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Multi-objective robust optimization model for social responsible closed-loop supply chain solved by non-dominated sorting genetic algorithm

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Abstract

In this article a supply chain network design model has been developed considering both forward and reverse flows through the supply chain. Total Cost, environmental factors such as CO_2 emission, and social factors such as employment and fairness in providing job opportunities are considered in three separate objective functions. The model seeks to optimize the facility location problem along with determining network flows, type of technology, and capacity of manufacturers. Since the customer's demand is tainted with high degree of uncertainty, a robust optimization approach is proposed to deal with this important issue. An efficient genetic algorithm is applied to determine the Pareto optimal solutions. Finally, a case study is conducted on a steel industry to evaluate the efficiency of the developed model and its solution algorithm.

Keywords: supply chain; reverse logistic; social responsibility; robust optimization; multi-objective genetic algorithm.

1-Introduction

Closed loop supply chain problems consider facility location and allocation along with forward and reverse flows of materials and goods are optimized. Forward logistics investigate all the processes for delivering goods to the end customers. On the other hand, reverse logistics is related to the processes of gathering used products and making decision about recycling or discarding them. There is another case in which both forward and reverse flows are being considered simultaneously.

In the last two decades, design of logistic networks considering both forward and reverse flows has grown due to resource constrains, increased costs and consequences of utilizing new products instead of used products on environment. A rise in environmental contamination challenges such as greenhouse gases emission, necessity to consider human rights and collecting of returned products have encouraged governments to consider determining new controlling rules and as a result, different standards such as ISO 26000 (2006) have been developed. Standard ISO 26000 considers social responsibility concepts and issues, and provides an approach to integrate social responsibility with solutions, systems and current organizational activities.

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In real world, insufficiencies and inaccuracies in data can result uncertainties in designing an appropriate supply chain. To cope with uncertainties, robust programming approach has taken into consideration, since mean value of variables or other common approaches in literature do not provide a suitable representative of real world (Mulvey et al., 1995).

In most of the articles related to supply chain design, only profits and costs have considered to be optimized. Growing concern on environmental issues such as greenhouse gases emission and global warmth on one hand, and considering social responsibility issues in organizations, standards like ISO 26000 and other government disciplines on the other hand have influenced organizations to consider environmental issues and social responsibilities such as creating job opportunities and social development along with minimizing costs.

In this paper, a mixed integer programming model have been developed for supply chain design considering forward and reverse flows and factors such as social, economic and environmental issues. In addition, robust programming approach proposed by Mulvey et al. (1995) has been applied due to demand uncertainty. Apart from that a multi-objective genetic algorithm has been developed to solve the model and extract Pareto frontier.

The rest of the paper has been organized as follows. The literature of the scope has been reviewed in section 2. Robust optimization is described in section 3. Problem definition and mathematical modeling for deterministic and non-deterministic conditions are included in sections 4 and 5. The description of solution method is presented in section 6 and section 7 contains application of model on a real case. Finally, concluding remarks are given in section 8.

2- Literature review

2-1- Proposed supply chain models considering forward and reverse flows

Fleischmann et al. (2001) proposed a general facility locating problem which was one of the pioneer studies to consider forward and reverse flow at the same time. Sim et al. (2004) developed a multi-product, multi-period model with constraints in numbers and capacities of facilities. In their work, different transportation modes like marine transportation, road transportation, air and train transportation was considered and the model was solved with genetic algorithm.

Salema et al. (2005) also developed a supply chain model considering forward and reverse logistics. They have considered two periods. Decision making for facility locations happens in longer period and network flows decision making has been considered in short period. Their mathematical model was solved with branch and bound algorithm and a scenario-based approach was applied to include uncertainty. Salema et al. (2007) provided uncertainty of demand and return rate in their model using scenario generation, too.

Ko and Evans (2007) presented a mixed integer non-linear programming model for third party organizations and utilized genetic algorithm to solve the model. Lee and Dong (2007) addressed a two stage solution method and a tabu search meta-heuristic approach to deal with forward and reverse flows of computer products supply chain. Wang et al., (2010) developed a model for forward/ reverse logistics and applied a genetic algorithm based on spanning tree approach to solve the model.

Pishvaee et al. (2009) proposed a scenario based optimization model for closed loop supply chain design. In their work, demand, transportation costs, numbers of returned products, and quality of returned products were considered as uncertain parameters. Easwaran and Üster (2010) presented a model for closed loop supply chain and used Benders' decomposition method to solve it. El-Sayed et al. (2010) developed a multi- product multi-echelon multi-period model. They also included risk in their study.

Pishvaee and torabi (2010) addressed a fuzzy bi-objective mixed integer programming model with objective functions of cost minimization and customer response maximization for a supply chain design. The model was solved with a possibilistic fuzzy approach. In another study by Pishvaee et al. (2010) a bi-objective model was developed and solved with a heuristic algorithm. A robust programming approach was applied for forward and reverse flow logistics by Pishvaee et al. (2011) for the first time.

Das and Chowdhury (2012) developed a model for closed loop supply chain. They assumed that collected products have different quality levels and returned products can be recycled. Özkır and Başlıgil (2012) presented a mixed integer programming model for closed supply chain design and determined three options for recycling returned products; material recycling, component recycling, and product recycling.

Vahdani et al. (2013) developed a novel model considering reliability for closed loop network design. They considered failure probability for each collection center and used robust optimization model and queuing theory to cope with uncertainty. Hassani et al. (2012) addressed a supply chain design with uncertainty in demand and also purchasing costs. They considered robust programming approach and used Bill of Material (BOM) for new and returned products. Rosa et al. (2013) developed a robust model to minimize the regret of different scenarios and included uncertainty by log-normal distribution. They also considered three categories of small, medium and large warehouses and determined their optimum capacity.

Özkır and Başlıgil (2013) presented a multi-objective model for maximizing satisfaction level of trade, customer response, and profit. They used fuzzy numbers to include uncertain parameters in their model.

Ramezani et al. (2013a) developed a model for supply chain design to optimize forward and reverse flows. They defined three objective functions to optimize the profit, the service level both in forward and reverse logistics, and poor quality materials sent from supplier. Ramezani et al. (2013b) also developed another single objective model and used minimizing the maximum regret level rather than taking the average of different scenarios. They also introduced an algorithm to create different scenarios.

Subramanian et al. (2013) presented a mixed integer programming model to determine optimum locations of plants, distribution centers, recycling centers and disposal centers, and to optimize material flows among these facilities. They used simulated annealing meta-heuristic approach to solve their model.

Keyvanshokooh et al. (2013) considered both pricing and forward and reverse supply chain design and in their model, each customer decided about returning used products based on the proposed price. They also assumed that the products can be transferred inside one echelon of supply chain. The studies which considered environmental and social issues are investigated in the following as well.

2-2- Papers considering environmental issues

Amin and Zhang (2013) presented a multi-product bi-objective model considering cost and use of environmental friendly material in a closed loop supply chain. They employed weighted sum method and ε-constraint method to solve their model. Pishvaee and Razmi (2013) addressed a fuzzy programming model and considered environmental effects as their second objective function. Wang et al. (2012) developed a multi-objective model for minimizing cost, CO_2 emission and waste. The model was also proposed to determine optimum locations of plant of new and remanufactured products, distribution centers, and recycling centers along with optimum flows among facilities.

2-3- Papers considering social issues

Cartend and Jennings (2002) surveyed social effects of purchasing on supply chain performance and showed that the purchasing based on social criteria has direct and positive impacts on suppliers performance. They did not include a mathematical model in their study. Cruz and Wakolbinger (2008) and Cruz (2009) proposed a theoretical framework to model and analyze supply chain network according to multi-criteria decision making approach. Dehghanian and Mansour (2009) developed a model for forward and reverse supply chain and included three objective functions to consider cost, environmental contamination and social criteria such job opportunities, local development, product risk, and hazardous work conditions. Their model was solved with multi-objective genetic algorithm. Pishvaee et al. (2012) proposed a robust model for forward supply chain. They considered some social criteria such as employment rate, job opportunities development, waste rate, and hazardous products rate received to customers.

Literature review indicates that there are not many works which consider cost functions, social effects and environmental effects simultaneously and under uncertainty conditions. There are also a few works that consider technology selection criterion and variable capacities for facilities. In literature surveyed here, variable capacity for facilities along with different technologies availability is not assumed. There is also no work to consider fairness in providing job opportunities.

In this study, a model is developed for forward and reverse supply chain considering objective functions of costs, environmental effects such as CO_2 emission quantity, social effects such as job opportunities and fairness in developing job opportunities. In this regard, it has been assumed that by opening facilities with low capacities but in different spots, it is possible to provide fairness in job opportunities and maximize network security. In addition, demand is assumed to be uncertain and robust programming approach is employed to handle this uncertainty. Also other than optimum location of facilities and flows among them as a manifest of such models, technology type and capacity of facilities are determined, too. Finally, a multi-objective genetic algorithm combined with a linear solver is developed for proposed model and is implemented in order to extract non-dominated solutions of a case study in steel industry.

3- Robust optimization

Mulvey et al. (1995) proposed a new robust programming model considering different discrete scenarios. Their approach is described as follows.

$$MinC\text{^}T\ x + d\text{^}T\ y \quad (1)$$

$$s.t$$

$$Ax = b \quad (2)$$

$$Bx + Cy = e \quad (3)$$

$$x, y \geq 0 \quad (4)$$

Equation (2) stands for deterministic parameters and (x, y) is defined as the vector of design and controlling decision variables. b and d are random technology coefficients matrixes and e represents right hand side vector. Ω is indicative of different scenarios and is defined as $\Omega = \{1,2,..,s\}$. Probability of each scenario is p_S and we assume that$(\sum_s p_s = 1)$. $\{z_1, z_2, \dots z_s\}$ is the set of error variables which show infeasibility degrees for infeasible constraints. So, the model developed by Mulvey et al. (1995) turns to be as follows.

$$min \quad \sigma(y_1, y_2, \dots y_s) + \omega\rho(z_1, z_2, \dots z_s) \quad (5)$$

$$s.t$$

$$Ax = b \quad (6)$$

$$B_S x + C_S y_S + z_S = e_S \quad for\ all\ s\epsilon\Omega \quad (7)$$

$$x\ , y_S, z_S \geq 0 \qquad for\ all\ s\epsilon\Omega \quad (8)$$

We represent uncertain parameters$B$, C, e as B_s, C_s, e_s for each scenario $s\epsilon\Omega$. Γ is the cost or profit function and is shown by $f(x, y)$ and for different scenarios it is defined as $\Gamma_s = f(x, y_s)$. The more the variance of$\Gamma_s = f(x, y_s)$, the more the risky will be decision making. This is shown in Mulvey et al. (1995) as follows.

$$\sigma(0) = \sum_{s\epsilon\Omega} p_s\Gamma_s + \lambda \sum_{s\epsilon\Omega} p_s\, (\Gamma_s - \sum_{s\epsilon\Omega} p_s\Gamma_s)^2 \quad (9)$$

Where λ is the weight given by decision maker for robust counterpart of the model. Yu and Li (2000) considered another approach to obtain standard deviation of solutions that is shown by:

$$\sigma(0) = \sum_{s\epsilon\Omega} p_s\Gamma_s + \lambda \sum_{s\epsilon\Omega} p_s\, |\Gamma_s - \sum_{s\epsilon\Omega} p_s\Gamma_s| \quad (10)$$

Since the objective function is nonlinear, it can be changed to linear form by hypothesis proposed by Yu and Li (2000).

$$Min\ \ \sigma(0) = \sum_{s\epsilon\Omega} p_s\Gamma_s + \lambda \sum_{s\epsilon\Omega} p_s\, [(\Gamma_s - \sum_{s\epsilon\Omega} p_s\Gamma_s) + 2\theta_s] \quad (11)$$

$$(\Gamma_s - \sum_{s\epsilon\Omega} p_s\Gamma_s) + \theta_s \geq 0 \qquad \forall\ s\epsilon\Omega \quad (12)$$

$$\theta_s \geq 0 \qquad \forall\ s\epsilon\Omega \quad (13)$$

$\sum_{s\epsilon\Omega} p_s\delta_s$ is the penalty of objective function of model (11) and is used for situations where some of the scenarios are infeasible. λ, ω are weights which are determined by decision maker as well. Finally, the objective function is summarized as follows.

$$Min\ \ \sigma(0) = \sum_{s\epsilon\Omega} p_s\Gamma_s + \lambda \sum_{s\epsilon\Omega} p_s \left[(\Gamma_s - \sum_{s\epsilon\Omega} p_s\Gamma_s) + 2\theta_s\right] + \omega \sum_{s\epsilon\Omega} p_s\delta_s \qquad (14)$$

4- Problem definition

In this study, we represent a network with three kinds of facilities containing plants for producing initial and final products and distribution centers for forward logistic, and collection centers that are considered in reverse flow direction. Manufacturers of initial products supply a part of their raw materials from collection centers and the rest is purchased. The initial products follow their way to final products manufacturing plants and different products are produced and sent to distributors to reach end customers. These products are returned to collection centers after their life cycle. The wastes of manufacturing plants are also gathered in collection centers to be used for new products. Objective functions are designed to locate facilities optimally, optimize network flows, select technology type and determine plants capacity. This network is depicted in Figure (1) which is typical for industries like steel industries.

Model assumptions
- Manufacturing plants for initial products have different capacities with different technologies.
- Raw material is assumed to be infinite.
- Quality of collected products from different spots is the same.
- There is only one product in the network and is considered for one period.
- Manufacturing plants and customers locations are fixed are predefined.
- Demand is nondeterministic and is modeled through different scenarios.
- Facilities capacity is finite and deterministic.
- Manufacturing plants for initial products produce only one type of product.
- The percent of returned products and wastes is determined for final manufacturing plants.
- Network flows' capacity is considered to be infinite.
- For considering CO_2 emission and job opportunities in the model, it is assumed that the objective is to minimize total gas emissions and maximize total job opportunities in a geographical area.

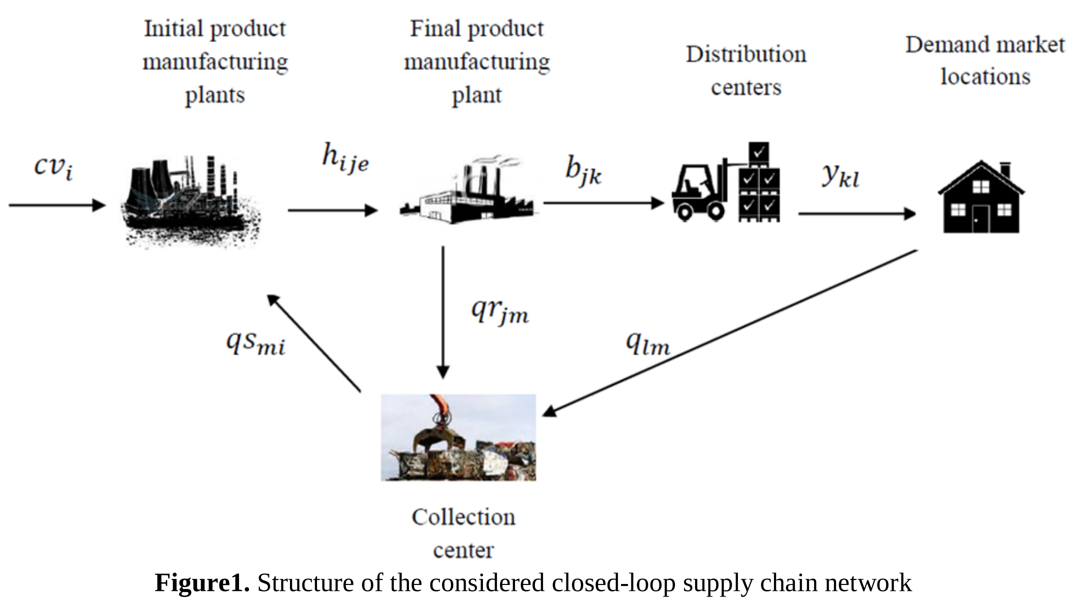

Figure1. Structure of the considered closed-loop supply chain network

5- Model description

The following notation is used in the formulation of the presented model.

Indices

i	index of potential locations of initial products manufacturing plants
j	index of fixed locations of converting raw materials to final products
k	index of potential distribution centers
l	index of fixed demand market locations
m	index of potential collection centers

Parameters

FX_i^{ce}	fixed cost of manufacturing initial product i using technology e with capacity c
g_k	fixed cost of opening distribution center k
o_m	fixed cost of opening collection center m
CX_i^c	capacity of initial product manufacturing plant with capacity level c
CY_j	capacity of final product manufacturing plant j
CZ_k	capacity of distribution center k
CW_m	capacity of collection center m
v_{ab}	distance between facilities a, b
pc_i^{ec}	cost of manufacturing initial products in plant i with capacity c and technology e
jc_j	cost of manufacturing final product in plant j
CY_j	capacity of final product manufacturing plant j
kc_k	operational cost of each product in distribution center k
mc_m	operational cost of each product in collection center m
μ	transportation cost of each unit product per kilometer
en_e	environmental effects of manufacturing each initial product using technology e
ρ	environmental effect of transportation of each product per kilometer
wc_e	water consumption for manufacturing each initial product using technology e
β	number of opened plants
r_j	production rate of final manufacturing plant j
d_l	demand quantity in demand market l
f_l	return rate of products in demand market l
jo_i^{ec}	number of job opportunities developed if plant is located at spot i with capacity c and technology e
jd_k	number of job opportunities developed if distribution center is located at spot k
jm_m	number of job opportunities developed if collection center is located at spot m

Variables

x_i^{ec}	if initial manufacturing plant is located in spot i with capacity c using technology e ,1 and otherwise 0
z_k	if distribution center is located in spot k ,1 and otherwise 0
w_m	If collection center is located in spot m ,1 and otherwise 0
cv_i	quantity of raw material received by initial product manufacturing plant i
h_{ije}	product quantity shipped by initial product manufacturing plant i to final product manufacturing plant j using technology e
b_{jk}	product quantity shipped from final product manufacturing plant j to distribution center k
y_{kl}	product quantity shipped from distribution center k to demand market l
q_{lm}	product quantity shipped from demand market l to collection center m
qs_{mi}	product quantity shipped from collection center m to initial product manufacturing plant i
qr_{jm}	product quantity shipped from manufacturing plant j to collection center m

5-1- Deterministic model

$$Min\ z_1 = \sum_e \sum_i \sum_C FX_i^{ce} x_i^{ec} + \sum_k g_k\, z_k + \sum_m o_m\, w_m + \sum_i \sum_e \sum_c \sum_j pc_i^{ec}\, h_{ije} + \sum_i \sum_j \sum_e v_{ij}\mu\, h_{ije} + \sum_j \sum_k (v_{jk}\mu + jc_j)\, b_{jk} + \sum_k \sum_l (v_{kl}\mu + kc_k) y_{kl} + \sum_l \sum_m v_{lm}\mu\, q_{lm} + \sum_j \sum_m (v_{jm}\mu)\, qr_{jm} + \sum_m \sum_i (v_{mi}\, \mu + mc_m) qs_{mi} \quad (15)$$

$$Min\ \ z_2 = \sum_i \sum_j \sum_e h_{ije} en_e + \sum_i \sum_j \sum_e v_{ij}\rho\, h_{ije} + \sum_j \sum_k v_{jk}\rho\, b_{jk} + \sum_k \sum_l v_{kl}\rho y_{kl} + \sum_l \sum_m v_{lm}\rho\, q_{lm} + \sum_j \sum_m v_{jm}\rho\, qr_{jm} + \sum_m \sum_i v_{mi}\, \rho qs_{mi} \quad (16)$$

$$Max\ z_3^1 = \beta \quad (17)$$

$$Max\ z_3^2 = \sum_i \sum_e \sum_c jo_i^{ec}\, x_i^{ec} + \sum_k jd_k z_k + \sum_m jm_m w_m \quad (18)$$

$$\beta = \sum_e \sum_i \sum_c x_i^{ce} \quad (19)$$

$$\sum_k y_{kl} = d_l \ \ \forall l \quad (20)$$

$$\sum_m q_{lm} = y_{kl} * f_l \ \ \forall l \quad (21)$$

$$\sum_j b_{jk} = \sum_l y_{kl} \quad \forall k \quad (22)$$

$$(1 - r_j) \sum_i \sum_e h_{ije} = \sum_m qr_{jm} \quad \forall j \quad (23)$$

$$r_j \sum_i \sum_e h_{ije} = \sum_k b_{jk} \ \ \forall j \quad (24)$$

$$\sum_m qs_{mi} + cv_i = \sum_j \sum_e h_{ije} \quad \forall I \quad (25)$$

$$\sum_i qs_{mi} = \sum_j qr_{jm} + \sum_l q_{lm} \quad \forall m \quad (26)$$

$$\sum_j h_{ije} \leq \sum_c CX_i^c X_i^{ec} \quad \forall i, e \quad (27)$$

$$\sum_l y_{kl} \leq CZ_k Z_k \quad \forall k \quad (28)$$

$$\sum_i qs_{mi} \leq CW_m W_m \quad \forall m \quad (29)$$

$$\sum_i \sum_e h_{ije} \leq CY_j \quad \forall j \quad (30)$$

$$\sum_e \sum_c x_i^{ec} = 1 \qquad \forall\ I \quad (31)$$

$$x_i^{ec}, z_k, w_m \epsilon \{0,1\} \quad (32)$$

$$cv_i\ , h_{ije}, b_{jk}, y_{kl}, q_{lm,} qr_{jm}\ , qs_{mi} \geq\ 0 \quad (33)$$

In the first objective function (z_1), three initial terms are related to the fixed costs of facilities. Forth expression shows the costs related to initial product manufacturing plants. Fifth term shows the shipment costs from initial product manufacturing plans. Sixth and seventh expressions are operational costs for manufacturing plants and distribution centers. Eighth and ninth expressions are related to shipment costs from demand markets to collection centers and from manufacturing plants to collection centers. The last expression is representative of the shipment cost from collection centers to initial product manufacturing plants and operational costs in collection centers. In the second objective (z_2), first part minimizes CO_2 emission in initial product manufacturing plants and the rest minimizes CO_2 emission of material shipments. The third objective function (z_3^1) determines number of plants to provide fairness in job opportunities and to optimize network security. The last objective function (z_3^2) maximizes job opportunities developed by facility locating process. Constraint (19) is related to the number of initial product manufacturing plants. Constraint (20) determines that the products shipped from distribution centers should satisfy demand in demand markets. Constraint (21) represents that all returned products from demand markets are collected. Constraints (22-24) assure equilibrium between input and output flows in distribution centers and initial product manufacturing plants. Constraint (25) shows equilibrium conditions in initial product manufacturing plants. Constraint (26) is equilibrium expression in collection centers. Constraints (27-30) are capacity constraints for network facilities. Constraint (31) guarantees that only one manufacturing plant with certain capacity and certain technology will be located in each spot. Constraints (32) and (33) determine non-negativity and binary conditions for variables.

5-2- Robust model

Model developed in previous section is deterministic, in which all parameters have deterministic values. To cope with real world conditions and to consider demand uncertainty, demand is assumed to be uncertain and is modeled by different scenarios.

In literature mean value of different scenarios is taken into consideration and a deterministic model is represented, but this assumption is not enough to handle uncertain nature of parameters. In addition, model may have infeasible solutions for some scenarios. In this study we utilize the methodology proposed by Mulvey et al. (1995). Besides it, we have considered mean absolute deviations and have included infeasibility penalties for over-demands which make the model infeasible.

To develop robust counterpart of model according to approach explained in Section 3, it is needed to define sets and notations as presented in the following:

s	finite set of scenarios,
pb_s	probability of scenario s,
θ_{1s}	linearity coefficient for first objective function,
θ_{2s}	linearity coefficient for second objective function,
λ_1, λ_2	weights devoted to variability parts of objective functions,
ω	Infeasibility penalty of non-deterministic constraints.

The model is changed as below to form robust structure.

$$\begin{aligned} Min\, z_1 = & \sum_e \sum_i \sum_C FX_i^{ce} x_i^{ec} + \sum_k g_k\, z_k + \sum_m o_m\, w_m \quad + \sum_s pb_s \Big(\sum_i \sum_e \sum_c \sum_j pc_i^{ec}\, h_{ijes} + \\ & \sum_i \sum_j \sum_e v_{ij} \mu\, h_{ijes} + \sum_j \sum_k (v_{jk}\mu + jc_j)\, b_{jks} + \sum_k \sum_l (v_{kl}\mu + kc_k) y_{kls} + \sum_l \sum_m v_{lm} \mu\, q_{lms} + \\ & \sum_j \sum_m v_{jm} \mu\, qr_{jms} + \sum_m \sum_i (v_{mi}\, \mu + mc_m) qs_{mis}\Big) \quad + \lambda_1 \sum_s pb_s \Big[\Big(\sum_i \sum_e \sum_c \sum_j pc_i^{ec}\, h_{ijes} + \\ & \sum_i \sum_j \sum_e v_{ij}\, \mu\, h_{ijes} + \sum_j \sum_k (v_{jk}\mu + jc_j)\, b_{jks} + \sum_k \sum_l (v_{kl}\mu + kc_k) y_{kls} + \sum_l \sum_m v_{lm}\, \mu\, q_{lms} + \\ & \sum_j \sum_m v_{jm} \mu\, qr_{jms} + \sum_m \sum_i (v_{mi}\, \mu + mc_m) qs_{mis}\Big) - \sum_{s'} pb_{s'} \Big(\sum_i \sum_e \sum_c \sum_j pc_i^{ec}\, h_{ijes} + \\ & \sum_i \sum_j \sum_e v_{ij}\, \mu\, h_{ijes} + \sum_j \sum_k (v_{jk}\mu + jc_j)\, b_{jks} + \sum_k \sum_l (v_{\ kl} + kc_k) y_{kls} + \sum_l \sum_m v_{lm} \mu\, q_{lms} + \\ & \sum_j \sum_m v_{jm} \mu\, qr_{jms} + \sum_m \sum_i (v_{mi}\mu + mc_m) qs_{mis}\Big) + 2\theta_{1s}\Big] + \omega \sum_s \sum_l pb_s\, \delta_{sl} \end{aligned} \tag{34}$$

$$\begin{aligned} Min\, z_2 = & \sum_s pb_s (\sum_i \sum_j \sum_e en_e h_{ijes} + \sum_i \sum_j \sum_e v_{ij} \rho\, h_{ijes} + \sum_j \sum_k v_{jk} \rho\, b_{jks} + \sum_k \sum_l v_{kl} \rho y_{kls} + \\ & \sum_l \sum_m v_{lm} \rho\, q_{lms} + \sum_j \sum_m v_{jm} \rho\, qr_{jms} + \sum_m \sum_i v_{mi}\, \rho qs_{mis}) + \lambda_2 \sum_s pb_s\, [(\sum_i \sum_j \sum_e en_e h_{ijes} + \\ & \sum_i \sum_j \sum_e v_{ij} \rho\, h_{ijes} + \sum_j \sum_k v_{jk} \rho\, b_{jks} + \sum_k \sum_l v_{kl} \rho y_{kls} + \sum_l \sum_m v_{lm} \rho\, q_{lms} + \\ & \sum_j \sum_m v_{jm} \rho\, qr_{jms} + \sum_m \sum_i v_{mi}\, \rho qs_{mis}) - \sum_{s'} pb_{s'}\, (\sum_i \sum_j \sum_e en_e h_{ijes} + \sum_i \sum_j \sum_e v_{ij} \rho\, h_{ijes} + \\ & \sum_j \sum_k v_{jk} \rho\, b_{jks} + \sum_k \sum_l v_{kl} \rho y_{kls} + \sum_l \sum_m v_{lm} \rho\, q_{lms} + \sum_j \sum_m v_{jm} \rho\, qr_{jms} + \\ & \sum_m \sum_i v_{mi}\, \rho qs_{mis}) + 2\theta_{2s}] \end{aligned} \tag{35}$$

$$Max\, z_3^1 = \beta \tag{36}$$

$$Max\, z_3^2 = \sum_i \sum_e \sum_c jo_i^{ec}\, x_i^{ec} + \sum_k jd_k z_k + \sum_m jm_m w_m \tag{37}$$

$$\beta = \sum_e \sum_i \sum_c x_i^{ce} \tag{38}$$

$$\sum_k y_{kls} + \delta_{ls} = d_{ls} \quad \forall l, s \tag{39}$$

$$\sum_m q_{lms} = \sum_k y_{kls} * f_l \quad \forall l, s \tag{40}$$

$$\sum_j b_{jks} = \sum_l y_{kls} \quad \forall k, s \tag{41}$$

$$(1 - r_j) \sum_i \sum_e h_{ijes} = \sum_m qr_{jms} \quad \forall j, s \tag{42}$$

$$r_j \sum_i \sum_e h_{ijes} = \sum_k b_{jks} \quad \forall j, s \tag{43}$$

$$\sum_m qs_{mis} + cv_{is} = \sum_j \sum_e h_{ijes} \quad \forall i, s \tag{44}$$

$$\sum_i qs_{mis} = \sum_j qr_{jms} + \sum_l q_{lms} \quad \forall m, s \tag{45}$$

$$\sum_j h_{ijes} \le \sum_c CX_i^{ec} x_i^{ec} \quad \forall i, e, s \tag{46}$$

$$\sum_l y_{kls} \le CZ_k Z_k \quad \forall k, s \tag{47}$$

$$\sum_i qs_{mis} \le CW_m W_m \quad \forall m, s \tag{48}$$

$$\sum_i \sum_e h_{ijes} \le CY_j \quad \forall j, s \tag{49}$$

$$\sum_e \sum_c x_i^{ec} = 1 \quad \forall \ I \tag{50}$$

$$x_i^{ec}, z_k, w_m \epsilon \{0,1\} \tag{51}$$

$$cv_{is}, h_{ijes}, b_{jks}, y_{kls}, q_{lms}, qr_{jms}, qs_{mis}, \theta_{1s}, \theta_{2s}, \theta_{3s} \ge 0 \tag{52}$$

It should also include new constraints as below to be linearized as mentioned in Section 3:

$$\begin{aligned}&\Big(\sum_i \sum_e \sum_c \sum_j pc_i^{ec} h_{ijes} + \sum_i \sum_j \sum_e v_{ij} \mu h_{ijes} + \sum_j \sum_k (v_{jk}\mu + jc_j) b_{jks} + \\ &\sum_k \sum_l (v_{kl}\mu + kc_k) y_{kls} + \sum_l \sum_m v_{lm} \mu q_{lms} + \sum_j \sum_m v_{jm}\mu qr_{jms} + \\ &\sum_m \sum_i (v_{mi} \mu + mc_m) qs_{mis}\Big) - \sum_s pb_s \Big(\sum_i \sum_e \sum_c \sum_j pc_i^{ec} h_{ijes} + \\ &\sum_i \sum_j \sum_e v_{ij} \mu h_{ijes} + \sum_j \sum_k (v_{jk}\mu + jc_j) b_{jks} + \sum_k \sum_l (v_{kl}\mu + kc_k) y_{kls} + \\ &\sum_l \sum_m v_{lm} \mu q_{lms} + \sum_j \sum_m v_{jm}\mu qr_{jms} + \sum_m \sum_i (v_{mi} \mu + mc_m) qs_{mis}\Big) + \\ &\theta_{1s} \ge 0 \ \forall s\end{aligned} \tag{53}$$

$$\begin{aligned}&(\sum_i \sum_j \sum_e en_e h_{ijes} + \sum_i \sum_j \sum_e v_{ij}\rho h_{ijes} + \sum_j \sum_k v_{jk}\rho b_{jks} + \\ &\sum_k \sum_l v_{kl}\rho y_{kls} + \sum_l \sum_m v_{lm}\rho q_{lms} + \sum_j \sum_m v_{jm}\rho qr_{jms} + \\ &\sum_m \sum_n v_{mi} \rho qs_{mis}) - \sum_s pb_s (\sum_i \sum_j \sum_e en_e h_{ijes} + \sum_i \sum_j \sum_e v_{ij}\rho h_{ijes} + \\ &\sum_j \sum_k v_{jk}\rho b_{jks} + \sum_k \sum_l v_{kl}\rho y_{kls} + \sum_l \sum_m v_{lm}\rho q_{lms} + \sum_j \sum_m v_{jm}\rho qr_{jms} + \\ &\sum_m \sum_i v_{mi} \rho qs_{mis}) + \theta_{2s} \ge 0 \quad \forall s\end{aligned} \tag{54}$$

$$(\sum_i \sum_j \sum_e wc_e h_{ijes}) - \sum_s pb_s (\sum_i \sum_j \sum_e wc_e h_{ijes}) + \theta_{3s} \ge 0 \quad \forall s \tag{55}$$

6- Solution method

In population-based algorithms like genetic algorithm, certain processes are applied on population of solutions in each iteration to solve the multi-objective optimization problems (Gen and Cheng, 2000). The first multi-objective genetic algorithm was proposed by Schaffer (1985) called Vector Evaluated Genetic Algorithm (VEGA). After that, other multi-objective genetic algorithms were proposed like Niched Pareto Genetic Algorithm (NPGA) (Horn et al., 1994), Strength Pareto Evolutionary Algorithm (SPEA) (Zitzlern and Thiele 1999) and next edition of it (SPEA2) (Zitzlern et al. 2001), and Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb 1994). The only difference between NSGA and the basic genetic algorithm is in their selection mechanism. The complexity of this algorithm has been reduced through improving its non-dominated sorting and applying a new measure for solutions dispersion along Pareto frontier which let to introduce NSGA II (Deb et al., 2002, Deb et al., 2000) and employ to solve many of multi-objective optimization problems. NSGA II is applied to obtain Pareto solutions here, as well.

6-1- Proposed algorithm

Step 1: Initialize the parameters of problem and algorithm.
Step 2: Repeat the following steps for pop_size replication:
- Determine binary variables randomly.
- Solve the linearized model objected to randomly weighted summation of three normalized objective functions. If the solution is feasible, calculate objective functions value for obtained solution and penalize objective functions with worst possible values, otherwise.

Step 3: Sort the population as proposed in Deb et al. (2002).
Step 4: Replicate the following procedures until termination condition is satisfied:
- Choose parents pairs from current population as many as one forth $CrossOver\_size$
- Recombine binary part of parent pairs
- Solve the linearized model for new offspring with different random weights of normalized objectives for two times. If the solutions are feasible, calculate the objective functions' values and penalize the objective functions with worst possible values, otherwise.
- Repeat real variables crossover for pair of children which have same binary variables and produce new children until numbers of children reach $\mathrm{CrossOver\_size}$.
- Choose as many as $\mathrm{Mutation\_size}$ parents from current population
- Apply mutation operator on binary part of parents and solve the linear programming model with different random weights of normalized objectives. If the model is feasible, calculate the objective functions' values and penalize the objective functions with worst possible values.
- Sort entire current population and offspring resulted from mutation and crossover as proposed in Deb et al. (2002).
- Retain as many as $\mathrm{pop\_size}$ from entire population and ignore the rest of solutions.

6-1-1- Chromosome representation

A vector like one depicted in Figure (2) is used to represent the chromosomes in proposed algorithm. In figure (2), solution string is divided into two parts: one for binary variables and another for real variables. Binary variable part is coded by vectors z_k, $\mathrm{w_m}$, and x_{iec}. A vector of ordered pairs is used to code x_{iec} which determines the capacity and technology in initial product manufacturing plants. First element of this ordered pair is assigned to technology and the latter is representative of capacity of plant i. The part related to real variables is followed by binary variable part. This method of representing solutions results in feasibility of children solutions through crossover and mutations operators.

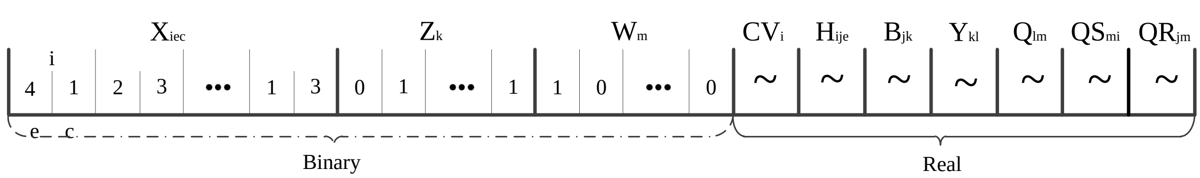

Figure 2. Solution chromosome of proposed algorithm.

6-1-2- Solution evaluation

One of the difficulties of multi-objective optimization problems and Pareto frontier determination is to determine fitness of solutions and their survival transmission pattern to the next generation. Different methods are proposed by previous studies to evaluate the solutions e.g. Deb et al. (2000) which is often based on the quality of objective functions.

In proposed algorithm, objective functions are considered to evaluate fitness of solutions and their selection is performed based on non-domination rank and crowding distance (Deb et al., 2000). In this approach, a solution is non-dominated if it has less non-domination rank in the first instance, and if the solutions have the same non-domination rank solution with more crowding distance. So, the population is sorted and the best solutions are survived to the next generation.

It should be noted that in the proposed algorithm, to produce initial population and children through crossover and mutation, real variables of children are determined by solving linear programming model resulted from predetermined binary variables. In this linear programming model, random-weight method is applied to change the problem to a single-objective one (Murata et al., 1996). This enables the algorithm to obtain a uniform sample of Pareto solutions (Schaffer 1985). To reach this goal, objective functions are normalized and rewritten as a weighted sum with random weights as presented in equation (56):

$$Z = \sum_{i=1}^{3} w_i f_i^{normal}(x) \tag{56}$$

where $f_i^{normal}(x)$ is the ith normalized objective function and w_i is random weight related to that objective function which should satisfy equation (57).

$$\sum_{i=1}^{3} w_i = 1 \tag{57}$$

6-1-3- Crossover

In the proposed algorithm, one of the single point crossover, double point crossover and uniform crossover are selected randomly as the crossover operator of binary part of solutions. Applying any of these operators results' in two children which their real part is obtained after solving the linear programming model with different weights for twice. If the solutions are feasible, real variables part of them are determined and four children are generated. If one or more of children become infeasible, numbers of feasible generated children would be less than the determined number which decreases the dispersion of search and as a result the efficiency of algorithm goes down. To prevent this, for real-variable part of children which have the same binary-variable part, crossover operator is applied and new children are generated. To recombine their real-variable part *Blending* operator is utilized which is a linear random combination of parents.

6.1.4 Mutation

In the proposed algorithm, mutation operator is applied for binary variables. First, one of the elements of binary part of parents solution is selected randomly and then, suitable flip operation is performed according to the fact that it is in z_k, w_m or x_{iec} variable domain. In other words, if it is in z_k or w_m variable domain, it is enough to exchange the element with the opposite value. But if it is in x_{iec} variable domain, the selected element should exchange with a new and different value of available set.

6.1.5 Selection

Parents' selection for crossover and mutation is based on elitism in proposed algorithm. In this method, certain fraction of the best elements of population can be uniformly selected. This method is able to strengthen convergence strategies with respect to extension of solution space.

7- Case study and results

We have performed a case study in a steel industry. In this network, scrap parts are collected and along with purchased raw material purchased are utilized for manufacturing products in raw steel plants as a forward flow. Then raw steel is shipped to other plants and final products are manufactured which are then shipped to demand markets through distribution centers. The used products and scrap of manufacturing plants are entered to collection centers to be sending and recycling in initial product manufacturing plants.

Data needed to solve the model, has collected from different sources such as steel industries experts, earlier studies (Vahdani et al., 2013 and Strezov et al., 2013) and ECO-it software (relating environmental issues) which is provided in Table 1.

Table 1. The data of the case study

Parameter	Value	Parameter	Value
pc_i^{2c}	$Uniform\ (90-120)$	f_l	$Uniform\ (.2-.35)$
jc_j	$Uniform\ (25-35)$	r_j	$Uniform\ (.85-.97)$
kc_k	$Uniform\ (2-5)$	FX_i^{11}	$Uniform\ (330000-960000)$
mc_m	$Uniform\ (2-5)$	FX_i^{12}	$Uniform\ (300000-900000)$
CX_i^{1e}	$Uniform\ (1500-3000)$	FX_i^{21}	$\alpha * FX_i^{11}$
CX_i^{2e}	λCX_i^{1e}	FX_i^{22}	$\alpha * FX_i^{12}$
λ	$Uniform\ (.4-.6)$	α	$Uniform\ (.5-.7)$
CY_j	$Uniform(1500-3000)$	g_k	$Uniform\ (5000-10000)$
CZ_k	$Uniform\ (800-1800)$	o_m	$Uniform\ (1000-5000)$
CW_m	$Uniform\ (800-1800)$	pc_i^{1c}	$Uniform\ (60-90)$

First, to show the efficiency of robust model in relation to deterministic model, third and fourth objective function are normalized and combined with the weights of 0.4 and 0.6. Then second and third objective functions are considered as constraints and are solved with ε-constraint method for different values of ε. The most probable scenario is taken into account as deterministic counterpart. To compare rest of the scenarios, the criterion is that if manufacturing quantity is less than quantity of the most likely scenario, shortage costs will be considered but if it is more than quantity of the most likely scenario, inventory costs will be included. Results of 10 randomly selected among 5 possible scenarios with different probabilities are gathered in Table 2 where ε_1 and ε_2 indicate second and third objective functions in normalized form respectively which are fixed to certain amount and the amount of first objective function is reported. This table provides a comparison between deterministic and robust model in terms of average and standard deviation of the objective amounts of the 10 mentioned scenarios which indicates the efficiency of robust counterpart since mean and standard deviation of costs are less than deterministic model.

Table 2. Comparing robust and deterministic model

No.	scenario	$\varepsilon_1, \varepsilon_2$		$\varepsilon_1, \varepsilon_2$		$\varepsilon_1, \varepsilon_2$		$\varepsilon_1, \varepsilon_2$		$\varepsilon_1, \varepsilon_2$	
		0.4, 0.4		0.4, 0.6		0.6, 0.6		0.8, 0.6		0.8, 0.8	
		Robust model	Deterministic model	Robust model	Deterministic model	Robust model	Deterministic model	Robust model	Deterministic model	Robust model	Deterministic model
1	1	4049109	3807072	4010494	3845352	4096306	3925273	4481379	4091905	4929985	4505603
2	2	4027428	4593125	4052498	4703290	4137151	4767932	4374299	4994218	4816953	4774688
3	1	4049109	3807072	4010494	3845352	4096306	3925273	4481379	4091498	4929985	4505603
4	3	5448573	6069462	5533587	6181334	5618147	6245319	5222133	6470989	5012438	6053721
5	3	5448573	6069462	5533587	6181334	5618147	6245319	5222133	6470989	5012438	6053721
6	4	4316131	3925338	4262354	3945806	4350986	4018610	4671952	4163283	5138187	4942840
7	1	4049109	3807072	4010494	3845352	4096306	3925273	4481379	4091498	4929985	4505603
8	3	5448573	6069462	5533587	6181334	5618147	6245319	5222133	6470989	5012438	6053721
9	5	4633990	4070161	4659161	4109250	4680839	4168795	4796523	4313403	5280315	4751043
10	2	4027428	4593125	4052498	4703290	4137151	4767932	4386759	4994218	4816953	4774688
Mean		**4549802**	4681135	**4565875**	4754169	**4644949**	4823505	**4734007**	5015299	**5038586**	5058885
Standard deviation		**648321**	1001905	**696234**	1036168	**695045**	1031062	**359628**	1062239	**140794**	678739

The relationship between the total cost and infeasibility penalty of non-deterministic constraints is depicted in Figure 3. As can be seen, penalty cost increases exponentially as the total cost increases that is in accordance with what is addressed in Mulvey et al. (1995).

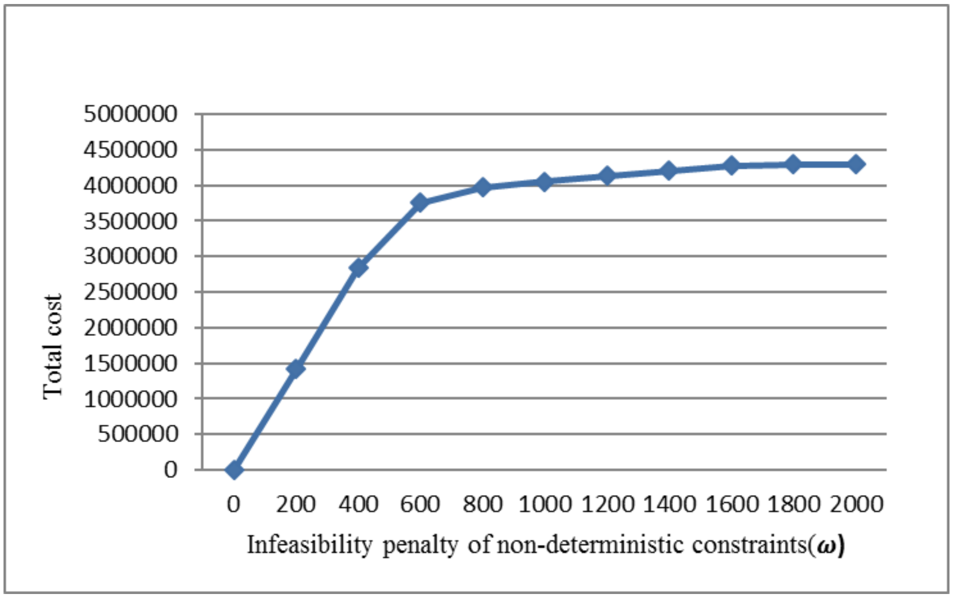

Figure3. Trade-off between ω and total cost

The proposed algorithm is programmed in MATLAB and its efficiency is checked by applying it on a problem. In this regard, one of the objective functions is considered to be fix and the two others are compared with solutions obtained from ε-constraint approach which indicates little difference (Figure 4). It should be noted that the objective functions are normalized and changed into maximization form in Figure 4.

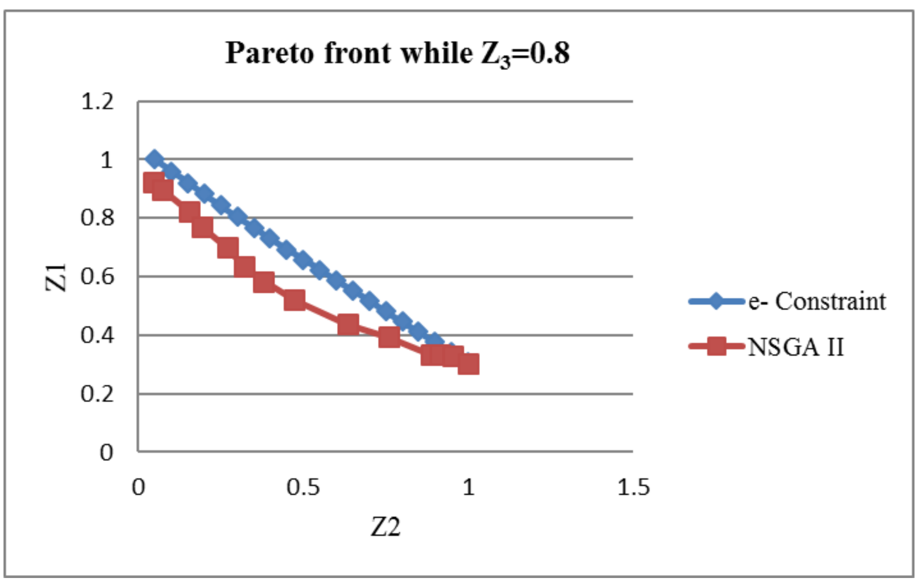

Figure4. Comparing Results obtained from Genetic algorithms and GAMS

Resulted surface is depicted in Figures 5 and its two dimensional views are shown in Figure 6. Figure 5 and 6 show that increasing objective function of social utility results in an increase in cost objective function. We need to locate many small factories to increase fairness in distributing jobs in different spots and then to increase social objective function. Also, we need more facilities and new technology to provide more job opportunities. As a result, costs increase and cost utility decreases. An increase in environmental objective function e.g. using green technology with less harm to environment causes increase in cost. Hence, decision maker decides about supply chain network by considering objective function's utility.

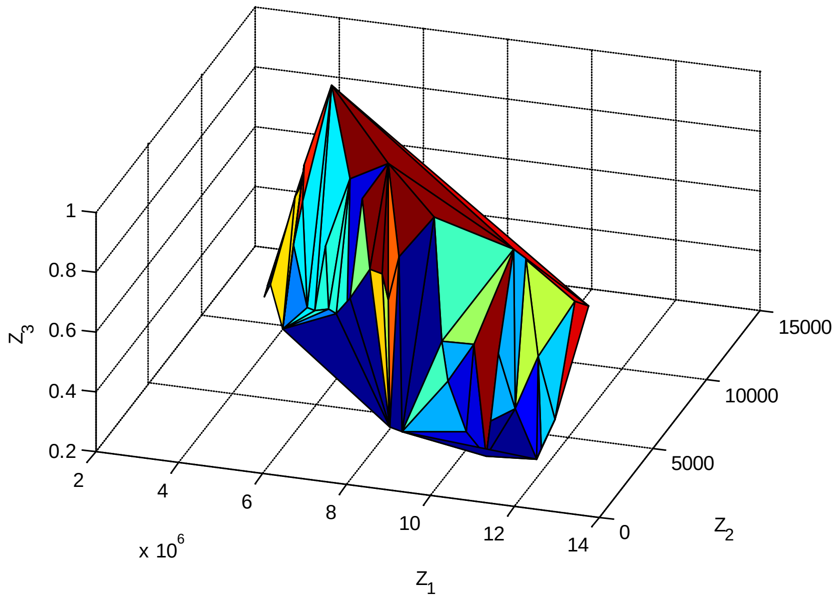

Figure5. Pareto solutions surface for three objective functions problem

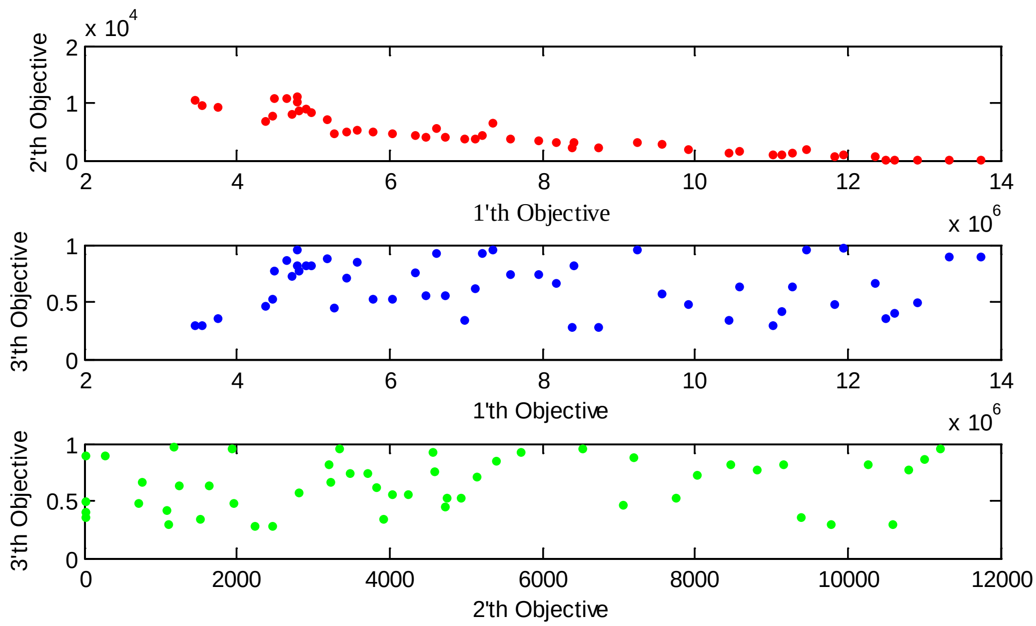

Figure6. Two dimensional view of Pareto surface

8- Conclusion

In this paper a multi-objective model is proposed considering both forward and reverse flows of supply chain with objective functions designed for costs, environmental factors such as CO_2 emission, and social factors such as employment and fairness in providing job opportunities according to ISO 26000 standards. A case study of steel manufacturing and recycling industry is presented since this industry is one of the important industries which creates vast job opportunities and has a great role in environmental contamination. Since demand has non-deterministic nature, a robust programming model is developed to cope with uncertainty and the mean and standard deviation of costs are taken into consideration. Results show that robust model is more efficient in relation to deterministic model. To solve the model, a multi-objective genetic algorithm is applied and results show its efficiency in generating Pareto solutions.

It seems that it is useful to consider multi-period and multi-product problems in future research. Considering different transportation modes and delineating appropriate ways of calculating economic, social and environmental impacts can be added to extend the study. For future direction, we suggest considering other environmental and social factors such as energy consumption level, local suppliers' priority, industrial centers adjacency, and facilities' distance related to providing new job opportunities.

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