MINITAB software version 17 is used. A 95% confidence level is also considered. As can be observed from Tables 5, 6, 7 and 8, the null hypothesis of the first and third indices is accepted because the $P$-values for the index of the first and third objective functions are higher than the significant level. In other words, considering the 95% confidence level, there is no significant difference between the answers achieved in the value of the first and third objective functions. The null hypothesis for the second objective function and the CPU time is rejected because its $P$-value is less than 0.05 (Figs. 5, 6, 7 and 8).

4.5 Numerical examples for the exact methods in large scale

In this section, meta-heuristic algorithms are utilized for increasing the search speed in a large-scale problem. The meta-heuristic methods are efficient for finding the optimal solution, but they cannot ensure a comprehensive solution. Considering that the proposed model belongs to the NP-hard problems, in this study, MOPSO, and NSGA-II as meta-heuristic algorithms are used. To evaluate the solving methods, Mean Ideal Distance (MID), The Spread of Non-Dominance Solutions (SNS), Number of Pareto Solutions (NPS), and CPU time are determined as four criteria. The software MATLAB R2019a software and with a system, CPU = Core i9 9900 K and RAM = 32 GIG DDR5 is used to implement these algorithms.

Afterward, 15 numerical examples on large scale are employed for comparing the solution methods. Tables 9 and 10 present these numerical examples and their parameter values, respectively.

Furthermore, Table 11 presents the parameters of the MOPSO and NSGA-II algorithms.

The final solution is commonly a trade-off between the different objective function values in the multi-objective models. Table 12 demonstrates the results achieved by the two algorithms of MOPSO and NSGA-II. These results show that the MOPSO is a better method based on the SNS, NPS, and MID but the NSGA-II is a better method on the basis of the CPU time.

| Parameter | Value | Parameter | Value |
|-----------|-------|-----------|-------|
| DEK_ecki | U (20000,30000) | DR_ip | U (5,15) |
| DEL_fksi | U (20000,30000) | TCT | U (4,6) |
| CI1_in | U (12,13) | TCKG | U (4,6) |
| CI2_in | U (12,13) | TCE | U (4,6) |
| CSKk | U (10,15) | TCF | U (4,6) |
| CSLi | U (10,15) | BI_i | U (2,3) |
| PCBjm | U (3,5) | BSj | U (2,3) |
| PCE_z | U (3,5) | CAN1_in | U (100000,500000) |
| PCF_z | U (3,5) | CAN2_in | U (100000,500000) |
| PE_e | U (20,25) | CAB_ip | U (100000,500000) |
| PF_f | U (20,25) | CAE_ip | U (100000,500000) |
| DS1_np | U (1,5) | CAP_ip | U (100000,500000) |
| DS2_np | U (1,5) | CARFrj | U (100000,500000) |
| DKkp | U (1,5) | CAQ_qj | U (100000,500000) |
| DPRlpr | U (1,5) | FCTpj | U (10,20) |
| DPRlpr | U (1,5) | RSP | U (0.35,0.40) |
| DRQtq | U (1,5) | RSS | U (0.35,0.40) |
| DQqm | U (5,15) | DR1_kqes | U (0.05,0.15) |

| Numerical Examples | LP-metric | E-constraint |
|-------------------|-----------|--------------|
| | Z1 | Z2 | Z3 | CPU | Z1 | Z2 | Z3 | CPU |
| 1 | 4.23E + 08 | 3.51E + 09 | 0.404 | 1.074 | 1.24E + 09 | 4.20E + 08 | 0.475 | 32.203 |
| 2 | 6.05E + 08 | 3.08E + 09 | 0.418 | 1.131 | 8.07E + 08 | 6.05E + 08 | 0.481 | 33.533 |
| 3 | 5.32E + 08 | 4.56E + 09 | 0.421 | 0.722 | 8.72E + 08 | 4.56E + 08 | 0.492 | 21.916 |
| 4 | 7.24E + 08 | 8.93E + 09 | 0.398 | 1.341 | 2.03E + 09 | 7.24E + 08 | 0.506 | 96.894 |
| 5 | 2.75E + 08 | 6.83E + 09 | 0.356 | 0.973 | 1.20E + 09 | 2.75E + 08 | 0.478 | 40.286 |
| 6 | 1.95E + 08 | 7.03E + 08 | 0.406 | 0.587 | 2.97E + 08 | 1.95E + 08 | 0.483 | 12.752 |
| 7 | 1.82E + 08 | 9.16E + 08 | 0.367 | 0.595 | 4.02E + 08 | 9.16E + 08 | 0.423 | 12.727 |
| 8 | 8.12E + 08 | 2.66E + 10 | 0.442 | 17.018 | 3.69E + 09 | 8.10E + 08 | 0.471 | 176.996 |
| 9 | 1.84E + 08 | 5.19E + 09 | 0.418 | 1.131 | 9.38E + 08 | 5.19E + 09 | 0.466 | 34.419 |
| 10 | 3.02E + 08 | 2.10E + 09 | 0.418 | 1.341 | 3.13E + 09 | 2.10E + 09 | 0.498 | 18.217 |
| 11 | 9.05E + 08 | 4.25E + 10 | 0.409 | 57.355 | 4.78E + 09 | 4.25E + 10 | 0.469 | 384.478 |
| 12 | 6.00E + 08 | 4.43E + 09 | 0.392 | 1.115 | 9.38E + 08 | 4.43E + 09 | 0.481 | 83.579 |
Table 5 Results of the statistical hypothesis test for 1st objective function

| Objective Function | Mean      | St. Dev    | S.E. Mean  | T-Value | P-Value |
|--------------------|-----------|------------|------------|---------|---------|
| LP-Metric          | 491548979 | 236271564  | 61005056   | -0.38   | 0.706   |
| E-Constraint       | 523601833 | 223898096  | 57810240   |         |         |

Table 6 Results of the statistical hypothesis test for 2nd objective function

| Objective Function | Mean      | St. Dev    | S.E. Mean  | T-Value | P-Value |
|--------------------|-----------|------------|------------|---------|---------|
| LP-Metric          | 8914802819| 11434561956| 2952391204 | 2.42    | 0.028   |
| E-Constraint       | 1681056071| 1336430719 | 345064927  |         |         |

Table 7 Results of the statistical hypothesis test for 3rd objective function

| Objective Function | Mean      | St. Dev    | S.E. Mean  | T-Value | P-Value |
|--------------------|-----------|------------|------------|---------|---------|
| LP-Metric          | 0.404133333 | 0.022749778 | 0.005674792 | 2.04    | 0.094   |
| E-Constraint       | 0.480866667 | 0.02120265  | 0.00528887 |         |         |

Table 8 Results of the statistical hypothesis test for CPU Time

| CPU Time | Mean | St. Dev | S.E. Mean | T-Value | P-Value |
|----------|------|---------|-----------|---------|---------|
| LP-Metric | 5.8  | 14.9    | 3.9       | -2.73   | 0.018   |
| E-Constraint | 74.2 | 95      | 26        |         |         |

Fig. 5 Box diagram and individual values of the first objective function

Fig. 6 Box diagram and individual values of the second objective function
Fig. 7  Box diagram and individual values of the third objective function

Fig. 8  Box diagram and individual values of the CPU time

Table 9  Large-scale numerical examples

|      |  n  | en | i  | j  | e  | p  | f  | k  | l  | r  | q  | m  | s   |
|------|-----|----|----|----|----|----|----|----|----|----|----|----|-----|
| 1    | 130 | 129| 91 | 192| 172| 131| 65 | 103| 124| 64 | 110| 95 | 139 |
| 2    | 108 | 152| 112| 135| 125| 76 | 53 | 171| 91 | 61 | 120| 69 | 53  |
| 3    | 95  | 50 | 163| 126| 130| 179| 56 | 158| 112| 135| 151| 200| 134 |
| 4    | 175 | 154| 142| 137| 139| 72 | 62 | 117| 108| 148| 56 | 59 | 135 |
| 5    | 67  | 153| 138| 84 | 177| 129| 115| 59 | 195| 109| 170| 116| 89  |
| 6    | 59  | 171| 133| 195| 59 | 56 | 141| 90 | 106| 159| 98 | 100| 94  |
| 7    | 196 | 160| 180| 142| 119| 171| 93 | 108| 184| 132| 107| 52 | 152 |
| 8    | 130 | 122| 165| 149| 187| 101| 139| 122| 192| 156| 129| 152| 109 |
| 9    | 129 | 105| 87 | 56 | 127| 51 | 142| 190| 153| 50 | 55 | 149| 98  |
| 10   | 109 | 147| 125| 158| 78 | 86 | 143| 197| 95 | 75 | 79 | 175| 109 |
| 11   | 153 | 65 | 109| 175| 175| 50 | 145| 164| 98 | 115| 53 | 192| 83  |
| 12   | 63  | 176| 188| 107| 88 | 59 | 54 | 74 | 200| 125| 142| 102| 155 |
| 13   | 94  | 175| 193| 195| 109| 172| 61 | 134| 107| 132| 140| 111| 63  |
| 14   | 175 | 103| 133| 57 | 136| 85 | 114| 182| 133| 112| 159| 75 | 116 |
| 15   | 127 | 181| 69 | 174| 196| 200| 56 | 184| 98 | 162| 138| 107| 147 |

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Table 10 The parameters values used in the numerical example

| Parameter | Value      | Parameter | Value      |
|-----------|------------|-----------|------------|
| DEK\_ks   | U (200000,400000) | DR\_r   | U (25,40)  |
| DEL\_ks   | U (200000,400000) | TCT     | U (10,20)  |
| C1\_ps   | U (50,80)  | TCG\_k  | U (10,20)  |
| C2\_ps   | U (60,90)  | TCE     | U (10,20)  |
| CS\_ks   | U (70,85)  | TCF     | U (10,20)  |
| CSL\_k   | U (70,85)  | BI       | U (15,45)  |
| PCB\_ps  | U (20,40)  | BS\_k   | U (20,30)  |
| PE\_p    | U (20,40)  | CAN\_1\_p| U (500000,1000000) |
| PCF\_f   | U (20,40)  | CAN\_2\_p| U (500000,1000000) |
| FF\_f    | U (50,70)  | CAE\_p  | U (500000,1000000) |
| DS\_1\_p | U (10,15)  | CAP\_p  | U (500000,1000000) |
| DS\_2\_p | U (10,15)  | CARF\_f | U (500000,1000000) |
| DK\_p    | U (10,15)  | CAQ\_p  | U (500000,1000000) |
| DP\_s\_p | U (10,15)  | FCT\_p  | U (40,80)  |
| DR\_r\_p | U (10,15)  | RSP     | U (0.60,0.90) |
| DB\_f\_p | U (10,15)  | RSS     | U (0.60,0.90) |
| DL\_Q\_p | U (10,15)  | DR\_1\_p| U (0.25,0.45) |
| DQ\_ap\_p| U (25,40)  | DR\_2\_p| U (0.25,0.45) |

Table 11 The algorithms parameters

| NSGA-II Parameters | Value | MOPSO Parameters | Value |
|--------------------|-------|-----------------|-------|
| Max iteration      | 90    | Max iteration   | 90    |
| Size of Population | 60    | Size of Population | 60  |
| Percentage of Crossover | 0.7  | Size of Repository | 60  |
| Percentage of Mutation | 0.4  | Weight of Inertia | 0.5  |
| Rate of Mutation   | 0.28  | Grids per Dimension Number | 25   |
|                    |       | Rate of Inflation | 0.25  |
|                    |       | The pressure of Leader Selection | 1    |
|                    |       | The pressure of Deletion Selection | 1    |
|                    |       | Rate of Inertia Weight Damping | 0.70  |
|                    |       | Personal Learning Coefficient | 2    |
|                    |       | Global Learning Coefficient | 2    |
|                    |       | Mutation | 0.3    |

Table 12 Results of NSGA-II and MOPSO algorithms

| Numerical Example | MOPO | NSGA-II | MOPO | NSGA-II |
|-------------------|------|---------|------|---------|
|                   | NPS  | MID     | SNS  | CPU Time | NPS  | MID     | SNS  | CPU Time |
| 1                 | 3    | 0.745354| 1.806027| 126.576  | 8    | 0.830785| 0.563988| 89.518    |
| 2                 | 4    | 0.563864| 1.42231 | 747.570  | 7    | 0.979046| 0.72459 | 489.251   |
| 3                 | 7    | 0.836885| 1.020588| 547.694  | 4    | 0.736535| 1.482149| 511.644   |
| 4                 | 3    | 0.787407| 2.044317| 592.074  | 5    | 0.852959| 1.3101  | 565.590   |
| 5                 | 5    | 0.672826| 1.440064| 937.829  | 5    | 1.051435| 1.51066 | 821.280   |
| 6                 | 5    | 0.95537 | 1.606716| 1085.056 | 6    | 1.115651| 1.022658| 1013.433  |
| 7                 | 8    | 0.817906| 1.204072| 896.723  | 6    | 0.934385| 0.869949| 786.538   |
| 8                 | 4    | 0.83116 | 1.7401  | 1433.941 | 9    | 0.948448| 0.384807| 1366.819  |
| 9                 | 6    | 0.876148| 1.095822| 1773.753 | 6    | 1.098646| 0.990254| 2129.189  |
| 10                | 7    | 0.870196| 1.017683| 3602.249 | 5    | 0.931538| 1.348343| 3392.061  |
| 11                | 4    | 0.740737| 1.763231| 724.573  | 8    | 1.046803| 0.536964| 681.329   |
| 12                | 4    | 0.792402| 1.737288| 1685.490 | 8    | 0.953873| 0.57923 | 1643.828  |
| 13                | 5    | 0.955252| 1.478877| 2817.744 | 5    | 1.003671| 1.423109| 2570.862  |
| 14                | 3    | 0.795677| 2.059532| 5489.759 | 5    | 0.956556| 1.359782| 4820.086  |
| 15                | 6    | 0.769536| 1.320584| 3885.986 | 5    | 1.000088| 1.419917| 3817.762  |
| MEAN              | 4.93333333| 0.8007147 | 1.5171474 | 1723.1345 | 6.13333333| 0.9626946| 1.0346527| 1646.6127 |
Table 13 The statistical hypothesis test results for MID

| Variable      | Mean | St. Dev | S.E. Mean | T-Value | P-Value |
|---------------|------|---------|-----------|---------|---------|
| LP-Metric     | 0.799| 0.101   | 0.027     | −4.39   | 0.000   |
| ε-constraint  | 0.961| 0.102   | 0.027     |         |         |

Fig. 9 Mean MID of MOSPO and NSGA-II algorithms

Fig. 10 Linear chart based on a MID index
Table 14  The statistical hypothesis test results for SNS

| Variable | SNS  | Mean  | St. Dev | S.E. Mean | T-Value | P-Value |
|----------|------|-------|---------|-----------|---------|---------|
| LP-Metric | SNS  | 1.516 | 0.342   | 0.090     | 3.56    | 0.001   |
| ε-constraint | SNS  | 1.034 | 0.398   | 0.11      |         |         |

Table 15  Results of the statistical hypothesis test for NPS

| Variable | NPS  | Mean  | St. Dev | S.E. Mean | T-Value | P-Value |
|----------|------|-------|---------|-----------|---------|---------|
| LP-Metric | NPS  | 4.95  | 1.59    | 0.42      | -2.11   | 0.041   |
| ε-constraint | NPS  | 6.14  | 1.52    | 0.40      |         |         |
Fig. 13 The NPS index average for MOSPO and NSGA-II algorithms

![Individual Value Plot of NPS](image)

**Data**

| Variable | NPSI ndex |
|----------|-----------|
| MOPSO    |           |
| NSGA-II  |           |

Fig. 14 The NPS values for two meta-heuristic methods

![NPS](image)

Table 16 The statistical hypothesis test results for CPU Time

| Variable   | CPU Time Mean | St. Dev | S.E. Mean | T-Value | P-Value |
|------------|---------------|---------|-----------|---------|---------|
| LP-Metric  | 1714          | 1481    | 379       | 0.15    | 0.884   |
| ε-constraint | 1651         | 1421    | 367       |         |         |
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4.6 Statistical analysis

The performance analysis of the proposed algorithms in terms of the specified parameters is as follows.

Table 13 and Fig. 9 show the statistical analysis based on MID in both algorithms. There is a major difference between the mean of LP-Metric and ε-constraint algorithms in terms of MID regarding the P-value. MID values for 15 numerical examples are shown in Figs. 10 and 11.

Table 14 and Fig. 11 show the statistical analysis based on SNS in both algorithms. There is a major difference between the mean of LP-Metric and ε-constraint algorithms in terms of SNS. Also, SNS values for 15 numerical examples are shown in Fig. 12.

Table 15 and Fig. 13 show the results of a statistical analysis based on NPS. With respect to the P-value, there is a major difference between the mean of LP-Metric and ε-constraint algorithms in terms of NPS. NPS values for 15 numerical examples are shown in Fig. 14.

Table 16 and Fig. 15 show the results of a statistical analysis based on CPU time. With respect to the P-value, there is a major difference between the mean of LP-Metric and ε-constraint algorithms in terms of CPU time. Its values for 15 numerical examples are shown in Fig. 16.
5 Conclusion

This research is the first study to develop a mathematical model for redesigning a sustainable and resilient closed-loop supply chain under the two super disruptions of the COVID-19 pandemic and sanctions simultaneously on the steel industry. To this aim, a multi-objective mathematical model was presented by using an uncertainty approach to make results more consistent with reality. In the proposed model, three objective functions are designed to achieve the dimensions of sustainability, namely economic, social, and environmental. The first goal is related to the economic aspect which is determined to maximize the profits of the entire supply chain network. The second goal is related to the environmental aspect to focus on minimizing water and energy consumption, CO₂ emissions in the manufacturing process in various technologies, and other air pollutants that are emitted through industrial emissions and exhaust gases. Finally, the social goal is to minimize the spread of coronavirus in industrial environments. As a solution to solve the model in conditions of uncertainty, the robust optimization approach was also employed. The presented results indicated that the model has essential efficiency in both large and small dimensions and can be of real use to managers in similar situations. Eventually, some statistical analyses were provided to validate and verify the solving methods. For this purpose, four indexes of NPS, MID, SNS, and CPU Time were utilized. Since the steel industry is a major sector of the global supply chains and is considered one of the basic and strategic industries of the countries, the results and findings can be used to rebuild the resilience of the supply chain of other related and similar industries. Therefore, the proposed model can be used in the real world, for redesigning the supply chain of businesses to reduce the operational risks due to the inability of their networks to increase resilience in the face of disruptions such as COVID-19 and sanctions.

Although the developed multi-objective mathematical model has considered various aspects of redesigning a sustainable and resilient closed-loop supply chain under uncertainty, there are still some limitations left for future study. Firstly, in the steel industry, fines and bonuses are incorporated into the contracts for purchasing raw materials and selling final products. Failure to meet the quality limits for materials and products in the contracts will lead to an increase in supply chain costs that will have a significant impact on the total profit. Due to the confidentiality of the information inside the contracts, it is difficult to access this data and the contractual items, therefore this item could not be applied in the study that needs to be explored in future research. Secondly, because there is no comprehensive information about the source and price of scraps in this market and also, the pricing method determined by customers to send back their wasted billets is not clear, this case could not be considered in the current research. Accordingly, in the future study, different prices for the purchase of scrap can be taken into consideration depending on the amount and quality of scrap provided from one source and customers who return their scrap to the producer setting discounts. Thirdly, in spite of the fact that transport systems have different capacities and levels of CO₂ emissions in the steel industry, they were not employed in the proposed model. Thus, various modes of transport with different capacities and levels of CO₂ emissions can be added to new models for studying transport costs and their environmental impacts, accurately. As the last suggestion, considering different capacities for supply chain facilities and assigning specific job opportunities and expenses to increase capacity has the potential for a new field of research in the future.

Declarations

Ethical approval The manuscript has complied with all of the ethical standards.

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Conflicts of interest The authors have no competing interests to declare that are relevant to the content of this article.

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