Designing a new multi-echelon multi-period closed-loop supply chain network by forecasting demand using time series model: a genetic algorithm

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Abstract

Demand plays a vital role in designing every closed-loop supply chain network in today's world. The flow of materials and commodities in the opposite direction of the standard supply chain is inevitable. In this way, this study addresses a new multi-echelon multi-period closed-loop supply chain network to minimize the total costs of the network. The echelons include suppliers, manufacturers, distribution centers, customers, and recycling and recovery units of components in the proposed network. Also, a Mixed Integer Linear Programming (MILP) model considering factories' vehicles and rental cars of transportation companies is formulated for the proposed problem. Moreover, for the first time, the demand for the products is estimated using an Auto-Regressive Integrated Moving Average (ARIMA) time series model to decrease the shortage that may happen in the whole supply chain network. Conversely, for solving the proposed model, the GAMS software is utilized in small and medium-size problems, and also, genetic algorithm is applied for large-size problems to obtain initial results of the model. Numerical results show that the proposed model is closer to the actual situation and could reach a reasonable solution in terms of service level, shortage, etc. Accordingly, sensitivity analysis is performed on essential parameters to show the performance of the proposed model. Finally, some potential topics are discussed for future study.

Keywords  Closed-loop supply chain network · Demand forecasting · Mathematical model · ARIMA time series model · Genetic algorithm

Introduction

Designing the transportation network in the supply chain has attracted much attention in today’s competitive world (Chan et al. 2016). Providing better services by companies to satisfy customers, decreasing costs, and increasing net profit is one of the consequences of this competition (Xu et al. 2017). Supply chain network design is a strategic issue that helps to select the best combination of a set of facilities to achieve an efficient and effective network (Almaraj and Trafalis 2019). Designing a distribution network is one of the critical issues in the design of the supply chain network, which offers a substantial potential factor to reduce costs and improve service quality (Margolis et al. 2018, Goodarzian...
et al. 2021a, 2021b; Mosallanezhad et al. 2021). Therefore, the design of a supply chain network plays an outstanding role in long-term strategic decision-making (Wu et al. 2017). Also, researchers in recent years have paid more attention to the multi-product nature of such problems (Wang and Gunasekaran 2017). In this research, modeling the design of transportation networks in the supply chain and its solution by meta-heuristic methods are developed and discussed.

Over the past two decades, there have been tremendous global changes due to advances in technology, the globalization of markets, and the new economic-political conditions (Ghasemi et al. 2017). Due to the growing number of competitors in the global class, organizations were forced to quickly improve intra-organizational processes to stay in the worldwide competition. In the 1960s–1970s, organizations tried to develop detailed market strategies that have mainly focused on satisfying customers (Mohtashami et al. 2020). They realized that robust engineering and design and coherent production operations were the prerequisite for achieving market requirements and thus more market share. Therefore, designers were forced to incorporate the ideals and needs of their customers into their product design, and in fact, they had to supply a product with the maximum possible level of quality, at minimum cost considering the customer’s desired ideals (Hassanpour et al. 2019; Modibbo et al. 2019, 2021; Ali et al. 2021).

In this research, a new mathematical model for optimizing the closed-loop supply chain, whose main objectives include determination of the optimal amount of products and components in each segment of the network, minimizing the total cost of the system, optimizing the amount of transportation in the entire system has been proposed. This research aims to design a closed-loop supply chain network that includes suppliers, manufacturers, distribution centers and customers, collection and disassembly centers, product, and component recovery units, as well as a facility for destruction and burial of damaged and polluting components.

Figure 1 shows a closed-loop supply chain network of this study. Suppliers send components to factories, and factories produce products based on received demand from customers. The generated products are sent to distribution centers by factories’ trucks or transportation companies in order to be delivered to the customers. In order to increase the speed of transporting products to meet the customers’ needs without encountering bottlenecks and shortages of vehicles, the trucks of the factories and the transportation companies have been used simultaneously. A few products are returned by consumers and are gathered in the product collection centers. The collection center divides the products into two parts, including usable and unusable sections. Some after-consumption products that have not yet finished their lifetime can be reused again by some repairing. They are sent to the product recovery centers from the product collection center to be recovered. Then, these products are sent to distribution centers after recovery and repairs. Unusable products are disassembled into components in disassembly centers. The components that are usable can be reused after repairing by the repairing and recovery centers, but some useless components should be destroyed or buried. These types of components, such as chemical batteries, chips, various types of chemicals and plastics, and various types of pollutants, are harmful to the environment, and they take many years to be recovered. Therefore, these components have been considered waste and are gathered in destruction and burial centers for technological clearing. Because the capacity of the recovery unit for components is limited, several recovery centers are needed. After the recovery phase, the reconstructed components are taken to the

Fig. 1 The schematic view of closed-loop supply chain network with multiple manufacturers
warehouse section of the factories to be used as new components. Due to the fact that the recovery and collection centers are limited, new components are purchased from suppliers based on demand and the number of recovered components.

The autoregressive integrated moving average (ARIMA) was proposed three decades ago, and it is widely used by many researchers to forecast the features they need to be estimated. The ARIMA models can also be used to build various exponential smoothing techniques. In this study, we have used the ARIMA time series model to estimate the value of demand which is the input parameter for the proposed supply chain network. No study in the supply chain considers forecasting demand by the ARIMA timer series model, so, in this paper, for the first time, we will estimate the demand by utilizing this technique as we propose it in the “Demand forecasting” section separately.

In the present research, for the first time, we will discuss the issue of service level, the possibility of a shortage, and other related parameters and variables in the multi-period closed-loop supply chain network. Therefore, discussing, modeling, and solving the closed-loop supply chain problem considering the specific service level to demand, as well as considering the cost of not satisfying the total amount of demand in the cost objective function, are one of the contributions of this research.

This research has been compiled into six sections. The “Literature review” section deals with the literature review. In the “Problem statement” section, the mathematical model is presented. The “Solving algorithm” section describes the solution algorithm, and in the “Computational results” section, the computational results are presented, and finally, the conclusion will be presented in the “Conclusion” section.

**Literature review**

Meng et al. (2016) developed a simulation-based hierarchical particle swarm optimization algorithm to solve a multi-criteria production–distribution program. Their integrated program included three objectives of minimizing all costs, including regular labor costs, overtime, outsourcing, inventory maintenance, shortage, recruitment, expulsion, and distribution costs, reducing the work level changes, and minimizing inefficiency of work levels. Below are the levels of work. They validated their proposed algorithm with a zero/one hierarchical genetic algorithm. Phuc et al. (2017) investigated the reverse logistics of salvage cars. In their model, the objective functions were fuzzy, and the parameters were deterministic. The problem included four fuzzy objectives: minimizing delivering and transportation costs, minimizing warehouse establishment costs, maximizing reverse service in return flows. The model’s results indicated a 15% reduction in total system costs. Zheng et al. (2017) formulated a multi-objective linear programming model for optimizing the operations of integrated logistics, reverse logistics, and returned products in a given supply chain. Factors such as the return of used products and subsidies by government agencies were considered in the formulation of the model. They were considering the model as decentralized and incomplete information was one of the innovations of this research. Habibi et al. (2017) designed a three-level supply chain while simultaneously examining the total cost and disassembling effects of different commodities. Their model was a single-product and single-period research, including manufacturers, distribution centers, and customers. After defining the model using linearization methods, the optimal solution of the problem was obtained by employing an interactive method. In this study, tactical decisions on the selection of transportation systems were also considered. Li et al. (2017) examined the supply chain network, including suppliers, factories, and distribution centers. Decisions to be made in this network included setting up the factories and distribution centers, the amount of production, and the volume of products. The objective function was defined as the minimization of costs. To solve this model, a genetic algorithm based on a spanning tree was used, and the validity of this method was measured by comparing it with the traditional method of genetic algorithm. Pedram et al. (2017) presented a multi-period model for maximizing the reverse supply chain profit of recycled tires. In their proposed model, the recycling capacity was set to minimize the total cost. The advantage of this research was considering strategic and tactical decisions simultaneously. The results indicated the appropriate performance of the proposed model. Kim et al. (2018) presented a robust mathematical model for reverse supply chain management with uncertain demand. Considering budget constraints and prioritizing suppliers were of the innovations of this research. To verify the validity of the proposed model, robust optimization was used, and to deal with the uncertainty of the problem, and simulation was used. Sobotka et al. (2017) investigated the reverse supply chain projects of recycled and resilient materials. Considering the cost of repairs was one of the issues addressed in this study. The results of the numerical examples indicated that the increase in the number of recycled materials leads to a rise in the cost of repairs to a certain level. Yu and Solvang (2018) examined the multi-period and multi-product supply chain. Considering the capacity constraints of facilities and resilience in the supply chain were of the strengths of this research. To model this problem, a two-level approach was used, which in the first level, strategic decisions including allocation of capacity, and in the second level, operational decisions including the reduction of supply chain costs were made. Mota et al. (2018) explored an integrated and resilient supply chain in the chain stores in Europe. Considering the location of facilities and the prioritization of suppliers
were the most important objectives of this research. The use of social, economic, and environmental factors in the constraints made this research different than similar studies.

Flygansvær et al. (2018) presented a mixed-integer nonlinear programming model for the design of a direct and reversed integrated logistics network for logistics service providers. Their case study was 102 electronic industry contractors. To deal with the current uncertainty of the conditions, the characteristics of the problem were determined for each period, and in the next period, the model was again solved for new characteristics. Cheraghalipour et al. (2018) investigated the logistics of a physical section of the supply chain, which involved all activities related to the flow of materials and commodities from the stage of providing the raw materials to the production of the final product, including transportation and warehousing. One of the new trends in logistics management is the recycling or reuse of products. In this method, products that reach the end of their useful life will be re-purchased from the final consumer, and once disassembled, reusable components of the product will be recycled in the form of salvage products. Heydari et al. (2018) presented a zero/one two-level mixed-integer programming model considering the direct and inverse flow of recycling of components. The problem was formulated as an incapacitated mathematical model. Thinking of the model as decentralized and solving it with a heuristic method were of the innovations of this research.

Eydi et al. (2020) proposed a multi-period multi-echelon forward and reverse supply chain network for product distribution and collection with transportation mode selection. In addition, they formulated a new mixed-integer nonlinear programming model for their problem based on different levels of facility capacities with the maximum profit objective function. Finally, a genetic algorithm was used to solve their model. Antucheviciene et al. (2020) developed sustainable reverse supply chain planning under uncertainty. Their main aims were to maximize the total profit of operation, minimize adverse environmental effects, and optimize customer and supplier service levels. Then, scenario-based robust planning was used to tackle uncertain parameters. To solve their model, non-dominated sorting genetic algorithm II was employed. Finally, they provided actual data from a case study of the steel industry in Iran. Gao and Cao (2020) provided a new sustainable reverse logistics supply chain network by reconstructing the existing facilities into hybrid processing facilities. They presented a multi-objective scenario-based optimization model to maximize the expected total monetary profits, minimize the expected total carbon emission costs, and maximize the expected total created job opportunities. They used the weighted-sum and augmented-constraint approaches to solve their model. Eventually, a real case study in the tire industry was considered to demonstrate the performance of their model. Sajedi et al. (2020) introduced a two-objective probable mixed integer programming for the design of a closed-loop supply chain. In their model, the reverse flow was considered along with the direct flow as well as strategic decisions along with tactical decisions. Consideration demand as uncertain was one of the innovations of this research. The results indicated a reduction of 8% in the costs of the system.

Shadkam (2021) designed a complex integer linear programming model for an integrated direct logistics and reverse logistic network design considering waste management. Their main aims were to minimize the costs related to the fixed expenses, material flow costs, and the costs of building potential centers. Eventually, their model was solved utilizing the cuckoo optimization algorithm. Parast et al. (2021) formulated a bi-objective mixed-integer linear programming model to design a green forward and reverse supply chain under uncertainty. They provided a new location-inventory-routing problem with simultaneous pickup and delivery, scheduling of vehicles, and time window. Their main goals were to minimize total costs and lost demands simultaneously. Moreover, an approach according to the fuzzy theory was presented to cope with uncertain parameters. Finally, they considered a real case study to show the performance and efficiency of their model. Another study was done by Gerdrodbari et al. (2021) presented a bi-objective mixed-integer linear programming (MILP) model to design a multi-level, multi-period, multi-product closed-loop supply chain (CLSC) for timely production and distribution of perishable products, considering the uncertainty of demand. To face the model uncertainty, they used the robust optimization (RO) method to solve and validate the bi-objective model in small-size problems, and then, they used a non-dominated sorting genetic algorithm (NSGA-II) for solving large-size problems.

Only one study considered the time series model when designing a supply chain network. Ghaderi et al. (2016) utilized auto-regressive moving average (ARMA) time series models to estimate the number of bioethanol demand in their network. Then, they used the estimated demand as an input into their model to design a switchgrass-based bioethanol supply chain network.

Based on what we have reviewed so far, the issue of service level, the possibility of a shortage, and other related parameters and variables in the multi-period closed-loop supply chain network have not been considered by researchers. More interestingly, the ARIMA time series model has not been included in any studies in the past, so the main contribution of this study is as follows:

- Considering service level and the possibility of shortage in the proposed mathematical model.
• Utilizing the ARIMA time series model to estimate the demand of supply chain as an input parameter into the model, and
• We are applying a genetic algorithm to solve the proposed mathematical model for a large-size problem.

On the other hand, the goal of this research is to determine to identify the optimal number of products and components in each section of the network by minimizing the total costs of the system and optimizing the number of transporting products in the system. More interestingly, also, reducing the production costs and using an appropriate producer with lower production costs are other objectives of this model. In the next section, first, we discuss how to forecast demand using the ARIMA time series model and then present the problem statement of this research study by formulating the mathematical model in the “Problem statement” section.

Demand forecasting

Demand plays a crucial role when designing an efficient supply chain network. Indeed, the central part of each supply chain network is to have a reasonable estimation for demand. In this way, this study has utilized the Auto-Regressive Integrated Moving Average (ARIMA) to forecast the number of products demands. On the other hand, knowing the excellent estimation of demand can help us to know the actual costs of the designed network as well as respond to the customers’ needs in a proper time. The general equation of ARIMA is brought in Eq. (1) as follows.

\[ \hat{Y}_t = \mu + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta_q e_{t-q} \]

To forecast the demand, we have used the demand dataset between the years 2017 and 2020, which is shown in Fig. 2. As we can see, there are NO seasonality patterns for the period that we have investigated our data for products. Therefore, utilizing the ARIMA model can help us to have good predictions based on our dataset.

Based on Fig. 2, it is clearly visible that the trend of demand of products shows the smooth line that is constant from one period to another period (month). Furthermore, the forecasting of demand has been brought in Table 1. As we can see, the demand is predicted for the year 2021 based on the ARIMA timer series model, so, in this table, we have:

### Table 1: Forecasting demands for the year 2021 (12 months)

| Month | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   | 9   | 10  | 11  | 12  |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Demand| 526 | 502 | 645 | 697 | 723 | 576 | 518 | 599 | 464 | 520 | 575 | 608 |

**Problem statement**

In this section, we aim to state the problem that we are planning to solve. As we have shown in Fig. 1, the suppliers prepare raw materials for the manufacturers, and then, the raw materials will be used by manufacturers based on the Bill of Material (BOM) to produce goods. Then, the generated goods will be sent to the distribution centers to be transferred to the customers. The returned products will be collected by product collection centers. These returned products will be checked if they are in good condition or not, and based on that, they will send to either the product recovery center or disassemble and separation centers. If these returned products are sent to the product recovery center, then they will transfer to the distribution centers to be distributed in the network again. If the collected products are disassembled in disassemble and separation centers, they will have two results. If they are usable, they will send to repairing recovering components centers for repairing. If these products cannot be functional, they will be destructed in destruction and burial centers.

The purpose of the proposed model is to identify the optimal number of products and components in each section of the network by minimizing the total costs of the system and optimizing the number of transporting products in the system. Also, reducing the production costs and using an appropriate producer with lower production costs are other objectives of this model. Indeed, this model plans to determine the allocation of orders to the factories according to the optimal amount of product and customer demand as well.
Before proposing the mathematical model, we have considered some assumptions that are as follows:

- The mathematical model is assumed to be multi-period, multi-product, and multi-echelon.
- The demand is estimated by the ARIMA time series model.
- Recovered components will be taken to the factory warehouse after rebuilding to be distributed to the network.
- The shortage has been considered in the model and is allowed in all periods of time.
- The transportation system of factories has two states: first, the factory’s trucks have been used for shipping products in the network. Second, the transportation companies are utilized for having some alternatives to the model to decrease the total costs of transportation in the system.

**Symbols and sets:**
Symbols used in the mathematical model of this research are as follows:

- $i$: index of components ($i \in I$)
- $j$: index of products ($j \in J$)
- $k$: index of suppliers ($k \in K$)
- $m$: index of manufacturers ($m \in M$)
- $n$: index of distribution centers ($n \in N$)
- $l$: index of recycling and recovery units of components ($l \in I$)
- $q$: index of customers ($q \in Q$)
- $a$: index of factories’ vehicles ($a \in V$)
- $a'$: index of rental cars of transportation companies ($a' \in V'$)
- $t$: index of periods

**Subsets**

- $J_j$: The set of products that have the component $j$

**Parameters**

- $S_{jm}$: Sales price of each unit of the product $j$ by the manufacturer $m$
- $C_{jm}$: The final production cost of each unit of the product $j$ by the manufacturer $m$
- $Y_{qt}$: The service level of customer $q$ in period $t$
- $D_{jqt}$: Demand for the product $j$ by the customer $q$ in period $t$
- $d_j$: Disassembly cost for separation of product $j$
- $f_i$: The separation cost of component $i$
- $h_i$: Destruction or burial cost of component $i$
- $o_{it}$: The cost of recovering the component $i$ at the recovery center $l$
- $r_{ik}$: The purchase price of component $i$ that is supplied through the supplier $k$
- $C_{oj}$: The collection cost of product $j$
- $O_{ij}$: The recovery cost of product $j$
- $G_{il}$: The maximum capacity of recovery center $l$ in period $t$
- $\text{Cap}_1$: Maximum capacity of the product recovery unit in period $t$
- $\text{Cap}_2$: Maximum capacity of disassembly and separation unit in period $t$
- $B_k$: Maximum capacity of supplier $k$
- $v_n$: Maximum capacity of distribution center $n$
- $H_{jt}$: Maximum return percentage of product $j$ in period $t$
- $O_{it}$: Maximum percentage of component $i$ that is usable in period $t$
- $A_m$: Maximum capacity of factory $m$
- $O''_j$: Maximum percentage of returned product $j$ that is recoverable
- $q_{ij}$: The number of components $i$ required to produce a unit of product $j$ in period $t$
- $\text{Tr}_{silm}$: The transportation cost of the component $i$ from the supplier $k$ to the producer $m$
- $\text{Tr}_{rjq}$: The transportation cost of product $j$ from customer $q$ to the product collection unit
- $\text{Tr}_{r'_{jmn}}$: The transportation cost of the product $j$ from the factory $m$ to the distribution center $n$ by the truck $a$ (owned by the factory $m$)
- $\text{Tr}_{r''_{jmn}}$: The transportation cost of the product $j$ from the factory $m$ to the distribution center $n$ by the truck $a'$ (owned by the transportation companies)
- $\text{Tr}_{d_{jqa}}$: The transportation cost of product $j$ from distribution center $n$ to customer $q$
- $\text{Tr}_{a_j}$: The transportation cost of the product $j$ from the product collection unit to the product recovery unit.
- $\text{Tr}_{f_{jn}}$: The transportation cost of the product $j$ from the product recovery unit to distribution center $n$
- $\text{Tr}_{a_j}$: The transportation cost of the product $j$ from the collection unit to disassembly and separation unit
- $\text{Tr}_{b_{il}}$: The transportation cost of the component $i$ from disassembly and separation unit to the component recovery center $l$
- $\text{Tr}_{c_{ilm}}$: The transportation cost of the component $i$ from recovery center $l$ to the manufacturer $m$
- $sco_{ij}$: The cost of not meeting the demand for the product $j$
- $\text{Cap}_3$: Maximum number of trucks $a$ in period $t$
- $\text{Cap}_4_{a'}$: Maximum number of trucks $a'$ belonging to the transportation company in period $t$
**Decision variables**

- $P_{jmnt}$: The number of products $j$ produced by the manufacturer $m$ and sent to the distribution center $n$ in the period $t$
- $Crp_{jpt}$: The number of products $j$ returned by the customer $q$ in period $t$
- $Q_{ikmt}$: The number of components $i$ to be supplied by the supplier $k$ and sent to the manufacturer $m$ in period $t$
- $w_j$: The number of recoverable products $j$ brought from the collection unit to be recovered.
- $T_{ilt}$: The number of components $i$ disassembled by the disassembly unit and sent to the component recovery center $l$ in period $t$
- $X_{ilmt}$: The number of components $i$ that should be rebuilt by the recovery unit $l$ and sent to the manufacturer $m$ in period $t$
- $V_i$: The number of components $i$ that should be destroyed.
- $R_{jt}^i$: The number of products $j$ collected to be sent to the disassembly segment in period $t$
- $Y_{jmt}$: The number of recovered products $j$ sent to the warehouse of the distribution center $n$ in period $t$
- $Y_{jnt}$: The number of products $j$ sent from the distribution center $n$ to the customer $q$ in period $t$
- $nhl_{jpt}$: The number of product $j$ shortages for customer $q$ in period $t$
- $X_{jmnart}$: The number of products $j$ sent by the truck $a$ from the manufacturer $m$ to the distributor $n$ in period $t$
- $X_{jmnart'}$: The number of products $j$ sent by the truck $a'$ (owned by the transportation companies) from the manufacturer $m$ to the distributor $n$ in period $t$

**Model constraints**

- $\sum_{m \in M} X_{ilmt} = T_{ilt} \forall i, l, t$ (3)
- $W_j = O_j \sum_{q \in Q} Crp_{jqt} \forall j, t$ (4)
- $R_{jt}^i = \left(1 - O_j\right) \sum_{q \in Q} Crp_{jqt} \forall j, t$ (5)
- $\sum_{q \in Q} Y_{jmnt} = \sum_{m \in M} P_{jmnt} + Y_{jmt} \forall j, n, t$ (6)
- $\sum_{n \in N} Y_{jnt} = W_j \forall j, t$ (7)
- $Crp_{jpt} = \sum_{n \in N} H_{jt} \cdot Y_{jipt} \forall j, q, t$ (8)
- $D_{jpt} \cdot Y_{jpt} = \sum_{n \in N} Y_{jipt} + nhl_{jpt} \forall j, q, t$ (9)
- $\sum_{l \in L} T_{ilt} = O_{it} \sum_{j \in J} q_{jt} \cdot R_{jt}^i \forall i, t$ (10)
- $V_i = \left(1 - O_i\right) \sum_{j \in J} q_{jt} \cdot R_{jt}^i \forall i, t$ (11)
- $\sum_{t \in T} \sum_{m \in M} Q_{ikmt} \leq B_k \forall k, t$ (12)
- $\sum_{a \in a_m} X_{jmnart} + \sum_{a} X_{jmnart'} = P_{jmnt} \forall j, m, n, t$ (13)
- $\sum_{j \in J} \sum_{w \in W} P_{jmnt} \leq A_m \forall m, t$ (14)
- $\sum_{q \in Q} \sum_{t \in T} Y_{jnt} \leq v_n \forall n, t$ (15)
- $\sum_{t \in T} \sum_{n \in N} Y_{jnt} \leq Cap1 \forall t$ (16)
- $\sum_{t \in T} \sum_{l \in L} T_{ilt} \leq Cap2 \forall t$ (17)

The objective function includes minimizing the total cost of the system which is shown by Eq. (2).

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The proposed mathematical model in this section is formulated as Mixed Integer Linear Programming (MILP) model. Therefore, We have

$$
\text{Min} C = \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} f_{jw} \cdot Q_{jw} + \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} C_{jw} \cdot Crp_{jwt} + \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} O_j \cdot W_j + \sum_{j \in J} \sum_{w \in W} \sum_{t \in T} d_j \cdot R_{jt}^i \\
+ \sum_{i \in I} \sum_{t \in T} \sum_{q \in Q} \sum_{j \in J} \sum_{m \in M} q_{jt} \cdot X_{jmnt} + \sum_{i \in I} \sum_{t \in T} \sum_{q \in Q} \sum_{j \in J} \sum_{m \in M} C_{jw} \cdot P_{jmnt} + \sum_{i \in I} \sum_{t \in T} \sum_{q \in Q} \sum_{j \in J} \sum_{m \in M} L_j \cdot T_{ilt} \\
+ \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} X'_{jmnt} + \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} Q_{jmnt} \cdot T_{jmnt} + \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} Krp_{jpt} \cdot Tr_{jpt} + \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} W_j \cdot Tw_{j} \\
+ \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} Crp_{jpt} \cdot Tr_{jpt} + \sum_{j \in J} \sum_{t \in T} \sum_{q \in Q} \sum_{i \in I} \sum_{m \in M} W_j \cdot Tw_{j}$$

(2)
\[
\sum_{i \in I} \sum_{m \in M} X_{ilm} \leq G_{il} \forall i, t \tag{18}
\]
\[
\sum_{j \in J} \sum_{m \in M} \sum_{n \in N} X'_{jmnt} \leq \text{Cap}3_{j} \forall a, t \tag{19}
\]
\[
\sum_{j \in J} \sum_{m \in M} \sum_{n \in N} X''_{jmnt} \leq \text{Cap}4_{j} \forall a', t \tag{20}
\]
\[
\sum_{n \in N} \sum_{j \in J} q_{j} \cdot P_{jmnt} \leq \sum_{i \in I} X_{ilm} + \sum_{k \in K} Q_{kmt} \forall i, m, t \tag{21}
\]
\[
p_{jmnt} \cdot C_{ipq}, q_{ijt}, Q_{kmt}, W_{j}, T_{i}, X_{ilm}, V_{i}, \hat{K}_{ip}, \hat{Y}_{pm}, nhl_{jqt}, X'_{jmnt}, X''_{jmnt}, X''_{jmnt} \geq 0 \tag{22}
\]

Constraint (3) states that the number of disassembled components is equal to the number of components recovered by the component recovery centers. Constraint (4) indicates that the usable products are equal to a percentage of returned products. Constraint (5) indicates that unusable products are equal to a percentage of returned products. Generally, constraints (4) and (5) show the percentage of the products recovered by recovery centers and the percentage of products collected to be sent to the separation and disassembly units. Constraint (6) states that the number of products sent to customers is equal to the sum of recovered products and produced products. Constraint (7) indicates that the number of usable collected products is equal to the number of recovered products. Constraint (8) shows that returned products are equal to a percentage of products purchased by customers. Constraint (9) ensures that the minimum demand should be met, and the shortage should be minimized. Constraints (10) and (11) specify the number of usable and unusable components in the disassembly unit and determine the percentage of waste and usable components. Constraint (12) specifies the maximum capacity of supplier k. Constraint (13) states that the number of produced components sent to distribution centers is equal to the number of products sent by the factory and rental trucks. The constraints (14) and (15) show, respectively, the capacity constraints of the factories and the distribution centers. Constraints (16) and (17) indicate, respectively, the capacity constraints of the product recovery unit and disassembly section. Constraint (18) shows the capacity constraints for component recovery units. Constraints (19) and (20) also indicate the capacity constraints of containers. Constraint (21) states that the number of produced components is equal to the total number of recovered components and purchased components from suppliers. Finally, constraint (22) shows the nature of decision variables in the model.

**Solving algorithm**

In this study, the exact solution algorithm is used to solve the model on a small and medium scale, and the genetic algorithm (GA) is applied to solve the model on a large scale. The flowchart of the GA, which displays an overview of how the algorithm is executed, is shown in Fig. 3. The selection of the fittest individuals from a population begins the natural selection process. They generate offspring who inherit the parents’ qualities and are passed down to the next generation. If parents are physically active, their children will be fitter than they are and have a better chance of surviving. This procedure will continue to iterate until a generation of the fittest individuals is discovered.

**Display of the chromosome**

The first step after determining the technique used to convert each solution to a chromosome is to create an initial population of chromosomes. At this stage, the initial solution is usually generated by a random function. Here, for example, the chromosome of the variable nhl_{jqt} is shown in Fig. 4 as follows:

As we defined earlier, the variable nhl_{jqt} is the number of shortages of product j for customer q in period t. The two indices of q and t are considered columns, and the index of j is regarded as a row to generate the initial chromosome of this problem. For instance, the number 96 shows the value of product 2, customer 2 in time period 2. This number will go through GA procedure as we defined in Fig. 4 to generate its optimal number at the end of the maximum iteration of the algorithm, so this number is not an optimal number at this stage for the variable nhl_{jqt}.

**Genetic operations**

Genetic operations imitate the inherited gene transfer process for the creation of new children in each generation. An essential part of the genetic algorithm is the creation of new chromosomes called children through some of the old chromosomes called parents. In general, this operation is performed by two major operators: mutation operator and crossover operator.

**Crossover operators**

There are the operators that select one or more points from two or more solutions and change their values. These operators consider a solution and exchange some locations of the solution with other solutions for creating new solutions. These operators are called crossover operators. In fact, on the remaining chromosomes of the initial population, a
crossover is performed. Here in Fig. 5, a two-point crossover is used.

**Mutation operators**

There are the operators that select one or more genes from a chromosome and change their values. In these operators, one or more locations of a character string with a specific length are considered, and the values of the characters in those locations are changed. In this type of operator, the solution information is used to create another answer. This change may be too little or too much, and too little or too much information is used based on the amount of change. In other words, the more the differences are, the solution will be more random; and this randomness is helpful for entering the new genetic materials into the population. When the population converges towards a particular solution, the probability of a mutation must be increased to prevent this, and vice versa; if the population has non-identical solutions, the
probability of mutation must be reduced (Fig. 6). Here, for a mutation operator, a row is randomly selected and reversed.

**Stopping criteria**

After the birth of children generating a new generation and calculating its fitness function, there is a need for a criterion to end the algorithm that we refer to as some of the most common ones.

- Implementation of the program is often carried out for a predetermined number of generations. For example, at the beginning of the program, the number of generations is 50 for repetition.
- Sometimes, computing time is considered a criterion to stop the algorithm.
- Sometimes, this criterion is based on the extent of the dispersion of genes within the population.

In the problem-solving approach of some algorithms, time, and in some others, a maximum number of generations is used.

For statistical analysis, we use the least significant difference method (LSD) to find significant differences (Chouhan et al. 2021, Arani et al. 2021, Dehdari Ebrahimi et al. 2017, Ahmed et al. 2020). Figure 7 shows the output of the LSD method using the MINITAB statistical software. According to the results, it can be concluded that the genetic algorithm has a better performance in a discrete state than the rest of the algorithms.

**Computational results**

After determining the optimal parameters of the algorithms, for evaluating the performance of the meta-heuristic method, the exact solution is considered. Due to the high solution time of the exact methods for large-scale problems, problem solution is not possible with the GAMS software, so the meta-heuristic method has been applied in this study. According to the complexity of solving the mathematical model by increasing the scale of the problem, calculating the optimal amount is a complicated task. Therefore, the judgment criterion is the solution of the GAMS software, which is a solution close to optimal. Table 2 shows the scale of the test problems at a small level.

Table 3 shows the results of the model solution on a small and medium scale. The first column of the table is
the problem number. The first five problems are on a small scale, and the next five are on a medium scale. According to the results obtained from the problem-solving algorithms and the GAMS software, we found that on a small scale and in most cases, the solution obtained from algorithms was better than the solution proposed by the GAMS software which shows the efficiency of the algorithms. By increasing the scale of the problem, the GAMS software cannot solve the problem at a reasonable time, but other algorithms give a near-optimal solution at a very appropriate time. As shown in Table 3, the average error is 0.7%. Also, the problem-solving time of the exact solution is significantly increased by increasing the scale of the problem, while this time for the genetic algorithm is much lower and has a lower rate, so given the above explanations, the genetic algorithm can be trusted to solve large-scale problems.

To solve the problem in large scale, there are 30 product types, 35 customers, 2 periods, 4 suppliers, 2 manufacturers, 2 distributors, and 3 recycling centers. Table 4 shows the results of a large-scale model solution. This table shows the shortage of product $j$ for the customer $q$ in the period $t$, which is the result of the variable $nhl_{jqt}$.

Table 5 shows the number of returned products $j$ in period $t$ by customer $q$. This table is the result of the variable $crp_{jpt}$.

Figure 8 shows the value of objective functions calculated by the genetic algorithm in terms of various parameters. As can be seen, the calculated values have a reasonable convergence, so we can also rely on the results of a large-scale model solution that can also be trusted.

Figure 9 shows the relationship between the rates of returned products in each period with the value of the objective function. It is evident that increasing the rate of return could increase the cost. For example, an increase in the rate of return up to 94 units has resulted in a cost of 434,418 $ and growing it to 100 units leads to result in a cost of 482,687 units.

Figure 10 shows the relationship between the service levels in each period with the value of the objective function. As it is evident, increasing service level leads to reductions in costs. For example, an increase in service level up to 1.7 units has resulted in a cost of 490,318 units, and an increase of up to 2 units leads to result in a cost of 438,789 units.

### Table 2

| No | Supplier no | Factory no | Distribution center no | Customer no | Product no | Factor multiplication |
|----|-------------|------------|------------------------|-------------|------------|-----------------------|
| 1  | 1           | 2          | 2                      | 3           | 1          | 12                    |
| 2  | 1           | 2          | 3                      | 3           | 2          | 36                    |
| 3  | 2           | 2          | 2                      | 4           | 2          | 64                    |
| 4  | 2           | 3          | 3                      | 4           | 2          | 144                   |
| 5  | 3           | 2          | 3                      | 5           | 3          | 270                   |

### Conclusion

To design an efficient supply chain network, organizations need to design an efficient transportation network. In general, the design of the supply chain network is considered one of the essential issues in the field of optimization. In this research, a closed-loop supply chain network was studied and modeled in the form of a MILP model. The objective of this study was to minimize the total costs considering a specific service level to demand, as well as considering the cost of not satisfying the total amount of demand. Therefore, demand points have a certain amount of demand that its certain level must be supplied and, in proportion to the non-satisfied amount of demand, the related cost is added to the objective function. Also, since this problem has a high computational complexity, it is categorized as NP-hard, so the genetic algorithm was used to solve the proposed model. The results of the sensitivity analysis indicated that increasing the rate of return could increase the total costs of the whole network.

One of the most important management insights that we can pinpoint for this study is that the proposed model has been solved by GA that has wide applicability to solve various large-size problems in reality. Indeed, the managers and decision-makers can get benefit by applying the proposed
methodology in their industry by minimizing costs of the supply chain network as well as decreasing the shortage of their products during transmission of goods in the network.

Therefore, the results of this research can be useful and efficient for industries such as wood and paper, petrochemical industries, and medical equipment. The main limitation of this research are as follows:

- The ARIMA time series model utilized in this study can be used for data with constant trends overall. If someone has a database without a stable trend, they cannot use the ARIMA model. In this way, it is highly suggested to use some other techniques like the Long Short-Term Memory (LSTM) to estimate demand.
The proposed model can be tested on other meta-heuristics algorithms like Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) and then compared together to find the best algorithm in terms of their performances.

Several aspects can be considered for future research, which is as follows:

- Considering the capacity constraint for inventory storage in factories, warehouses, and distribution centers,
- Considering the facility location problem for factories and distribution centers,
- Considering a variety of sales policies such as gradual discounts and incremental discounts for production costs,
- Considering the single-source state to meet demands, it means that each customer is only connected with one distribution center, and
- Fuzzification of numbers of the problem and getting closer to the real world.

**Author contribution** Shahab Safaei: conceptualization. Peiman Ghasemi: mathematical model, software, investigation, methodology. Fariba Goodarzian: data curation, writing—reviewing and editing. Mohsen Momentabar: data curation, writing—reviewing and editing.

**Availability of data and materials** The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Declarations**

**Ethical approval and competing interests** All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellec-
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