Journal of Optimization in Industrial Engineering 22 (2017) 81-91
DOI: 10.22094/joie.2017.279

The Bi-Objective Location-Routing Problem Based on Simultaneous Pickup and Delivery with Soft Time Window

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Received 17 April 2014; Revised 23 May 2015; Accepted 24 June 2015

Abstract

The location-routing problem, while being new, is the most significant research field in location problems; features of vehicle-routing problem have been simultaneously considered along with the original problem for achieving high-quality integrated distribution systems, in addition to the global optimum. Contribution to the existing research presents the bi-objective multi-depot capacitated location-routing problem based on simultaneous pickup and delivery with soft time window (BOCLRPSPDSTW). Reasonable grounds that exhorted authors to get involved in this area and whence arising simultaneous pickup and delivery based on time window are the two main characteristics of logistic management that have been used separately in most of the location routing problem in spite of their various real-life applications with each other. Furthermore, market world competition circumstances always compel distribution managers to try creating a distribution system layout along with the lowest total system cost and enhancing service levels for providing customers' satisfaction, such that they can make the perpetuity of the distribution systems possible in the competition. Accordingly, to achieve the main goal within the demonstrative bi-objective mixed-integer linear programming model for BOCLRPSPDSTW, this study addresses the minimization of summation of all problem costs and minimization of maximum summation of delivery times and service times for meeting customer service level with respect to simultaneous pickup and delivery with soft time windows. Since this type of problem is NP-hard, NSGAII and NRGA are proposed to attain the Pareto frontier for the given problem. To validate the performance of the proposed algorithms in terms of solution quality and diversity levels, various problems are carried out, and their efficiency based on some comparison metrics is compared.
Key words: Location-routing problem with time window, Location-routing problem, Simultaneous pickup and delivery, Mixed integer linear programming, Bi-objective location-routing problem.

1. Introduction

Within developing and competitive world throughout the future, paying attention to logistic prospects is one of the principle indicators of a company's success. Undeniably, these centers deal with strategic, tactical, and operational decisions. Among them, two decisions, namely location and routing, which are strategic and operational decisions, play a crucial role. Location of depots, allocation of customers to each depot, and transportation policies for determining routes for establishing depots to all of the devoted customers are imperative sides with which managers cope. For a long time, researchers have separately considered the drawn problems with regard to their complex combination. An important question, which comes to mind of operation managers, is why Location problem and Routing have to be combined with each other. Salhi and Rand (1989) proved that considering location and routing problem separately obtains a sub-optimal solution. Hence, for having global optimum and efficient distribution system, both of the problems have to be combined with each other. Nagy and Salhi (2007) presented an exhaustive survey of LRPs proceeding to 2006. They suggested a classified method and considered a variety of the location-routing problem from the different aspects. According to the article, the obvious difference between location-routing problem (LRP) and location allocation problem (LAP) is that the latter one considers the occasion in the facility is located and assumes the straight-line, whereas the former involves a visit of customers through tours and tries to find the optimal facility location and route design at the same time.

Various traits have been described in LRP papers, but one of the important specifics that is not used significantly is simultaneous pickup and delivery problem. This is the linkage point of LRP with reverse logistic. In comparison to LRP, which presumes that all customers have just delivery demand, customers can actually have pickup and delivery demands in the real world. In their view, both demands should be met at the same time and all cumulative pickups should be returned to the depots. By taking this kind of demand structure, LRP with simultaneous pickup and delivery (LRPSPD)

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opens a new field in LRP research. The main cause of simultaneous pickup and delivery is reducing cost and using it in reverse logistics. In addition, in the prior item, every customer is intended to be served in time window framework. To meet this problem, time windows are occupied in supply chain and distribution corporations. In the last decades, the latter research field in the VRP is tended to give acceptable service for all customers in each customer time range (Wang and Chen, 2012). One of the reputable functions of LRPSPD is in the beverage industry (e.g., distributing beer, juice, etc. and collecting empty bottles for reusing) and the grocery store chains that have been remarked in most of the relation papers (karaoglan et al., 2012). In most real cases of supply chains, service level of customers tremendously depends on the minimizing maximum delivering and serving times; the role of the second objective in the proposed model meets the important one: having useful position in the supply chains and obtaining the most quota of the markets in the competitive business arena. Without a doubt, the outstanding effect of the second objective definition is on the time-sensitive systems such as food delivery, military services, and healthcare (Ghaffari-nasab et al., 2013). The imperative job is in the healthcare systems which necessarily revolve around the restoration of some drugs, predominantly expired medications, and switching devices.

Consequently, there is an occasion to attract all attentions and do research in the bi-objective LRP alongside the simultaneous pickup and delivery with soft time windows. Considering the mentioned areas, contribution of the article is introduced as modeling and solving of the multi-objective capacitated location-routing problem based on simultaneous pickup and delivery with soft time window and multi depot (BOCLRPSPDSTW). The proposed model encompasses efficiency (in the sense of cost minimization) and effectiveness (in connection with customer service level) of the distribution systems for leading customer satisfaction. Furthermore, two metaheuristic algorithms, NSGAII and NRGA, are advised for solving this model. Comparing these methods is placed in an important section of this paper.

the current paper is organized as follows. Brief surveys of the LRP: LRP with simultaneous pickup and delivery and LRP based on time window are expressed in section 2. In Section 3, BOCLRPSPDSTW mathematical model is presented. Section 4 contains a detailed execution of NSGAII and NRGA for solving the BOCLRPSPDSTW. Computational results obtained by applying the presented solution scheme to a series of test problem instances are reported in Section 5. Section 6 is dedicated to the final and concluding point of this paper .

2. Literature Review

Location routing problem can be categorized from a variety of outlooks. The prevalent classifications seen in most of the research studies are made up of PLRP (Periodic LRP), LRP with hub idea, LRPTW(LRP with time window), and LRPSPD(LRP based on simultaneous pickup and delivery). The last two criteria, regardless of the first two, are discussed in the current article in detail. Nevertheless, the worthwhile research papers have been done in the first two fields. Prodhon and Prins (2008) used memetic algorithm with population management for solving periodic location routing problem. Their goal was to consider multiple decision levels concurrently. A large variable neighborhood search was proposed by (Pirkwieser and Raidl, 2010). Prodhon (2011) demonstrated mathematical model and hybrid evolutionary algorithm for solving this model. The algorithm is the combination of the extended local search and Clarke and Wright algorithm. One of the studies in the hub LRP was done by (Setak and Karimi, 2013). Their study is about incomplete networks in hub LRP grounds, related to urban transportation. There is a lot of literature review about the LRP which is written from diverse features like mathematical model and demonstrating exact algorithms and metaheuristic ones. Albareda-sambola et al. (2005), Prins et al. (2006), Mariankis et al. (2008), and Duhamel et al. (2010) are some of the related researchers. Whereas the BOCLRPSPDSTW is not mentioned in the literature in advance, outlining the related works with this problem would be of priority. The BOCLRPSPDSTW consists of two sub problems: the facility location problem (FLP) and the vehicle routing problem with simultaneous pickup and delivery (VRPSPD) based on soft time windows. The previous one is composed of two sub problems: VRPSPD and VRPSTW. FLP, VRPSPD, and VRPSTW are among the research subjects that have been studied over the decades. (Parragh et al., 2008) and (Smith et al., 2009) are the survey articles in the VRPSPD and FLP, in that order. Concerning VRPSPDSTW, the keen readers can refer to (Wang and Chen, 2012) research. LRPSPD was considered by (Moshiev, 1994) for the first time. His research is based on travelling salesman location problem with pickup and delivery. The author’s contemplated customer demands are stochastic variables used for solving the presented model; heuristic approach is founded on customers rankings. LRPSPD is also the expansion of the LRP in terms of each customer demand which is composed of pickup and delivery problems simultaneously. To many, LRP (MMLRP) introduced by (Nagy and Salhi, 1998) is the general form of LRPSPD. In this problem, numerous customers desire to send products to another; in addition, streams between depots are acceptable. The prominent studies in LRPSPD were conducted by (Karaoglan et al., 2011), (Karaoglan et al., 2012); they are labeled as the leading and inspirational sources for the current authors. In the first paper, a new model from a new vision was suggested for the LRPSPD based on arc routing problem. In the advised model, the number of vehicles is not considered. For solving this NP-hard problem, exact and branch-and-cut algorithms have been used. Besides the arc presented model in the first paper, in the last demonstrated article, node-based model was depicted. To solve the large-sized LRPSPD, a two-phase heuristic algorithm was derived from simulated annealing; for tp_SA initial solution, the heuristic algorithm was developed.

In perusing literature of LRPTW, one of the salient works is related to (Nikbakhsh and Zegordi, 2010). They presented 4-index non-linear 2-layer model for the LRP with soft time windows. For solving this model, heuristic approach based on Or-opt has been utilized. Numbers of multi-objective LRP works are as follows: Lin and Kwok (2006) offered multi-objective metaheuristic algorithm for LRP with multiple uses of vehicles. Tabu search and simulated annealing metaheuristics were used for solving the problem. At last, their performance was compared. The multi-objective model of (Caballero et al., 2007) was based on four-objective that tabu search metaheuristic algorithm has applied for real instances. In addition to the usual cost of objective function, there are social objectives (social rejection by towns on the vehicle routes, maximum risk as a fairness scale, and the adverse effect on the plant closing towns). Hassan-Pour et al. (2009) offered a new bi-objective mathematical programming model for a stochastic location-routing problem (SLRP) with the cost objective; the second objective maximizes the probability of delivery to customers. This model is solved in two steps: phase one involves solving the FLP by a mathematical algorithm, and phase two involves solving the multi-objective multi-depot vehicle routing problem (MO-MDVRP) by an SA algorithm with genetic operators. Demonstrating a new model for bi-objective LRP was done by (Tavakkoli moghaddam et al., 2012). The first objective, as all single objectives, is cost; the second objective function maximizes the whole demand served. This objective function reveals that responses to all customers are not done. Concerning the solution method, scatter search was used for solving the model. Bi-objective model of (Ghaffari-nasab et al., 2012) had stochastic time variable as the second objective involves minimizing the maximum expected delivery time to the customers. A variable neighborhood descent-based heuristic to solve the outcome model was suggested. Ghaffari-nasab et al. (2013) determined integer linear mathematical model for MOCLRP. This model aims to minimize the cost and the maximum delivery time to the customers. Furthermore, heuristic simulated annealing is used to solve the model.

3. Problem Definition and Mathematical Programming Formulation

The main point of this paper does not indicate the number of vehicles. The reason for that matter comes back to the authors' strategic point of view for determining their number, which helps to use the resources economically. In the present problem, every customer is assigned to one supplier depot. In addition to original vehicle routing problem and location routing problem, each route customer is served by one and the same vehicle. Concerning BOCLRSPDSTW, the goal is to determine the location of potential depots, vehicle routes from depots for fulfilling the pickup and delivery demands of each customer simultaneously in the time window outline in order to convince the objective functions.

3.1. Problem assumption

- The mentioned problem is defined in a completed, directed graph where customers and depots are placed in their nodes
- Customer demands are deterministic and composed of pickup and delivery simultaneously
- All of the vehicles are homogeneous and capacitated
- At any node, total load of vehicle cannot surpass its capacity
- Total pickup and total delivery of the assigning customer to each establishing depot do not exceed its capacity

3.2. Parameters and variables of the proposed model

Let G=(N,A) be the directed weighted completed network, where A={(i,j)|i,j∈N}is the edge between two nodes, travelling cost between i,j is c_{ij}. N=C∪D where C and D indicate costumers and depots, respectively. d_j and p_j are delivery and pickup of customer j. Q_k is capacity of each depots, V is capacity of vehicles, O_i is fixed cost of depot establishing, F is fixed cost of vehicle employing, s_j is service time for jth costumer, t_{ij} is travelling time between i,j, l_j and u_j are correspondingly lower and upper bounds of time window for jth costumer, and eventually α_j, β_j depict penalties for arriving after the upper bound and before the lower bound of time window. The subsequent binary variables are: x_{ij}=1 if vehicle travels directly from i to j, z_i=1; if depot i is opened, y_{ji}=1; if costumer j is allocated to depot i, at_j will be the arriving time to jth node, SD_j is delivery load on vehicle before having serviced customer j, SP_j is pickup load on vehicle after having serviced customer j. Violation of the time window for the upper and lower bounds is E_j, L_j, respectively. The mathematical programming for BOCLRPSPDSTW can be expressed as follows:

$$min \sum_{i\in N}\sum_{j\in D} c_{ij}x_{ij} + \sum_{i\in D}\sum_{j\in C} Fx_{ij} + \sum_{i\in D} O_i Z_i + \sum_{j\in C} E_j\alpha_j + \sum_{j\in C} L_j\beta_j \quad (1)$$

$$Min\ max\left(\sum_{i\in N}\sum_{j\in N, i\neq j} t_{ij}x_{ij} + \sum_{n\in N}\sum_{j\in C, n\neq j} x_{nj}s_j\right) \quad (2)$$

St:

$$\sum_{j\in N} x_{ij} = 1 \quad (\forall i \in C, i\neq j) \quad (3)$$

$$\sum_{j\in N} x_{ji} - \sum_{j\in N} x_{ij} = 0 \quad (\forall i \in N, i\neq j) \quad (4)$$

$$\sum_{k\in D} y_{ik} = 1 \quad (\forall i \in C) \quad (5)$$

$$x_{ik} \leq y_{ik} \quad (\forall i \in C, k \in D) \quad (6)$$

$x_{ki} \leq y_{ik}\ (\forall i \in C, k \in D)$ (7)

$x_{ij} + y_{ik} + \sum_{m \in D, m \neq k} y_{jm} \leq 2\ (\forall i, j \in C, k \in D, i \neq j)$ (8)

$\sum_{i \in C} d_i\, y_{ik} \leq Q_k z_k\ \ (\forall k \in D)$ (9)

$\sum_{i \in C} p_i y_{ik} \leq Q_k z_k\ \ (\forall k \in D)$ (10)

$SD_{j'} - SD_j + V x_{jj'} + (V - d_j - d_{j'}) x_{j'j} \leq (V - d_j)\ \ (\forall j, j' \in C, j \neq j')$ (11)

$SP_j - SP_{j'} + V x_{jj'} + (V - p_j - p_{j'}) x_{j'j} \leq (V - p_{j'})\ \ (\forall j, j' \in C, j \neq j)$ (12)

$SD_j - d_j + SP_j \leq V\ \ (\forall j \in C)$ (13)

$SD_j \geq d_j + \sum_{j' \in C, j' \neq j} d_{j'} x_{jj'}\ \ (\forall j \in C)$ (14)

$SP_j \geq p_j + \sum_{j' \in C, j \neq j'} p_{j'} x_{j'j}\ \ (\forall j \in C)$ (15)

$SD_j \leq V - (V - d_j) \sum_{i \in D} x_{ji}\ \ (\forall j \in C)$ (16)

$SP_j \leq V - (V - p_j) \sum_{i \in D} x_{ij}\ \ (\forall j \in C)$ (17)

$at_j + s_j + t_{jj'} - T(1 - x_{jj'}) \leq at_{j'}\ \ (\forall j \in N, j' \in C, j \neq j')$ (18)

$E_j \geq at_j - u_j\ \ (\forall j \in C)$ (19)

$L_j \geq l_j - at_j\ \ (\forall j \in C)$ (20)

$L_j \geq 0\ \ (\forall j \in C)$ (21)

$E_j \geq 0\ \ (\forall j \in C)$ (22)

$x_{ij} \in \{0,1\}\ \ (\forall i, j \in N)$ (23)

$y_{ji} \in \{0,1\}\ \ (\forall j \in C, i \in D)$ (24)

$z_i \in \{0,1\}\ \ (\forall i \in D)$ (25)

$at_i = 0\ (\forall i \in D)$ (26)

$at_j \geq 0\ (\forall j \in C)$ (27)

The first objective function minimizes summation of transportation cost, establishment of fixed cost of depot, and vehicles fixed cost. The last two parts of it present penalty costs due to the violation of the upper and lower bounds of time window. The role of the second objective is minimizing maximum summation of travelling time and service time between two nodes. Constraint (3) shows that each customer has to be visited just once. The forth describes a number of arcs in which entering to the node and removing it are alike. Equation (5) is used for allocation of just one depot to each customer. Constraints (6) -(8) forbid all of the unauthorized routes between depot and customer and also between the customers. In fact, the eighth equation shows that arc between two customers exists when both of them are allocated to the same depot. Constraints (9), (10) show that the total delivery related to a depot and the total pickup of a depot must be less than depot capacity. Equations (11), (12) are sub tour eliminations. Full amount load on any arc does not exceed total load on vehicle; it is presented in equation (13). Constraint (14) explains that delivery load on vehicle before serving jth customer should be larger than the consumer delivery and delivery of the next customers, which are connected with each other. In constraint (15), the previous state is adopted to the pickup, but it describes the pickup after serving the jth customer due to the pickup's additional variable definition. Regarding equations (16),(17), they indicate relations between the additional variables and vehicle capacity in the last customer and the first customer for delivery and pickup's additional variables, respectively. Constraint (18) is a special constraint for the time window as it explains the relation between receiving time for every node and the previous time of it. T is a sufficiently large number. Equations (19),(20) specify penalties constraints. The rest of the constraints are zero, one, and integer constraints.

The second objective function in the presented model is of non-linear type. In MILP, it has to be linearized. The following model causes a linearization corresponding to the previous model except altering objective function (2) and adding another constraint, thanks to the linearization:

Objective function (1):

$min\, TT$ (28)

St:

$\sum_{i \in N} \sum_{j \in N, i \neq j} t_{ij} x_{ij} + \sum_{n \in N} \sum_{j \in C, n \neq j} x_{nj} s_j \leq TT$ (29)

(3)- (26) (30)

$TT \geq 0$ (31)

4. Methods for Solving BOCLRPSPDSTW

In the current section, the main approaches for solving the suggested multi-objective model are presented. Nagy and Salhi (2007) demonstrated that LRP is composed of two Np-hard sub problems: location and routing; as a result, their combination will be surely of NP-hard kind. Since the description model is NP-hard, a favorable solution to ε-constraint for large-sized problem is not achieved. Hence, metaheuristics are necessary to obtain solutions for these problems. In the existing research, NSGA-II and NRGA are the reputable approaches for solving multi-objective problems applied.

4.1. Solution representation

A suitable representation for solving NP-hard problems is important. Without a doubt, solution structure besides the coding methods should satisfy all constraints. Definitions of two matrices, A and P, and the use of coding approaches can obtain this aim of the article problem. Structure of the solution is like figure 1.

Additionally, the structure is a linear matrix with one row, and the number of columns is equal to the number of customers. Every element of this matrix indicates which customer is devoted to each open depot. It is of significance to mention that the initial solution used by the algorithm is generated randomly. In P matrix, there is one row and column points for the customer serving priority. If a customer cannot be served with respect to satisfying constraint in this priority, another customer has to be served from this depot.

4.1.1. Using operators

To solve the presented model by using proposed algorithms, two-crossover and two-mutation operators for each matrix are applied.

Crossover operator

An important part of evolution in the nature depends on chromosomes and parent election methods for their combination in the right way. Each solution chromosome is composed of two matrices (A, P). When crossover is done on parent's chromosomes, in fact, this operation is done on each matrix (A and P). However, by paying attention to shape and structure of matrices, different operators can be used. Crossover operator used by matrix A is uniform and for P is a single-point crossover, but this is the kind used in permutation structures.

Because of the permutation trait of P, it is necessary to consider the justified action when it operates. This sufficient action prevents gene duplication. For using this method, at first, the crossover point is selected. The genes before this point are transferred directly; to compose the rest of the chromosome in the first individual, all of the second parent's genes are considered and compared among the selected gens. If there are not repetitive onces, the next gene is set in the first individual. Concerning the second offspring, polar action is operated. This operation is shown in figures 2.a and 2.b. According to the second parent's genes, the rest of the first offspring will be 5, 2, and this matter about the second offspring with respect to the first parent will be 3, 2.

Mutation over A matrix

For Mutation over A matrix, in the first step, it is necessary to create a random matrix with the same size of A. In the next one, the elements, whose amount is less than mutation rate, are found. Their amount with the random number generated in the [1, D] is changed. Suppose that over 1 to 7 positions of parents' mutation occur. In this state, according to produced randomized depots, new depots would be replaced by mutation elements. These kinds of mutation are depicted in figure 3.

Mutation over P matrix

Due to the permutation specification of this matrix, there are two steps available:

1) Randomly choose two elements (two customers) from a row.

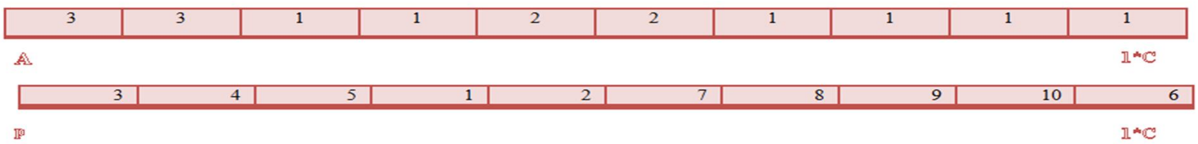

Fig. 1. A, P using matrix in solution structure

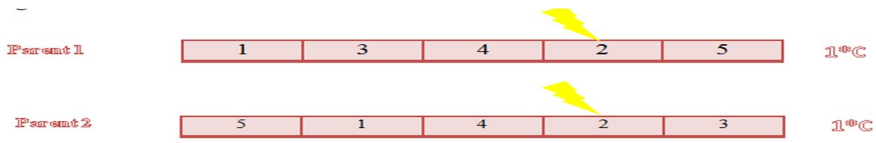

Fig. 2.a. the crossover point in p matrix

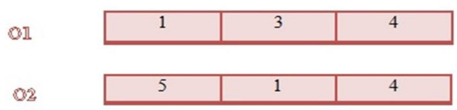

Fig. 2.b. the first three gens of offspring's point in p matrix

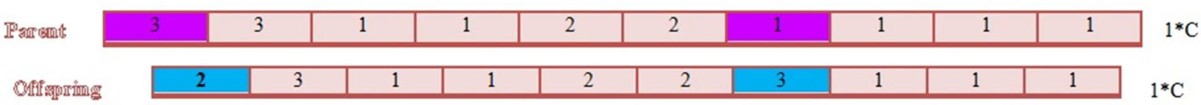

Fig. 3. Mutation over A matrix

2) One of the swap, insertion, and reversion operators is chosen randomly and operates on the two-selected customer in the previous step.

It is possible for each of these operators to have similar actions to another. So, all of these states have to be emitted.

5. Computational Study

In this section, the result of applying NSGA-II and NRGA to BOCLRPSPDSTW is done and shown. The algorithms have been coded in MATLAB R 2010b and run on a laptop with an Intel Core i5 CPU (2.27 GHZ) and 4 GB memory. In order to evaluate performance of the proposed algorithms, there is no benchmark problem for the presenting model. Nonetheless, there is a benchmark for LRPSPD (Karaoglan et al., 2012), without considering time window concept. For this reason, the current authors had to make samples with their own instances for the time window part. Of course, it is essential to mention that the fundamental dataset of the research paper of (karaoglan et al., 2012) is based on different methods: that of Nagi and Salhi and Angelelli and mansini's approaches, which are mentioned in their papers extensively; the parts of the pickup and delivery data cited in this paper are related to Angelelli and Mansini's approach. Time windows should be adjusted to the customers with respect to their conditions.

5.1. Comparison metrics

Overall, in contrast to single objective, diversity of pareto solutions and also their convergence are important factors in the multi-objective problems (Deb et al., 2002). The following four comparison metrics are applied.

5.1.1 The number of Pareto solutions (NPS)

This metric shows the number of pareto optimal solutions found by each algorithm (Schaffer, 1985).

5.1.2 Diversification metric (DM or diversity)

The diversification of metric measures spread the solution set and is defined by (Zitzler, 1999).

$$D = \sqrt{\sum_{i=1}^{n} \max(\|x_t^i - y_t^i\|)}$$

Where the parenthesis statement indicates Euclidean distance between the nondominated solutions x_t^i , y_t^i.

5.1.3. Mean Ideal distance (MID)

Proximity of answers from ideal point that is equal to (0, 0) on the pareto front appraisal. The next equation shows that algorithm efficiency is high if this scale is the least (Rahmati et al., 2012).

$$MID = \frac{1}{NOS} \sum_{i=1}^{NOS} c_i \qquad where\ c_i = \sqrt{\sum_{j=1}^{m} f_{ji}^2}$$

5.1.4. Time

Time is the most important and main scale in comparing the two algorithms.

5.2. Parameter setting

Parameter tuning may affect computational results of quality. For having accurate comparison between two algorithms, it is necessary to consider both of them in the same situation. One of them is to have the same solution. Due to this fact, regarding the number of iteration, nIt, paying attention to the number of population, npop, is logical. In the initial experiments, different combinations of parameters in NSGA-II and NRGA were considered and tested on the set of test problem samples. Table 1 specifies ranges of parameter used.

Table1
Factor domains in NSGA-II and NRGA

Methodology	Parameter	Range
NSGAII& NRGA	$npop$	50-150
	p_c	0.3-0.7
	p_m	0.1-0.3
	$muterate$	0.1-0.3

RSM is an approach, which is utilized in this study for parameter tuning. (MID/Diversity) is used for determining the surface parameter. Considering two important scales simultaneously will be useful, thanks to the effect of two scales instead of just one of it. In the recent parameters, the number of iteration appoints tuning stopping criteria. The tuning parameters are as follows:

Table 2
The final value of parameters

Variable	Value
npop_nasgaII, nrga	50,50
Pc_nasgaII, nrga	0.3,0.3
Pm_nasgaII, nrga	0.3, 0.1
Mutarate_nasgaII, nrga	0.1358432, 0.1928898
Itr_nasgaII, nrga	400, 400

5.3. NSGAII and NRG applied in the proposed instances

To compare the performances of NSGAII and NRGA, forty-six data instances are applied for the comparison. C and D depict the number of customer and depots, sequentially. C= {5, 10, 20, 30, 50, 70, 85, 100, 130}; D= {2, 3, 5, 10}. For eliminating the effect of the problem size, RPD can be a suitable alternative while it demonstrates what the distance from the best answer is. It is palpable that the smaller RPD is preferred. Each problem is solved by both of the algorithms for a number of times. The best-earned amount of all executed solutions, $Best_{sol}$, and best result in each algorithm execution, Alg_{sol}, are required for calculating this criterion.

$$RPD = |\frac{Best_{sol} - Alg_{sol}}{Best_{sol}}| * 100 \qquad 0 \leq RPD \leq 100$$

Tables 3, 4, 5 are boded rudimentary information, NRGA_soft time window, and NSGAII_soft time window, respectively. The premier algorithm on every scale is evident in every table.

Table 3
Problem sets

NO. Problem	C	D
1,2,3,4,5	5	2
6,7,8,9,10	10	3
11,12,13,14,15	20	4
16,17,18,19,20	30	5
21,22,23,24,25	50	5
26,27,28,29,30	70	5
31,32,33,34,35,36	85	5
37,38,39,40,41	100	10
42,43,44,45,46	130	10

Table 4
NRGASTW data for 46 instances based on RPD for specified scales

NRGA Soft time				
NO	*Time*	*MID*	*NOS*	*iversity*
1	0.772863	0	0	0
2	2.409761	0	0	0
3	0.50088	0	0	0
4	0.667278	0	0	0
5	0.464601	0	0	0
6	1.624327	1.009599	0	1.662791
7	0.237595	0.060216	0	9.023723
8	2.27473	1.737393	5.333333	28.11407
9	0.761783	0.477358	0	0.602053
10	3.292692	1.571357	0	0.394194
11	0.590778	5.076662	0	9.778235
12	0.809944	4.874079	0	58.58097
13	0.408034	2.955823	0	42.35477
14	0.381083	5.26368	0	25.39495
15	1.193283	2.912137	0	15.34058
16	0.564504	3.617438	0	7.420764
17	0.299521	3.292353	0	24.8128
18	1.36843	15.71823	0	22.23356
19	0.124688	23.00818	0	6.010909
20	0.792779	5.216887	0	40.24925
21	3.622071	2.338783	12	31.92788
22	0.90811	3.512944	0	26.73429
23	1.593041	25.23109	0	10.25493
24	1.200471	53.93842	0	44.01779
25	2.570975	34.00389	0	5.026764
26	0.674021	25.17249	0	8.107787
27	0.778242	31.85526	7.333333	16.71129
28	1.092601	13.46713	0	20.76698
29	1.766958	34.59931	20	23.23657
30	0.706008	28.42181	0	6.168346
31	0.389208	3.336406	0	19.22575
32	0.388953	31.23681	0	11.24359
33	1.392422	48.5841	0	15.75162
34	0.333445	3.776477	0	2.731522
35	0.908368	23.77685	1.333333	2.966864
36	4.663841	63.99159	0	60.01375
37	0.780217	3.480382	0	14.23946
38	0.547341	3.108366	0	16.19428
39	0.761793	2.208324	0	31.10337
40	1.415069	1.599568	0	61.1555
41	0.05733	9.969489	0	19.01801
42	3.274297	6.196479	13.33333	89.15355
43	0.816231	6.35798	0.666667	15.46045
44	1.408124	4.211084	0	20.28767
45	3.604788	19.70887	0	10.56465
46	1.066261	8.102646	0	21.5335
Average	1.223038	12.36909	0.666667	19.4689

Table 5
NSGAIISTW data for 46 instances based on RPD for specified scales

	NSGAII Soft time			
NO	Time	MID	NOS	Diversity
1	15.28785	0	0	0
2	14.46466	0	0	0
3	14.73761	0	0	0
4	13.80934	0	0	0
5	14.26584	0	0	0
6	12.8255	0.941327	0	2.125825
7	11.26376	0.484793	0	1.023621
8	13.98364	2.653868	0	41.81161
9	16.76081	1.327427	0	0.297188
10	14.26562	1.009495	0	1.478771
11	17.06871	2.176083	0	21.50496
12	19.27681	2.664158	0	82.08265
13	13.78907	9.922356	0	18.68973
14	13.00622	12.19372	0	21.69011
15	14.71064	1.929128	0	91.50016
16	18.03104	0.341245	17.33333	33.70718
17	14.80539	0.089967	0	38.26812
18	13.10365	3.930674	2.666667	37.45488
19	12.1101	8.5466	20.66667	16.02499
20	14.82475	12.33096	0	17.74501
21	20.09309	3.059908	16.66667	13.19752
22	19.36737	32.35872	0	1.681491
23	20.66797	10.31834	3.333333	5.350535
24	14.11241	4.961019	27.33333	8.622017
25	17.70484	56.51873	0	4.510175
26	19.07172	31.86853	0	17.45887
27	20.12235	24.40208	0	11.17128
28	16.27579	1.995579	0	5.290688
29	17.25804	17.0554	0	11.69719
30	15.14101	11.63378	26.66667	22.0109
31	18.2394	0.256969	0	25.39966
32	19.94126	29.88079	0	15.39121
33	19.25241	17.9812	8	7.673533
34	17.44217	1.285776	0	11.0257
35	32.00408	15.02207	0	21.46733
36	22.82753	33.84727	0	89.43411
37	18.32891	1.549423	4	17.79227
38	20.59575	0.030756	0	14.6112
39	21.12924	5.940559	0	2.374059
40	19.03236	4.598122	0	90.81477
41	19.05277	4.308765	0	6.032499
42	23.70133	6.014172	0	30.94327
43	24.41533	3.441457	0	7.395457
44	23.59575	13.03484	0	2.953348
45	6.398642	24.63632	0	13.08281
46	30.87608	4.508756	0	24.95307
Average	17.5878	9.153285	2.753623	19.7335

Evaluations of the two algorithms are depicted in figure 4 which lightly proves the excellent one in each scale.

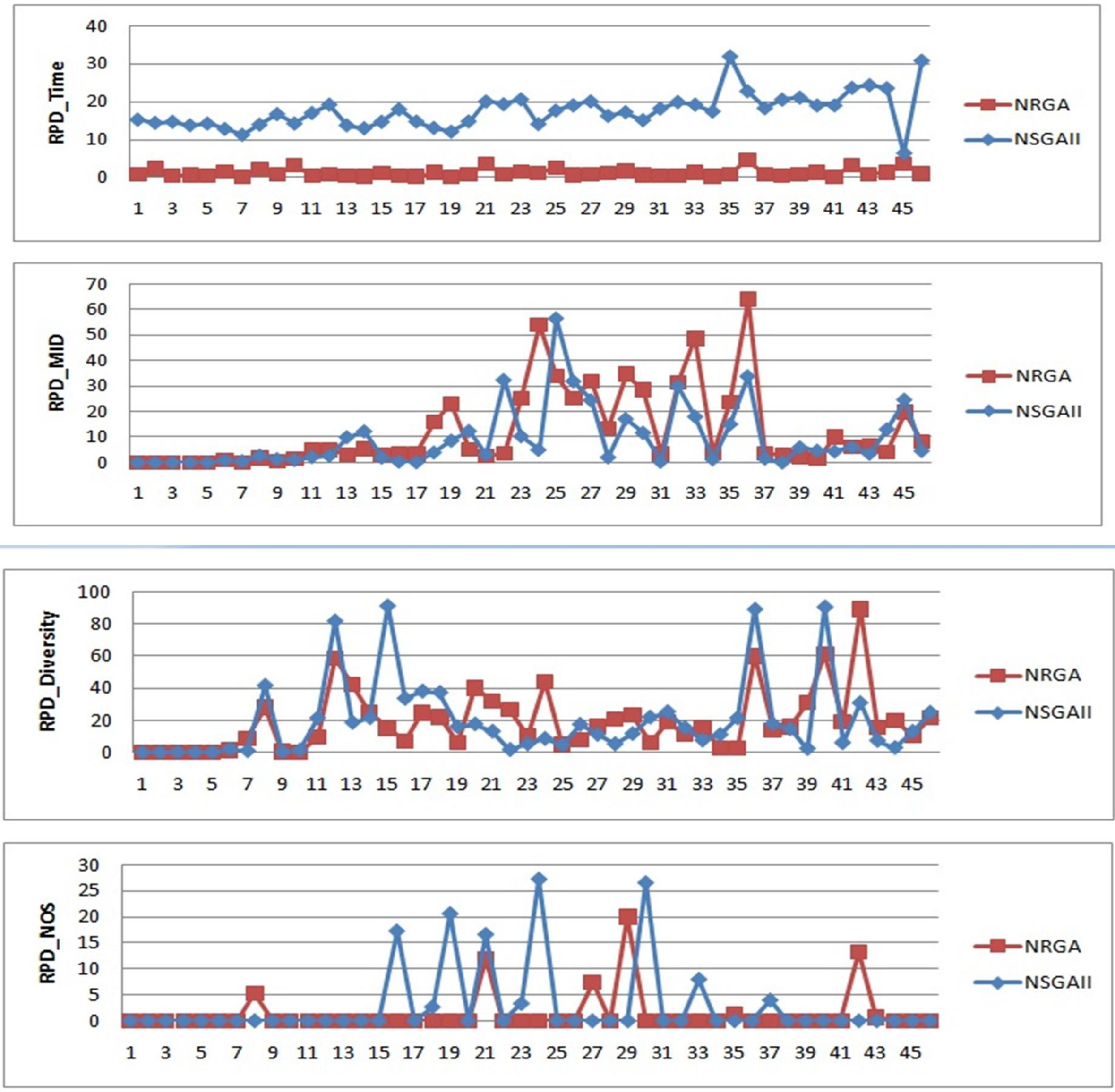

Fig. 4. Graphic diagrams of comparision between two algorithm based on 4scales

In accordance to tables 4, 5 and figure 4, the average performances of both algorithms in each scale can be comprehended. Table 6 contains these averages in each scale for both algorithms established upon RPD.

Table 6
Average performance of NSGAII and NRGA

Algorithm	MID	Diversity	Time	NOS
NRGA	12.36909	19.4689	1.223038	0.666667
NSGAII	9.153285	19.7335	17.5878	2.753623

How these algorithms work in every scale is that in MID, NSGAII is preferable to NRG; in the rest of the scales, NRGA is better than the second one. For enriching comparison statistical analysis, F-test has been done by Minitab16 statistical software. In the statistical analysis, if p-value is smaller than 5%, null hypothesis (P_0) is not accepted. Hypothesis refusal demonstrates salient difference between performance evaluation criteria of the algorithms, and vice versa. Variance analysis output in table 7 is presented.

Table7
Average performances of NSGAII and NRGA

Scale name	P-value
MID	0.275

Diversity	0.954
NOS	0.227
Time	0.000

Table 7 displays Time scale; P_0 is accepted in others. Accordingly, there is no significant difference between the algorithms and in the MID; Diversity and NOS algorithms are competitive and reactionary to each other. Both Figures 6 and 7 are Pareto optimal curves for NRGA and NSGAII, respectively.

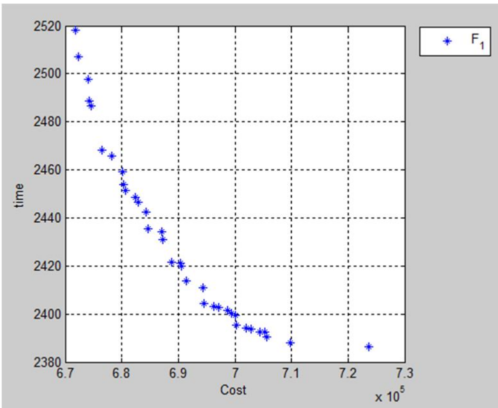

Fig. 5. NRGA Pareto Curve

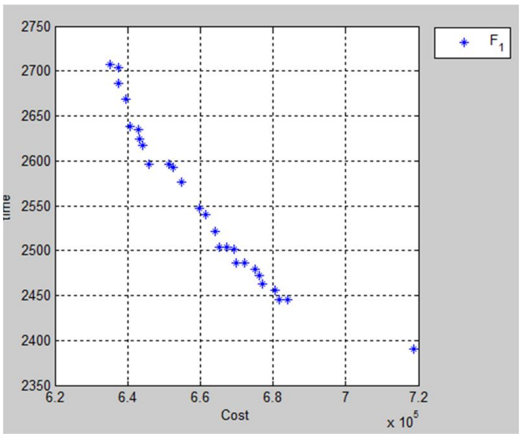

Fig. 6. NSGAII Pareto Curve

As it is clear from figures 5 and 6, there is an obvious conflict in the most points between two objective functions of the problem (total cost and maximum summation of delivery time and service time). But, the important and noteworthy point of the pareto optimal curves is that in some points, there is no complete conflict. In fact, when the decision maker wants to minimize time, cost maximization is not mandatory in some cases, because in these events that time minimization is not salient, cost raise will not occur. Chiefly, conflict occurs when time decreasing is high and sensible. In other words, if time has a main role in the decision, surely, choosing a solution with low service time and deliery time is logical even if it incurs high cost. For instance, in critical cases like in medical, food distribution, and military cases, the key role is to take over the role of time minimiziation, although spending much more cost has to be obligatory. In multi-objective problem, there is no priority between objectives, the same as in the above figures is depicted; it is required to define metrics in order to compare the algorithms.

One of the obvious results of the soft time window which is caused by increasing penalty cost for some customers, amount of E_j , L_j is decreased and arriving time for these customer sets in the time window. This outcome can be due to the greater impact of the penalties on the values of the objective function of the soft time windows.

5. Conclusion

In this paper, BOCLRPSPDSTW was presented intensely out of the presented mathematical model and also solutions derived from metaheuristic algorithms. This paper dealt with the problem for the first time, since it can be used for the diverse real-world cases in the distribution networks, particularly for the reverse logistics and time-sensitive cases like healthcare, militery service, the food distribution. In most of these real conditions, the primary goal of the supplier is to meet all costumer needs, or at least the overall time and cost. Bi-objective mathematical programming models were applied to the problem formulation; besides, two algorithms were presented for solving problem. Whereas dealing with this problem was done for the first time, there were not any benchmark set and obtained solutions by metaheuristic algorithms. For this reason, problem sets that were made with respect to the literature and authors were tested by both of NSGAII and NRGA; at last, comparing each algorithm's solution based on four metrics was done. Pareto non-dominated solution curve evidently implied the nature of the bi-objective problem due to the relative conflicting total cost function and maximizing the summation of delivery time and service time. This research can provide a new opportunity in the real world application, especially with fuzzy or statistic parameters. The noticable, yet interesting point of this paper is reflecting on the special state of period aspect with (p=1) day of service. Periodic attribute to several serving days is one of the practical position, rarely received attention by researchers.

References

Albareda-Sambola, M., Fernandez, E., & Laporte, G. (2007). Heuristic and lower bound for a stochastic location-routing problem. *European Journal of Operational Research*, 179, 940–955.

Caballero, R., Gonzalez, M., Guerrero, FM., Molina, J., & Paralera, C. (2007). Solving a multiobjective location routing problem with a metaheuristic based on tabu search Application to a real case in Andalusia. *European Journal of Operational Research*, 177, 1751–63.

Deb, K. (2001). Multi-Objective optimization using evolutionary algorithms. Chichester, UK: Wiley.Duhamel, C., Lacomme, P., Prins, C., Prodhon, CA. (2010). GRASP * ELS approach for the capacitated location-routing problem. *Computers and Operations Research*, 37, 1912–23.

Ghaffari-Nasab, N., Jabalameli, Aryanezhad, M.B., & Makui, A. (2012). Modeling and solving the bi-objective capacitated location- routing problem with probabilistic travel times. *Int J Adv Manuf Technol*.

Ghaffari-Nasab, N., Jabalameli, M.S., & Saboury, A. (2013). Multi-objective capacitated location-routing problem: modelling and a simulated annealing heuristic. *Int. J. Services and Operations Management*, 15(2).

Hassan-Pour, H.A., Mossadegh-Khah, M., & Tavakkoli-Moghaddam, R. (2009). Solving a multi-objective multi-depot stochastic location-routing problem by a hybrid simulated annealing algorithm. *Journal of Engineering Manufacture*, 223, 1045-1054.

Karaoglan, I., Altiparmak, F., Kara, I. & Dengiz, B. (2011). A branch and cut algorithm for the location-routing problem with simultaneous pickup and delivery. *European Journal of Operational Research*, 4, 318-332.

Karaoglan, I., & Altiparmak, F., Kara, I. and Dengiz, B. (2012). The location-routing problem with simultaneous pickup and delivery: Formulations and a heuristic approach. *Omega*, 40, 465-477.

Lin, CKY. & Kwok, R.C.W. (2006). Multi-objective metaheuristics for a location-routing problem with multiple use of vehicles on real data and simulated data. *European Journal of Operational Research*, 175, 1833–49.

Marinakis Y, & Marinaki M. (2008). A particle swarm optimization algorithm with path relinking for the location routing problem. *Journal of Mathematical Modelling and Algorithms*, 7, 59–78.

Mosheiov, G. (1994). The travelling salesman problem with pick-up and delivery. European Journal of Operational Research, 79, 299–310

Nagy, G., & Salhi, S. (1998). The many-to-many location-routing problem. TOP, 6, 261-75.

Nagy, G., & Salhi, S. (2007). Location-routing: issues, models and methods. EuropeanJournal of Operational Research, 177, 649– 672.

Nikbakhsh, E., & Zegordi, S.H. (2010). A heuristic algorithm and a lower bound for the two-echolen location-routing problem with soft time window constraints. *Scintia Iranica*, 36-47.

Parragh, S. N., Doerner, KF., & Hartl, RF. (2008). A survey on pickup and delivery problems. part I: transportation between Customers and depot. *Journal fur Betriebswirtschaft*, 58, 21–51.

Pirkwieser, S., & Raidl, G. R. (2010). Variable neighborhood search coupled with ILP based large neighborhood searches for the Periodic Location-routing problem. Lecture Notes in Computer Science: Springer, 43-57.

Prins C, Prodhon C, & Wolfler-Calvo R. (2006) Solving the capacitated location-routing problem by a GRASP complemented by a learning process and a path relinking. 4OR, 4, 221–38.

Prodhon, C. (2007). An iterative metaheurtistic for the periodic location-routing problem. In: Nickel, S., Kalcsics, J.(Eds.). Operations Research Proceedings Springer, 159–164.

Prodhon, C., & Prins, C. (2008). A memetic algorithm with population management (MA|PM) for the periodic location-routing Problem. Lecture Notes in Computer Science: Springer, 174–189.

Rahmati, S.H.A., Zandieh, M., & Yazdani, M. (2012). Developing two multi-objective evolutionary algorithms for the multi- objective flexible job shop scheduling problem. *Int J Adv Manuf Technol*.

Salhi, S., & Rand, G. (1989). The effect of ignoring routes when locating depots. *European Journal of Operational Research*, 39,150-156.

Schaffer, J. (1985). Multiple objective optimization with vector evaluated genetic algorithms. In: Schaffer JD, editor, Genetic algorithms and their applications, proceedings of the first international conference on genetic algorithms.Hillsdale, New Jersey:
Lawrence Erlbaum, 93–100.

Setak, M., Karimi, H., & Rastani, S. (2013). Designing incomplete hub location-routing network in urban transportation problem. *International Journal of Engineering*, 26, 997-1006.

Smith, HK., Laporte, G., & Harper PR. (2009). Locational analysis: highlights of growth to maturity. *Journal of the Operational Research Society*, 60, 140-8.

Tavakkoli-Moghaddam, R., Makui,A.,& Mazloomi,Z. (2010). A new integrated mathematical model for a bi-objective multi-depot location-routing problem solved by a multi-objective scatter search algorithm. *Journal of Manufacturing Systems*, 29, 111-119.

Wang, H-F., & Chen, Y-Y. (2012). A genetic algorithm for the simultaneous delivery and pickup problems with time window. *Computers & Industrial Engineering*, 62, 84–95.

Zitzler, E. (1999). Evolutionary Algorithms for MultiobjectiveOptimization:Methods and Applications. PhD. Thesis, DissertationETH No. 13398, SwissFederal Institute of Technology (ETH), Zürich, Switzerland.

This article can be cited: Jelodari Mamaghani, E. & Setak, B. (2017). The Bi-Objective Location-Routing Problem Based on Simultaneous Pickup and Delivery with Soft Time Window. *Journal of Optimization in Industrial Engineering.*10 (22), 81-91.

URL: http://qjie.ir/article_279.html

DOI: 10.22094/joie.2017.279