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***Abstract*—This paper proposes an ant colony optimization (ACO) to solve the full-truckload selective multi-depot vehicle routing problem under time windows constraints (denoted by FT-SMDVRPTW). The objective is to construct a solution composed of a set of routes associated with the trucks, aiming at maximizing the total profit. Each order is a pickup and delivery order associated with an origin, a destination, two time windows, and a price for serving the order paid by its corresponding shipper. Each route is a sequence of selected orders to serve so that the operational constraints are respected. Our problem appears clearly when the vehicles return back. It is not obligatory to serve all orders. The motivation of this study is to solve this problem by using an ant colony optimization metaheuristic, called ant colony system, which was originally implemented for solving the basic vehicle routing problem (VRP). We modify the algorithm to incorporate a robust optimization methodology, so that the full truckload can be handled. Finally, we give a numerical example on a randomly generated instance to illustrate our approach.**

Keywords—Vehicle routing problem; time windows; multi depots; full truckload; profit; ant colony algorithm

I. INTRODUCTION

The vehicle routing problem (VRP) is a combinatorial optimization problem that has been extensively studied in the literature since it was introduced by [1]. Its application is very important in many fields such as transportation, logistics, communications, manufacturing, and so on. In the traditional VRP, client's request consists, generally, of an amount of goods. These goods are delivered to their corresponding clients using a set of homogeneous vehicles based at a single depot. The problem aims to find a set of minimum cost routes to serve the clients respecting vehicle-capacity constraints. The cost of a route can be the total distance or time travelled by the vehicle associated with it. Given the importance of the VRP, many extensions have been formulated thereafter [2- 3]. These allow modeling of additional constraints occurring in realistic scenarios. An important example is the full truckload (FTL) VRP. It arises when the load of the vehicle is given and it has to be transported directly from its origin to its destination. Similarly, FTL VRPTW (when time windows exist) and multi depot FTL VRPTW may be defined. A detailed description of various versions of the problem can be found in [4-5].

Since the VRP is an NP-hard problem [6], all variants of the VRP are also NP-hard problems. Various heuristic algorithms have been proposed for finding good solutions, not necessarily optimal, in reasonable running time. These algorithms include the simulated annealing (SA) [7], tabu search (TS) [8], genetic algorithm (GA) [9- 10], and ant colony optimization [11; 12]. Ant colony system (ACS) is an improvement of ant colony optimization (ACO) which has been applied widely in routing problem [13]. The solution of ACS is iteratively constructed by the collective behavior of ants. The ants choose their route according to the pheromone and attractiveness level of each path. The pheromone laid on the road is the indirect communication media between ants in order to find the shortest route to the food source [14]. Ants tend to choose the route which has a higher pheromone level.

The problem encountered in this paper is a generalization of the vehicle routing problem. It is about full truckload selective vehicle routing problem with time windows, heterogeneous fleet and multiple depots. The problem consists of selecting orders and determining their ordering of passage for the delivery and pick up as well as the vehicles to use. The problem assumes that one pickup point corresponds to one delivery point only, and one order is served by the same vehicle only. There is a profit associated with each order visit. The objective is to maximize the profits of the logistics company. We refer to this problem as the ''full-truckload selective multi-depot vehicle routing problem with time windows", and denote it as FT-SMDVRPTW. Since the problem includes the VRP, it is also NP-hard. It is difficult to solve the large scale problem with an exact algorithm; therefore, an Ant Colony System (ACS) is proposed to solve it. The proposed algorithm was tested on a randomly generated instance. The Ant colony optimization (ACO) approaches are used quite often to solve vehicle routing problems. To our best knowledge there is no work described in the literature that uses ACO type approaches for FTLVRP.

The rest of this paper is structured as follows: section II presents the definition of the problem. A brief literature review on FTVRP is exposed in section III. Section IV is dedicated to describe our approach. Section V evaluates the approach by a randomly generated instance. Finally, section VI concludes the paper.

II. PROBLEM DEFINITION

The FT-SMDVRPTW involves two types of objects: nodes and vehicles. The nodes are the points of extremity {(L_i, U_i); i = 1, ... n} of n orders that are associated with two sets of points: D = {D_k; k = 1, ..., m} and A = {A_k; k = 1, ..., m}, representing the set of departure and arrival points of trucks respectively. Each order O_i has both a pickup point L_i and a delivery point U_i. Let K={V_1,…, V_m} be the vehicle set, where m is the number of available vehicles in the fleet. For each order O_i (i = 1, ..., n), the profit p_i, the distance d_i between the departure point and the arrival point, the loading time window [L_i^{min}, L_i^{max}], unloading time window [U_i^{min}, U_i^{max}], the traveling cost C^c_i loaded O_i and the traveling time t_i between the departure point and the arrival point are known in advance. The distance, traveling time and empty traveling cost between the unloading point of the order O_i and the loading point of the order O_j are denoted by d_{ij}, t_{ij} and C_{ij}, respectively. The distance, traveling time and traveling cost between the departure point D_k and the loading point are denoted by d_{0i}^k, t_{0i}^k and C_{0i}^k, respectively. The distance, traveling time and traveling cost between the unloading point of order O_i and the arrival point A_k are denoted by d_{in+1}^k, t_{in+1}^k and C_{in+1}^k, respectively. If a truck on the route is not moving, a penalty of waiting time will be imposed. Let C^a be the unit cost of waiting before loading or unloading of an order. $t^k_{i,L}$ is the time to begin loading order i on the vehicle k. $t^k_{i,U}$ is the time to begin unloading order i of vehicle k. t^k_0 is the departure time of vehicle k from Dk. t^k_{n+1} is the arrival time of vehicle k at Ak. A feasible solution to the FT-SMDVRPTW must satisfy the following constraints:

(1) Each route must satisfy the time windows at every pickup point and delivery point.
(2) At the level of an order, the delivery time has to be superior to the sum of the picking time and the distance of the order.
(3) Picking of the order O_i can begin only after moving the vehicle to the departure point.
(4) For two successive orders, the picking of the next one can't be started unless the previous order is delivered and the displacement has taken place.
(5) The vehicle can't deliver the order until it is possible to arrive to the arrival point before the latest time.
(6) Each time the truck k visits the unloading and/or the loading point only one exit to any other point (loading, unloading or arrival points) can be fulfilled.
(7) Each truck could start from one departure point. Once the truck loads a commodity, it has obligatorily to arrive at an unloading point.
(8) Each truck has to go back to the arrival point.
(9) No truck can return to its departure point and the arrival point of each truck must be the last point of its route.

The objective function of our problem is the maximization of the profit, which is equal to total revenue minus the total cost.

III. LITERATURE REVIEW

The routing problem addressed in this paper is related to the routing that includes the selection of the truckload, the notion full truckload, time windows constraint and multi-depots. We have focused on the publications of the last two decades that apply the exact, heuristic and the meta-heuristic methods to solve the FTVRP.

In terms of exact algorithms, Desrosiers et al. [4] have presented a branch and bound approach based on an algorithm developed for the asymmetrical traveling salesman problem to solve the FTVRP. There are no time windows requirements for delivery or pickup at customers or terminals. Arunapuram et al. [15] have presented an exact algorithm for solving the FTVRP. They introduce a column generation method that takes advantage of the special structure of the linear programming sub-problems at the nodes of the branch-and-bound tree. The algorithm also takes into consideration the time-window constraints and waiting costs. However, the exact algorithm is unable to solve the instances when the number of lanes exceeds 200. Huo [16] and Gronalt et al. [17] present different heuristic algorithms for the problem that permits to obtain a realizable solution in a reasonable time. These algorithms are based on the well-known savings algorithm (SA) proposed by [18]. Although many heuristic and metaheuristic approaches have been proposed for the VRP, they cannot be applied directly because of three major differences between the VRP and FTVRP. First, in the VRP, each order has only one full-truckload demand while the FTVRP allows each order demand to be any multiple integer of full truckload. Second, in the FTVRP, all the orders are directed while in the VRP transportation orders are undirected. Finally, in the FTVRP with multi-depots, vehicles are located at several depots while in VRP each vehicle starts and returns to one designated depot. So far, few researchers have investigated the FTVRP using heuristic and metaheuristic methods.

Wei [19] used genetic algorithm to solve FTVRP with a driving distance restriction. Liu [20] introduced a task selection and routing problem in which a truckload carrier received tasks from shippers and other partners, and made a selection between a private vehicle and an external carrier to serve each task. These authors develop a memetic algorithm to solve the problem. Sun [21] dealt with a variant of FTVRP in which vehicles were not required to return to the depot after they completed the task. He proposed an adaptive genetic algorithm and PSO algorithm with near neighbor interactions to solve it. Li and Lu [22] dealt with a new variant of FTVRP in which there are more than one delivery points corresponding to the same pickup point, and one order is allowed to be served several times by the same vehicle, or different vehicles. They proposed a hybrid genetic algorithm to solve it. In our earlier publications [10], we have presented a new crossover operator to solve the full-truckload selective multi-depot vehicle routing problem with time windows (FT-SMDVRPTW) using GA with the objective function to maximize the profit.

IV. ANT COLONY SYSTEM (ACS)

In this section, we briefly give background information about our ACS approach, which is the main contributor of the proposed algorithm to solve the introduced problem in this study.

ACS usually consists of three main phases: initialization, pheromone update and solution construction. All of these phases constitute a complete search of the global optimum through multiple iterations.

A. Solution construction

The principle of using ACS in FT-SMDVRPTW is that each ant starts its route from a departure point of vehicle and it constructs a route by successively selecting customers (orders) under some time constraints. The process is performed incrementally until a feasible solution can be obtained.

At every step t, each ant $k \in \{1, ..., m\}$ located on unloading point of order i will select the next order j according to the following pseudo-random-proportional rule. A random variable q uniformly distributed over [0, 1] is evaluated, and if $q \geq q_0$ the order j is chosen based on (1).

$$j = \arg\max_{l \in J_k(i)} \left\{ \left[\tau_{il}(t)\right] . \left[\eta_{il}(t)\right]^{\beta} \right\} \tag{1}$$

Otherwise, an ant selects other orders by following the standard ACO rule P_{ij} mentioned in (2):

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right].\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{l \in J_k(i)} \left[\tau_{il}(t)\right].\left[\eta_{il}(t)\right]^{\beta}}; & if \;\; j \in J_k(i) \\ 0 & ; otherwise \end{cases} \tag{2}$$

$J_k(i)$ is a set of unvisited feasible orders (i.e. the orders which are directly accessible from order i and not previously visited).The parameter β defines the relative importance of the pheromone trace and the visibility of the ants. $\tau_{iu}(t)$ is the amount of pheromone associated with the edge between the current order i and the next possible order u at time t. The initial pheromone quantity is fixed at a value τ_0.

In the classical ACO approach, the value of the heuristic information (the visibility) between a pair of customers is the inverse of their distance. In our approach, the value of the heuristic information associated with the edge (i, u) defined by

$$\eta_{iu} = \frac{p_u}{c_{iu} + c_u} \tag{3}$$

B. Pheromone updating

This step of pheromone updating is very important. It's a key element of ACS and it allows the improvement of future solutions in the next iteration. The aim is to exchange information of colonies by pheromone updating; it simulates the real evaporation of pheromone. For this reason, it's necessary to update this information locally for each ant and globally for changing the entire quantity. The local update is performed every time an ant traverses an arc (i, j) and the pheromone is modified as follows:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \rho.\tau_0 \tag{4}$$

ρ is the trail evaporation $(0 \prec \rho \leq 1)$ and $1-\rho$ can be interpreted as trail persistence.

The global update, however, is only carried out by the ant that produced the best solution found so far; it is implemented by the following equations for each arc of the best solution:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \rho.\Delta\tau_{ij}(t) \tag{5}$$

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{1}{C} & if\ (i,j) \in Best\, solution \\ 0 & otherwise \end{cases} \tag{6}$$

where C is the cost of the best solution in iteration t.

Fig. 1 shows the outline of the proposed ACS for the FT-SMDVRPTW. In our ACS, the stopping criterion is set to the time when a number of iterations has been performed.

```
Fixing the number of ants
Fixing the maximum number of iterations
Pheromone initialization: τij = τ0  ∀ i,j ∈ N
iter ← 0
while(iter < itermax)
                    For each ant k
    do
      Random choice of an unused truck
      Build route for this truck using (1), (2)
      Local updating the pheromone τij by (4)
    Until Ant k has completed its solution
  End for
  Save the best solution found by the ants
  Update the pheromone τij globally using (5)
    iter ← iter + 1
End while
```

Fig. 1. Description of the proposed ACS algorithm for the FT-SMDVRPTW.

V. COMPUTATIONAL RESULTS ON A RANDOMLY GENERATED INSTANCE

The ACS algorithm introduced in the earlier section was coded in Matlab and tested on a PC 2.4 GHz CPUs, 4096 MB Memory and windows 7 operating system. Because no similar study has been found in the literature, the problem instance that was generated randomly based on the well-known datasets proposed in [23] for VRPTW is used to evaluate the performance of the proposed ACS on the FT-SMDVRPTW.

A. Parameters Settings

The parameter settings for the ACS algorithm are shown in Table I, and Tables II to IV provide different data of the problem.

TABLE I. PARAMETERS OF ACS

parameter	**value**
β	2
ρ	0.9
τ_0	0.0001
q_0	0.95

TABLE II. CUSTOMERS AND DEPOTS INFORMATION

Point i	**x-coordinate**	**y-coordinate**
1	40.00	50.00
2	45.00	68.00
3	45.00	70.00
4	42.00	66.00
5	42.00	68.00
6	42.00	65.00
7	40.00	69.00
8	40.00	66.00
9	38.00	68.00
10	38.00	70.00
11	35.00	66.00
12	35.00	69.00
13	25.00	85.00
14	22.00	75.00
15	22.00	85.00
16	20.00	80.00
17	20.00	85.00
18	18.00	75.00
19	15.00	75.00
20	15.00	80.00

TABLE III. PARAMETERS OF ACS

O_i	L_i	U_i	L_i^{min}	L_i^{max}	U_i^{min}	U_i^{max}
1	1	6	0	1236.00	15.00	67.00
2	1	14	0	1236.00	30.00	92.00
3	9	11	255.00	324.00	357.00	410.00
4	12	10	448.00	505.00	534.00	605.00
5	10	7	534.00	605.00	621.00	702.00
6	5	3	727.00	782.00	825.00	870.00
7	2	1	912.00	967.00	0	1236.00
8	4	8	65.00	146.00	170.00	225.00
9	18	19	99.00	148.00	179.00	254.00
10	20	16	278.00	345.00	384.00	429.00
11	17	15	475.00	528.00	567.00	620.00
12	13	1	652.00	721.00	0	1236.00

TABLE IV. AVAILABILITY OF DATA OF 2 TRUCKS

Truck *k*	D_k	A_k	D_K^{min}	A_K^{max}
1	1	1	0	1236.00
2	1	1	0	1236.00

From this data, we can generate the time matrix t_{ij}, the cost matrix c_{ij}, the profit p_i and the traveling cost C^c_i for each order.

B. Computational results of our approach

The obtained results are shown in Fig.2 and Table V. The orders assigned to the fleet of vehicles and the orders that are not selected are shown separately in the table. Then, routes of orders served by the fleet are presented. Other items such as profit, number of vehicles used, and the CPU execution time in seconds are also shown in the Table V. The proposed approach has obtained a good solution with a reasonable computational time to the generated instance. The vehicle 1 has well transported the orders 1, 8, 3, 4, 5, 6, 7 in this sequence. The vehicle 2 has well transported the orders 2, 9, 10, 11, and 12.

TABLE V. COMPUTATIONAL RESULTS

Orders served by the fleet of vehicles	$\{O_1, O_2, O_4, O_3, O_5, O_6, O_7, O_8, O_9, O_{10}, O_{11}, O_{12}\}$
Routes of orders	V_1 : D_1 - O_1 - O_8 - O_3 - O_4 - O_5 - O_6 - O_7 - A_1 V_2 : D_2 - O_2 - O_9 - O_{10} – O_{11} - O_{12} - A_2
Total profit	481.15
CPU Time(s)	2.05

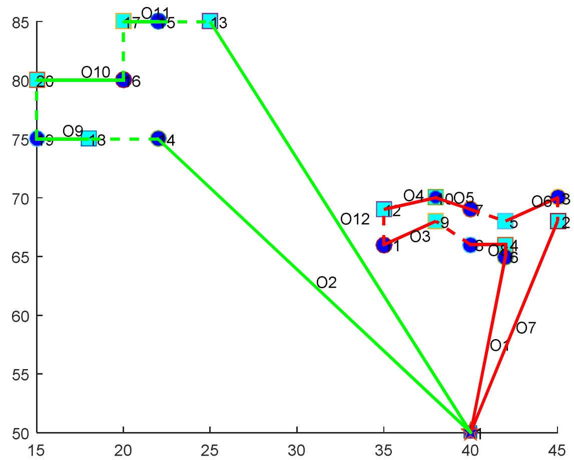

Fig. 2. Vehicle tours for test instance.

So as to prove the efficiency of our solution approach, we test it also on the classical vehicle routing problem with time window.

TABLE VI. COMPARISON BETWEEN BEST SOLUTIONS OF RELATED WORKS AND OUR SOLUTIONS

	best *			ACS		Gap
Instance	NV	TD	Ref	NV	TD	
C101	10	828.93	[25]	10	828.93	0,00
C102	10	828.937	[25]	10	828.93	0,00
C103	10	824.06	[24]	10	833.02	0,01
C104	10	828.2	[25]	10	828.2	0,00
C105	10	828.9	[25]	10	828.93	0,00
C106	10	828.937	[25]	10	828.3	0,00
C107	10	828.937	[25]	10	862.8783	0,04
C108	10	828.94	[24]	10	828.93	0,00
C109	10	828.94	[24]	10	831.8495	0,02
R101	20	1642.87	[24]	21	**1362.98**	**-0,21**
R102	17	1486.12	[24]	21	**1370.89**	**-0,08**
R103	14	1243.22	[25]	18	**1138.87**	**-0,09**
R104	10	982.01	[24]	11	1178.55	0,17
R105	14	1377.11	[24]	15	**1298.51**	**-0,06**
R106	12	1252.03	[24]	14	1438.34	0,13
R107	11	1100.25	[25]	12	**1062.83**	**-0,04**
R108	9	958.66	[25]	15	**809.67**	**-0,18**
R109	12	1101.99	[25]	12	1140.19	0,03
R110	12	1119.53	[25]	12	1141.77	0,02
R111	12	1091.11	[25]	13	1308.25	0,17

The Table VI below reports the best solution found in terms of the total distance of transport in many papers; we compare them with our solutions.

The column best* shows the best results obtained by a group of studies done between 1995 and 2012.

Where:

- $\text{Gap} = \dfrac{\text{best}^* - \text{ACS result}}{\text{best}^*}$
- NV : number of vehicles used
- TD : total distance

The ACS column presents the solutions found by our solution approach. We can see clearly from table VI that, in some cases, our proposed algorithm finds best results. But in the majority of cases, it approaches to best solutions found in literature. While other instances require being more improved.

VI. CONCLUSION

In this paper, we address the full-truckload selective multi-depot vehicle routing problem with time windows (FT-SMDVRPTW) with the objective function to maximize the profit, which is calculated as total collected revenue (prizes) minus total travel cost. To solve this problem efficiently, we have developed an ant colony system (ACS) equipped with a new visibility. To the best of our knowledge, this is the first ACO approach proposed for this problem. The computational results on a randomly generated instance indicate that the proposed approach can obtain a high quality solution within a short period of computational time.

Our future work aims to make our algorithm simpler and more effective. First, we plan to develop adaptive parameters of global ACS. Second, we will ensure the generation of bigger instances on FTVRP and further evaluate the ACS's performance on these instances. Third, comparison of results obtained with Cplex (for small instances) with other meta-heuristic approaches is required to see the importance of the proposed approach.

REFERENCES

[1] G.B. Dantzig and J.H. Ramser, "The truck dispatching problem," Manage. Sci ., vol. 6, no. 1, pp. 80-91, 1959.

[2] G. Laporte, "Fifty Years of Vehicle Routing," Transp. Sci., vol. 43, no. 4, pp. 408–416, 2009.

[3] P. Toth, and D.Vigo, "The vehicle routing problem," SIAM monographs on discrete mathematics and applications. Philadelphia, PA: Society for Industrial and Applied Mathematics, 2002.

[4] J. Desrosiers, G. Laporte, M. Sauve, F. Soumis, and S.Taillefer, "Vehicle routing with full loads," Comput. Oper. Res., vol. 15, no.3, pp. 219–226, 1988.

[5] A. Annouch, K. Bouyahyaoui and A. Bellabdaoui," A literature review on the full trackload vehicle routing problems," 2016 3rd International Conference on Logistics Operations Management (GOL), pp. 1 - 6, DOI: 10.1109/GOL.2016.7731723.

[6] J. K. Lenstra, and A. H. G. Rinnooy-Kan,"Complexity of Vehicle Routing and Scheduling Problems," Networks, vol. 11, no. 2, pp. 221–227, 1981.

[7] K. Braekers, A. Caris, and G. K. Janssens, “A deterministic annealing algorithm for a bi-objective full truckload vehicle routing problem in drayage operations,” Procedia - Soc. Behav. Sci., vol. 20, pp. 344–353, 2011.

[8] P. Badeau, F. Guertin, M. Gendreau, J.-Y. Potvin and E. Taillard, “A Parallel Tabu Search Heuristic for the Vehicle Routing Problem with Time Windows,” Transportation Research Part C: Emerging Technologies, vol. 5, no. 2, 109–122, 1997.

[9] B. M. Baker and M. a. Ayechew, “A genetic algorithm for the vehicle routing problem,” Comput. Oper. Res., vol. 30, no. 5, pp. 787–800, 2003.

K. EL Bouyahyiouy and A. Bellabdaoui, “A new crossover to solve the full truckload vehicle routing problem using genetic algorithm,” 2016 3rd International Conference on Logistics Operations Management (GOL).Pages: 1 - 6, DOI: 10.1109/GOL.2016.7731675.

[10] L.M.Gambardella, E. Taillard and G. AGAZZI, “New ideas in Optimization, chapitre MACS-VRPTW: A Multiple Ant Colony for vehicle routing problem with time windows”. pp. 63-76. McGrawHill, 1999.

[11] A. Abbassi, K. EL Bouyahyiouy, A. A.El Hilali, and A. Bellabdaoui, “A HYBRID ALGORITHM FOR VEHICLE ROUTING PROBLEM WITH TIME WINDOWS AND TARGET TIME,” Journal of Theoretical and Applied Information Technology vol. 95, no. 1, pp. 210–219, 2017.

[12] B. Yu , Z.-Z. Yang ,and J.-X. Xie , “A parallel improved ant colony optimization for multi-depot vehicle routing problem,” J. Oper. Res. Soc., vol. 62, no. 1, pp. 183–188, 2011.

[13] M. Dorigo and C. Blum , “Ant colony optimization theory: A survey,” Theor. Comput. Sci., vol. 344, pp. 243–278, 2005.

[14] S. Arunapuram, K. Mathur, and D. Solow, “Vehicle Routing and Scheduling with Full Truckloads,” Transp. Sci., vol. 37, no. 2, pp. 170–182, 2003.

[15] J. Huo, and L. Zhang, “Savings based algorithm for full truckload vehicle routing problem with time window, ” Industrial Engineering and Management , vol.11, no. 4, pp. 39-42, 2006.

[16] M. Gronalt, R. F. Hartl, and M. Reimann, “New savings based algorithms for time constrained pickup and delivery of full truckloads,” Eur. J. Oper. Res., vol. 151, no. 3, pp. 520–535, 2003.

[17] G. Clark and J.W. Wright, “Scheduling of vehicles from a central depot to a number of delivery points,” Oper. Res., 12, pp. 568–581, 1964.

[18] H. Wei, J. Li, and J. Wei, “Vehicle routing problem with full load and driving distance restriction,” Journal of Southwest Jiaotong University, vol.40, no. 6, pp. 798-802, 2005.

[19] R. Liu, Z. Jiang, X. Liu, and F. Chen, “Task selection and routing problems in collaborative truckload transportation,” Transp. Res. Part E Logist. Transp. Rev., vol. 46, no. 6, pp. 1071–1085, 2010.

[20] G. H. Sun, “Modeling and algorithm for open vehicle routing problem with full-truckloads and time windows,” Systems Engineering-Theory & Practice, Practice, vol. 32, no.8, pp.1801-1807, 2012.

[21] J. Li and W. Lu, “Full Truckload Vehicle Routing Problem with Profits,” Cictp 2014, vol. 1, no. 2, pp. 864–875, 2014.

[22] M.M. Solomon, “Algorithms for the vehicle routing and scheduling problems with time window constraints,” Oper. Res., vol. 35, no. 2, pp. 254–265, 1987.

[23] Y. Rochat and E. Taillard,“Probabilistic diversification and intensification in local search for vehicle routing,” Journal of Heuristics, vol.1, pp. 147-167, 1995.

[24] B. Yu, Z. Z. Yang and B. Z. Yao,“A hybrid algorithm for vehicle routing problem with time windows,” Expert Systems with Applications, vol. 38, no. 1, pp. 435–441, 2011.