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Research Article

A Sustainable Transportation Location Inventory Routing Problem

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Abstract

A sustainable transportation location inventory routing problem (TLIRP) has been studied in this paper. The sustainable objective functions have been developed as three pillars of minimizing the distribution cost, minimizing the environmental effect of Co_2 emission, fuel consumption, and minimizing the social effect of discrimination and priority on the customers. Mathematical model conducted with transportation consideration in the first phase. At first, the number of trucks to be shipped to the distribution centers (DCs) and the number of each type of goods are calculated. The location routing problem as the second phase, decides about optimal DCs to be open, and the sequence of assigning the customers to the routes to get service. For small size of the problem exact solution used but because of the NP-hard nature of the problem two meta-Heuristic algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) have been implemented to solve the problem and then the result has been compared in terms of their metrics.

1. Introduction

There are some distribution activities affect the environment, so the companies have to consider the environmental regulations such as ISO 14000 and ISO 50001[1]. According to [2] customers are willing to purchase lower carbon emission products with carbon footprint label. In addition, the global warming increasement has high relationship to the CO2 emission amount, which [3] proposed a novel technology to reducing the emission amount using absorption techniques [4][5] deployed a new unmanned technology, drones, for a last mile delivery system with coordination of public transportation to deliver products to customers. This is a new and efficient way as the perspective of environmental and economical sides which cut delivery time, reducing the CO_2 emission. So, they formulated the vehicle routing problem (VRP) to optimize the problem.

One method used to solve location routing problem (LRP) in the perishable products issue is Lagrangian Relaxation method in a stochastic environment applied by [6]. As the extension of LRP, [7] proposed a new sustainable network to the application of perishable items using two-compartment vehicles which simultaneously deliver product and gather the expired items. They formulated an LRP with sustainable objective functions which minimize the distribution cost, CO_2 emission and maximizing the satisfactory of the customers as the economic, environmental and social pillars of sustainability, respectively. [1] introduced a transportation-location-routing problem (TLRP) which decides about the truck's quantities in the first phase of the problem. [8] proposed LIRP which is the

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combination of location, routing and inventory problems. In the LIRP, we have a general perspective of the inventory routing problem, location inventory problem, and location routing problems. They considered that the demand is normally distributed, and the amount of safety stock could be determined by the DCs. To solve this problem, one can use either of exact or heuristic methods which in heuristic, simulated annealing algorithm, and hybridization of tabu search could be applied. In [9] using a LRP, the DCs were located in the vicinity of the city and in each vehicle's route, the order of the customers got determinized. Also, in [10] the location of the ambulance stations and the number of perishable drug's order were determined by a location inventory problem. [11] Present an optimized policy regarding space allocation in freight transportations that benefits the stakeholders by minimizing the cost. Based on [12] the inventory routing problem decides about how the customers in routes and their inventory levels get permutated. [13] utilized the Generalized Benders Decomposition method to optimize the location, inventory and routing problem. [14] studied a model which depots and retailers can maintain inventory where the stock-out situation is not permitted. Their model could be considered as a two echelon LIRP with a deterministic demand. To overcome a high computation time, they faced using the exact method, they introduced a meta-heuristic method as a solving method. In [15][16], a single-objective optimization problem is considered to minimize a cost function using a classical method such as least squares and robust methods including M and Fast-Tau estimates. Also, as the application of the above minimization methods, they calculated the process capability indices [17].

In supply chain, decision level contains three main levels as strategic, tactical and operational [18]. In this research, we considered facility location problem, inventory control problem, and routing problem in strategic, tactical, and operational level, respectively. Conclusively, we focused on all the above problems together as the transportation location inventory routing problem. We add transportation approach at the first phase to decide about the quantities of trucks to be shipped from plant to DCs and in the second phase the model should investigate about the optimality of DCj to be opened or not and the sequence of the customers should assign to the route in a way that has a minimum discrimination and priority on the service time between customers.

2. Model Description

Transportation location inventory routing problem considers customers with deterministic demands. Their request will respond by set of plants. Each plant has max a_{gk} capacity to produce product g. Each end customer i has d_{git} demand for product g in period t. As plants cannot transfer the products directly to end customer; therefore, it is required some DCs to be responsible for this transfer. There is a condition for trucks which carry the products from factory to the cities that cannot enter the metropolis or allow a certain location of the city; in some cities it is only possible to enter the city after midnight. Vehicles provided by distribution centers drive to the trucks and discharged their loads. Each DC_j has to pay f_j for opening the distribution center and the capacity of each center for holding products is b_{gj}.

TLIRP includes two phases. In the first phase, products transport to DCs and in second phase, the optimal allocation of end customers to each rout will be recognize. In this sustainable model, three objective functions are considered, including economic cost reduction, reduction of negative environmental effects and reduction of negative social effects. Economic cost function includes transportation and routing costs and costs of opening distribution centers, production costs, inventory costs in each period and the cost of ordering products. Environmental cost function such as the cost of carbon dioxide emissions, the fuel cost of trucks and vehicles, which the model tries to reduce the cost of malware to the environment. The third function considers social issues which all the customers have no excellence toward each other, and it should be the same attitude for starting service time to each customer; so, the difference between the starting time of service to customer i and the mean starting time of service to all customers should be minimized. In f fact, by this approach, there is no priority among customer to service first at the specific route.

- It is required to make some assumptions:
- There are P plants to produce products.
- There are G types of products.
- Demand is deterministic.
- Each plant can work with its maximum capacity for each product a_{gk} expressed in units of product g
- The finished goods inventories from plants depot must transfer to DCs by trucks with maximum capacity Qt expressed in weight
- Retailers have a soft time window based on their customer's behavior for receiving the demands. There is a penalty if the vehicles violate the retailers' due dates.
- Vehicles have a maximum capacity Q_v expressed in weight
- $Q_v \geq Q_t$
- No shortage occurs.

Notations are described as follow:
Sets:

K ∈ {1, 2, . . . , p}	Set of indexes -plants
J ∈ {1, 2, . . ., m}	Set of indexes -DCs
I ∈ {m + 1, m+ 2, . . ., m + n}	Set of indexes - clients
G ∈ {1, 2, . . ., g}	Set of indexes -products
T :1, 2…, t	Set of time periods

Parameters:

P: Number of plants

M: Number of potential locations for DC location

N: Number of clients

G_i: Number of goods in the product range

w_g: Weight of good g

a_{gk}: Production capacity in plant k

h_{kj}: Cost of sending a truck from plant k to DC j

r_{kj}: Distance from plant k to DC j

Qt: Capacity of Trucks

Wt_0: Weight of no-load truck

Wt*: Weight of full load truck ($Wt^* = Wt_0 + Qt$)

ρt_0 : Fuel consumption rate of empty truck

ρt^*: Fuel consumption rate of fully loaded truck

f_j: Fixed cost for opening and operate DC j

b_{jg}: Capacity of DC j for product g

d_{git}: Demand of customer i for Good's g at period t

c_{ij}: Cost of visiting client/DC j right after client/DC i in the route

Qv: Vehicle weight capacity

Wv_0: Weight of empty vehicle

Wv*: Weight of fully loaded vehicle ($Wv^* = Wv_0 + Qv$)

ρv_0 : Fuel consumption rate of empty vehicle

ρv^*: Fuel consumption rate of fully loaded vehicle

r_{ij}: Distance from client/DC i to client/DC j

R: Maximum possible total traveling distance of each vehicle

ff: Fixed cost of 1 liter fuel

ce: CO2 emission cost of 1 liter fuel consumption

tij: Traveling time from client/DC *i* to client/DC *j*

eit: Earliest time of customer *i* time windows at time period t

lit: Latest time of customer *i* time windows at time period t

pe: Violation penalty of earliest time of time windows

pl: Violation penalty of latest time of time windows

M*:* Big number

a_{jg} : inventory holding cost of good of type g at DC j

a_{ig} : inventory holding cost of good of type g at client i

LT_{kjg} : Lead Time for supply of good type g from plant k to DC j

Variables:

sit : Starting service time at customer *i* at period t

Veit: Violation amount of earliest time window at customer *i at time period t*

Vlit: Violation amount of latest time window at customer *i at time period t*

Vgkjt : Amount of product *g* sent from plant *k* to DC *j at time period t*

ntkj: Number of trucks sent from plant *k* to DC *j at time period t*

u_{it} : Load of vehicle after visiting customer *i at time period t*

o_{it}: The distance which vehicle traveled after visiting customer *i at time period t*

X_{jigt} :number of goods of type g shipped from DC j to client i at time period t

ID_{jgt}: Inventory level of goods g in the DC j at time period t

IR_{igt}: Inventory level of goods g in the client i at time period t

$$y_j = \begin{cases} 1, & \text{If DC } j \text{ is opened} \\ 0, & \text{Otherwise.} \end{cases}$$

$$z_{ijt} = \begin{cases} 1, & \text{if client } i \text{ is assigned to DC } j \text{ at time period t} \\ 0, & \text{Otherwise.} \end{cases}$$

$$x_{0i}^{jt} = \begin{cases} 1, & \text{if client } i \text{ is the first client in any route of DC } j \text{ at time period } t \\ 0, & \text{Otherwise.} \end{cases}$$

$$x_{i0}^{jt} = \begin{cases} 1, & \text{if client } i \text{ is the last client in any route of DC } j \text{ at time period } t \\ 0, & \text{Otherwise.} \end{cases}$$

$$x_{il}^{jt} = \begin{cases} 1, & \text{if client } l \text{ is visited just after client } i \text{ in any route of DC } j \text{ at time period } t \\ 0, & \text{Otherwise.} \end{cases}$$

2.1 Mathematical Formulation

We proposed a multi-objective mixed integer nonlinear programming for the TLIRP that extends the formulation provided by [1]. The extend terms added due to:

- Determining inventory level in each period.
- Balance the inventory level in DCs centers and customers.
- Defining new social objective to have a same attitude to all customers, try not to make discrimination among customers for the starting time of their services.

Economic objective:

$$\text{Min } f_1 = \sum_k \sum_j \sum_t h_{kj} nt_{kjt} + \sum_j f_j y_j + \sum_i \sum_j \sum_t (c_{ji} x_{0i}^{jt} + c_{ji} x_{i0}^{jt}) + \sum_t \sum_j \sum_i \sum_{l \neq i} c_{il} x_{il}^{jt} + \quad (1)$$

$\sum_t \sum_i (p_e ve_{it} + p_l vl_{it}) + \sum_g \sum_j \sum_t a_{jg} \times ID_{jgt} + \sum_g \sum_i \sum_t a_{ig} \times IR_{igt}$

Green objective:

$$\text{Min } f_2 = \sum_t \sum_k \sum_j (ff+ce) r_{kj} \rho t^* [\frac{\sum_g w_g * v_{gkjt}}{Qt}] + \sum_t \sum_k \sum_j (ff+ce) r_{kj} (\rho t_0 + (\frac{\rho t^* - \rho t_0}{Qt}) \left(\sum_g w_g * v_{gkjt} - Qt[\frac{\sum_g w_g * v_{gkjt}}{Qt}]\right)) + \sum_t \sum_k \sum_j (ff+ce) r_{kj} \rho t_0 nt_{kjt} + \sum_t \sum_j \sum_i (ff+ce) r_{ij} (\rho v_0 x_{0i}^{jt} + (\frac{\rho v^* - \rho v_0}{Qv}) \left(u_{it} + \sum_g w_g d_{git}\right) x_{0i}^{jt} + \sum_t \sum_{l \neq i} \sum_i (ff+ce) r_{ij} (\rho v_0 \sum_j x_{il}^{jt} + (\frac{\rho v^* - \rho v_0}{Qv}) \left(u_{it} \sum_j x_{il}^{jt}\right) + \sum_t \sum_j \sum_i (ff+ce) r_{ij} \rho v_0 x_{i0}^{jt} \quad (2)$$

Social objective:

$$\text{Min } f_3 = \sum_t \sum_i (s_{it} - mean(s_{it}))^2 \quad (3)$$

Subject to:

$$\sum_{j \in J} v_{gkjt} \leq a_{gk} \quad \forall k \in K, \forall g \in G \quad (4)$$

$$nt_{kjt} \geq \frac{\sum_{g \in G} w_g v_{gkjt}}{Qt} \quad \forall k \in K, \forall j \in J \quad (5)$$

$$\sum_{k \in K} v_{gkjt} \leq b_{jg} y_j \quad \forall j \in J, \forall g \in G \quad (6)$$

$$\sum_{k \in K} v_{gkjt} \geq \sum_{i \in I} d_{gi} z_{ijt} \quad \forall j \in J, \forall g \in G \quad (7)$$

$$\sum_{j \in J} z_{ijt} = 1 \quad \forall i \in I \quad (8)$$

$$\sum_{\substack{i \in IU\{0\} \\ l \neq i}} X_{li}^{jt} = z_{lj} \quad \forall i \in I, \forall j \in J \quad (9.1)$$

$$\sum_{\substack{i \in IU\{0\} \\ l \neq i}} X_{li}^{jt} = z_{ij} \quad \forall i \in I, \forall j \in J \quad (9.2)$$

$$\sum_{i \in I} x_{0i}^{jt} = \sum_{i \in I} x_{i0}^{jt} \quad \forall i \in I \quad (10)$$

$$u_i - u_l + Qv\left(\sum_{j \in J} X_{li}^{jt}\right) \leq Qv - \sum_{g \in G} w_g d_{gi} \quad \forall i.l \in I, i \neq l \quad (11)$$

$$\sum_{g \in G} w_g d_{gi} \leq u_i \leq Qv \quad \forall i \in I \quad (12)$$

$$o_i - o_l + (R + r_{il}) \sum_{j \in J} X_{li}^{jt} + (R - r_{li}) \sum_{j \in J} X_{li}^{jt} \leq R \quad \forall i.l \in I, i \neq l \quad (13)$$

$$\sum_{j \in J} r_{ji} x_{0i}^{jt} \leq o_i \leq R + \sum_{j \in J} (r_{ji} - R) x_{0i}^{jt} \quad \forall i \in I \quad (14)$$

$$o_i \leq R - \sum_{j \in J} r_{ji} x_{0i}^{jt} \quad \forall i \in I \quad (15)$$

$$IR_{ig(t-1)} + \sum_i X_{jigt} - ID_{igt} = IR_{igt} \ \forall i, g, t \quad (16)$$

$$S_i + M\left(1 - x_{0i}^{jt}\right) \geq 0 + t_{ji} \quad \forall i \in I, \forall j \in J \quad (17)$$

$$S_i + M\left(1 - x_{il}^{jt}\right) \geq S_i + t_{il} \quad \forall i.l \in I, i \neq l, \forall j \in J \quad (18)$$

$$ve_i \geq e_i - S_i \quad \forall i \in I \quad (19)$$

$$vl_i \geq S_i - l_i \quad \forall i \in I \quad (20)$$

$$y_j \in \{0,1\} \quad (21)$$

$$z_{ijt} \in \{0,1\} \quad (22)$$

$$x_{0i}^{jt} \in \{0,1\} \quad (23)$$

$$x_{i0}^{jt} \quad (24)$$

$$X_{li}^{jt} \in \{0,1\} \quad (25)$$

$$v_{gkjt} \geq 0 \quad (26)$$

$$nt_{kjt} \in Z_+ \quad (27)$$

$$o_i \geq 0 \quad \forall i \in I \quad (28)$$

$$S_i \geq 0 \quad \forall i \in I \quad (29)$$

$$u_i \quad \forall i \in I \quad (30)$$

$$\text{ID}_{\text{jgt}} \geq 0 \quad \forall j \in J, g \in G, t \in T \quad (31)$$

$$\text{IR}_{\text{igt}} \geq 0 \quad \forall i \in I, g \in G, t \in T \quad (32)$$

The first objective function includes cost of transportation from plant to DCs, cost of opening new distribution center, cost of transportation from DCs to end customers, cost of inventory and cost of ordering cost, respectively. In Eq. (1) economic function cost is minimized. Eq. (2) minimize the negative impact of environmental issues. In second objective function, all terms consider the cost of fuel consumption and co_2 emission, for fully loaded trucks, part-loaded trucks, which are leaving the firms, and the empty trucks coming back from DC_j to plant k, respectively. Also, cost of fuel consumption and co_2 emission based on both weight of vehicles and distance are measured in the second stage, for loaded vehicle from DC_j to first customer i, loaded vehicles in optimal routes, which lose their weight by visiting each customer, and empty vehicles coming back from customer i to DC_j, in order. The third objective, Eq. (3), controls customers selection and try to minimize the staring service time of customer i towards mean of starting service time. In this case, there is no priority among customers.

Eq. (4) indicates that all products from one type that shipped from specific plant to DCs at the period t cannot be higher than the maximum capacity of mentioned plant for producing product g. Eq. (5) considers the amount of product which transport from plant k to a DC at the period t and the number of trucks is needed. If a DC is opened then the amount of product which transfer to this DC should be lower than the capacity of the DC in Eq. (6). As it can see in Eq. (7) all amount of product type g can be higher than the demands of customer of DC_j,that's mean maintaining inventory is not forbidden. Eq. (8) indicates customer i cannot allocate to more than one DC.

Eq. (9.1) ensures that each client must be visited immediately after exactly one DC or after another client, and Eq. (9.2) imposes that exactly one client or DC must be visited immediately after. Also, they enable routes only between clients assigned to the same DC.

Number of vehicles depart the DC_j to their destination should be equal to number of vehicles return which is defined in Eq. (10).

Eq. (11) considers a sub-tour elimination and constraint (12) prevents from loading more than the capacity of vehicle. Constraint (13) will calculate the variable o_i.

Eq. (14) keeps the vehicle fuel tank limitation translated to maximum length limit R that a vehicle could travel. There is an inventory balance for DC_j at the end of period t in Eq. (15) and there is an inventory balance for customer i at the end of the period t in Eq. (16). Eq. (17) to (20) are related to time windows. Eq. (21) to (32) indicates variable's types and ranges.

3. Methodology

Transportation location inventory routing problem is categorized in Np-Hard group. Therefore, it is required an algorithm to have high performance and efficiency in large scale of the problem. Two meta heuristic method is implemented to this problem. The first algorithm is Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the other one is Multi-objective Particle Swarm Optimization (MOPSO).

3.1. Solution Representation

There are different scenarios to execute meta heuristic to this problem. Taking a random solution and try to reach to a feasible area is one of those scenarios, in this condition if it does not find any feasible solution that meets all the constraints, it considers a penalty violation in objective function. Finding a feasible solution in advance and try to develop this solution is another way to solve the problem. Second scenario is employed to this model. It should be considered that better initial solution leads to better CPU time and decrease the complexity of solving. Hence, note that a best represent solution has to be capable of producing developed and complex solutions.

In this paper, the proposed chromosome is a $T \times (P + M + N)$ matrix which denotes T as time period, P as number of plants, M as number of potential DC's locations, N as number of customers. The proposed chromosome has three genes that are related to plants, DC's locations and customers, respectively. Figure 1 displays the structure of proposed chromosome with considering p=2 plants, M=4 potential DC's location, N=4 customers and T=3 periods of time and priority procedure.

To obtain optimal variables, it is required a decoding method to understand the generated solutions. One of decoding method is priority policy which is implemented to this problem. In order to encode the chromosomes, backward induction is employed in which the chromosome will sort in descending order and in the next step, last genes will select for starting the encode procedures.it concludes two phases: Transportation-location phase and location-routing phase. In routing phase, the procedure allocates customers to DC'S and in the transportation phase DC's assigned to plants. In routing phase, the customer with high priority select to assign to a DC that has higher priority rank, either. After assigning the first customer, the next high priority customer is taken to allocate to that DC. This procedure continue until the specific DC can't response more demands which are higher than its capacity. In next stage, it can be recognized which DC's assigned to plant k.

Time periods	Plants 1	Plants 2	Potential locations 1	Potential locations 2	Potential locations 3	Potential locations 4	Customers 1	Customers 2	Customers 3	Customers 4
1	0.32	0.54	0.21	0.19	0.67	0.82	0.34	0.59	0.06	0.71
2	0.11	0.91	0.38	0.27	0.79	0.53	0.82	0.22	0.64	0.93
3	0.69	0.32	0.21	0.55	0.61	0.33	0.13	0.02	0.48	0.49

Chromosome with sorted genes

0.32	0.54	0.19	0.21	0.67	0.82	0.06	0.34	0.59	0.71
0.11	0.91	0.37	0.38	0.53	0.79	0.22	0.64	0.82	0.93
0.32	0.69	0.21	0.33	0.55	0.61	0.02	0.13	0.48	0.49

Priorities

1	2	2	1	3	4	3	1	2	4
1	2	2	1	3	4	2	3	1	4
2	1	1	4	2	3	2	1	3	4

Figure 1. An example of chromosome

3.2. Non-dominated Sorting Genetic Algorithm

The Non-dominated Sorting Genetic Algorithm is a Multiple Objective Optimization (MOO) algorithm and is an instance of an Evolutionary Algorithm from the field of Evolutionary Computation. Refer to for more information and references on Multiple Objective Optimization. NSGA is an extension of the Genetic Algorithm for multiple objective function optimization. The objective of the NSGA algorithm is to improve the adaptive fit of a population of candidate solutions to a Pareto front constrained by a set of objective functions. The algorithm uses an evolutionary process with surrogates for evolutionary operators including selection, genetic crossover, and genetic mutation. The population is sorted into a hierarchy of sub-populations based on the ordering of Pareto dominance. Similarity between members of each sub-group is evaluated on the Pareto front, and the resulting groups and similarity measures are used to promote a diverse front of non-dominated solutions. Flowchart of proposed algorithm is illustrated in Figure 2.

3.2.1. NSGA-II Operator

For having more efficient solution, some operators such as crossover and mutation can employ to help the algorithm to construct better chromosome. All this work is to search all of the solution space and to be sure not to take place in local optimum. By means of crossover we can generate better gene of chromosome and by means of mutation we will be ensure of variation of solutions and prevent the algorithm from falling into local area.

3.2.2. Crossover

Figure 3 illustrates how new chromosome is generated by their parents and the way of combining the genes with each other. There are variety of techniques to execute crossover on the parent's chromosome, for simplicity of the model we employed the single point cross over. In this method: first, a random number is generated that shows the position of crossover point in both parents. Then, the first child takes the first part of its vector from the first parent, which is the beginning part until crossover point of parents' vector and it takes the second part of its vector from the second parent, which is a copy from the crossover point to the end of parents' vector.

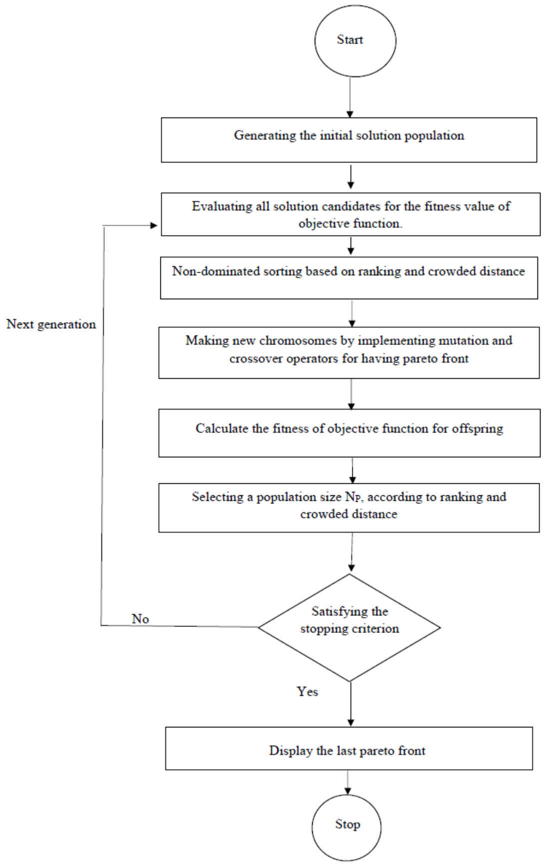

Figure 2. The flowchart of NSGA-II

3.2.3. Mutation

Inversion mutation method is employed to proposed NSGA-II as depicted in Figure 4. As it can see in the figure two mutation points are chosen randomly. The elements between this to part (W_1 and W_2), will inverted backwardly.

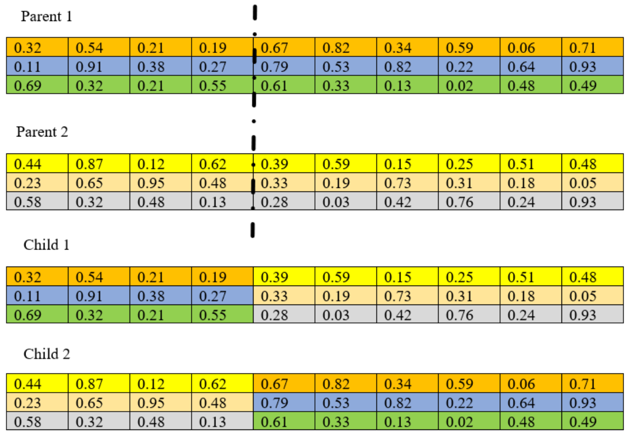

Figure 3. A single point crossover

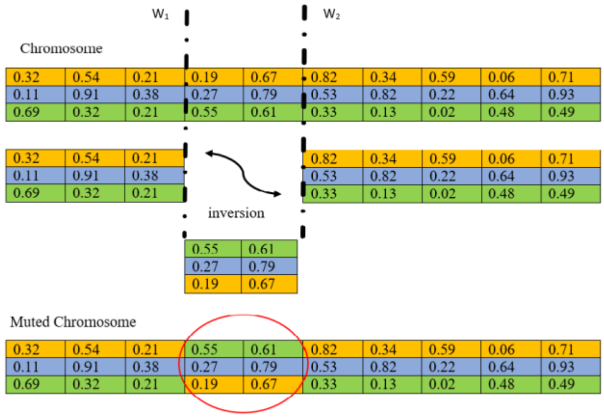

Figure 4. Inversion mutation

4.3-Multi-Objective Particle Swarm Optimization

Any solution in this algorithm is a particle that makes a swarm. This optimization method is based on the intelligence group in which each particle has knowledge of its previous best experience x_{pbest}). and the best global experience of entire swarm (x_{gbest}). Updating the velocity and the position of particle p at iteration t denoted by v_p(t) and $x_p(t)$. is performed as follow:

$$v_p(t) = wx_p(t-1) + c_1\, r_1 \left(x_{pbest}(t) - x_p(t)\right) + c_2\, r_{12} \left(x_{gbest}(t) - x_p(t)\right) \tag{33}$$

$$x_p(t) = x_p(t-1) + v_p(t) \tag{34}$$

where the local and global ability of the particle is influenced by inertia factor w, c_1 and c_2 as the cognitive and social learning coefficients control the effect of (x_{pbest}) and (x_{gbest}) respectively. Eventually, r_1 and r_2 are random numbers between 0 and 1.

4.3. Parameter Tuning

It's better to calibrate the parameters of algorithm to generate better solution that leads to a better value for objective functions of the problem. [19] used Taguchi method to calibrate and design the parameters for better optimality of their problem. A three level Taguchi design is employed to this parameter for NSGA-II algorithm. It is considered three level for N_P, P_C, P_m, Max-Iteration in Table 1, respectively. We want to investigate the effect of parameters on objective functions, for inspecting this issue more deeply, it's better to look at Figure 5.

Table 1. Level of parameters for NSGA-II

parameter	NSGA-II		
	Low	mean	High
N population	50	75	100
P crossover	0.4	0.6	0.8
P mutation	0.3	0.5	0.7
Max-Iteration	75	100	150

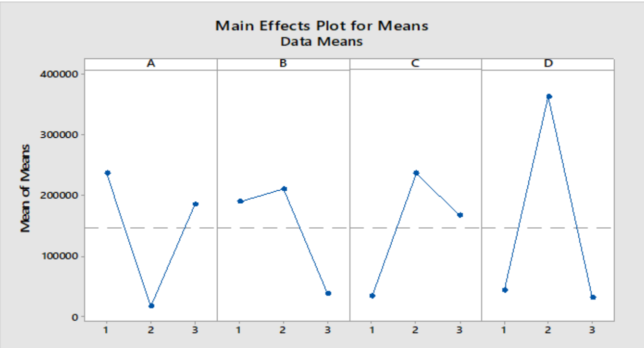

Figure 5. Analysis diagrams of NSGA-II parameters tuning by Taguchi DOE

The factors A, B, C, D denote N_P, P_C, P_m, Max-Iteration and 1,2 and 3 denote low, mean and high level that illustrated in Figure 5. In order to take optimal parameters calibration, we have to inspect every factor with objective functions. Hence, due to minimization, we should search for lower value that each factor will generate among three level that is determined in Table 1. The best of each parameter's value is in Table 2.

Table 2. Best parameters value for NSGA-II

Algorithm	Parameters							
	It_{max}	N_{pop}	P_c	P_m	N_r	w	c_1	c_2
NSGA-II	150	75	0.8	0.3	-	-	-	-

4. Computational Results

4.1. Problem Validation

This problem is validated with GAMS software in small scale. It is used CPLEX solver to solve the mixed integer non-linear problem. As the problem categorized in Np-Hard group, it takes a long time to run the TILRP.A small size of this problem is executed by GAMS. Because of lack of real examples in literature, random decisions are made for parameters.it is assumed the number of plants equal to P=3, the number of distributers and customers generally j=9, the number of types of products G=3 and the number of time period is to be t=3 .In Table 3, the Non-dominated solutions are investigated.

Table 3. Pareto solutions Obj function's value

Pareto solutions	Economic Obj value	Environmental Obj value	Social Obj value
1	42441.490	33796.814	26.526
2	71583.798	35776.814	14.601
3	71586.518	35776.814	14.601
4	71561.969	35776.814	16.238
5	71610.152	35776.814	13.229
6	101534.963	37756.814	11.443
7	131843.596	39736.814	9.405
8	133160.573	39846.814	7.367

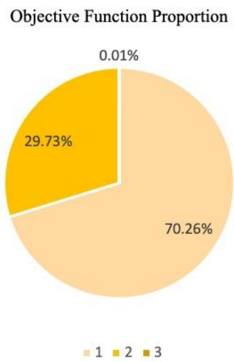

Figure 6. Objective function proportion

As it can see in Figure 6 More than 70% of costs assigned to economic objective function; therefore, to decrease amount of costs it's better to focus on this part rather than other functions.

The output of above example which is implemented by GAMS is illustrated in Figure 7. There are three periods in which it should make decision on the number of trucks transfer to each DCj, the amount of goods should send from each type to specific distributer, the inventory level at each period and determining routs to cover customer's demands. In the first period, one truck from plant 1 is sent to DC_1 which includes 9.2 amount of goods 1. The parenthesis on marks indicates the number of trucks, amount of goods 1,2,3 which transfer from plant 1, respectively. We rand up the amount of goods because in real world goods amounts are integer. So, it is sent 10 goods from type one instead of 9.2.

32 trucks which include 77 goods of type one, 82 of type two and 94 of type three departs the plant 2 to DC_1.Not any goods transfer from plant 3 and no customer allocated to DC_2.In this period no inventory left. In routing phase all customers are assigned to DC $_1$ and in wo parts the delivery will accomplishment. At first, the vehicle visits customer 3,8,5,9 respectively and finally turns back to its previous place (DC_1). Second, another route include customer 4,7,6 in order will visit. In the second peiod,11 trucks that involve 86 goods type 1 and 14 goods of type 3 from plant 1,10 trucks which include 2 goods of type 2 and 77 goods of type 3 from plant 2 and 11 trucks which carry 75 goods of type 2 from plant 3 is sent to $DC_{1.}$ In this period, all customers are allocated to DC_1 and again like previous period the delivery task will done in two phases. First vehicle visits customer 3,8,9,6 in phase 1 and customer 4,5,7 in order in another phase 2. In this period the inventory levels of goods type 1,2 and 3 are 25, 25 and 23 units, respectively.

In the third and last period only 32 trucks form plant two which carry 84 goods of type 1,84 of goods type 2 and 82 goods of type 3. All customers are assigned to $DC_1$and the vehicle visits the customer 3,8,5,7 in phase 1 and 6,9,4 in another phase. No inventory level left in this period.

It is employed some test instances, but before presenting this problem, we should state the size of the problem that is defined by (P, M, N, G, T) that the first vector implies number of plants, M as the number of potential locations for DCs, N as the number of customers, G as the number of types of products and T as time period.

After validating the proposed model, to assess the effectiveness of the proposed solution approaches, some problem instances are provided in this section. Both of the NSGA-II and MOPSO algorithms are coded in MATLAB R2017a software and executed on an Intel Corei7 PC with 12 GB of RAM and over 1.8 GHz CPU.

4.2. Problem Instances

Due to lack of benchmark in this problem, it is employed random parameters in this part for instances. It is conducted small, medium and large scale and the comparison results are in Table 4. Each instance is implemented 5 times and the average value of them is saved for each example.

The last instance which is (10,15,70,3,8) is executed and its pareto front solutions in NSGA-II and MOPSO is illustrated in Figure 8 and Figure 9.

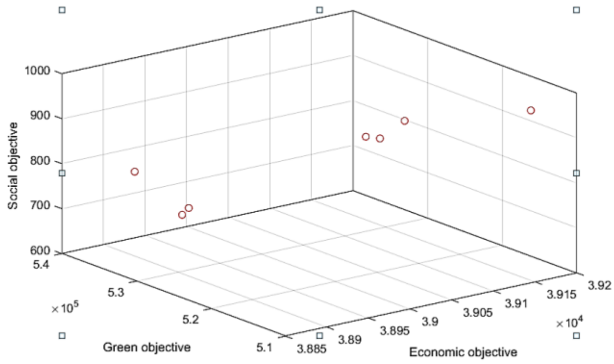

Figure 8. Pareto front for problem 14. (NSGA-II)

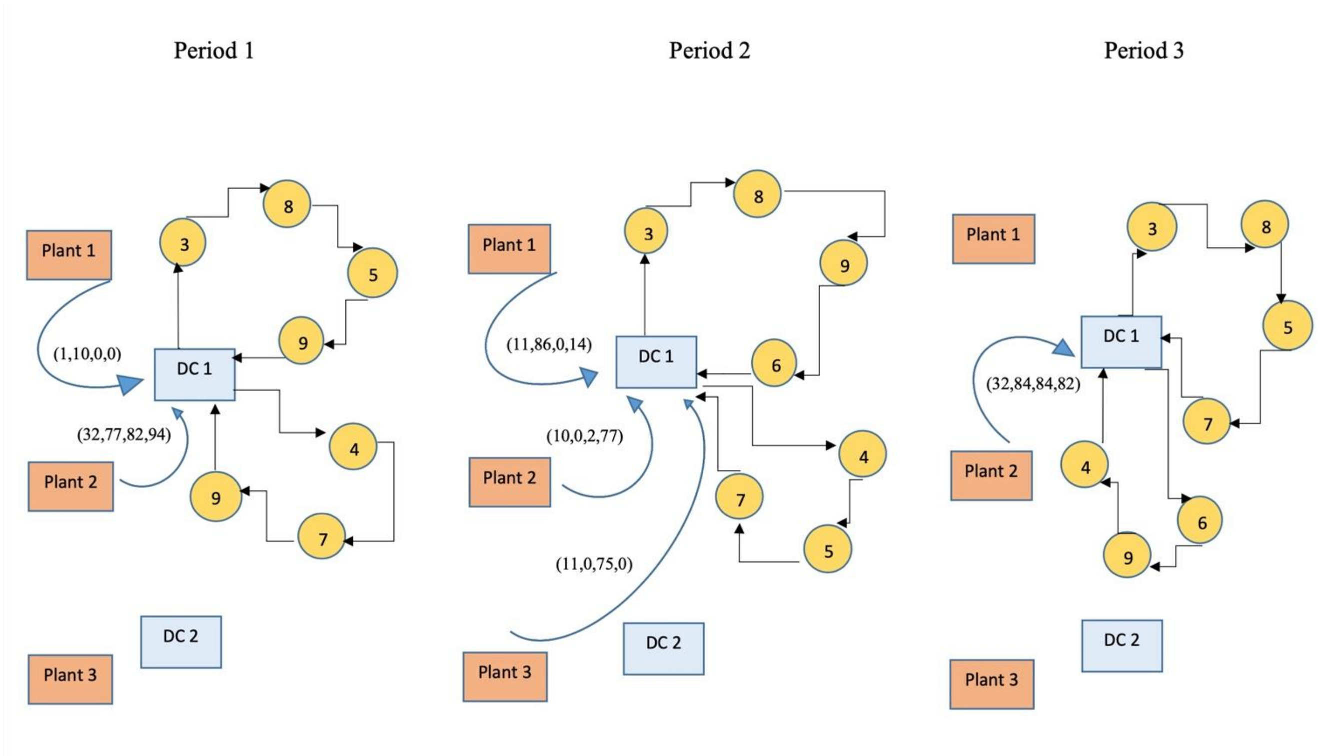

Figure 7. Output of an instance by GAMS

Table 4. Comparison metrics for small, medium and large size instances for NSGA-II and MOPSO

NO.	Size	NSGA-II				MOPSO			
		CPU	QM	DM	SM	CPU	QM	DM	SM
1	(2,4,7,2,3)	26.57	3.4	8901.954	2008.22	11.37	4	17384.81	1493.70
2	(2,5,8,2,2)	26.80	3.2	6277.792	1401.34	11.43	4	35678.75	8933.70
3	(3,5,10,3,3)	27.07	3.8	9544.532	1623.40	11.56	4.6	53024.21	8731.20
4	(4,7,12,3,3)	27.13	5.2	21486.74	4177.79	12.56	5.4	89136.71	21939.35
5	(3,6,12,2,3)	27.14	4.6	6184.518	773.33	12.05	4.4	32314.4	7665.41
6	(5,9,15,3,4)	28.32	5.2	18941.81	2568.92	12.60	4.8	60839.8	9326.59
7	(4,8,20,4,3)	28.15	6.4	42262.90	9605.78	14.97	5.8	156589.6	29111.40
8	(6,10,25,4,4)	32.13	6.8	33423.91	4090.37	16.76	7.8	229315.7	28059.45
9	(6,10,30,3,3)	34.30	7	44582.91	12092.01	17.46	7.6	187769.1	17315.74
10	(8,12,35,3,5)	34.71	9	22936.43	1324.77	18.40	8.4	340095.2	22930.36
11	(6,10,45,3,5)	35.77	11.6	33386.82	24329.68	20.14	9.4	672846.3	88331.54
12	(6,10,55,4,8)	38.81	8.4	177031.8	47153.59	21.79	7.4	685040.6	76017.01
13	(8,14,60,4,6)	39.21	9.4	49945.41	8149.04	22.02	6.8	513847.9	50100.03
14	(10,15,70,3,8)	41.65	11.8	32334.55	2724.36	24.70	8.2	693754.9	72472.17
Average		31.98	6.84	36231.58	8715.90	16.27	6.328	269117	31601.98

4.3. Comparison Metrics

To analyze the efficiency of algorithm and to have a comparison between these two algorithms, some metrics is defined and employed to illustrate better their performances. These metrics are as follows:

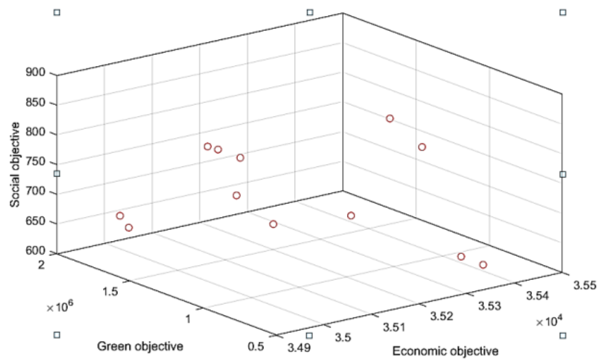

Figure 9. Pareto front for problem 14. (MOPSO)

4.3.1. Number of Pareto Front Solutions (NPS)

The algorithm which finds more pareto front solutions can be capable of generating better solutions compared to the algorithm has a lower number of Pareto frontier. The comparison of NPS between these two algorithms is depicted in Figure 10.

4.3.2.CPU Time

Whatever this metric be lower leads to a better efficiency time for finding optimal fronts. The comparison of CPU time is displayed in Figure 11.

4.3.3. Diversity Metric

The comparison between two algorithms base on diversity metric is illustrated in Figure 12.

4.3.4. Spacing Metric

As it depicted in Figure 13, it is obvious that NSGA-II has lower spacing metric's amount toward MOPSO metric's amount.

5.4. Comparison Result

While In terms of CPU time, diversity and spacing metric, MOPSP shows better performance rather than NSGA-II, in terms of quantity metric non-dominated sorting genetic algorithm displays better implementation in this issue. NSGA-II can generate more optimal frontier in this problem.

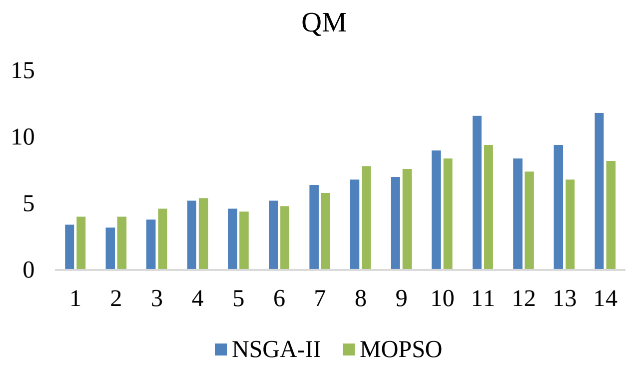

Figure 10. Comparison of proposed algorithms in terms of quantity metric

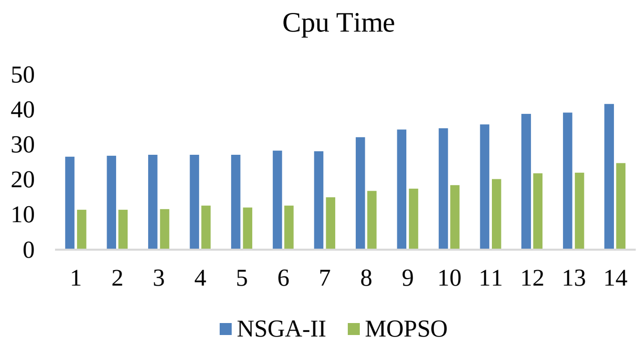

Figure 11. Comparison of proposed algorithms in terms of CPU time

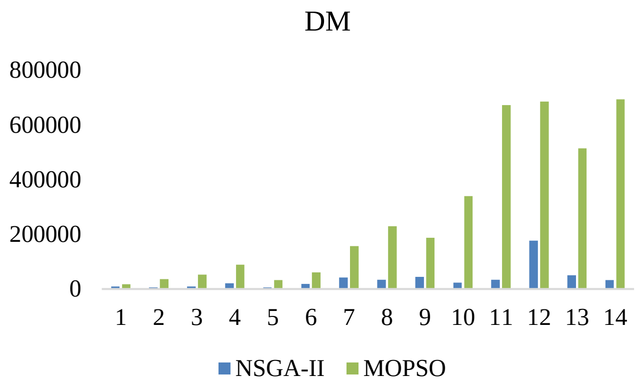

Figure 12. Comparison of proposed algorithms in terms of diversity metric

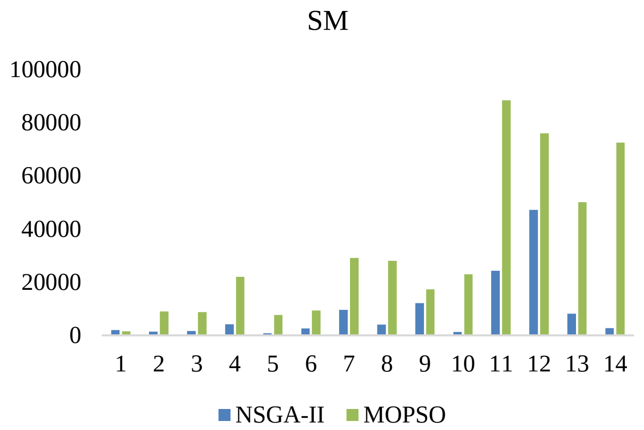

Figure 13. Comparison of proposed algorithms in terms of spacing metric

5. Conclusion

In this paper, a sustainable transportation location inventory routing problem (TLIRP) has been studied. For the term of sustainability three objective functions including economic cost reduction, reduction of negative environmental effects and reduction of negative social effects has been considered. Cost objective function such as transportation and routing costs and costs of opening distribution centers, production costs, inventory costs and the cost of ordering products, Environmental cost function includes the cost of carbon dioxide emissions, the fuel cost of trucks and vehicles, which the model tries to reduce the cost of malware to the environment, and the third objective function focus on not having any discrimination and priority among customers by minimizing difference between the starting time of service to a customer and the mean starting time of service to all customers. In this problem some decision's question were answered such as which distribution center (DC) is more beneficial to be open, the number of trucks to be ship to the DC, inventory level of DCs and customers. To solve the small size of the problem Gams is used. Since the NP-Hard nature of the for large size problem, NSGA-II and MOPSO were implemented. MOPSO algorithm shows better result in the Number of Pareto front Solutions (NPS), Spacing Metric (SM), and diversification of solutions in the space (DM) comparison to the NSGA-II algorithm while NSGA-II has the shorter computational CPU time (CT) than MOPSO.

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