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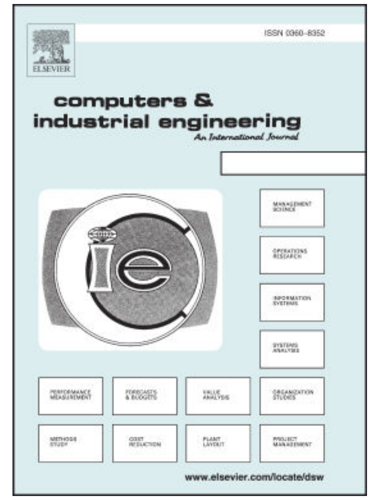

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Robust Optimization and modified genetic algorithm for a closed loop green supply chain under uncertainty: Case study in Melting Industry

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Abstract

Today, due to the increasing environmental hazards and governmental regulations, as well as the limitation of sources of production, researchers have paid special attention to the design of closed-loop green supply chain networks. The closed-loop supply chain networks (CLSCN) include the returns processes and the producers aim to capturing additional value considering further integration of all supply chain activities. Therefore, all return processes need to be optimized as well as considering environmental impacts leading to form a closed-loop green supply chain network (CLGSCN). For decision making purposes, operational and tactical decision making levels are integrated to configure a coordinated supply chain network aiming to maximize profit while keeping environmental-friendly policies. The case is more sophisticated in melting industries where the collection and categorization in return process and different environmental challenges should be considered at the same time. Thus, in this paper, a CLGSCN of a melting industry is modeled with respect to environmental hazards to optimiza overall profits. Since real-world demand in melting industry under study is uncertain, the robust optimization has been employed, and while the optimization of the proposed mathematical model is time consuming, an improved version of the genetic algorithm has been implemented as a solution method. This study has been carried out at Melting Imen Tabarestan (MIT) company in Iran. The proposed model along with the solution method are investigated in the case study. The results imply the effectiveness and applicability of the model and provide tactical considerations for the managers and practitioners.

Keywords: Robust optimization; genetic algorithm (GA); closed-loop green supply chain networks (CLGSCN).

1. Introduction

The closed loop supply chain involves designing, controlling and implementing a system to maximize the value created over the lifetime of the product, by generating a dynamic value of the various returning products over time (Govindan et al., 2015).

Reducing harmful environmental impacts was considered as a major goal in the supply chain. The carbon dioxide emission index is extensively considered to determine environmental impacts which can be used during the supply chain environmental modeling. Many indicators have also been investigated in the study of environmental impacts including energy consumption, solid waste, water consumption, and waste water. These indicators are analyzed in an article by Ahi and Searcy (2015). Borumand and Rasti-Barzoki (2019) studied greening, pricing, and advertising policies in a supply chain with government intervention. The supply chain had two elements of a manufacturer seeking to determine the wholesale price and the greening level and a retailer that has to determine the advertising cost and the retail price. Green supply chain is closely influenced by the type of production system being very significant to try to reduce the carbon impact in melting related industries.

The design of a closed loop supply chain is a problem that has attracted much attention in recent years. In general, most of the interesting researches considered single goal, which mainly involves minimizing fixed costs of launch, operation, and transportation. Also, optimization approaches employed in the literature for closed loop or green supply chains included both certain and uncertain namely, stochastic programming, robust optimization, genetic algorithm, hybrid particle swarm-genetic algorithm and other metaheuristics. A summary of the literature review is given in Table 1. In closed loop supply chain it is important to provide profit for the system while controlling costs. In the literature mostly cost managemet was targeted since in nowadays comptetive mark profit is more attractive.

Table 1. Summary of literature review

Researchers	Problem	Objective	Solution approach
Pishvaee et al. (2010)	Reverse multilateral logistics network	Minimize shipping costs and fixed setup costs	simulated annealing
Pishvaee et al. (2011)	Reverse logistics network	Minimize cost and maximize response levels	mimetic multipurpose algorithm

Alshamsi and Diabat (2015)	Reverse logistics	Minimize costs	Mathematical optimization
Pishvaee et al. (2012)	Closed loop supply chain	cost minimization	Possibilistic programming
Abdallah et al. (2012)	Closed loop supply chain	carbon emission minimization	
Amin and Zhang (2013)	closed-loop supply chain network	Facility location	Uncertain mathematical optimization
Ahi and Searcy, (2015)	green and sustainable supply chains	environmental factors	Performance measurement
Diabat and Al-Salem (2015)	integrated supply chain problem	environmental considerations	Mathematical optimization
Diabat (2016)	capacitated facility location and inventory management	Single sourcing	Mathematical optimization
Al-Salem et al. (2016)	closed-loop supply chain management problem	Cost optimization	Reformulation and piecewise linearization
Diabat and Theodorou (2015)	location–inventory supply chain problem	Cost optimization	Reformulation and piecewise linearization
Govinden et al. (2015)	Reverse logistics and closed-loop supply chain	Multiple objectives	Deterministic models
El-Sayed et al. (2010)	forward–reverse logistics	Risk optimization	stochastic model
Pishvaee et al. (2012)	green logistics	Cost optimization	Credibility-based fuzzy mathematical programming
Ramezani et al. (2013)	forward/reverse logistic network	Cost optimization	multi-objective stochastic model
Soleimani and Govindan, (2015)	closed-loop supply chain network	Cost optimization	hybrid particle swarm optimization and genetic algorithm
Santibanez-Gonzalez and Diabat (2013)	reverse supply chain	Cost optimization	improved Benders decomposition
Diabat and Deskores, 2016)	integrated supply chain	Cost optimization	hybrid genetic algorithm based heuristic
Alshamsi and Diabat, (2017)	Reverse Logistics	Cost optimization	Genetic Algorithm
Hiassat et al. (2017)	location inventory-routing problem	Routing cost	genetic algorithm
Zohal and Soleimani, (2016)	green closed-loop supply chain	Cost optimization	ant colony
Wang et al. (2016)	closed-loop supply chain	Cost optimization	cross-entropy
Kumar et al. (2014)	forward/reverse supply chain	Forecasting return products	ANFIS

Software packages like Lingo and GAMS and programming environments such as CPLEX and MATLAB were mostly used for implementing optimization approaches to obtain solutions. But, optimization software was mostly used for small echelon or scale problems (El-Sayed et al. 2010; Wang et al. 2013; Özkir and Basligil, 2013; Soleimani et al. 2013). Scenario-based planning under uncertainty was handled using decomposition techniques or exploratory algorithms. This robust modeling technique is aimed at producing feasible and optimal solutions for the worst control parameters to achieve the goals (Ramezani et al. (2013). Uncertainty is inevitable in real industrial systems specifically in the current comptetive market where systems face with various circumstances that should interact and decide so that to keep the system active and obtain economic advantages.

In summary the main focus of the reviewed past researches are listed below:

- ✓ Most of the researches considered single product closed loop supply chain but many multi-product manufacturing systems fail in configuring a comprehensive green closed loop supply chain;
- ✓ Cost optimization was a main objective function considered in past works, while in the tactical level decision making the profit is significant;
- ✓ The quality of the products was considered almost the same while in the reality the quality of products can not be same;
- ✓ Uncertainty was considered on specific parameters and not a comprehensive model based on scenarios;
- ✓ Using genetic optimization algorithm was very common in the published papers but all of them used the standard form despite different problems have various setting of parameters.

The contributions of this paper can be roughly summarized as follows:

- The concept of grading for multi-product closed loop supply chain is firstly considered.
- The model is solved by using the modified genetic algorithm. It is then updated with a robust optimization approach to obtain a faster and more reliable solution. Seriously, at the beginning of the original algorithm, a local search has been developed that can produce optimal solutions faster. In fact, the comparison between the results is expressed.
- The proposed genetic algorithm in this work is slightly different from other studies in the literature. The initial population is produced in a way that many of the constraints are met based on a heuristic generation of feasible solutions. Therefore, this can help the genetic algorithm to be more agile in iterations and generating populations.
- The goal is to maximize profits in the network having a melting process in a reverse flow. The proposed model is for a multi-level closed loop green supply chain, on the other hand, the new multi-product approach makee this study more practical.

In the next section, the problem is formulated. Section 3 explains solution approach. Section 4 presents a numerical implementation to illustrate the effectiveness of the proposed model and to analyze the results. More analysis and managerial implications are give nin Secton 5. We conclude in Section 6.

2. Statement of the problem and mathematical formulation

The problem under study consiers a closed-loop supply chain in which the reverse process triggers to collect products so that to increase the total profit. The elements in forward flow are suppliers of raw materials, manufacturers, distributors and customers. In the reverse flow collection centers, disassembly centers and disposal centers are considered. The significance is to keep environmental-friendly ploicies in all processes of the proposed closed-loop green supply chain network. The specific industrial case of melting company is considered.

The supply chain begins with the provision of raw materials from suppliers. It is assumed that all stages of production are within the organization and are carried out within the desired production centers. Finally, the products are sent to the customers. In the reverse flow of the proposed network, products purchased by customers and depreciated at their end of use stage; and the returned products due to deficiencies both are collected and transferred to disassembly centers. The inspection and separation are performed to categorize the reverse products into usable and useless. The usable products are the ones which can be reused with respect to the appropriate quality and the manufacturing level of the original product. These products are transferred to the production centers for refurbishment. The useless products are the ones that can not be used anymore and considered as wastes to be transferred to disposal centers. The case study of this paper is a melting industry that the CLGSCN and the proposed mathematical model are developed accordingly.

Melting of metals, glass, and other materials has been a vital manufacturing process for several thousand years, producing molten liquids that can be poured and solidified into useful shapes. Although the basic process continues to be the same, the utility of cast products has come a long way.

The melting of any industrial metal used in manufacturing involves the following steps:

1. Preparing the Metal and Loading – removing dirt and moisture and sometimes, preheating the charge material, such as scrap metal or ingot; and introducing solid charge into the furnace system;

2. Melting the Metal – supplying energy from combustion of fuels, electricity or other sources to raise the metal temperature above its melting point to a pouring temperature;
3. Refining and Treating Molten Metals – introducing elements or materials to purify, adjust molten bath composition to provide a specific alloy chemistry and/or affect nucleation and growth during solidification;
4. Holding Molten Metal – maintaining the molten metal in molten state until it is ready for tapping;
5. Tapping Molten Metal – transferring the molten metal from the furnace to transport ladle;
6. Transporting Molten Metal – moving the molten metal to the point of use and keeping the metal in molten state until it is completely poured.

Material and energy losses during these process steps represent inefficiencies that waste energy and increase the costs of melting operations. Modifying the design and/or operation of any step in the melting process may affect the subsequent steps. It is, therefore, important to examine the impact of all proposed modifications over the entire melting process to ensure that energy improvement in one step is not translating to energy burden in another step.
In the reverse flow, collected materials are sent to the disassembly center and then the six steps of melting are performed. The remainder is also sent to the disposal center. To kepp the environment green it is necessary to recycle the materials have more side effects on the environment with higher priority. This way, metal melting is aimed here. A configuration of the CLGSCN in a melting industry embedded with the six steps of melting process is depicted in Figure 1.

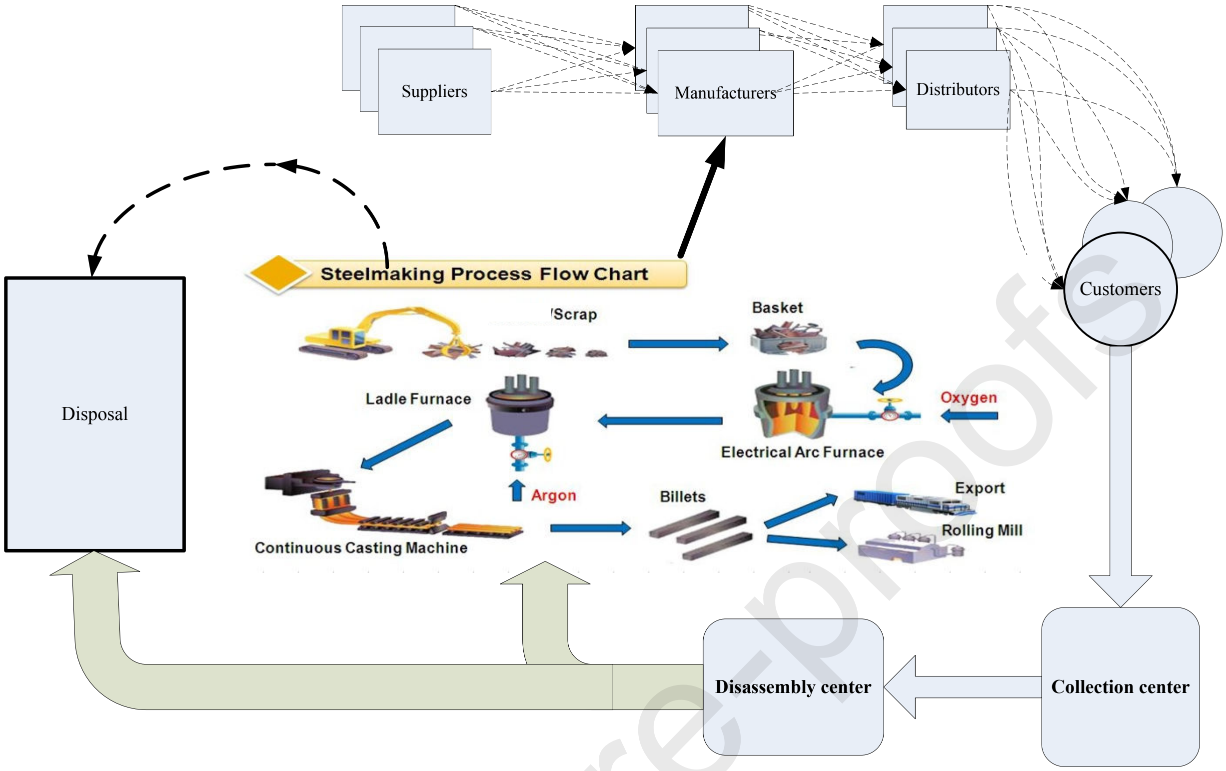

Figure 1. The configuration of the proposed CLGSC

As shown in Figure 1. The forward flow is composed of suppliers, manufacturers, distributors and finally customers that forms a supply chain network. In the reverse flow, on the other hand, in the collection center the returned products are collected and then classified, and then in the disassembly center the parts are separated and forwarded to the six step melting process. The output is sent to the manufacturing center for reprocessing. Also, the remainders are sent to disposal center.

According to the melting process in the reverse flow and the materials supplied by the suppliers in the forward flow, two types of products are produced by manufacturers namely grade 1 and 2. Grade 1 products are reffered to the one that are produced by the materials supplied by the suppliers and grade 2 are composed of materials that are inserted from the melting process in the reverse flow.

The following assumptions are considered to formulate the mathematical model:

- The customers' demands are uncertain;
- Deficiencies are not allowed;
- The location of facilities is known and fixed;
- The flow of products, parts, and materials can only occur between two successive supply chain layers. The flow of products between similar facilities is not possible;
- The operations of the proposed CLGSCN are performed under capacity constraints;
- The cost of adjusting a facility is considered as a part of its operational cost;
- The inspection and separation costs are considered at the disassembly center.

With respect to the problem definition and assumptions explained above, the mathematical notations are presented in Table 2.

Table 2. Mathematical notations of the proposed CLGSCN

Index		
M	Piece of product set	$M = 1, \ldots, m$
q	Quality set	$q = \begin{cases} 1 & \textit{Piece of product quality reusable} \\ 2 & \textit{The quality of the waste Piece of product} \end{cases}$
T	Period set	$T = 1, \ldots, t$
R	Raw material set	$R = 1, \ldots, r$
I	Suppliers set	$I = 1,\ldots,i$
D	Distributors set	$D = 1,\ldots,d$
J	Manufacturers (producerc) set	$J = 1,\ldots,j$
C	Collecting centers set	$C = 1,\ldots,c$
P	Disassembly centers set	$P = 1,\ldots,p$
F	Disposal centers set	$F = 1,\ldots,f$

L	Customers set	$L = 1,\ldots,l$

Parameters	
Pr_{rijt}	The cost of purchasing raw materials r from the supplier i for the production center j in the period t
PM_{mit}	The cost of producing a Piece of product m in the j production center during period t
HM_{jt}	The cost of assembly of the product at the j production center in the period t
opc_{kt}	Operational cost of distribution center k in period t
PB_t	The cost of purchasing a returning item from the customer at the collection centers in the period t
PC_{pt}	Operational cost of the P disassembly center during the period t for each unit of return product
PD_{ft}	The operating cost of the disposal center f for each product in period t
TC_{ijrt}	The cost of the transferring raw materials r from the supplier i to the production center j during the period t
TC_{jkt}	The cost of transferring each product unit from the production center j to the distribution center k in period t
TC_{klt}	The cost of transferring each product unit from the distribution center k to the customer l during period t
TC_{cpt}	The cost of transferring each unit of returned product from the collection center c to the disassemble center p in period t
TC_{pjmt}	The cost of transferring each Piece of product unit m from the center of disassemble p to the production center j in period t
TC_{pfmt}	The cost of transferring a unit of product m from the center of the disassemble P to the disposal center f during period t
$De1_{lt}$	Customer demand for the first grade product in the period t
$De2_{lt}$	Customer demand for the second grade product in the period t
α_{lt}	The return rate of first grade product used by the customer l in the period t
β_{lt}	The return rate of second grade product used by the customer l in the period t
μ_{mr}	The rate of using the raw material r in the Piece of product m
$QF1_{lt}$	The selling price of the first-grade product to the customer l in the period t

$QF2_{lt}$	The selling price of the second-grade product to the customer l in the period t
$BigM$	A big number
Cap_{ir}	The supplier i capacity to supply raw materials r
Cap_j	Production capacity at the production center j
Cap_k	Capacity of distribution center k
φ_t	The rate of return of reusable parts from melting process at the disassemble center in period t
γ_m	The use rate of piece m in the product
Decision variables	
X_{rijt}	The amount of raw material r delivered from the supplier i to the production center j in period t
X_{mjt}	The amount of the first-grade piece of product of type m produced at the production center j in period t
$X1_{jkt}$	The amount first-grade product produced at the production center j and shipped to the distribution center k in period t
$X2_{jkt}$	The amount second-grade product produced at the production center j is shipped to the distribution center k in period t
$X1_{klt}$	The quantity of the first-grade product that shipped from the distribution center k to customer l during period t
$X2_{klt}$	The quantity of the second-grade product that shipped from the distribution center k to customer l during period t
X_{lct}	The amount of returned product shipped from customer l to the collection center c in period t
X_{ct}	The total amount of returning product available at the collection center c that is shipped to the disassembly center in period t
X_{mpjqt}	The amount of the product m which is of $q = 1$ quality and is reusable and shipped from the center of disassembly p to the j production center during period$t$.
X_{mpfqt}	The amount of the product m, which is of $q = 2$ quality, and considered as wastes to be shipped from the center of the disassembly p to the disposal center f at period t
Y_{lc}	1, If the collection center c collect the returned product from customer l is open, otherwise
U_{kl}	1, If the distribution center k served customer l, otherwise 0

The formulations of the problem follows here.

Objective function and constraints:

$$\begin{aligned} max = \sum_{k,l,t} X1_{klt}QF1_{lt} + X2_{klt}QF2_{lt} - \sum_{r,j,i,t} X_{rijt}Pr_{rijt} - \sum_{m,j,t} X_{mjt}PM_{mit} - \sum_{j,k,t} HM_{jt}(X1_{jkt} + X2_{jkt}) \\ - \sum_{k,l,t} opc_{kt}(X1_{klt} + X2_{klt}) - \sum_{l,c,t} X_{lct}PB_t - \sum_{r,w,s,v,t} X_{ct}PC_{pt} - \sum_{p,f,m,t} PD_{ft}X_{pfmq2t} - \sum_{r,j,i,t} X_{rijt}TC_{rijt} \\ - \sum_{j,k,t} TC_{jkt}(X1_{jkt} + X2_{jkt}) - \sum_{k,l,t} TC_{klt}(X1_{klt} + X2_{klt}) - \sum_{p,c,t} X_{ct}TC_{pct} - \sum_{p,j,m,t} TC_{pjmt}X_{pjmq1t} \\ - \sum_{p,f,m,t} TC_{pfmt}X_{pfmq2t} \end{aligned} \quad (1)$$

S.t:

$$\sum_{i} X_{rijt} = \sum_{m} \mu_{mr} X_{mjt} \qquad \forall j,r,t \quad (2)$$

$$\sum_{j} X_{rijt} \le Cap_{ir} \qquad \forall r,i,t \quad (3)$$

$$\sum_{j} X1_{jkt} = \sum_{l} X1_{klt} \qquad \forall k,t \quad (4)$$

$$\sum_{j} X2_{jkt} = \sum_{l} X2_{klt} \qquad \forall k,t \quad (5)$$

$$\sum_{l} (X1_{klt} + X2_{klt}) \le Cap_k \qquad \forall k,t \quad (6)$$

$$\sum_{k} X1_{jkt}\gamma_m \le X_{mjt} \qquad \forall m,j,t \quad (7)$$

$$\sum_{k} X2_{jkt}\gamma_m \le \sum_{p} X_{pjmq1(t-1)} \qquad \forall m,j,t \quad (8)$$

$$\sum_{k} (X1_{jkt} + X2_{jkt}) \le Cap_j \qquad \forall j,t \quad (9)$$

$$\sum_{l} X1_{klt} \ge De1_{lt} \qquad \forall l,t \quad (10)$$

$$\sum_{l} X2_{klt} \ge De2_{lt} \qquad \forall l,t \quad (11)$$

$$\sum_{c} X_{lct} = (\alpha_{lt} De1_{lt}) + (\beta_{lt} De2_{lt}) \qquad \forall l,t \qquad (12)$$

$$\sum_{l} X_{lct} = X_{ct} \qquad \forall c,t \qquad (13)$$

$$\sum_{p,j} X_{pjmq1t} = \sum_{c} \varphi_t \gamma_m X_{ct} \qquad \forall m,t \qquad (14)$$

$$\sum_{p,f} X_{pfmq2t} = \sum_{c} (\varphi_t - 1) \gamma_m X_{ct} \qquad \forall m,t \qquad (15)$$

$$(X1_{klt} + X2_{klt}) \leq BigMY_{kl} \qquad \forall k,l,t \qquad (16)$$

$$X_{lct} \leq BigMU_{lc} \qquad \forall l,c,t \qquad (17)$$

$$U_{lc}, Y_{kl} \in \{0,1\} \qquad \forall k,l,c \qquad (18)$$

$$X_{ct}, X1_{klt}, X2_{klt}, X1_{jkt}, X2_{jkt}, X_{lct}, X_{pjmq1t}, X_{pfmq2t}, X_{rijt}, X_{mjt} \geq 0 \qquad \forall i,r,j,m,q,t,k,l,p,f,c,t \qquad (19)$$

The objective function (1) maximizes the total profit in the CLGSCN. The benefit is obtained by differentiating revenue and cost. Sources of revenue are the products, both grades 1 and 2, sold to customers. The total cost to the company includes operating and shipping costs.

Therefore, the operating costs incurred in each period in the forward flow are costs of purchasing raw materials, the production of grade 1, the assembly of products grades 1 and 2, as well as operating costs of distribution centers. The reverse chain requires to pay for purchasing used products from customers. Also, the cost of separating returned products, testing the quality of the separated parts that are included in the operating cost of the disassembly center and the cost of disposal of the waste parts are included in the reverse flow.

The shipping costs include the cost of transportation of raw materials, all products (grades 1 and 2) from manufacturing centers to distribution centers and from distribution centers to customers in the forward chain; transportation costs of products return from collection centers to disassembly centers, the cost of transporting reusable parts from disassembly centers being used in the melting process to production centers, and the cost of transporting waste pieces to disposal centers.

Constraint (2) emphasizes that the amount of raw materials purchased from suppliers is equal to the amount of raw materials required for the production of grade 1 products. Constraint (3) shaows that the total amount of raw material shipped from each supplier cannot exceed the supply capacity of the supplier. Constraint (4) shows that the amount of the grade 1 products produced carried from the production centers to the distribution centers is equal with the amount of the first grade products carried from the distribution centers to customers. Constraint (5) shows that the amount of grade 2 products shipped from production centers to distribution centers is equal to grade 2 products shipped from distribution centers to customers. Constraint (6) ensures that in each period, the flow of output from each distribution center does not exceed its capacity. Constraint (7) shows the number of pieces required for the production of first-grade products. Constraint (8) shows the number of pieces required for the production of second-grade products. Constraint (9) ensures that in each period, the flow of output from each production center does not exceed its production capacity. Constraint (10) ensures that a shortage is not allowed in each period for each customer for the first-grade product. Constraint (11) ensures that a shortage is not allowed in each period for each customerfor the second-grade product. Constraint (12) computes the total number of returned products of the first and second grades. Constraint (13) calculates the total number of returning products to each collection center. Constraint (14) calculates the amount of reusable parts inserted into the melting process. Constraint (15) shows the amount of waste pieces to be disposed. Constraint (16) shows that in each period, each distribution center serves the customert that is assigned to. Constraint (17) shows that in each period, each collection center can only collect returning products from each customerthat is assigned to. Constraints (18, 19) show binary variables and also indicates the integrity of the variables.

2.1. Uncertainty in the model

In the real world CLGSCN several parameters are not definite. The reasons could be, fluctuations in customers needs, material cost variations, differences in production cycle time, and etc. To achieve more realistic results, it is logical to consider uncertainty as much as possible (Qin and Ji, 2010; Pishvaee et al., 2012; Gholizadeh et al., 2018; Gholizadeh et al., 2020). To address this challenge, a robust optimization approach has been used. Mulvey et al. (1995) presented a framework for optimization that includes two important definitions of "stable response" and "solid model". That is, an answer to the optimization model is called a steady response and remain optimal under all scenarios; and it is called "solid" when a model is almost justified under all scenarios. According to these definitions, researchers have developed a robust optimization model, which is related to data sets related to different scenarios. Mulvey and Ruszczynski (1995) stated that mathematical programming models are faced with oscillatory and reliable data leading to probabilistic uncertainty. In general, in confronting with our optimization model, we have a structural part, which is constant and free of any fluctuations in the input data; and the control part having functions with uncertain data. We consider three demand scenarios and update the model accordingly. Below, the required mathematical notations for uncertain model are given and the robust counterpart mathematical model is formulated accordingly.

The robust mathematical notations are as follows:

Index	
S	Demand scenario (high, average, low) $s = 1, \ldots, S$

Parameters	
P_S	Probability of scenario s
w	Weight for the violated constraints
λ	Constant values

Decision variables	
θ_s	The linearization coefficient under the scenario s
$\delta 1_{lts}$	The amount of unsuccessful demand first-grade product in the scenario s
$\delta 2_{lts}$	The amount of unsuccessful demand second-grade product in the scenario s

$$
\begin{aligned}
max = \sum_{s} P_s \Big[& \sum_{k,l,t,s} X1_{klts} QF1_{lt} + X2_{klts} QF1_{lt} - \sum_{r,j,i,t,s} X_{rijts} Pr_{rijt} - \sum_{m,j,t,s} X_{mjts} PM_{mit} - \sum_{j,k,t,s} HM_{jt} (X1_{jkts} + X2_{jkts}) \\
& - \sum_{k,l,t,s} opc_{kt} (X1_{klts} + X2_{klts}) - \sum_{l,c,t,s} X_{lcts} PB_t - \sum_{p,c,t,s} X_{cts} PC_{pt} - \sum_{p,f,m,t,s} PD_{ft} X_{pfmq2ts} - \sum_{r,j,i,t,s} X_{rijt,s} TC_{rijt} - \sum_{j,k,t,s} \\
& TC_{jkt} (X1_{jkts} + X2_{jkts}) - \sum_{k,l,t,s} TC_{klt} (X1_{klts} + X2_{klts}) - \sum_{p,c,t,s} X_{cts} TC_{pct} - \sum_{p,j,m,t,s} TC_{pjmt} X_{pjmq1ts} - \sum_{p,f,m,t,s} TC_{pfmt} X \\
& {}_{pfmq2ts} \Big] + \lambda \sum_{s} P_s \Bigg[\Bigg(\sum_{k,l,t,s} X1_{klts} QF1_{lt} + X2_{klts} QF1_{lt} - \sum_{r,j,i,t,s} X_{rijts} Pr_{rijt} - \sum_{m,j,t,s} X_{mjts} PM_{mit} - \sum_{j,k,t,s} HM_{jt} (X1_{jkts} \\
& + X2_{jkts}) - \sum_{k,l,t,s} opc_{kt} (X1_{klts} + X2_{klts}) - \sum_{l,c,t,s} X_{lcts} PB_t - \sum_{p,c,t,s} X_{cts} PC_{pt} - \sum_{p,f,m,t,s} PD_{ft} X_{pfmq2ts} \\
& - \sum_{r,j,i,t,s} X_{rijt,s} TC_{rijt} - \sum_{j,k,t,s} TC_{jkt} (X1_{jkts} + X2_{jkts}) - \sum_{k,l,t,s} TC_{klt} (X1_{klts} + X2_{klts}) - \sum_{p,c,t,s} X_{cts} TC_{pct} - \sum_{p,j,m,t,s} TC_{pjmt} X \\
& {}_{pjmq1ts} - \sum_{p,f,m,t,s} TC_{pfmt} X_{pfmq2ts} \Bigg) - \sum_{S'} P_{s'} \Bigg(\sum_{k,l,t,S'} X1_{kltS'} QF1_{lt} + X2_{kltS'} QF1_{lt} - \sum_{r,j,i,t,S'} X_{rijtS'} Pr_{rijt} \\
& - \sum_{m,j,t,S'} X_{mjtS'} PM_{mit} - \sum_{j,k,t,S'} HM_{jt} (X1_{jktS'} + X2_{jktS'}) - \sum_{k,l,t,S'} opc_{kt} (X1_{kltS'} + X2_{kltS'}) - \sum_{l,c,t,S'} X_{lctS'} PB_t \\
& - \sum_{p,c,t,S'} X_{ctS'} PC_{pt} - \sum_{p,f,m,t,S'} PD_{ft} X_{pfmq2tS'} - \sum_{r,j,i,t,S'} X_{rijt,S'} TC_{rijt} - \sum_{j,k,t,S'} TC_{jkt} (X1_{jktS'} + X2_{jktS'}) - \sum_{k,l,t,S'} TC_{klt} (X1 \\
& {}_{kltS'} + X2_{kltS'}) - \sum_{p,c,t,S'} X_{ctS'} TC_{pct} - \sum_{p,j,m,t,S'} TC_{pjmt} X_{pjmq1tS'} - \sum_{p,f,m,t,S'} TC_{pfmt} X_{pfmq2tS'} \Bigg) + 2\theta_s \Bigg] + w \sum_{l,t,s} P_s (\delta 1_{lts} \\
& + \delta 2_{lts})
\end{aligned}
\tag{20}
$$

S.t:

$$\sum_{i} X_{rijts} = \sum_{m} \mu_{mr} X_{mjts} \qquad \forall j,r,t,s \tag{21}$$

$$\sum_{j} X_{rijts} \leq Cap_{ir} \qquad \forall r,i,t,s \tag{22}$$

$$\sum_{j} X1_{jkts} = \sum_{l} X1_{klts} \qquad \forall k,t,s \qquad (23)$$

$$\sum_{j} X2_{jkts} = \sum_{l} X2_{klts} \qquad \forall k,t,s \qquad (24)$$

$$\sum_{l} (X1_{klts} + X2_{klts}) \leq Cap_{k} \qquad \forall k,t,s \qquad (25)$$

$$\sum_{k} X1_{jkts}\gamma_{m} \leq X_{mjts} \qquad \forall m,j,t,s \qquad (26)$$

$$\sum_{k} X2_{jkts}\gamma_{m} \leq \sum_{p} X_{pjmq1(t-1)s} \qquad \forall m,j,t,s \qquad (27)$$

$$\sum_{k} (X1_{jkts} + X2_{jkts}) \leq Cap_{j} \qquad \forall j,t,s \qquad (28)$$

$$\sum_{l} X1_{klts} \geq De1_{lts} + \delta 1_{lts} \qquad \forall l,t,s \qquad (29)$$

$$\sum_{l} X2_{klts} \geq De2_{lts} + \delta 2_{lts} \qquad \forall l,t,s \qquad (30)$$

$$\sum_{c} X_{lcts} = (\alpha_{lt} De1_{lts}) + (\beta_{lt} De2_{lts}) \qquad \forall l,t,s \qquad (31)$$

$$\sum_{l} X_{lcts} = X_{cts} \qquad \forall c,t,s \qquad (32)$$

$$\sum_{p,j} X_{pjmq1ts} = \sum_{c} \varphi_{t}\gamma_{m} X_{cts} \qquad \forall m,t,s \qquad (33)$$

$$\sum_{p,f} X_{pfmq2ts} = \sum_{c} (\varphi_{t} - 1)\gamma_{m} X_{cts} \qquad \forall m,t,s \qquad (34)$$

$$(X1_{klts} + X2_{klts}) \leq BigMY_{kl} \qquad \forall k,l,t,s \qquad (35)$$

$$X_{lcts} \leq BigMU_{lc} \qquad \forall l,c,t,s \qquad (36)$$

$$\Big[\sum_{k,l,t,s} X1_{klts}QF1_{lt} + X2_{klts}QF1_{lt} - \sum_{r,j,i,t,s} X_{rijts}Pr_{rijt} - \sum_{m,j,t,s} X_{mjts}PM_{mit} - \sum_{j,k,t,s} HM_{jt}(X1_{jkts} + X2_{j}$$
$$- \sum_{l,c,t,s} X_{lcts}PB_t - \sum_{p,c,t,s} X_{cts}PC_{pt} - \sum_{p,f,m,t,s} PD_{ft}X_{pfmq2ts} - \sum_{r,j,i,t,s} X_{rijt,s}TC_{rijt} - \sum_{j,k,t}$$
$$TC_{klt}(X1_{klts} + X2_{klts}) - \sum_{p,c,t,s} X_{cts}TC_{pct} - \sum_{p,j,m,t,s} TC_{pjmt}X_{pjmq1ts} - \sum_{p,f,m,t,s} TC_{pfmt}$$
$$QF1_{lt} + X2_{klts}QF1_{lt} - \sum_{r,j,i,t,s} X_{rijts}Pr_{rijt} - \sum_{m,j,t,s} X_{mjts}PM_{mit} - \sum_{j,k,t,s} HM_{jt}(X1_{jkts} \qquad \forall s \qquad (37)$$
$$+X2_{klts}) - \sum_{l,c,t,s} X_{lcts}PB_t - \sum_{p,c,t,s} X_{cts}PC_{pt} - \sum_{p,f,m,t,s} PD_{ft}X_{pfmq2ts} - \sum_{r,j,i,t,s} X_{rijt,s}T($$
$$- \sum_{j,k,t,s} TC_{jkt}(X1_{jkts} + X2_{jkts}) - \sum_{k,l,t,s} TC_{klt}(X1_{klts} + X2_{klts}) - \sum_{p,c,t,s} X_{cts}TC_{pct} - \quad p$$
$${}_{pfmt}X_{pfmq2ts}\Big) + \theta_s\Big] \geq 0$$

$$U_{lc}, Y_{kl} \in \{0,1\} \qquad \forall k,l,c \qquad (38)$$

$$X_{cts}, X1_{klts}, X2_{klts}, X1_{jkts}, X2_{jkts}, X_{lcts}, X_{pjmq1ts}, X_{pfmq2ts}, X_{rijts}, X_{mjts} \geq 0 \qquad \forall i,r,j,m,q,t,k,l,p,f,c,t \qquad (39)$$

In the relation (20), the objective function consists of three parts, the first two are the mean and the variance of the total time of the CLGSCN;the third part measures the objective functionrobustnessconsidering uncertain values of control constraints under each scenario. Constraints (21) to (36) are similar to the ones in the definite model under different scenarios. The constraint (37) is added to the model for converting the nonlinear objective function to a linear one. And constraints (38) and (39) indicate the type of variables and the assurance of non-negativity. Since the model assumptions state that the deficiency is not allowed, the unresolved demand is $\delta 1_{lts} = 0$ *and* $\delta 2_{lts} = 0$.

To optimize such a complex multi period tobust mathematical model, while the complexity increases by adding the number of scenarios and period of times. Thus, a meta-heuristic optimization approach is required. Next, we develop a modified version of genetic algorithm as a solution approach.

3. Solution Approach

3.1. Modified Genetic Algorithm

The genetic algorithm (GA) creates an initial population for the optimization purpose. Each person is tested against a set of data, and the most suitable ones (perhaps 11% of the most suitable ones) are left out. The rest is set aside, the most suitable individuals mating together, the displacement of the DNA elements leading to random changes of DNA elements. We aim to modify the local search process of classic GA while the number of iterations influence the outputs of the optimization.

The procedure is to define an objective/fitness function, and set the GA operators (such as population size, parent/offspring ratio, selection method, number of crossovers, and mutation rate); then randomly generate the initial population, as the current parent population; next the objective function is evaluated and a new generation of an offspring is populated; the objective function is evaluated and a local search on each offspring is performed to evaluate fitness of each new location, and replace the offspring if there exists a locally improved solution (this modification is peformed on the general GA to decrease the optimization time); decide about a replacement and check the stopping criterion.

In this algorithm, the chromosome is composed of seven parts. All of these parts are composed of strings of real value in the range [0,1]. Together, they create an answer to the problem that the values of the variables and the objective function can be calculated; we now detail each of the steps proposed for the developed robust mathematical model.

Step 1: This step consists of a five-dimensional matrix measuring$[K * L * Q * T * S]$. The real numbers are in the range [0,1]. This step specifies that each customer in each period, receives the required grade 1 products from distributors.

Step 2: This step is the same as in the previous step, with the distinction being the relationship between the customer and the distributor.It consists of a matrix with dimensions $[J * K * Q * T * S]$ and the allocation method is quite similar to the first step.

Step 3: After determining the demand of production for each of the manufacturers from steps 1 and 2, the third part of the chromosome for supplying the required raw materials identifies the relationship between the producers and the suppliers of the raw materials. In this step, a matrix of $[I * J * R * T * S]$ is formed and, as in the previous steps, specifies how the material flows.

Step 4: In the fourth step, the chromosome consists of a $[L * C * T * S]$ matrix that determines how to send the returned products to the collection center.

Step 5: Once the amounts collected products in the collection centers have been determined, in the fifth step of the chromosome, sending products from the collection centers to the disassembly centers is carried out. This step consists of a matrix $[C * P * T * S]$.

Step 6: Once the materials are collected and sent to the disassembly centers, these centers divide the products into two usable (to be sent to the melting process) and useless categories. This step consists of a matrix $[P * J * T * S]$ determining how to ship recycled materials to manufacturers based on their needs.

Step 7: In this step, a chromosome with $[P * F * T * S]$ unused products is sent from disassembly centers to disposal centers.

Step 8: In the crossover process, P_n is considering as a crossover probability. Randomly, two chromosomes are selected as parents of the population. For two-parent chromosomes, a random number r is determined in the interval [0,1]. Then, the middle point of the two parents' chromosomes are changed to produce their offsprings.

Step 9: After the crossover process, we populate the population with mutation operations. In the process of mutation P_m is considered as a probability of mutation. A multi-point mutation operation is used for population renewal. For each chromosome, a random number *r* is defined in interval [0,1]. In order to mutate in each of the chromosome portions, two rows or two columns are randomly selected, and using the local search the optimal pointsbetween them are displaced, invertly.

Step 10: After selection, crossover and mutation, a new population is created. The genetic algorithm is terminated up to a maximum number of G repetitions.

The process of our proposed modified GAis depicted in Figure 2.

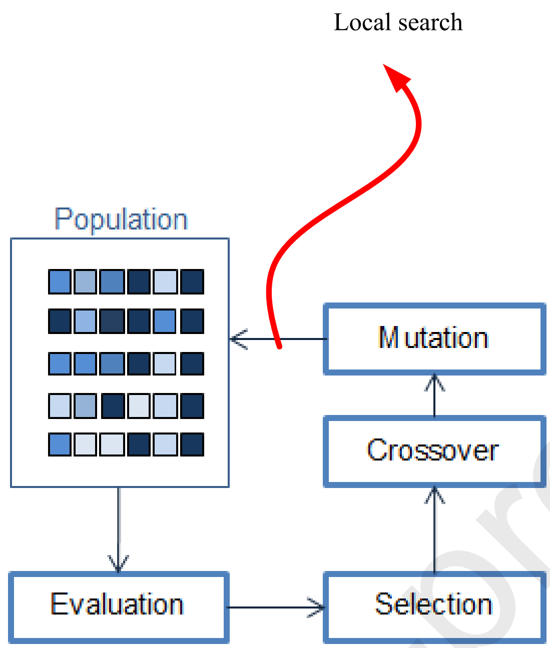

Figure 2. Overview of the Modified GA

4. Numerical case study

In this section, numerical experiments are carried out to evaluate the proposed model's behavior and solution. Solutions methods are encoded in MATLAB environment.

The melting industry (called Melting Imen Tabarestan company) , which is considered in this research, is an industrial furnace manufacturing company located in North part of Iran. Production of industrial furnaces has been widely used to supply industrial companies using casting and foundary shops. Given the demand for melting furnaces, time for delivery and recycling are especially important. At present, the company is under great pressure to recycle the materials used because of government regulations and economic benefits. We apply a scenario-based linear programming model for this closed-loop green supply chain network problem. Initially solved in small dimensions in the Lingo software; and then we solve the larger dimension with the modified genetic algorithm encoded in MATLAB environment. The genetic algorithm is developed using the MATLAB 2014 programming language. Using a 1.6 GHz computer with a capacity of 6 GB, the generated code is executed and the results are shown in the following tables. To solve large dimensions, 30 sample instances were selected and each problem was replicated 5 times and solved individually. The dimensions of the sample problems listed in Table 3.

The values of the parameters used in the model are based on the collected data from the case study that are fitted on probability distributions using the goodness of fit technique; some data are also randomly generated from the probabilityfunctions listed in Table 4and employed in each step of the modified genetic algorithm.

Table 3. Problem dimensions

Problem No	Number of suppliers	Number of manufacturers	Number of distribution centers	Number of customers	Number of collections centers	Number of disassemble centers	Number of disposing centers	Number of period	Number of piece product	Number of materials	Number of strategies
1	3	2	2	3	2	2	2	3	2	2	3
2	3	2	2	3	2	2	2	3	2	2	3
3	3	3	2	3	2	2	2	3	2	2	3
4	4	3	3	3	2	2	3	3	3	3	3
5	4	3	3	3	2	2	3	3	3	3	3
6	4	4	3	4	4	3	3	4	3	3	3
7	5	4	4	4	4	3	4	4	4	4	3
8	5	3	4	4	4	3	4	4	4	4	3
9	5	5	4	4	4	3	4	4	4	4	3
10	5	2	3	4	4	3	3	4	5	5	3
11	5	2	3	3	5	4	3	5	5	5	3
12	5	4	3	7	5	4	3	5	5	5	3
13	5	5	3	7	5	4	2	5	6	6	3
14	6	2	4	4	5	4	8	5	6	6	3
15	6	4	4	4	3	4	4	5	6	6	3

16	6	2	4	6	3	5	3	6	7	3	3
17	6	8	4	6	3	5	5	6	7	2	3
18	6	3	3	7	4	5	6	6	7	8	3
19	7	5	3	7	4	5	3	6	4	4	3
20	7	7	8	6	5	5	5	6	6	3	3
21	7	7	8	6	5	6	5	7	6	6	3
22	7	7	8	6	5	6	5	7	9	6	3
23	8	8	8	5	5	6	8	7	9	6	3
24	8	8	8	5	6	6	8	7	9	8	3
25	8	6	6	5	6	6	8	7	10	8	3
26	8	6	6	7	6	4	8	8	10	8	3
27	8	6	6	7	6	4	8	8	10	8	3
28	9	7	9	7	5	4	4	8	5	6	3
29	9	7	9	8	5	5	4	8	5	6	3
30	9	7	9	8	5	5	4	8	5	6	3

Table 4. Parameters values

Parameters	Probability distribution function
Pr_{rijt}	U[4,19]
PM_{mit}	U[32,65]
HM_{jt}	U[50,155]
opc_{kt}	U[105,185]
PB_{t}	U[85,220]
PC_{pt}	U[45,105]
PD_{ft}	U[50,110]
TC_{ijrt}	U[20,35]
TC_{jkt}	U[20,35]
TC_{klt}	U[20,33]
TC_{cpt}	U[20,33]
TC_{pjmt}	U[20,32]
TC_{pfmt}	U[20,32]
$De1_{lt}$	U[0,200]
$De2_{lt}$	U[0,100]
α_{lt}	U[0.52,0.78]
β_{lt}	U[0.28,0.56]
μ_{mr}	U[0.37,0.67]
$QF1_{lt}$	U[2000,12000]
$QF2_{lt}$	U[1950,11950]
Cap_{ir}	U[60000,120000]
Cap_{j}	U[15000,75000]
Cap_{k}	U[10000,20000]
φ_{t}	U[0.2,0.6]
γ_{m}	U[0.37,0.57]

$BigM$	U[10000,100000]
P_s	U[0,1]
λ	U[1000,10000]
w	U[0.2,0.65]

In the following experiments, we consider the number of repetitions G = 150 and pop-size = 250. In addition, we perform the algorithm based on P_n , P_m. The results are shown in Table 5. We used relative percent deviation (RPD) to compare our results.

Table 5. Results obtained from the modified GA algorithm and Lingo

Problem No.	P_c	P_m	**Modified GA objective function**	**Elapsed time**	**RPD**	**objective function Lingo**	**Elapsed time Lingo**
1	0.9	0.1	10225622	109.3354	0.0471	11005413	1
2	0.9	0.1	11366666	111.9889	0.007	10363216	1
3	0.9	0.1	15561965	112.5743	0.1132	15344758	1
4	0.9	0.1	20438669	113.1315	0.0381	20483956	2
5	0.9	0.1	15911009	128.5515	0.2351	16050510	7
6	0.9	0.1	29796618	122.1124	0.0849	28996989	5
7	0.9	0.1	21563661	136.0714	0.4116	20668679	41
8	0.9	0.1	22010916	134.3176	0.066	22790123	32
9	0.9	0.1	24985003	141.5507	0.0195	23998908	38
10	0.9	0.1	15807592	239.3354	0.2742	14999575	279
11	0.9	0.1	114874615	385.3631	0.05	106452114	307.5
12	0.9	0.1	117178746	405.1270	0.044	110167849	409.531
13	0.9	0.1	103721244	493.9971	0.0121	102725266	592.4571
14	0.9	0.1	103751814	585.3685	0.0955	102891418	643.2241
15	0.9	0.1	108934385	604.1986	0.02	113925483	623.4512
16	0.9	0.1	112178223	584.5906	0.0435	109173224	598.6574
17	0.9	0.1	118857453	657.2647	0.0421	105485326	689.5785
18	0.9	0.1	109827650	631.3870	0.0031	101817560	687.5421
19	0.9	0.1	128224137	664.5361	0.0041	115143714	712.1435
20	0.9	0.1	125731184	6612.794	0.0331	-	-
21	0.9	0.1	120771813	6802.066	0.0096	-	-
22	0.9	0.1	120516772	6543.759	0.2048	-	-
23	0.9	0.1	125489941	6541.040	0.0071	-	-
24	0.9	0.1	132010034	6627.233	0.0198	-	-
25	0.9	0.1	135226526	6793.165	0.0358	-	-
26	0.9	0.1	133784253	6871.449	0.0146	-	-
27	0.9	0.1	126342144	6827.041	0.0151	-	-
28	0.9	0.1	131081973	6908.552	0.0229	-	-

29	0.9	0.1	138118163	6972.706	0.0271	-	-
30	0.9	0.1	128224137	7049.317	0.0111	-	-

According to Table 5, in the evaluation of the first nineteen instances, the exact solution was obtained by LINGO. The exact solution time of LINGO and the outcomes of modified GA are compared in Figure 3. The results show that the solutions of the proposed modified GA are close to the exact solution of the problem. Therefore, the modified GA is appropriate to provide efficient solutions.

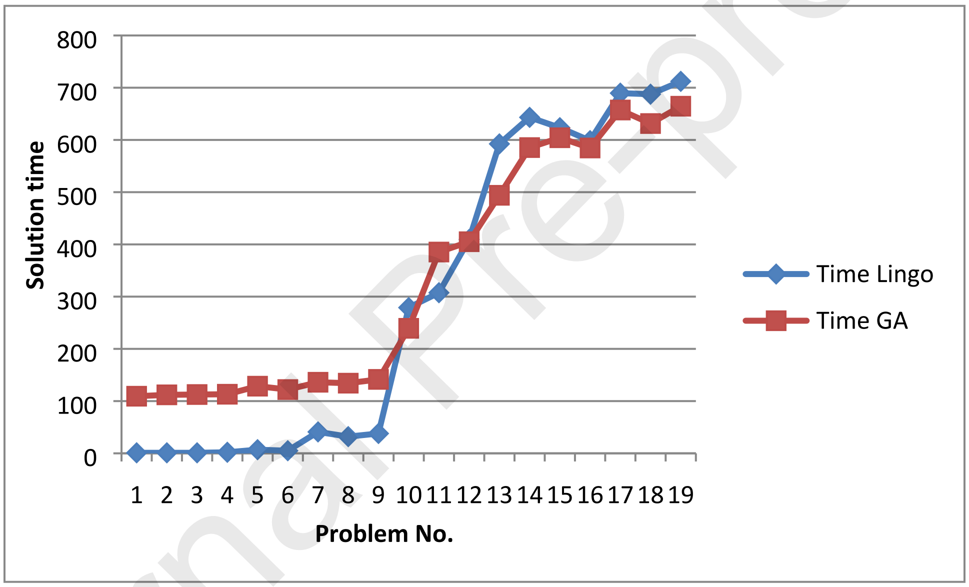

Figure 3: Comparing the Solution Time in LINGO and Modified Genetic Algorithm

According to Figure 4, in evaluating the the first 9 instances, the time needed to provide a solution has increased significantly, even beyond the modified genetic algorithm. But from the ninth instance onwards, the solution time of the modified genetic algorithm has increased. In the evaluation of the ninth and later samples, the criteria for stopping the modified genetic algorithm from 150 to 170 were modified.

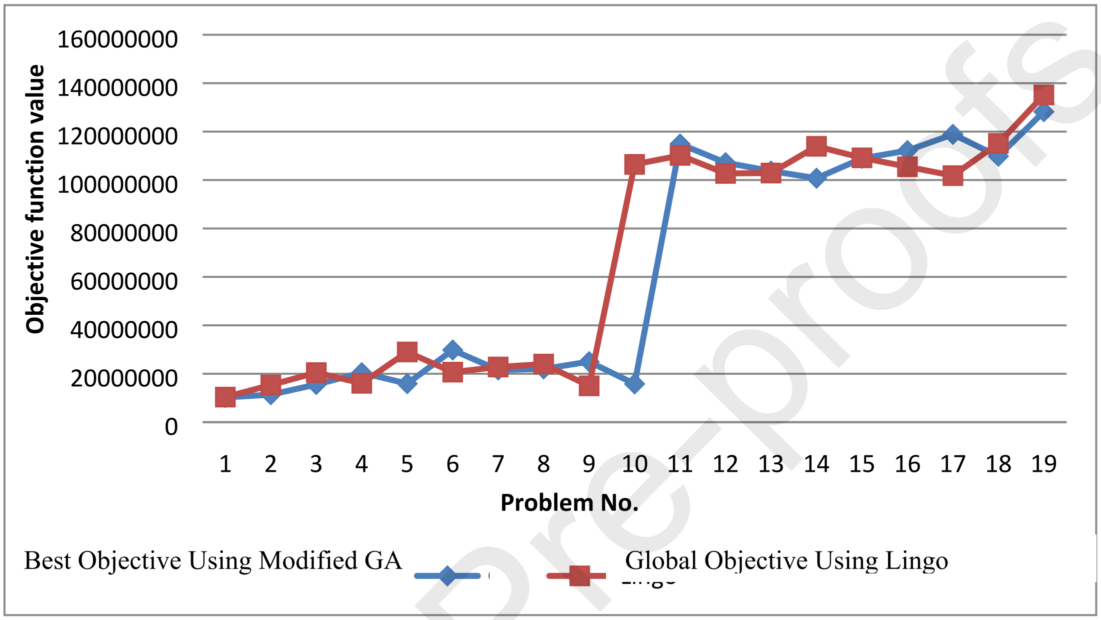

Figure 4: Objective value comparison between LINGO and GA

Meanwhile, the time required for the modified GA is increased to provide a much better and more resonable solution than LINGO. From sample nineteen to thirteen, no precise solution has been provided by LINGO in about 1200 seconds. However, the proposed modified genetic algorithm obtained solutions in less than two hours. These results are shown in Table 5. Items 19 to 30 have larger dimensions and their solutions are shown in Table 5.

Compared to the optimal objective value obtained by Lingo software, the desired value obtained from the modified genetic algorithm can be considered as an optimal optimum value. As can be seen, the proposed modified GA is applied with a scenario-driven optimization model to maximize the total profit of the closed-loop green supply chain. Based on the numerical examples and results, the modified GA is an efficient approach for optimization of the problem. Thus, the outputs of the proposed modified GA are efficient in comparison to the exact solutions. Also, the modified GA is effective for obtaining solution of larger sized problems. The solution time of the modified GA is very satisfactory for different problem sizes.

5. Analysis and managerial implications

In this section analyses are performed to investigate the efficiency of the proposed modified GA. As explained in Section 1, in past researches classic GA was used to optimize a CLGSCN. Therefore, we modified the classic GA to strengthen its performance. Nonetheless, the best comparison would be between classic GA and our modified GA to investigate the efficiency. Two dimensions of solution time and objective function value are considered for comparison purposes. Also, it should be note that our proposed modified GA performs very close to the exact method in small size problems and outperforms the exact method for larger sizes since exact method could not obtain the results in reasonable time. Here, the developed robust mathematical formulation is implemented using classic GA. It should be note that the setting and other require data were exactly as modified GA. The results are shown in Table 6.

Table 6. Comparison between classic GA and modified GA

Problem No.	P_c	P_m	Modified GA objective function	Elapsed time	Classic GA Objective function	Elapsed time
1	0.9	0.1	10225622	109.3354	10125622	111.5364
2	0.9	0.1	11366666	111.9889	11335341	113.7889
3	0.9	0.1	15561965	112.5743	14678695	113.6787
4	0.9	0.1	20438669	113.1315	19235512	115.2367
5	0.9	0.1	15911009	128.5515	15815321	129.7756
6	0.9	0.1	29796618	122.1124	28654512	124.2143
7	0.9	0.1	21563661	136.0714	20432521	138.9845
8	0.9	0.1	22010916	134.3176	21820715	136.7649
9	0.9	0.1	24985003	141.5507	23768992	144.7689
10	0.9	0.1	15807592	239.3354	14987571	242.5693
11	0.9	0.1	114874615	385.3631	10875214	389.6798
12	0.9	0.1	117178746	405.1270	109788766	410.6523
13	0.9	0.1	103721244	493.9971	102625354	498.7736
14	0.9	0.1	103751814	585.3685	102641734	591.7864
15	0.9	0.1	108934385	604.1986	107835487	611.3569
16	0.9	0.1	112178223	584.5906	111098723	597.8923
17	0.9	0.1	118857453	657.2647	117937763	664.8741
18	0.9	0.1	109827650	631.3870	108937762	638.6893
19	0.9	0.1	128224137	664.5361	128224137	672.9635
20	0.9	0.1	125731184	6612.794	124821475	6731.528
21	0.9	0.1	120771813	6802.066	119861923	6915.266
22	0.9	0.1	120516772	6543.759	119546891	6725.371
23	0.9	0.1	125489941	6541.040	124569762	6638.075
24	0.9	0.1	132010034	6627.233	131923078	6711.466
25	0.9	0.1	135226526	6793.165	134678789	6862.315
26	0.9	0.1	133784253	6871.449	132894567	6964.772
27	0.9	0.1	126342144	6827.041	125678435	6973.347
28	0.9	0.1	131081973	6908.552	130976870	7082.223
29	0.9	0.1	138118163	6972.706	137896254	7190.512
30	0.9	0.1	128224137	7049.317	127657234	7279.559

To analyze the differences, objective valuaes of both aalgorithms are depicted in Figure 5. It is clear that the objective function values of the modified GA outperforms the classic GA specifically in larger size problems. It is necessary to emphazie that in maximixation problem the objective value is the more the better. This performance is due to the activation of the local search inserted in the GA where it finds better initial solution for the replications of GA operators.

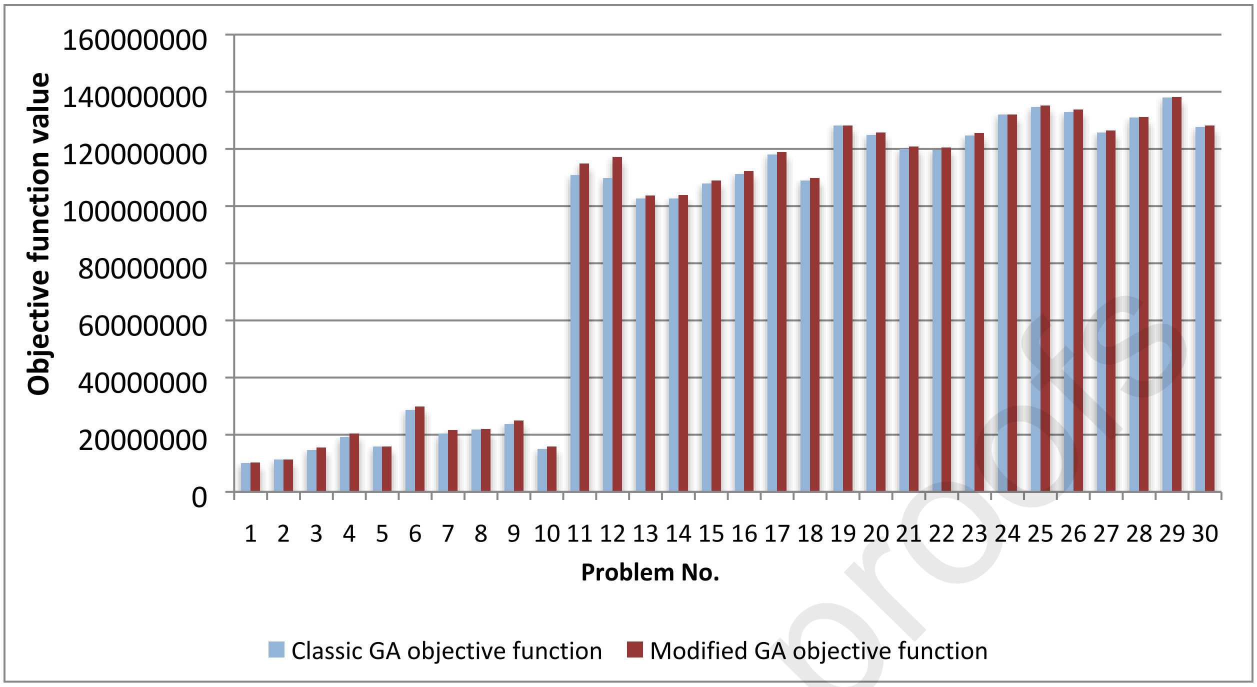

Figure 5. Comparison of objective function values- classic GA versus modified GA

Another analysis is performed on the solution times of the two algorithms. The comparsion of solution time is shown in Figure 6. In small size problems the solution times are almost similar but for larger sizes the modified GA solves the problems in less time (consider the dashed curve). It is due to the omission of extra solutions via local search since the population size deacreases and the solution time is reduced.

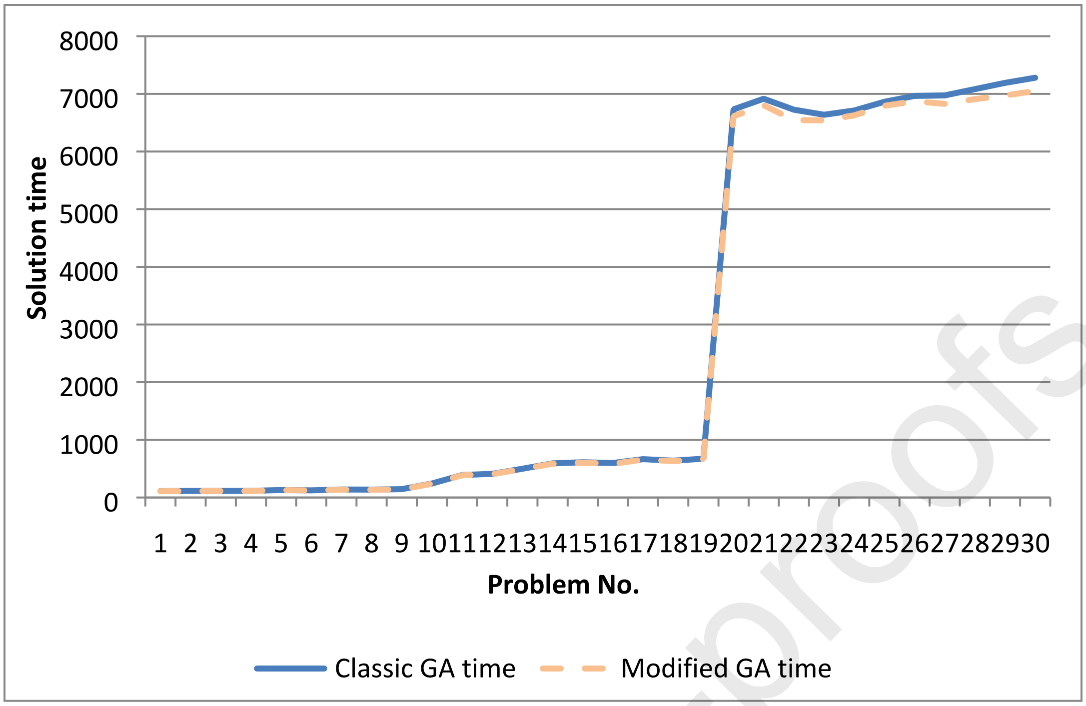

Figure 6. Comparison of solution time- classic GA versus modified GA

These comparisons show the efficiency of the modified GA being effective on tactical decisions of the proposed CLGSCN. Managers and policy makers need to know the amounts of decision variables and also the output of different scenarios in both economic and timely aspects. It is necessary to handle the operational decisions so that minimum environmental side effects are incurred to the CLGSCN.

Managers will be benefited by the outputs of the model. Since uncertainty is inavoidable in melting industry, then it is necessary to be prepare to encounter different scenarios in production system. In some circumstances, interaction among scenarios is important. Consider, demand reduction, raw material costs increase, and operator dismiss occur at the same time. Then, the manager needs to know which grade of product and to what amount to produce and with which price to maximiza the revenues while at the same time the overall costs are rising. Due to the velocity of the fluctuations athe level of dynamism is also changed leading to essense of rapid decisions to keep existing in the competitive market. Another decision being based on the conditions, is applying reusable material in grade 2 products which is inevitable to expand markets to a low income market.

6. Conclusions

In this paper, the closed loop green supply chain has been studied as a very challenging issue in the contemporary world. Based on literature research gap, a closed-loop green supply chain with different grades extracted from a melting process in a reverse flow were investigated. Scenario based demand planning was considered to handle uncertainty of the model. Modeling emphasizes high profitability due to uncertainty in demand. To investigate various issues in this field, a robust optimization approach was used and embedded with a modified GA as an optimization approach. In order to prove the strength and convergence of GA, the proposed model was encoded and implemented in the LINGO 15.0 package and the results were compared with the proposed modified GA in small size problems. According to the results, the convergence of the proposed algorithm was proved to guarantee accuracy. As for future research, measuring the reliability of parts and products is suggested. In pricing, we can use various pricing strategies, including the game theory. Discount policies can be studied in the purchase of raw materials and products.

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The first author developed the mathematical model and optimization approach and also the related solution approach and additional discussions;

The second author worked on the uncertain model, literature review classification and related numerical analysis of the results.

All two authors worked on the writing, editing, preparing figures and tables.

Highlights

• Show how data are produced, captured, organized and analyzed in modifications and redesign for a closed loop green supply chain

• Highlight the impact of uncertainty and its application in robust optimization and genetic algorithm.

• Provide insights to industries Melting Imen Tabarestan (MIT) Company.

• We perform a sensitivity analysis to justify the robust optimization and genetic algorithm.