International Journal of Software Engineering and Computer Systems (IJSECS)
ISSN: 2289-8522, Volume 4 Issue 2, pp. 80-93, August 2018

DOI: https://doi.org/10.15282/ijsecs.4.2.2018.6.0050

A REVIEW OF SINGLE AND POPULATION-BASED METAHEURISTIC ALGORITHMS SOLVING MULTI DEPOT VEHICLE ROUTING PROBLEM

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ABSTRACT

Multi-Depot Vehicle Routing Problem (MDVRP) arises with rapid development in the logistics and transportation field in recent years. This field, mainly, faces challenges in arranging their fleet efficiently to distribute the goods to customers by minimizing distance and cost. Therefore, the decision maker needs to specify the vehicles to reach the particular depot which, serves the customers with the predetermined capacity. Hence, to solve the stated problems, there is a need to apply metaheuristic methods to get minimal transportation costs. This article reviews on single and population-based metaheuristic methods solving MDVRP from the year 2013 until 2018. The methods discussed were simulated annealing (SA), variable neighborhood search (VNS), ant colony algorithm (ACO), particle swarm optimization (PSO) and genetic algorithm (GA). From the previous works, it can be concluded that the application of population-based metaheuristic gives better solutions in solving MDVRPs.

Keywords: Metaheuristic, Multi Depot, MDVRP

1 INTRODUCTION

Nowadays, one of the great challenges due to their high operational costs faced by the distribution companies is to organize their fleet efficiently. Hence, to get optimal costs, an efficient schedule for fleet needs to be arranged well. MDVRP is aimed at minimizing the total cost that involves the fleet of the vehicle of combined routes. Basically, the goal of MDVRP is to find the optimal route for distance travelled by a vehicle since the cost is related to distance and the vehicles should not exceed the given capacity (Chen & Xu, 2008).

Furthermore, a good delivery decision will lead to the service number of customers with better satisfaction in reducing the time period (Prasad & Sathya, 2014). It is very crucial to have a good solution method with the necessary ability in selecting the best routes for the fleet of vehicle to deliver the goods which give minimal costs.

Metaheuristic algorithm is applied for routes construction to get the best result. This is because metaheuristic is known as an efficient method to solve many NP-hard problems and it has been proven that metaheuristic can provide excellent quality output within the reasonable time, even for MDVRP (Boussaïd, Lepagnot, & Siarry, 2013).

This paper presents a review of relevant literature on metaheuristic algorithm focus on single and population-based metaheuristic methods for solving MDVRP in recent years. The article is organized as follows: Section 2 briefly explains on MDVRP. While Section 3 is a review about metaheuristic methods and subsection of 3.1 explains about single based metaheuristic methods, while subsection 3.2 explains about population-based metaheuristic methods. Next, Section 4 discussed the application of metaheuristic algorithms for solving various MDVRP variants and Section 5 concludes the review article.

2 MULTI-DEPOT VEHICLE ROUTING PROBLEM (MDVRP)

MDVRP is the most popular variation used in vehicle routing problem (VRP) in the logistics field (Karakatič & Podgorelec, 2015). By comparing MDVRP and VRP's single-depot, MDVRP is said to be more practical and challenging in the real-life problem because it involved more than one depot. Due to many depots involved, decision-makers faced challenges in identifying appropriate depots that ability to serve the customers without exceeding the capacity constraints (Calvet et al., 2016). MDVRP also have many sub-variants such as time window, heterogeneous fleet, capacitated, periodic, pick-up and delivery and split delivery (Režnar et al., 2017). Figure 1 shows an illustration of MDVRP with two depots and 22 customers.

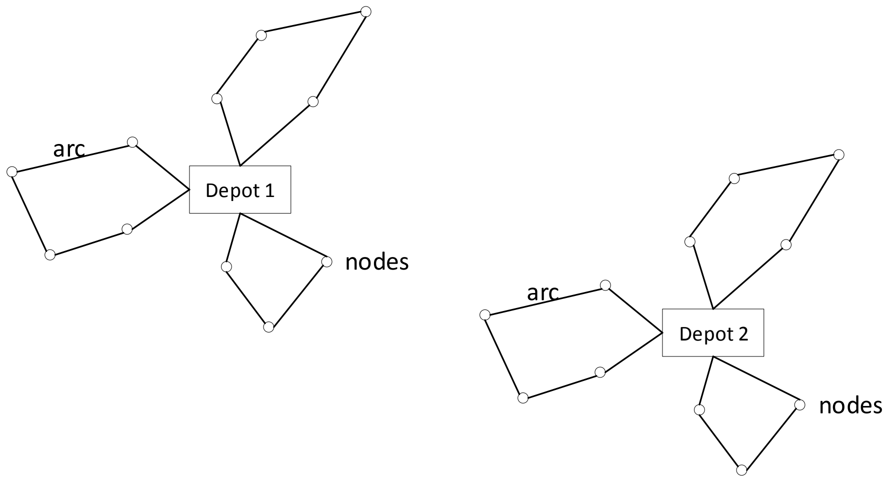

Figure 1 Multi-depot vehicle routing problem illustration (Montoya-Torres et al., 2015)

Figure 2 shows the order of decision for MDVRP. Firstly, the customer will be assigned to every depot. The aim is to make sure the distance travelled by the vehicle does not take a maximum time. Then, the customer will be assigned in each depot for every route. This is to minimize the number of vehicles used and routes, followed by the capacity constraints. Finally, every route in each depot will be sequenced to obtain an optimal sequence.

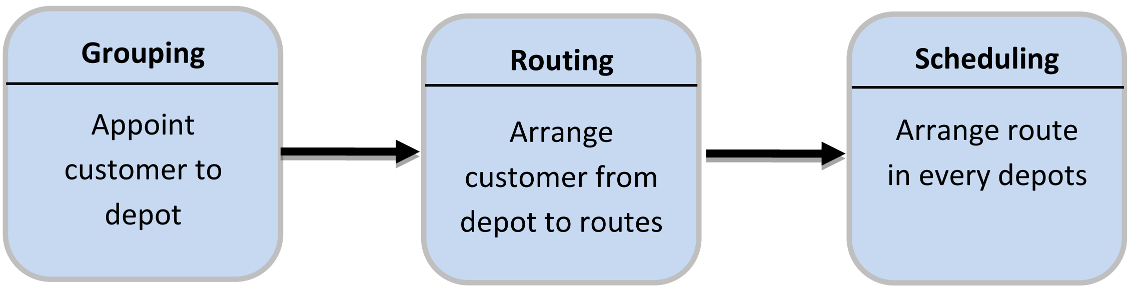

Figure 2 Steps for solving MDVRP (Surekha & Sumathi, 2011)

Basically, there are three solution methods applied to solve MDVRP which are exact, heuristic and metaheuristic methods. Since MDVRP is an NP-hard combinatorial optimization problem, hence solving MDVRP using exact method computationally is intractable and time-consuming whereas, in the heuristic method, the capability in the mathematical foundation is not strong enough (Geetha, Vanathi, & Poonthalir, 2012). Most researchers applied metaheuristic methods to solve MDVRPs, thus, further section discusses metaheuristic methods.

3 METAHEURISTICS METHODS

Metaheuristics have been discovered as the most effective method for solving many hard optimization problems because it has the capability to deal with NP-hard problems (Asih, Sopha, & Kriptaniadewa, 2017; Boussaïd et al., 2013; Gandomi, Yang, Talatahari, & Alavi, 2013). Metaheuristics is a computational method where the problem will optimizes to improve the candidate solution iteratively (Geetha et al., 2012). Many metaheuristic algorithms have been developed by impersonating the process that happens in real nature such as biological systems, chemical and physical process. Some implementations have facilitated logistics planners to carry out their day-to-day activities by using the approach realistically because able to obtain excellent results based on the execution times (Rincon-Garcia, Waterson, & Cherrett, 2017).

Based on Montoya-Torres (2015), there are 42% of research works on MDVRP using metaheuristic method to solve the problem. 33% used heuristic and 25% used the exact method for recent studies. Generally, metaheuristics provide the best solution method by determining a high potential area from the solution space and exploit them. (Rojas-Morales, Riff Rojas, & Montero Ureta, 2017). On the other hand, metaheuristic has the capabilities to figure out the solution space efficiently that avoid from falling into local optima and looked global optima (Asih et al., 2017). Besides that, through trial and error, metaheuristic can search every possible solution or combination because it provides an acceptable and efficient solution in a reasonably practical time for a hard problem (Gandomi et al., 2013). That is why metaheuristic often used to solve problem in MDVRP.

Metaheuristic algorithm is classified into several groups such as trajectory methods against the discontinuous method, population-based against single point search, memory usage against the memoryless method, one against various neighborhood structures, dynamic against static objective function and nature-inspired against non-nature inspiration (Raidl, Puchinger, & Blum, 2010). As stated earlier, this review paper will be focusing on the single and population-based metaheuristic algorithms. This class provides a better and convenient way to search a good solution in the search space (Birattari, Paquete, St, & Varrentrapp, 2001).

3.1 Single-based metaheuristic algorithm

In single based algorithms, it completes the search with only one initial point. It will explore its neighbourhood with a set of moves to improve their solution (Roeva, Slavov, & Fidanova, 2013). Table 1 show the examples of a single based algorithm for solving various variants of MDVRP which are simulated annealing (SA), tabu search (TS), variable neighbourhood search (VNS) and greedy randomized adaptive search procedure (GRASP). This article will be focus mainly on SA and VNS which have been widely used in the variants of MDVRP.

Table 1 Examples of a Single Based Algorithm for Solving Various Variants of MDVRP

Single Based Algorithm	**Authors**
SA	Allahyari, Salari, and Vigo, 2015; Dharmapriya, Kulathunga, and Jayathilake, 2014; Nadjafi and Nadjafi, 2016
TS	Freitas, 2012; Salhi, Imran, and Wassan, 2014; Surekha and Sumathi, 2011
VNS	Ghaffari-Nasab, Ahari, and Ghazanfari, 2013; Moh and Chiang, 2000; Polacek, Hartl, and Doerner, 2004; Wang et al., 2013; Yu, Redi, Hidayat, and Wibowo, 2017
GRASP	Nadjafi and Nadjafi, 2016; Polat, 2017

3.1.1 Simulated Annealing (SA)

SA is an algorithmic approach and stochastic gradient method to solve combinatorially and the global optimization problem (Ghaffari-Nasab, Ahari, & Ghazanfari, 2013). Besides that, SA is a local search procedure that able to search the solution space effectively and can avoid from being trapped in poor local optima (Yu, Redi, Hidayat, & Wibowo, 2017). To avoid from being trapped in poor local optima, SA obtains a worse solution with a probability and monotonically decreases by temperature (Ghaffari-Nasab et al., 2013). Among the strategies used in SA are selection strategies and additional random acceptance.

In order to improve SA, a different solution that belongs to the neighbourhood of the current solution will be selected. Basically, in SA algorithm, the temperature will be constantly decreased after reaching a high-level temperature (Chen and Xu, 2008). The basic pseudocode of SA is shown in Figure 3.

```
Step 0  : Start
Step 1  : Create a candidate x randomly;
Step 2  : Initialize temperature as T>0
Step 3  : If a stopping criterion is satisfied, then stop;
          otherwise,
        :    a) Exit loop if equilibrium is reached;
        :    b) Let x' be a randomly selected neighbor of x;
        :    c) Generate a uniform random number U in [0,1],
        :    d) If exp{-}
Step 4  : End
```

Figure 3: The basic pseudocode of SA (Moh and Chiang, 2000)

3.1.2 Variable Neighbourhood Algorithm (VNS)

VNS is discovered by (Polat, 2017) as a new solution to solve combinatorial and global optimization problems. VNS “explore increasingly” a space that far away from neighbourhoods of the current required solution, and if improvement has been made, it will jump from this solution (Polacek, Hartl, & Doerner, 2004). Shaking step is completed after choosing a solution from the first neighbourhood randomly. Then, the iterative improvement algorithm will be used until a new required solution is obtained and this process will be repeated continuously. If not found, one will jump to the next neighbourhood.

Hereby, the shaking step and the process of iterative improvement ends. If a new required solution is obtained, one begins with the first neighbourhood; otherwise, one will jump to the next neighbourhood, and so forth (Y. Xu, Wang, & Yang, 2013). The basic pseudocode of VNS is shown in Figure 4.

```
Step 0  :  Start
Step 1  :  Initialization
Step 2  :  Choose the set of neighbourhood structures N_k(k = 1, ..., k_max),
           that will be used in the search, find an initial solution
           x; choose a stopping condition;
Step 3  :  Repeat the following until stopping condition is met:
        :    1. Set k←1;
        :    2. Repeat the following steps until k = k_max
        :       (a) Shaking. Generate a point x' at random from
                    k^th neighborhood of x(x' ∈ N_k(x));
        :       (b) Local search. Apply some local search method
                    x' as initial solution; denote with x'' the so
                    obtained local optimum.
        :       (c) Move or not. If this local optimum x'' is better
                    than the incumbent, move there (x←x''), and
                    continue the search with N_1(k←1); otherwise,
                    k←k + 1;
Step 4     End
```

Figure 4 :The basic pseudocode of VNS (Polacek et al., 2004)

Table 2 shows some advantages and disadvantages of SA and VNS.

Table 2 The advantages and disadvantages for SA and VNS algorithm

Algorithm	Advantages	Disadvantages
(SA)	Able to take an unchanged or effective solution as a new current solution with an exact probability.	Long running time (Dharmapriya, Kulathunga, & Jayathilake, 2014)
	Provides the search from trapped in local optima and reaching global optimum (Wang, Zhao, Mu, & Sutherland, 2013)	
(VNS)	Created on the exploration of a number of neighbourhood structures that are used in steps of shaking and local search, with the aim to enhance the solution (Polat, 2017).	It is still easy to fall into the local optimal (Redi, Maghfiroh, & Yu, 2013).

3.2 Population-based metaheuristic algorithm

The population-based algorithm can complete the searching process with multiple initial points in a parallel approach (Beheshti, Mariyam, & Shamsuddin, 2013). The population-based algorithm has the advantage where it can provide the search space for the exploration in an effective way. This method is suitable for searching globally because it has the ability of global exploration and local exploitation.

Table 3 shows the examples of population-based algorithm that have been used for solving various variants of MDVRP which are ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), evolution strategies (ES), intelligent water drop algorithm and artificial bee colony (ABC). In this review paper, three types of population-based algorithms that widely used for solving a various variant of MDVRP will be briefly explained which are ACO, GA, and PSO.

Table 3 Examples of a Single Based Algorithm for Solving Various Variants of MDVRP

Population-based algorithm	Authors
ACO	Bernardes et al., 2016; Dorigo and Stützle, 2004; Ezugwu et al., 2018; Ge, Han, and Bian, 2016; Kao, Chen, and Huang, 2012; Pratiwi, Si, Matematika, and Sains, 2018; Ramalingam and Vivekanandan, 2014; Salehinejad and Nezamabadi-pour, 2015
(GA)	Gao, Liu, and Huang, 2012; Geetha, Poonthalir, and Vanathi, 2013; Ho, Ho et al., 2008; Ombuki-berman and Hanshar, 2009; Vikhar, 2016; Zhang, Zhang, and Liang, 2009
Intelligent water drop algorithm	Ezugwu et al., 2018
(ABC)	Pratiwi et al.,2018
(ES)	Bernardes et al.,2016

3.2.1 Ant Colony Optimization (ACO)

ACO is a member of swarm intelligence methods and it is a probabilistic technique used to solve computational problems. It was introduced by (Dorigo & Stützle, 2004) whereby it stimulates the ant behaviour and there are some artificial features added such as memory in order for solving complex problems. There is an interaction between two techniques usually found in the NP-hard problem which are construction algorithms and local search algorithm. For construction algorithms, it builds the solution in an incremental way, then, forms an empty solution and continuously adding suitable components without backtracking until the complete solution obtained.

Local search algorithms will complete an initial solution and searching for a better solution in the neighbourhood of the current solution space. Over the past few years, there are many modifications have been applied to ACO algorithms, however, the positive feedback process of fundamental ant behavioural mechanism is still not changed. (Salehinejad & Nezamabadi-pour, 2015). Figure 5 shows the basic pseudocode of the ACO algorithm.

```
Step 0  : Start
Step 1  : Initialize
Step 2  : While termination condition not met do
        : ConstructAntSolution
          ApplyLocalSearch
          UpdatePheromones
Step 3    End
```

Figure 5: The basic pseudocode of ACO (Jasser, Sarmini, & Yaseen, 2014)

3.2.2 Particle Swarm Optimization (PSO)

The principle of PSO is taken from the social behaviour of animals such as bird flocking, swarm theory and fish schooling. The emerging of the population that found by the population due to exchanges of the best global solution and the best individual solution found by each particle (Peng, Manier, & Manier, 2017). In PSO, The particles are coded as an integer string of length. The truck number is represented by each particle by using integer value and the corresponding customer that will be serviced by the truck represent by the particle position.

Similarly, in order to form a group within each cluster, all the customer are assigned to the appropriate vehicle. Finally, all destinations will be serviced by finding the best minimum routes for the corresponding customer. Figure 6 shows the basic pseudo code of PSO.

```
Step 0  :  Start
Step 1  :  Repeat while maximum iterations or minimum error criteria
           is not met
Step 2  :  For each particle, calculate fitness value

Step 3  :  set current value as the new pbest, If the fitness value
           is better than the previous best fitness value
Step 4  :  End for

Step 5  :  Choose the particle with the best fitness value of all the
           particles as the gbest
Step 6  :  For each particle
        :  Calculate particle velocity
        :  Update particle position
Step 7  :  End for
```

Figure 6**:** The basic pseudocode of PSO (Geetha, Poonthalir, & Vanathi, 2013)

3.2.3 Genetic Algorithm (GA)

GA was discovered in the year 1960s by John Holland and it is a stochastic optimization method (Ho, Ho, Ji, & Lau, 2008). GA is a part of a class of metaheuristic methods and an adaptive search technique that work on a population of solutions (Ombuki-berman and Hanshar, 2009). Basically, the idea of GA is to maintain the population of solution that expands under discriminate pressure. In order to find the best solution to the problem, GA uses recombination and mutation operators (Vikhar, 2016). In the initialization process of GA, each customer will be assigned to the first depot by using grouping strategy until all the customer have been assigned.

Next step, generating an initial pool of potential solution candidates (chromosomes). Route scheduler will transform every chromosome to a set of routes, then the chromosomes undergo to an evolutionary process until the optimal solution found or the termination condition is met. Figure 7 shows the basic pseudo code of GA.

```
Step 0  :  Start
Step 1  :  Initialize population;
Step 2  :  Evaluate population;

Step 3  :  While do
        :  Choose the best fit individuals for reproduction;
        :  Breed new individuals through mutation and crossover
           operations;
        :  Evaluate the individual fitness of new individuals;
        :  Replace least-fit population with new individuals;
Step 4  :  End
```

Figure 7: The basic pseudocode of GA (Rashid, Newton, Hoque, & Sattar, 2013)

Table 4 shows some advantages and disadvantages of ACO, PSO and GA.

Table 4 The advantages and disadvantages for ACO, PSO and GA algorithm

Algorithm	Advantages	Disadvantages
ACO	Able to cluster and build routes (Kao et al., 2012)	It is time-consuming to lay pheromone on trails used by ants as a communication medium (Kao et al., 2012)
		Able to fall easily into the trap of local optimum (Ge et al., 2016)
PSO	Very easy to implement (Azadeh & Farrokhi-Asl, 2017; P Stodola & Mazal, 2016; S.-H. Xu, Liu, Zhang, Wang, & Sun, 2015; Zhou, Baldacci, Vigo, & Wang, 2017).	Has problems in parameter selection due to its poor exploration
GA	It has an ability to prevent from fall into a local optimum with the help of mutation (Zukhri, Islam, and Zukhri, 2013)	The best solution very hard to obtain because GA easily falls into premature convergence. (Zukhri, Islam, and Zukhri, 2013)

4 Application of metaheuristic algorithms in MDVRP

Figure 8 shows the distribution of various variants in MDVRP that widely studied by researchers recently (based on table 5). From Figure 8, it can be seen that 50% of research focus only on a single MDVRP. This means that MDVRP is still a difficult task to solve by researchers and an effective way is still needed in order to solve the larger problem in this case. Other researches focus on variants of MDVRP such as time window (TW), heterogeneous fleet (HF), backhaul (B), and Min-max. Besides variants that have been mentioned in this review paper, there are still many other variants that exist in MDVRP. It can be concluded that there is a large opportunity for research in this field.

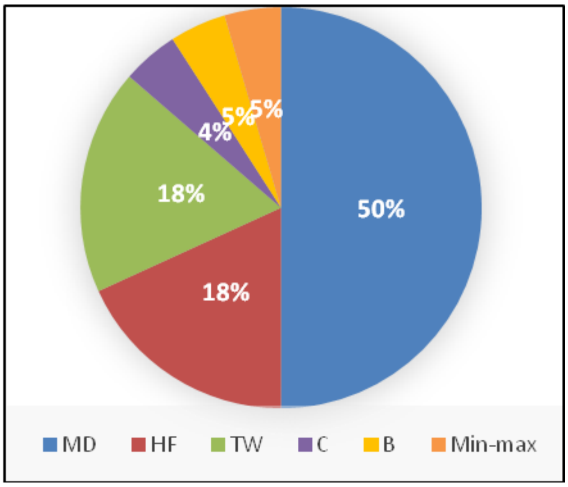

Figure 8: Distribution of various variants in MDVRP

Table 5 shows an application of single-based and population-based metaheuristic algorithm used in various variants of metaheuristic algorithms in multi-depot vehicle routing problem. Some remarks also have been made and shown in Table 5. Recently, the usage of the metaheuristic algorithms is emerged in solving MDVRP and its variants. This is because it has advantages of searching ability where it can search wider space compared to other methods such as heuristic and exact methods. However, all the metaheuristic algorithms have their own drawbacks and mainly, the constraints are due to slow convergence speed and easily trap in local optima. To overcome this problem, many research modified, improved and hybrid the algorithms for its advantages.

For examples, research from Kaabachi, Jriji, and Krichen (2017) has improved the ACO by adding local search to solve the problem. Besides that, Iván, Willmer, and Granada (2018) make modification on GA to find the minimal distance of routes by producing an initial population with heuristic solutions acquired from the heuristic algorithm. Yalian (2016) was improved based on the performance of ACO by using smooth mechanism and 3-opt algorithm for improving the local search strategy. This shows that by adding or combining the metaheuristic methods with other algorithms or techniques will help to improve the performances of the metaheuristics algorithm.

Table 5 also shows the different algorithms used to improve the same method. For examples, author Bernardes et al. (2016), Pratiwi et al. (2018) and Chávez et al. (2016) using the same method which is ACO algorithm but improved the solution with different techniques. Kaabachi et al. (2017) improved the solution by adding local search to the ACO algorithm and success improved the solution up to 4.79%. While Yalian (2016) used scanning algorithm, genetic operator, and smooth algorithm to improve the ACO algorithm and succeed to improve the solution less than 20% and Chávez et al. (2016) used an effective Pareto ACO for solving the problem and succeed to improve the solution between ranges 0.0157% and 7.4%. It can be concluded that different techniques used to improve the solution will give a different result. Hence, selection of techniques is essential to improve the algorithm.

Table 5 Previous works on the application of metaheuristic algorithm for solving a various variant of MDVRP.

AUTHOR(s)	**V**	**METAHEURISTIC ALGORITHM**					**T**		**REMARKS**
		SA	**VNS**	**ACO**	**PSO**	**GA**	**S**	**P**	
(Petr Stodola, 2018)	MD			/				/	Average improvement = 14.08%
(Iván et al., 2018)	HF					/		/	Average improvement = 0.25% to 4.7%.
(Zhou et al., 2017)	MD					/		/	Average improvement = 20%
(Kaabachi et al., 2017)	TW			/				/	Average improvement = 4.79% (runtime = 3.6s)
(Shen and Chen, 2017)	MD				/			/	Average improvement = 13.16%
(Biswas, 2017)	TW					/		/	Average improvement = 10%
(Azadeh and Farrokhi-Asl, 2017)	TW					/		/	For small/medium problem, the highest gap best= 0.731s
(P Stodola and Mazal, 2016)	C			/				/	Average improvement = less than 3%
(Mirabi, Shokri, and Sadeghieh, 2016)	TW					/		/	Average improvement = less than 10%

(Yalian, 2016)	MD			/				/	Average improvement = less than 20%
(Chávez et al., 2016)	B			/				/	Average improvement = 0.0157% and 7.4%.
(Yao et al., 2014)	MD			/				/	Average improvement = less than 3%
(Zeng, He, and Zheng, 2014)	MD			/					The algorithm reaching optimum result when solving the low dimension
(Ramalingam and Vivekanandan , 2014)	MD					/		/	Average improvement =96.61 to 94.99
(Dharmapriya et al., 2014)	TW	/					/		Average improvement = 10.8%
(Salhi, Imran, & Wassan, 2014)	HF		/				/		Cut 80% from the original amount of runtime
(Y. et al., 2014)	HF		/				/		Average improvement=3.49%
(Geetha et al., 2013)	MD				/			/	Improvement =The lowest deviation 1.79% and the highest is 23.99%.
(Benslimane and Benadada, 2013)	HF			/				/	Execution time decline once reaches large size instances of the problem.
(Venkata et al., 2013)	Min-max			/					Average improvement =20.5%
(Imran, 2013)	MD		/				/		Average improvement =0.68%

*V=variants, S=single point search, P=population-based, T=types, s=second, HF=heterogeneous fleet, MD=multi depot, TW=time window, C=capacitated,B=backhaul.

Figure 9 shows the highest percentage is given by ACO which is 38%, followed by GA, 33%, VNS, 14%, PSO, 10% and SA, 5%. This is because ACO shows better search performance and has the stronger searching ability and this statement was supported by (Yamina, Ahmed, & Kinza, 2013). Most of the algorithm used for solving MDVRP is came from population-based metaheuristic. It can be concluded that population-based metaheuristic can give promising results due to its capability of global exploration and local exploitation (Shamsuddin & Beheshti, 2013).

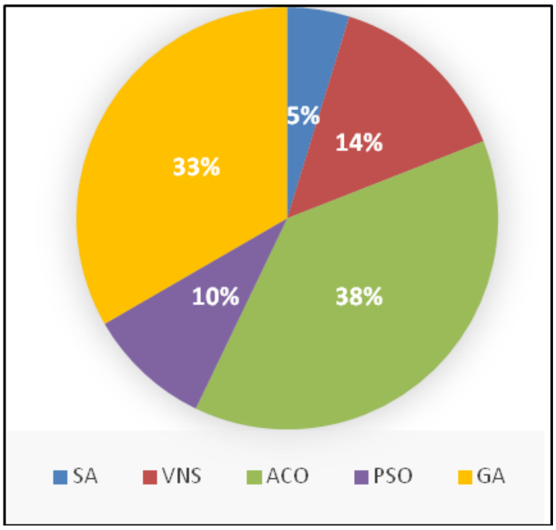

Figure 9: Distribution of metaheuristic method used in MDVRP (based on Table 5)

CONCLUSION

This paper has provided a review on single and population-based metaheuristic methods for solving MDVRP. The article has discussed five types of metaheuristic algorithm which consist of single-based and population-based algorithm along with the advantages and disadvantages of the algorithm. From this review paper, it can be concluded that population-based metaheuristic able to provide better performances for solving MDVRP. For future work, all the metaheuristic algorithms can improve their performance by hybridizing the algorithm whether by combining single-based algorithm with the population-based algorithm or hybridizing with the same class. These suggested future works able to solve MDVRPs constraints and sub-variants such as periodic MDVRP and pickup and delivery MDVRP constraints.

ACKNOWLEDGEMENT

This material is based upon work supported by research university grant [rug], Universiti Teknologi Malaysia under the vote no. 16h69 and Ministry of Higher Education [MOHE].

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