Asian Journal of Computer Science and Technology
ISSN: 2249-0701 Vol.7 No.3, 2018, pp. 1-6

Multi Objective Vehicle Routing Problem: A Survey

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Abstract **- In the last decades, a lot of research has been done on Multi Objective Vehicle Routing due to its rich real life applications. However, the related literature is yet not being summarized anywhere. This paper presents a broad survey on the considered problem. This paper broadly presents the objectives considered, approaches used to solve multi objective vehicle routing problem. Finally, the survey classifies the main features of recently published literature and also provides some future directions in the considered field.**
Keywords: **Vehicle Routing Problem, Multi objective VRP, Evolutionary Algorithms, Combinatorial Optimization, Discrete Optimization**

I.INTRODUCTION

Vehicle Routing Problem (VRP) [24] [26] is a NP Hard problem which is used to find the most optimal and cost effective routes for transporting goods between depot and customers by using number of homogeneous vehicles. However, this problem aims to minimize cost of solution as a single objective which is not suitable for real life instances. In real life there can be several other factors associated with a single cost. Moreover, the objectives may be conflicting in nature. For instance, in some sectors like delivery of perishable foods customer satisfaction and timely delivery is more important than cost. However, in some sectors fair distribution of work load among work is more important. In recent years, a variant of VRP called multi objective VRP (MOVRP) is proposed to deal with these real life instances. In literature [25] [3] lots of work have been done in the field of MOVRP like various solution approaches are proposed with different performance metrics, various applications areas with several objectives are proposed. However, to our best knowledge there is not a single survey paper which considers MOVRP from all aspects and along can help a reader to understand MOVRP. This paper covers definition of MOVRP along with its objectives, solution approaches used and also classifies the research work done from 2007 to 2016 by considering different parameters. Articles were selected both from journals and conference proceedings and their work is classified on various parameters. The main contribution of this survey paper is that it provides an in depth knowledge about MOVRP. After reading this paper an individual can be able to understand the MOVRP from all point of view. Moreover, the methods that are developed to solve MOVRP are widely applicable and also has a high theoretical value. Rest of the paper is organized as follows. Section 2 presents MOVRP definition, ways in which it can be applied to routing problems, objectives used and approaches used to solve MOVRP. Then based on this literature is survey in section 3. Section 4 presents the results of the survey. Finally, section 5 concludes the gaps in literature along with future direction.

II.MULTIOBJECTIVE VEHICLE ROUTING PROBLEM

This section presents the formal definition of MOVRP, ways of extension,objectives and solution approaches used for MOVRP. MOVRP is one in which overall optimization function is influenced by two or more parameters. These parameters are sometime conflicting in nature i.e there exists some trade-off between them. Formally MOVRP can be stated as [1] [2] [4]:

$$MOVRP = max/min\ F(x) = \left(f_1(x), f_2(x), \dots\ f_k(x)\right)$$
$$s.t.\quad x \in D \qquad (1)$$

Where $k \geq 2$ is the number of objective functions to be optimized.
$x = (x_1, x_2, \dots\ x_k)$is the decision variable vector.
D is the feasible solution space.
$F(x)$is the objective function.
The set $\Omega = F(D)$ corresponds to the feasible solutions in the objective space.

The solution to MOVRP is the set of non-dominated solution called Pareto set where Pareto dominance is defined as: A solution vector $y = (y_1, y_2, \dots\ y_k)$ dominates ($\prec$)a solution vector $y' = (y_1', y_2', \dots\ y_k')$ if y is not worse thany' in any objective function and it is strictly better in at least one objective function.Mathematically $\forall i \in \{1,2, \dots n\}, y_i \leq y_i'\ and\ \exists i \in \{1,2, \dots n\},\ y_i \leq y_i'$

MOVRP are mainly used in three ways

1. *Extending classical VRP:* MOVRP is one of the possible way to study some objectives other than initially defined. In the context problem definition remains unchanged and new objectives are added. The purpose of this category is to extend classical VRP in order to increase their practical applications. As an example we can consider some objectives like driver workload, customer satisfaction.Works of[6,8,13,19,20] can be referred.

2. *Generalization of VRP:* Another way to use MOVRP is to generalize classical problem by adding objectives instead of adding one or several constraints or parameters. For example, in VRPTW the time window constraint is often replaced by some objective functions.Works of [9] [10] [14] [15] [18] [21] can be cited.
3. *Studying Real Life Cases:* Various real life problems which cannot be seen as VRP are normally modeled as MOVRP. In these types of problems decision maker clearly specifies the objectives which they want to optimize. Paper of [4] [7] [9] [16] [27] comes under this category.

A. Most Common Objectives

1. Tour Related Objectives

*Cost:*Minimizing the tour cost is the most common objective of MOVRP. This objective is considered from economic point of view. Normally it is expressed in terms of total travel distance, number of customers visited and time needed. [4-10] considers cost as the objective.

*Make-Span:*Some studies consider cost minimization as secondary objective and tries to minimize make span i.e. the length of longest tour. This objective is mostly considered in sorting networks. [10, 20] can be referred here.

*Balance:*This type of objectives is considered to provide equity between workers and customers. They are considered to provide fairness among various elements of the problem. Most common considered objectives under this category are providing balance between traveling time, workload of drivers, tour workload. [11,16] considers this objective.

2. Resource Related Objectives

In MOVRP resources are mainly vehicles and goods. However, in literature most of the studies focuses on minimization of vehicles used. This objective is having both economic and environmental significance. As less number of used vehicles, less is the investment cost and less is the emission of CO_2. Beside this, an objective related to goods can be minimization of damage of goods. Work done in [4-11,15,17-22,24] focuses on minimization of vehicles.

3.Node/Arc Related Objectives

Most of the studies dealing with objectives related with arc/node involves time window. In this case the time window considered is replaced with minimization of time window constraints. Other objectives considered under this category are maximizing customer satisfaction, maximizing driver and customer relationship. Work done in [9,18,21,24]considers customer satisfaction as the main objective. Work in [5,7,14]focuses on driver rest period. On the other hand, work in [15,18,21,23] considers time windows constraints.

B. Solution Approaches

Over the last several years, many techniques have been proposed for solving MOVRP. Broadly these techniques are divided into three categories as:

1. Scalar Methods

These methods use the concept of weighted linear aggregation, goal programming, e- constraint methods etc. for solving the problem. Among these weighted linear aggregation is the most commonly used method. Although it is simple to use but has severaldisadvantages. Firstly, it is very difficult to set weights according to the importance of objectives. Secondly this method fails to find all Pareto optimal solutions. In a similar way in goal programming technique it is very difficult to define goal. Work done in [8, 16,24]uses scalar method for solving the problem.

2. Pareto Methods

This method directly applies the concept of Pareto dominance to evaluate the quality of solution provided by different methods. This approach was introduced by Goldberg for GA. This method is becoming more and more popular and is frequently used with EAs. [6,8-13,17-19, 22] uses pareto method for providing solution to the problem.

3. Non-Scalar and Non-Pareto Methods

Some studies neither applies Scalar methods nor Pareto methods. This category treats different objectives separately. In this case, these methods are based on GA’s, lexicographic strategies, ACO, or other specific heuristics. Non-scalar methods are used in [4,5,7,14-16,20,21, 23].

III.LITERATURE REVIEW

All PaolaPellegrini*et al.* [4] uses Ant Colony optimization to tackle the rich VRP problem. A multiple colonies framework consisting of two variants: ACS and Max-min AS is used. In addition to this Randomized Nearest Neighbor heuristic and Tabu search is also used. A case study of an Italian firm is also presented.In continuation to this K.C Tan *et al.* [5] uses the ideas of EA incorporating two VRPSD-specific heuristics for local exploitation and a route simulation method to evaluate the fitness of solutions. The proposed algorithm tries to optimize three objective functions: minimum travel distance, driver remuneration, and number of vehicles, while satisfying number of constraints. The proposed algorithm is validated on dataset adapted from Solomon benchmark problems.Abel Garcia-Najera, John A.Bullinaria [6] proposes an improved multiobjective EA for providing solution to MOVRPTW.

In addition to find lowest distance traveled other two parameters, total travel time and total vehicle used were also considered for minimization. Though the presented scheme proves effective for the problem but it works only on arcs and not the sequence of them.In addition to this Abel Garcia Najera [17] also applied EA approach to solve one variant called MOVRP with back hauls. Again three objectives were considered for minimization of total distance, uncollected backhauls and the total number of vehicles. M. Benjamin *et al.* [7] addresses another real life problem of waste collection in which three objectives are considered for optimization. Two of them are minimization of number of vehicles and totaled traveled distance and the third one considers driver rest period. The problem is solved heuristically using tabu search and variable neighborhood search. Data set having 2092 customers is solved using this algorithm.KeivanGhoseiri, SeyedFaridGhannadpour [8] solves the MOVRPTW with goal programming and genetic algorithm. This paper directly interprets the objective of classical VRPTW problem. Classical dataset proposed by Solomon is used for showing effectiveness of the algorithm.Radha Gupta *et al.* [9] addresses another variant of MOVRPTW in which stochastic parameters were taken. Four different objectives are considered. Three of them minimized fleet size, total distance traveled and total waiting time over vehicles and other maximizes average grade of customer satisfaction. Approach based on fuzzy logic and genetic algorithm is used for providing solution. Real data set of Jain University of Bangalore in Karnataka is taken for result validation.

Juan Castro-Gultierrez*et al.* [10] investigates the suitability of classical Solomon benchmark problem for MOVRPTW. They proposed a multiobjective oriented framework to compare different MOVRP problems. Furthermore, the instances are solved with standard EA and showed stronger evidence of multi-objective features.R. Chevrier*et al.* [11] considers dial-a-ride problem and tries to optimize three objectives concurrently namely route balancing, number of vehicles and Quality of Service. A hybrid approach of EA and local search is used for providing solution to the problem. Results obtained on random and realistic problems are detailed to compare three state-of-art algorithm.Wei Zhou *et al.* [12] solves the bi objective VRPTW using GA. In their work they considered simultaneous minimization of total traveling time and work load imbalance of vehicles. They had considered workload imbalance of vehicle as an objective function because in many cases weight is not as much of importance as of distance of active vehicles like in fresh food delivery. While using GA as a solution to the problem a complex chromosome representation is used. However, the proposed algorithm uses a complex chromosome representation and one-point crossover which is generally not suitable for VRPTW because of duplication of visited customers.

Raul Banos*et al.* [13] presents a multi start simulated annealing strategy for solving MOVRPTW. In their work in addition to minimization of total distance travelled, workload imbalance between vehicle loads were also considered. Hybridization of EA and simulated annealing (MMOEASA) based meta heuristics were used to solve the problem. Although the present algorithm is effective solution but no criteria is specified for choosing the first operator to be used.RajaaAayadi, YousefBenada [14] addresses the problem of MOVRP with multiple trips using memetic algorithm. In this problem the time horizon can be exceeded by the vehicle as they have restricted size. A mathematical model has been proposed for the VRPM. After this memetic and genetic algorithm are combined to solve the problem. The problem focuses on the simultaneous minimization of two objectives namely total distance and the maximum overtime of all the vehicles. ShuilongZou [15] addresses another variant of MOVRP i.e Multi Objective Pickup and Delivery problem with time windows. The objective of the problem is to minimize the number of vehicle utilized, the total travel distance and the total waiting time. Model formulation for the problem is done through mixed integer programming. Finally, PSO and VNS are used to solve the problem. Effectiveness and feasibility of the algorithm is done on existing benchmark instances.

Belen Mellian-Batista [16] consider bi-objective VRPTW, uses mixed integer linear model with scatter search (SS) to solve the problem. The present study is motivated from a real problem in Tenerife, Canary Islands, Spain. In their work two objectives were considered: minimization of TD and balancing of routes. An extensive computation has been carried out on a real data set and the result are compared with NSGA-II.SayedFaridGhannadpour*et al.* [18] proposed and solved a multi objective dynamic VRPTW. In this problem time windows are considered as fuzzy. Four objectives were considered: minimization of total travel time, number of vehicles, reduction of overall waiting time and maximization of customer satisfaction level. For solving the problem GA is used. Convex fuzzy number is used to represent customer satisfaction level. To solve this problem author has proposed a 3- stage model having 3 modules namely management module, strategy module and optimization module.

Tsung-Che Chiang *et al.* [19] addresses MOVRPTW with simultaneous minimization of number of vehicles and total distance. Knowledge based EA is used. Problem specific knowledge is incorporated into genetic operators. Standard Solomon data set is used for comparison of proposed algorithm with existing algorithm. Moreover, the proposed algorithm updates one third of the non-dominated solution.Ying Zhou and Jiahai Wang [20] solves MOVRPTW using different local search based methods. The proposed method LSMOVRPTW considers 5 objectives: number of vehicles, total travel distance, make span, total waiting time and total delay time. LSMOVRPTW uses local search for finding the solution in contrast to EA algorithms. However, a problem specific knowledge is needed to guide the search towards Pareto front.OmprakashKaiwartya*et al.* [21] solves another variant of MOVRP i.e. dynamic MOVRP using a time seed PSO (TS-PSO). In this problem five objectives are considered namely, geographical ranking of request, customer ranking, service time, expected reachability time and satisfaction level of the customers. Yutao qi *et al.* [22] presents an extension of memetic EA based on decomposition is used for solving the problem. To solve the duplicity among best solutions faced by the previous proposed model MOEA/D, the algorithm introduces three local search methods. John Jairo Santa Chavez *et al.* [23] addresses another variant of MOVRP with Backhauls with 3 objectives: TD, total time and total consumption of energy. Nature inspired ant colony algorithm is used to solve the problem. Keeping in view the environmental effects created by transportation, SayedFarid and MohserHooshfar [8] addressed MOVRPTW with three objectives: to minimize energy consumption, total vehicle and to maximize the customer satisfaction.

IV. RESULTS

The summary of the survey is presented in Table I. The first describes author name. The second column of the table discusses about the variant of MOVRP. The third column discusses about the objectives considered. This column is further split-ted into three parts: objectives related to tour, node and resources. Here TD and NV denotes total distance covered and total number of vehicles respectively. Next column presents the approaches used for solving problem and finally last columns represents data set used for respective problem variant.

TABLE I SUMMARY OF LITERATURE WORK

Author Name	**Problem**	**Objectives**			**Approach**	**Data Set**
		Tour	**Node**	**Resource**		
Paola Pellegriniet *al.* [4]	Rich MOVRP	TD	-	NV	Ant Colony	Real Life
K.C. Tan *et al.* [5]	VRPSD	TD, driver remuneration	-	NV	EA	Solomon
A.Najera, J. A. Bullinaria [6]	MOVRPTW	TD	-	NV	EA	Solomon, NSGA-II
A.M. Benjamin, J.E. Beasley [7]	Waste Collection VRP	TD	Driver Rest Period	NV	TS+VNS	Kim
KeivanGhoseiri, SeyedFaridGhannadpour [8]	MOVRPTW	TD	-	NV	GP and GA	Solomon
Radha Gupta *et al.* [9]	MOVRPTW with Fuzziness	TD, TWT	Customer Satisfaction	NV	GA	Real Life
Castro-Gutierrez *et al.* [10]	MOVRPTW	TD, TWT	Make Span, Total Delay Time	NV	EA	Real Life
R. Chevriere*t al.* [11]	Dial-a-Ride	Route Balancing	QoS	NV	EA	Real Life
Wei Zhou *et al.* [12]	BiObjective VRPTW	TD	-	Balance Distance	GA	Solomon
RaúlBaños*et al.* [13]	MOVRPTW	TD	Work Load	-	EA+SA	Solomon
RajaaAyadi, Youssef Benadada [14]	MOVRPTW with multiple trips	TD	maximum Over time	-	Memetic	Problem Specific
ShuilongZou*et al.* [15]	Pick Up and Delivery	TD, TWT	-	NV	PSO	Problem Specific
Belen Melian-Batista *et al.*[16]	Bi Objective VRPTW	TD, Balancing routes	-	-	MILP + SS	Real Life
Abel Garcia-Najera and John A. Bullinaria [17]	VRP with Backhauls	TD	Uncollected Back Hauls	NV	EA	Nagy
SeyedFaridGhannadpour*et al.* [18]	DVRPTW with fuzziness	TD, Total Travel Time	Max Customer Preference	NV	GA	Solomon
Tsung-Che Chiang n, Wei-Huai Hsu [19]	MOVRPTW	TD	-	NV	EA	Solomon
Ying Zhou and Jiahai Wang [20]	MOVRPTW	TD	Make Span, Total Waiting Time	NV	LS	Real Life
OmprakashKaiwartya *et al.* [21]	MDVRP	Reachability Time, Profit	Satisfaction Level	NV	PSO	Real Life
Yutao Qi *et al.* [22]	MOVRPTW	TD	-	NV	EA	Solomon
JhonJairo Santa Chávez [23]	MOVRPTW with Backhauls	TD, Total Travel Time	-	Consumption of energy	Ant Colony	Salhi and Nagy
SFaridGhannadpour and Mohsen Hooshfar [8]	MOVRPTW	-	Customer Satisfaction	NV	EA	Random

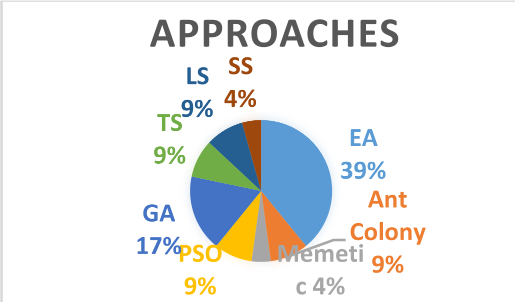

Fig.1 Approaches for MOVRP

From this table we have concluded that EA is the most commonly used method (39%) as shown in Fig.1 for solving the problem. GA is the second most solution technique with 17% for providing solution. Remaining 44 % is covered by other techniques like tabu, ant etc. Secondly we found that Solomon and real life data set is used for testing the effectiveness of the proposed algorithm as shown in Fig.2.

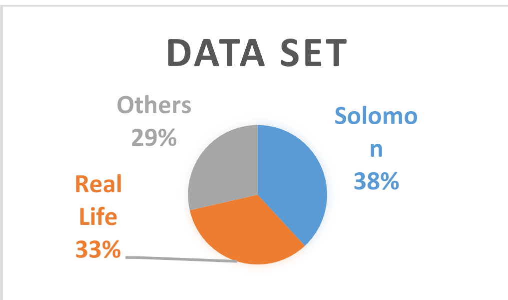

Fig.2Dataset for MOVRP

V. CONCLUSION AND FUTURE DIRECTION

The number of publications on MOVRP has been growing rapidly in recent years. The high computation power of computers makes it possible to solve almost every real life instance. This paper describes the multi objective VRP along with its objectives, performance evaluation metrics. Moreover, a survey of used approaches to solve MOVRP is also presented. Based on this survey we found that (1) EA is the most commonly used approach for providing solution to the problem. (2) Most of the EA and GA techniques are using simple operators which are used for classical VRP that deals with only single objectives. (3) Most of the methods deals with minimization of TD and NV and very few of them deals with maximization of objective functions like customer satisfaction. (4) Solomon and real life data set is widely used for comparison of results. From these observations some directions for future work are: (1) Development of operators for EA and GA that can handle multiple objectives simultaneously. (2) Generalization of objective function should be made. (3) Generalized performance metrics should be proposed as 50 % work is not using any kind of parameters. (4) Standard benchmarks for MOVRP should also be proposed as 29 % are using some other benchmarks beside real data set and Solomon data set.

REFERENCES

[1] N. Riquelme, C. Von Lücken and B. Baran, "Performance metrics in multi-objective optimization", Computing Conference (CLEI), *2015 Latin American, IEEE*, pp. 1-11, 2015.

[2] B. Ombuki, B. J. Ross and F. Hanshar, "Multi-objective genetic algorithms for vehicle routing problem with time windows", Applied Intelligence, Vol. 24, No. 1, pp. 17-30, 2006.

[3] N. Jozefowiez, F. Semet and E. G. Talbi, "Multi-objective vehicle routing problems", *European journal of operational research,*, Vol. 189, No. 2, pp. 293-309, 2008.

[4] P. Pellegrini, D. Favaretto and E. Moretti, "Multiple ant colony optimization for a rich vehicle routing problem: a case study", *International Conference on Knowledge-Based and Intelligent Information and Engineering Systems. Springer Berlin Heidelberg*, pp. 627-634, 2007.

[5] K. C. Tan, C. Y. Cheong and C. K. Goh, "Solving multiobjective vehicle routing problem with stochastic demand via evolutionary computation", *European Journal of operational research*, Vol. 177, No. 2, pp. 813-839, 2007.

[6] A. Garcia-Najera and J. A. Bullinaria, "An improved multi-objective evolutionary algorithm for the vehicle routing problem with time windows", *Computers & Operations Research*, Vol.38, No. 1, pp. 287-300, 2011.

[7] A. M. Benjamin and J. E. Beasley, "Metaheuristics for the waste collection vehicle routing problem with time windows, driver rest period and multiple disposal facilities", *Computers & Operations Research*, Vol. 37, No. 12, pp. 2270-2280, 2010.

[8] K. Ghoseiri and S. F. Ghannadpour, "Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm", *Applied Soft Computing*, Vol. 10, No. 4, pp. 1096-1107, 2010.

[9] R. Gupta, B. Singh and D. Pandey, "Multi-objective fuzzy vehicle routing problem: a case study", *Int. J. Contemp. Math. Sciences*, Vol.5, No. 29, pp. 1439-1454,2010.

[10] J. Castro-Gutierrez, D. Landa Silva and J. M. Pérez, "Nature of real-world multi-objective vehicle routing with evolutionary algorithms", *Systems, Man and Cybernetics (SMC), 2011 IEEE International Conference on. IEEE*, pp. 257-264, 2011.

[11] R. Chevrier, A. Liefooghe, L. Jourdan and C. Dhaenens, "Solving a dial-a-ride problem with a hybrid evolutionary multi-objective approach: Application to demand responsive transport", *Applied Soft Computing*, Vol.12, No. 4, pp. 1247-1258, 2012.

[12] W. Zhou, T. Song, F. He and X. Liu, "Multiobjective vehicle routing problem with route balance based on genetic algorithm", *Discrete Dynamics in Nature and Society*, 2013.

[13] R. BañOs, J. Ortega, C. Gil, A. L. MáRquez and F. De Toro, "A hybrid meta-heuristic for multi-objective vehicle routing problems with time windows", *Computers & Industrial Engineering*, Vol. 65, No. 2, pp. 286-296, 2013.

[14] R. Ayadi and Y. Benadada, "Memetic Algorithm for a Multi-Objective Vehicle Routing Problem with Multiple Trips", *IJCSA*, Vol. 10, No. 2, pp. 72-91, 2013.

[15] S. Zou, J. Li and X. Li, "A Hybrid Particle Swarm Optimization Algorithm for Multi-Objective Pickup and Delivery Problem with Time Windows", *JCP*, Vol. 8, No. 10, pp. 2583-2589, 2013.

[16] B. Melián-Batista, A. De Santiago, F. AngelBello and A. Alvarez, "A bi-objective vehicle routing problem with time windows: A real case in Tenerife", *Applied Soft Computing*, Vol. 17, pp. 140-152, 2017.

[17] A. Garcia-Najera and J. A. Bullinaria, "Optimizing delivery time in multi-objective vehicle routing problems with time windows", *International Conference on Parallel Problem Solving from Nature. Springer*, Berlin Heidelberg, pp. 51-60, 2010.

[18] S. F.Ghannadpour, S. Noori, R. Tavakkoli-Moghaddam and K. Ghoseiri, "A multi-objective dynamic vehicle routing problem with fuzzy time windows: Model, solution and application", *Applied Soft Computing*, Vol. 14b, No. 1, pp. 504-527, 2014.

[19] T. C. Chiang and W. H. Hsu, "A knowledge-based evolutionary algorithm for the multi objective vehicle routing problem with time windows", *Computers & Operations Research*, Vol. 45, pp. 25-37, 2014.

[20] Y. Zhou and J. Wang, "A local search-based multi objective optimization algorithm for multi objective vehicle routing problem

with time windows", *IEEE Systems Journal,* Vol. 9, No. 3, pp. 1100-1113, 2015.

[21] O. Kaiwartya, S. Kumar, D. K. Lobiyal, P. K. Tiwari, A.H. Abdullah and A. N. Hassan "Multiobjective dynamic vehicle routing problem and time seed based solution using particle swarm optimization", *Journal of Sensors,* 2015.

[22] Y. Qi, Z. Hou, H. Li, J. Huang and X. Li, "A decomposition based memetic algorithm for multi-objective vehicle routing problem with time windows", *Computers & Operations Research,* Vol. 62, pp. 61-77, 2015.

[23] J. Chávez, J. Escobar and M. Echeverri, "A multi-objective Pareto ant colony algorithm for the Multi-Depot Vehicle Routing problem with Backhauls", *International Journal of Industrial Engineering Computations,* Vol.7, No. 1, pp. 35, 2016.

[24] R. Goel and R. Maini, "Vehicle routing problem and its solution methodologies: a survey", *International Journal of Logistics Systems and Management,* Vol. 28, No. 4, pp. 419-435, 2017.

[25] N. Jozefowiez and E.G.Talbi, "From single-objective to multi-objective vehicle routing problems: Motivations, case studies and methods", The vehicle routing problem: Latest advances and new challenges. Springer, Boston, MA, pp. 445-471, 2008.

[26] B. L. Golden, S. Raghavan and E. A. Wasil, eds, "The vehicle routing problem: latest advances and new challenges", *Springer Science & Business Media*, Vol. 43, 2008.

[27] J. Wang, Y. Zhou , Y. Wang, J. Zhang, C. P. Chen , Z. Zheng, "Multiobjective vehicle routing problems with simultaneous delivery and pickup and time windows: formulation, instances and algorithms", *IEEE Transactions on Cybernetics,* Vol. 46, No. 3, pp. 582-594, 2016.