

A REVIEW ON DELIVERY ROUTING PROBLEM AND ITS APPROACHES

¹SITI NURBAYA ISMAIL, ²KU RUHANA KU-MAHAMUD, ³SYARIZA ABDUL-RAHMAN

¹Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA

²School of Computing, College of Arts and Sciences, Universiti Utara Malaysia

³School of Quantitative Sciences, College of Arts and Sciences, Universiti Utara Malaysia

E-mail: ¹sitinurbaya@kedah.uitm.edu.my, ²ruhana@uum.edu.my, ³syariza@uum.edu.my

ABSTRACT

In this paper, a review is conducted specifically in the delivery routing problem, so as to understand its problems and approaches on the current developments and publications. The variants of delivery routing problem were categorized according to the constraints considered in solving the problem. The solution algorithms for the delivery routing problem were classified into hybrid and non-hybrid approaches. A collection of benchmark datasets and real case studies is also presented in relation to the delivery routing problem. The review helps to summarize and record a comprehensive survey on the delivery routing problem. The aim is to organize the variants components of delivery routing problems in a manner that provides a clear view for the readers. New potential research directions resulting from the study is also presented.

Keywords: *Vehicle Routing Problem, Delivery Routing Constraints, Hybrid and Non-Hybrid Algorithm, Solution Algorithm, Delivery Dataset*

1. INTRODUCTION

Dantzig and Ramser (1959) formulated the Vehicle Routing Problem (VRP) as a simplification of the Traveling Salesman Problem (TSP) [1]. However, VRP still captures researchers' attention even after about half a decade of research. This is due to its flexibility in different applications and the complexity that makes the problem still not completely solved. VRP is used to construct a set of optimal routes for a fleet of vehicles in order to serve a set of customers, within a set of constraints. Briefly, VRP is classified into three types, which are (1) VRP for pickup and delivery, (2) VRP for collection and (3) VRP for delivery. This review is only focused on VRP for delivery.

The delivery routing problem attempts to determine an optimal route with the objective to minimize the total distance travelled by a fleet of vehicles to deliver goods to a set of customers, based on a given set of constraints. In this problem, vehicles which are loaded with customers' goods start its route, delivers the goods to customer and ends the journey at depot with empty capacity. Examples of real-world delivery problems that gain interest of researchers are cash money delivery [2] [3], newspaper distribution [4] [5] [6], transportation of hazardous materials [7], dairy

product delivery [8], food delivery [9] [10] [11], and postal and parcel delivery [12] [13] [14].

In the delivery routing problem, there are a number of constraints that can be considered. Among them are vehicle capacity (capacitated or uncapacitated), number of vehicle (limited or unlimited), time (time window or time period), route (symmetric or asymmetric), demand (known or unknown) and depot (single or multiple). Generally, these constraints are used as categorization in the delivery routing problem. Details on the constraints definition and descriptions are discussed in Section 2. Table 1 briefly simplifies constraints that are used as categorizations for the delivery routing problem.

In Table 1, it clearly shows that the variants of delivery routing problem are classified based on their constraints. TSP is the classic approach in delivery routing problem. This approach consider finding the best possible way of visiting all the cities and returning to the starting point that minimize the travel cost (or travel distance) when given a set of cities and the cost of travel (or distance) between each possible pairs [15]. TSP can be shown to be a specific case of VRP, where more than one vehicle used in the problem formulation [16]. In order to cope with



new problem domain, more constraints have been introduced that create more variants of delivery routing problem, where each constraints specially classified the variants.

Table 1: Classifications Of Constraints In Delivery Routing Problem.

Constraint	Characteristic	Delivery Routing Problems Variants
visit all cities, return to starting point	single salesman	Travelling Salesman Problem (TSP)
vehicle capacity	uncapacitated	Vehicle Routing Problem (VRP)
	capacitated	Capacitated Vehicle Routing Problem (CVRP)
demand	stochastic	Vehicle Routing Problem Stochastic Demand (VRPSD)
time	time window	Vehicle Routing Problem Time Window (VRPTW)
	random travel time	Vehicle Routing Problem Stochastic Demand With Time Window (VRPSDTW)
	capacitated	Capacitated Vehicle Routing Problem With Time Window (CVRPTW)
	multiple depot	Multiple Depot Vehicle Routing Problem With Time Window (MDVRPTW)
	open time window	Open Vehicle Routing Problem With Time Window (OVRPTW)
route	symmetric	Symmetric/Vehicle Routing Problem (SVRP/VRP)
	asymmetric	Asymmetric Travelling Salesman Problem (ATSP)
		Asymmetric Capacitated Vehicle Routing Problem (ACVRP)
vehicle type	heterogeneous	Heterogeneous Fixed/Fleet Vehicle Routing Problem (HFVRP/HFFVRP)
depot	multiple	Multi Depot Open Vehicle Routing Problem (MDOVRP)

The objective of this review is to summarize and record a comprehensive survey on the most three important component in solving delivery routing problem. Those components are (1) constraints, (2) solution algorithms and (3) delivery dataset. By providing the information related to the three main components, this study aims to inspire further research in exploring the new least studied area or any potential in the area of delivery routing problem with better insight into potential algorithms that can be applied. This review has concentrated on those publications that are considered most significant, within the authors' knowledge, to the delivery routing problem from 1996 to 2016.

The paper is organized as follows: in Section 2, the explanation on the constraints of the delivery routing problem from the related literature are presented. Next, in Section 3, the solution algorithms designed to solve the delivery routing problem are discussed and classified into hybrid and non-hybrid techniques. The classification of the solution algorithms is also based on the variants of delivery routing problem. Further, the delivery datasets used to justify the efficiency of the solution algorithms from the related literature are discussed in Section 4. Section 5 discusses on the research issues which are arise from the review. Finally, the

summary on the delivery routing problem with new potential research directions are presented in Section 6.

2. CONSTRAINTS ON THE DELIVERY PROBLEM

This section discusses on the constraints that have been used in the delivery routing problem. Fundamentally, in the delivery routing problem, constraints can be categorized as soft and hard constraints. Hard constraints can be defined as mandatory, that need to be fulfilled in any variants of delivery routing problem. Fail to fulfill this constraints will affect the feasibility of the constructed solutions. On the other hand, the soft constraints are considered as optional, where it can be ignored in certain situation when solving the problem. However it may affect the solution quality if the constraints is violated. The consideration of the two types of constraints is depended on the variants of delivery routing problem. A constraints can be hard in a study but can also be a soft constraint in other studies. As long as it fulfill the objective of delivery routing problem, then the solution is considered as good enough.

For example, studies by [10] and [11] focused on Vehicle Routing Problem Stochastic



Demand With Time Window (VRPSDTW). The time window in the studies is referred as a period of time whenever customers are served in the delivery process. This time window constraint can be a hard or soft constraint. Study by [11] applied hard time windows where it address on-time delivery. In the

case of hard time windows, late arrival vehicles are not allowed. On the contrary, study by [10] employed soft time window, where delivery failure will be defined whenever customers did not received the goods within the appointed time window, but nonetheless loss penalties are incurred. This means, in the case of soft time window, the constraint can be violated, but with a penalty cost which can reflect the solution quality. In both cases, early arrival vehicles must wait until the customer’s earliest acceptable service time begins. Then, stochastic demand constraints within VRPSDTW, are referred as to uncertainties in customer demands. Meaning that, the exact customer demands only will be known when the vehicle arrives at the customer’s location.

Clearly it can be stated that, although both studies are in the same variants of delivery routing problem, the consideration of hard and soft constraints are depended on their domain applications. This implies that hard constraints in some studies can be violated and become soft constraints in other studies. In conclusion, this scenario indicates that, the delivery routing problem is a dynamic expandable problem, used to model real-world situation in order to solve specific problems. The flexibility of the delivery routing problem has been one of the major reasons why studies on it have been conducted over half a century since it’s introduced.

Some of the major constraints in the delivery routing problem have been categorized in Table 1 to describe their variants. For example, Vehicle Routing Problem Stochastic Demand (VRPSD) is a VRP variants that consider stochastic demand in the problem domain. Stochastic demand here is referring to customer demands were assumed to be stochastic, such as that the exact demand value is known only upon the arrival of the vehicles at the customer location.

The constraints that are used as previous studies classification in this review are travelling distance, vehicle capacity, type and number of vehicle used in the routing, demand, route and service. Details on the constraints are described in Table 2. Table 3 had classified previous studies based on the discussed constraints in this review. Appendix I for Table 3. Each delivery routing

problem has their own constraints to be considered based on its implementation. The more constraints considered in a problem, the more complex the problem is and more complex solution algorithm is needed in solving the problem.

From the various literature that have been reviewed, it can be concluded that in the delivery routing problem, the soft and hard constraints are depended on the variants of delivery routing problem along with the implemented application domain.

Table 2: Details Description On Constraints Used As Previous Studies Classification.

Constraints	Descriptions
Travelling distance	travelling distance is referred to minimum total cost or minimum total travel times
Vehicle capacity	weight limitation or capacity is total demand of customer on the route that cannot exceed the capacity limit of the vehicle railway number is referred to a fixed railway network and equipment infrastructure
Vehicle type	homogenous is referred to identical vehicle heterogeneous is referred to different vehicle
Number of vehicle	limited number of vehicle is referred to a fixed number of vehicle used in the routing unlimited number of vehicle is referred to unfixed number of vehicle used in the routing
Demand	known demand is referred as customers’ demands are known beforehand stochastic demand is referred as customers’ demands are known only when the vehicle arrives to them
Time	time window is referred as a period of time whenever customers are served in the delivery process precision time is referred as on-time delivery where delivery must be made within given time
Route	symmetric route is consider as distance between two locations is the same in each opposite direction asymmetric route is consider as the distance might be different between two locations, where the distance is not the same in each opposite direction or paths may not exist in both directions
Service	service is referred as customer will only visited once by a single vehicle

3. TYPES OF SOLUTION ALGORITHM

Over the decade, there are tremendous algorithms proposed to solve the delivery routing problem. Therefore, choosing an appropriate solution, is the key success factor to achieve optimized results. The solution algorithms can be classified into two broad categories; (1) the exact algorithm and (2) heuristic algorithm, and then evolve rapidly over time as shown in Figure 1.

The exact algorithm is a solution algorithm that has the capability to provide an optimized solution for the optimization problem. Study [17] has reported that the key success factor of exact algorithm is the effective combination of the set partitioning formulation with families of cuts into column generation based algorithms. Several Exact algorithm that had been captured researcher interest are Branch-and-Price [41] and Set Partitioning [20]. Although the exact algorithm can provide the optimized solution, it has a very major limitation, which is, it cannot cope with large problems [18] as a restriction in computational requirements [19]. Subramanian et al. [20] stated that, constraints in exact algorithms are very time-consuming and can hardly solve VRP instances greater than 150 customers.

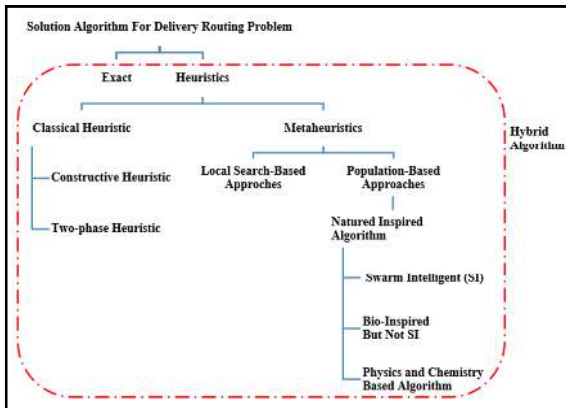


Figure 1: Solution Algorithm for Delivery Routing Problem

The Heuristic algorithm is introduced to solve optimization problems for large size of instances. Sweep Algorithm [3] [23] [34] and Nearest Neighbor Algorithm [3] [10] are examples of heuristic algorithm that have been studied recently. The heuristic algorithms have been considered as an approximate solution that finds possible solutions, but it will not guarantee the optimal solution found. This solution is occasionally being used to find a solution that is close to the best one with much faster speed. To overcome the limitation of finding the optimized solution in a large search area, the metaheuristic algorithm has been introduced. Metaheuristic is a high level heuristic algorithm. The strengths of metaheuristic is, it has the ability to utilize best capabilities of heuristic algorithm to compute for more effective solutions. This situation is achieved due to metaheuristic capability to avoid from being stuck in local minimum and also its capability to guide heuristic algorithm in the search space.

Metaheuristic algorithms can be classified into two which are (1) local search-based approaches and (2) population-based approaches. Examples of local search-based approaches are Simulated Annealing [38] [40] [44] and Tabu Search [33] [45]. Examples of population-based approaches are Genetic Algorithm [30] [32] [33]. In Population-based approaches, the nature-inspired algorithm is then introduced to optimize the delivery routing problem by using nature as an inspiration. The sources of the nature-inspired algorithms are diverse. Four classifications of bases have been identified which include (1) Swarm Intelligence (SI), (2) non-swarm bio-inspired, (3) physics and chemistry and (4) other algorithms [21]. Based on the studies conducted in [21], SI algorithms such as Ant Colony Optimization [9] [14] [29] [33] [35] [36] [38], Particle Swarm Optimization [26], Bat Algorithm [27] and Firefly Algorithm [6] are popular due to their high efficiency in solving delivery routing problem.

From the solution algorithms discussed above, it can be concluded that there are some limitations in every algorithm. For example, exact algorithm have limitation on size limits and execution time. As mentioned earlier, heuristics algorithm have limitation of finding the optimized solution in a large search area. Contrary to metaheuristic algorithm, only when the pure metaheuristic had achieved their limit, combination of different algorithms is used [22] in order to extend the capabilities of the combination of algorithms. Due to this situations, in order to complement each algorithm, so that an efficient result is achieved, the hybrid algorithm techniques have been introduced. The term hybrid is referred to a combination of algorithms to solve problems in their domain. The hybridization of metaheuristic algorithm is gaining more interest in the combinatorial optimization [22] as it has the ability to overcome the ineffectiveness of one another. A non-hybrid algorithm refers to a single algorithm used to solve the delivery routing problem. In this review, solution algorithms were categorized into two main categories: (1) hybrid and (2) non-hybrid algorithms. Table 3 presents the types of solution algorithms designed to solve the delivery routing problem which are grouped based on their variants. Refer to Appendix II.

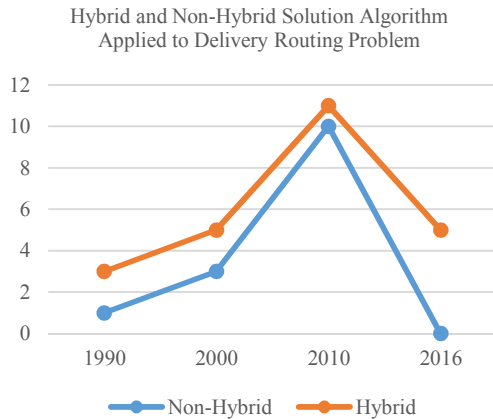


Figure 2: Hybrid and non-hybrid solution algorithm applied in delivery routing problem based on years.

Figure 2 shows the trend of solution algorithms used in solving optimization of the delivery routing problem. Starting in the 1990's, the hybrid solution algorithms has shown its popularity in solving the delivery routing problems. Further, it can be seen that the hybrid algorithms have been increasingly used by researchers in determining the best way to solve the optimization problems especially in the year 2010 compared to the non-hybrid solution algorithms. Even though the current research trend shows that hybrid solution algorithms are still popular compared to non-hybrid solution algorithms, however there is a decrement in its usage. This may be due to the limited publications in the area of delivery routing problem.

4. DELIVERY DATASET

In order to verify the solution algorithm derived from each of the literature, datasets are a very important element to be considered as they are used to test the solution algorithms. In this review, the dataset of the delivery routing problem, are classified into either symmetric or asymmetric. In the symmetric dataset, the route is consider as Euclidean distance, where the distance between two locations is the same in each opposite direction. Meanwhile, in the asymmetric dataset, the distance might be different between two locations, where the distance is not the same in each opposite direction or paths may not exist in both directions. Real-world situations are more towards the asymmetric problems, especially in urban area where there are many one way roads and highways.

Rodríguez and Ruiz (2012), in their study, stated that asymmetric degree in datasets strongly

affects solutions of delivery routing problem where more CPU time is needed to process the solutions which can weaken the quality of solutions obtained [23]. Although the real-world problems are more in asymmetric and there is a huge difference in finding solutions for the asymmetric data, there are still very limited studies on it [24].

In this review, the delivery dataset is categorized into (1) benchmark dataset and (2) case study dataset. In the academic world, there are some conflicts in using the benchmark dataset and case study dataset. The case study dataset provides constraints that are closed to real-world situations. Unfortunately, by using the case study dataset in the real world, comparison on the obtained optimal solution is difficult to make as the dataset cannot be shared and used for other studies. Therefore, sometimes it is hard to prove which solution algorithm can produce a better result.

On the other hand, the benchmark dataset will provide a set of tested datasets with optimal solutions to be used as a comparison. Optimal solution in benchmark dataset is known as Best Known Solution (BKS) or Best Known Result (BKR). By knowing the BKS for each instance in the benchmark dataset, researchers will have a guideline on the proven optimality for the instances. Therefore, this BKS value can be a standard value for them to challenge in order to prove the efficiency of their solution algorithm is more efficient in solving the delivery routing problem. The benchmark dataset can be found in various locations on the Internet, making it possible for researchers to use them in their study. Nonetheless, to date, benchmark datasets only provide a small amount of customers or nodes for the routing process and most of them had find their BKS. This scenario has led to the formulation of new benchmark datasets with a larger customer size to map the real-world situations and constraints [23].

This review has introduced a classification of datasets being used for the delivery routing problems. Table 4 simplified the classification by grouping the dataset according to the variants of delivery routing problem. Appendix III for Table 5. The details of the dataset are explained and their references are listed for further information.

From the articles used in this review, it is inappropriate to compare the BKS for each of the benchmark dataset. This is because, each proposed solution algorithm in the delivery routing problem may have different objective functions and constraints. It is known that different objective

functions and constraints resulted in different solution algorithms.

5. RESEARCH ISSUES

Several issues that can be highlighted based on the most three important components; (1) constraints, (2) solution algorithm and (3) datasets in solving delivery routing problem that has been discussed in this review are;

- Most solution algorithms that have been proposed on recent studies of delivery routing problem are specific to one variant and not suitable to other variants.
- Most of the previous studies has mentioned that it is a need to hybridizing more solutions algorithm to overcome flaw in a single solution algorithm.
- There is a need on finding a way to automatically produce the parameters (or to adapt the parameters during iterations) in order to reduce the interference of the human expert.
- Most of the benchmark datasets used to verify the solution algorithm need to be relevant in accordance to the real world situation, which is asymmetric.

6. SUMMARY

The delivery routing problem is an optimization problem that is flexible. It is a dynamic expandable problem that can be used to model any real-world situation in order to solve specific problems. In this review, three main components in the delivery routing problem have been explored: (1) constraints in delivery routing problem; (2) solution algorithms used; and (3) delivery datasets. It is worth pointing out that, the novelty of this study is the review is specifically made focusing on the delivery routing problem. Therefore, the three main components being discussed are tailored to each other and provide an effective and comprehensive information in the study domain.

Constraints in the delivery routing problem depends on the application domain of the problem. It is very interesting that many problems in the real world can be mapped into the delivery routing problem. Some of the interesting topics that can be considered in this study domain are the delivery of goods, lunch foods, perishable foods, mails, parcels, gas, toxic items, newspaper, cash delivery, and air cargo.

Based on the many articles that have been reviewed, the hybrid solution algorithms is the top

trend to solve the delivery routing problem. It is important to choose the right algorithm to hybridize with so that an optimal solution will be achieved when solving the related problem. From this review, it is found that a very promising result can be obtained if the bio-inspired algorithm is hybridized with the metaheuristic algorithm.

Between the case study dataset and benchmark dataset used to verify the solution algorithms in the delivery routing problem, it is suggested to first work with the benchmark dataset. This is because, the solution used can be compared with existing BKS and later it can be implemented to solve real-world problems. Studies related with asymmetric dataset is closed to real-world situations and is also needed as there are limited studies on it.

As discussed in this review, the delivery routing problem will remain an endless study domain in the future as its flexibility in different applications that can be mapped into real-world situations. It is also found that, several proposed solution algorithms that has been discussed are significant to be used and has been adapted in some real world situations.

ACKNOWLEDGMENTS

The authors wish to thank the Ministry of Higher Education Malaysia for funding this study under the Fundamental Research Grant Scheme, S/O code 13240 and RIMC, Universiti Utara Malaysia, Kedah, for the administration of this study.

REFERENCES:

- [1] G. B. Dantzig and J. H. Ramser, "The Truck Dispatching Problem," *Management Science*, vol. 6, no. 1, pp. 80–91, 1959.
- [2] V. Lambert, G. Laporte, and F. Louveaux, "Designing collection routes through bank branches," *Computers and Operations Research*, vol. 20, no. 7, pp. 783–791, Sep. 1993.
- [3] P. Boonsam, N. Suthikarnnarunai, and W. Chitphaiboon, "Assignment Problem and Vehicle Routing Problem for an Improvement of Cash Distribution," in *Proceedings of the World Congress on Engineering and Computer Science*, 2011, vol. II, pp. 1–5.
- [4] A. Boonkleaw, N. Suthikarnnarunai, and R. Srinon, "Strategic Planning for Newspaper Delivery Problem Using Vehicle Routing Algorithm with Time Window (VRPTW)," *Engineering Letter*, vol. 948, no. May, pp.



- 183–193, 2010.
- [5] W. Agyei, K. Darkwah, W. Obeng-Denteh, and E. Andam, “Modeling Newspaper Distribution as Capacitated Vehicle Routing Problem with Time Window: Case Study of Daily Graphic Newspaper, Ashanti Region, Ghana,” *Archives of Current Research International*, vol. 2, no. 1, pp. 12–22, 2015.
- [6] E. Osaba, X.-S. Yang, F. Diaz, E. Onieva, A. D. Masegosa, and A. Perallos, “A bio inspired discrete firefly algorithm to solve a rich vehicle routing problem modelling a newspaper distribution system with recycling policy,” *Soft Computing*, no. April, 2016.
- [7] C. D. Tarantilis and C. T. Kiranoudis, “Using the vehicle routing problem for the transportation of hazardous materials,” *Operational Research*, vol. 1, no. 1, pp. 67–78, 2001.
- [8] C. D. Tarantilis and C. T. Kiranoudis, “A Meta-heuristic Algorithm For The Efficient Distribution Of Perishable Foods,” *Journal of Food Engineering*, vol. 50, no. 1, pp. 1–9, 2001.
- [9] B. Yao, P. Hu, M. Zhang, and X. Tian, “Improved Ant Colony Optimization for Seafood Product Delivery Routing Problem,” *PROMET - Traffic&Transportation*, vol. 26, no. 1, pp. 1–10, 2014.
- [10] C. I. Hsu, S. F. Hung, and H. C. Li, “Vehicle routing problem with time-windows for perishable food delivery,” *Journal of Food Engineering*, vol. 80, no. 2, pp. 465–475, 2007.
- [11] J. Zhang, W. H. K. Lam, and B. Yu, “On-time Delivery Probabilistic Models For The Vehicle Routing Problem With Stochastic Demands And Time Windows,” *European Journal of Operational Research*, vol. 249, no. 1, pp. 144–154, 2016.
- [12] M. P. Fantì, R. Laraspata, G. Iacobellis, A. M. Mangini, W. Ukovich, and L. Abbatecola, “A Decision Support System Approach For The Postal Delivery Operations,” *IEEE International Conference on Automation Science and Engineering*, pp. 588–593, 2014.
- [13] Q. Song, X. Wang, X. Li, and C. Zhang, “Optimization of Postal Express Mail Network Based on Swarm Intelligence,” in *28th Chinese Control Conference*, 2009, pp. 591–596.
- [14] L. W. Dong and C. T. Xiang, “Ant Colony Optimization For VRP And Mail Delivery Problems,” in *2006 IEEE International Conference on Industrial Informatics*, 2007, pp. 1143–1148.
- [15] R. Matai, S. P. Singh, and M. L. Mittal, *Traveling Salesman Problem : An Overview of Applications, Formulations, and Solution Approaches*. 2010.
- [16] B. Eksioglu, A. V. Vural, and A. Reisman, “The vehicle routing problem: A taxonomic review,” *Computers & Industrial Engineering*, vol. 57, no. 4, pp. 1472–1483, 2009.
- [17] R. Baldacci, A. Mingozzi, and R. Roberti, “Recent exact algorithms for solving the vehicle routing problem under capacity and time window constraints,” *European Journal of Operational Research*, vol. 218, no. 1, pp. 1–6, 2012.
- [18] L. C. Yeun, W. a N. R. Ismail, K. Omar, and M. Zirour, “Vehicle Routing Problem : Models and Solutions,” *Journal of Quality Measurement and Analysis*, vol. 4, no. 1, pp. 205–218, 2008.
- [19] S. N. Kumar and R. Panneerselvam, “A Survey on the Vehicle Routing Problem and Its Variants,” vol. 2012, no. May, pp. 66–74, 2012.
- [20] A. Subramanian, E. Uchoa, and L. Satoru, “A hybrid algorithm for a class of vehicle routing problems,” *Computer and Operation Research*, pp. 1–26, 2013.
- [21] I. F. Jr, X. Yang, I. Fister, and J. Brest, “A Brief Review of Nature-Inspired Algorithms for Optimization,” *Elektrotehnikski Vestnik/Electrotechnical Review*, vol. 80, no. 3, pp. 116–122, 2013.
- [22] C. Blum, J. Puchinger, G. R. Raidl, and A. Roli, “Hybrid Metaheuristics In Combinatorial Optimization: A Survey,” *Applied Soft Computing*, vol. 11, pp. 4135–4151, 2011.
- [23] A. Rodríguez and R. Ruiz, “An study on the effect of the asymmetry on real capacitated vehicle routing problems,” *Computers & Operations Research*, vol. 39, pp. 2142–2151, 2012.
- [24] S. Almoustafa, S. Hanafi, and N. Mladenovic, “New exact method for large asymmetric distance-constrained vehicle routing problem,” *European Journal of Operational Research*, vol. 226, no. 3, pp. 386–394, 2013.
- [25] M. Abudiab, M. Starek, R. Lumampao, and



- A. Nguyen, "Utilization of GIS and graph theory for determination of optimal mailing route," *Journal of Computing Sciences in Colleges*, vol. 19, no. 4, pp. 273–278, 2004.
- [26] X. Yan, C. Zhang, and W. Luo, "Solve Traveling Salesman Problem Using Particle Swarm Optimization Algorithm," *International Journal of Computer Science Issues*, vol. 9, no. 6, pp. 264–271, 2012.
- [27] E. Osaba, X. Yang, F. Diaz, P. Lopez-garcia, and R. Carballedo, "An improved discrete bat algorithm for symmetric and asymmetric Traveling Salesman Problems," *Engineering Applications of Artificial Intelligence*, vol. 48, pp. 59–71, 2016.
- [28] M. Dorigo and L. M. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," *IEEE Transactions on Evolutionary Computation*, vol. 1, no. 1, pp. 53–66, 1997.
- [29] T. Gonsalves and T. Shiozaki, "Solving Capacity Problems As Asymmetric Travelling Salesman Problems," *International Journal of Artificial Intelligence & Applications (IJAA)*, vol. 6, no. 2, pp. 53–65, 2015.
- [30] Y. Nagata and D. Soler, "A new genetic algorithm for the asymmetric traveling salesman problem," *Expert Systems With Applications*, vol. 39, no. 10, pp. 8947–8953, 2012.
- [31] A. Ahmadi and A. Foroozantabar, "Ant colony system method to vehicle routing problems," *International Journal of Engineering and Applied Sciences*, vol. 6, no. 3, pp. 32–41, 2015.
- [32] A. K. M. Masum and M. F. Faruque, "Solving the Vehicle Routing Problem using Genetic Algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 7, pp. 126–131, 2011.
- [33] B. Yu, Z. Z. Yang, and B. Yao, "An improved ant colony optimization for vehicle routing problem," *European Journal of Operational Research*, vol. 196, no. 1, pp. 171–176, 2009.
- [34] M. Y. Khoshbakht and E. Khorram, "Solving the vehicle routing problem by a hybrid meta-heuristic algorithm," *Journal of Industrial Engineering International*, vol. 8, no. 1, p. 11, 2012.
- [35] R. M. Chen, F. R. Hsieh, and D. S. Wu, "Heuristics Based Ant Colony Optimization for Vehicle Routing Problem," *IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1039–1043, 2011.
- [36] C. Dhawan, "VRP Using ACO MetaHeuristic," *International Journal For Research in Applied Science and Engineering Technology*, vol. 2, no. IV, pp. 349–354, 2014.
- [37] M. M. Islam, S. Ghosh, and M. M. Rahman, "Solving Capacitated Vehicle Routing Problem by Using Heuristic Approaches: A Case Study," in *Global Engineering, Science and Technology Conference*, 2015.
- [38] C.-Y. Lee, Z.-J. Lee, S.-W. Lin, and K.-C. Ying, "An enhanced ant colony optimization (EACO) applied to capacitated vehicle routing problem," *Applied Intelligence*, vol. 32, no. 1, pp. 88–95, 2010.
- [39] D. Vigo, "A heuristic algorithm for the asymmetric capacitated vehicle routing problem," *European Journal of Operational Research*, vol. 89, no. 1, pp. 108–126, 1996.
- [40] F. Taner, A. Galić, and T. Carić, "Solving Practical Vehicle Routing Problem with Time Windows Using Metaheuristic Algorithms," *PROMET - Traffic&Transportation*, vol. 24, no. 4, pp. 343–351, 2012.
- [41] N. Azi, M. Gendreau, and J. Y. Potvin, "An Exact Algorithm For A Vehicle Routing Problem With Time Windows And Multiple Use Of Vehicle," *European Journal of Operational Research*, vol. 202, no. 3, pp. 755–766, 2010.
- [42] H. Akeb, U. De Picardie, J. Verne, and M. Neuf, "A Beam Search Based Algorithm for the Capacitated Vehicle Routing Problem with Time Windows," in *Federated Conference on Computer Science and Information Systems*, 2013, pp. 329–336.
- [43] M. Marinaki and Y. Marinakis, "A Glowworm Swarm Optimization algorithm for the Vehicle Routing Problem with Stochastic Demands," *Expert Systems With Applications*, vol. 46, pp. 145–163, 2016.
- [44] S. Ree and B. S. Yoon, "A two-stage heuristic approach for the newspaper delivery problem," *Computers and Industrial Engineering*, vol. 30, no. 3 SPEC. ISS., pp. 501–509, 1996.



- [45] P. Repoussis, C. Tarantilis, and G. Ioannou, "An Evolutionary Algorithm for the Open Vehicle Routing Problem with Time Windows," *Bio-inspired Algorithms for the Vehicle Routing Problem*, pp. 55–75, 2009.

APPENDIX I

Table 3: Delivery Routing Problem Constraints Classifications Based On Its Variants.

		TSP	ATSP	VRP	CVRP	ACVRP	VRPTW	CVRPTW	VRPSD	VRPSDTW	MDVRPTW	MDOVRP	OVRPTW	HFFVRP
Travelling distance	minimum total cost or	[25] [26]	[27] [28]	[1] [31]	[7] [12]	[20] [14]	[3] [4]	[5] [42]	[43]	[10] [11]	[44]	[9]	[45]	[8]
	minimum total travel times	[27] [28]	[29] [30]	[32] [33] [34]	[20] [35] [36] [37] [38]	[39] [23]	[13] [40] [41]							
Vehicle capacity	weight limitation			[1] [31] [33] [34]	[7] [12] [35] [37] [38]		[3]	[5] [42]		[10]	[44]	[9]		[8]
	railway number		[29]											
Vehicle type	homogenous			[1] [31]	[7] [12] [20] [38]	[20] [39]		[5] [42]				[9]		
	heterogeneous													[8]
Number of vehicle	limited				[37]	[14]	[4]	[5]		[10] [11]				[8]
	unlimited			[1] [31]	[35]	[23]	[40] [41]	[42]			[44]	[9]	[45]	
Demand	known			[31] [32]	[7] [12] [20] [36] [37] [38]	[20]	[3] [4] [40] [41]	[5] [42]			[44]	[9]	[45]	
	stochastic								[43]	[10] [11]				
Time	time window						[3] [4] [13] [40] [41]	[5] [42]		[10] [11]	[44]		[45]	
	precision						[3] [13]			[11]	[44]			
Route	symmetric	[25] [27] [28]		[1] [33]	[12] [20] [35] [37]			[5] [42]	[43]	[10] [11]	[44]	[9]	[45]	
	asymmetric		[27] [28] [29] [30]			[20] [14] [39] [23]	[13]							
Service	customer visited once	[26] [28]	[28] [30]	[1] [31] [32] [33] [34]	[7] [20] [35] [36]	[20] [14] [39] [23]	[4]	[5] [42]	[43]			[9]	[45]	[8]

APPENDIX II

Table 4: Types Of Solution Algorithm Designed To Solve Delivery Routing Problems Grouped By Variants.

	Hybrid		Non-hybrid	
	Algorithm	Reference	Algorithm	Reference
TSP	Improved Bat Algorithm (BA + 2-opt + 3-opt)	[27]	Bruce Force	[25]
	Ant Colony System(ACS) + 3-opt	[28]	Particle Swarm Optimization (PSO)	[26]
ATSP	Improved Bat Algorithm (BA + 2-opt + 3-opt)	[27]	Ant Colony Optimization (ACO)	[29]
	Ant Colony System(ACS) + 3-opt	[28]		
	New Genetic Algorithm (GA + Edge Assembly Crossover-EAX)	[30]		
VRP	Genetic Algorithm + Crossover Method	[32]	Ant System (ACO: single and multiple colony)	[31]
	IACO (Improved Ant Colony Optimization) (ACO + Tabu Search + Genetic Algorithm + 2-Opt)	[33]		
	Sweep Algorithm (SW) + Ant Colony System (ACS) + 3-opt	[34]		
CVRP	List Based Threshold Accepting + Local Search (2-opt)	[7]	Augment-insert Algorithm	[12]
	Ant Colony Optimization(ACO) + Semi Greedy +NEH	[35]	Ant Colony Optimization (ACO)	[36]
	Set Partitioning (SP) + (Iterated Local Search (ILS) + Mixed Integer Programming (MIP))	[20]	Fisher and Jaikumar Holmes and Parker Algorithm Fisher and Jaikumar	[37]
	Simulated Annealing(SA) + Ant Colony Optimization (ACO)	[38]		
ACVRP	Ant Colony Optimization + 2-Opt + λ interchange	[14]	AV	[39]
	Set Partitioning (SP) + (Iterated Local Search (ILS) + Mixed Integer Programming (MIP))	[20]	Clark and Wright (CW) Sweep Algorithm (SW) General Heuristic of Pisinger and Ropke (PR) Memetic Algorithm of Nagata (NA)	[23]
VRPTW	Route Planning Agent (Optimization Model + Route Data + Route_Planning_Algorithm)	[13]	Sweep Algorithm, Group Sweep Algorithm, Nearest Neighbor Algorithm	[3]
	Simulated Annealing + Iterative Local Search	[40]	Skipped Sweep Method	[4]
			Branch-and-Price	[41]
CVRPTW	Clark and Wright Savings + Local Search	[5]		
	Three-Phase Algorithm (3PA: k-means + Beam Search + Local Search)	[42]		
VRPSD	Combinatorial Neighborhood Topology Glowworm Swarm Optimization (CNTGSO) + Variable Neighborhood Search (VNS) + Path Relinking (PR)	[43]		
VRPSDTW	Resource Model + Probabilistic Model (RMPC)	[11]	Extended Time-Oriented Nearest-Neighbor Heuristic	[10]
MDVRPTW	Modified Simulated Annealing (Simulated Annealing + Half-Delivery Scheme)	[44]		
MDOVRP	Ant Colony Optimization + 2-opt	[9]		
OVRPTW	Evolutionary Algorithm (EA) + Tabu Search	[45]		
HFFVRP			Backtracking Adaptive Threshold Accepting	[8]

APPENDIX III

Table 5: Types Of Dataset Used To Test The Algorithm Designed In Solving Delivery Routing Problems.

Variants	Dataset	Details	References
TSP	Benchmark Dataset		
	TSPLIB Reinelt (1991)	<ul style="list-style-type: none"> • 22 instances 	[27]
	TSPLIB95	<ul style="list-style-type: none"> • contains variants of TSP dataset • 147 TSP dataset used in the reference • Oliver30 dataset being used in the reference 	[26] [28]
	Case Study Dataset		
	Distance between buildings in university	<ul style="list-style-type: none"> • 1 depot with 9 buildings as customer to deliver mail • geographical Information System (GIS) was utilized for the analysis of the delivery routes and the measurement of distance from building to building 	[25]
ATSP	Benchmark Dataset		
	TSPLIB Reinelt (1991)	<ul style="list-style-type: none"> • 15 instances 	[27]
	TSPLIB95	<ul style="list-style-type: none"> • Contains variants of TSP dataset • ry48p dataset being used in the reference • 27 ATSP datasets used in the reference 	[28] [30]
	Soler et. al	<ul style="list-style-type: none"> • 126 ATSP datasets used in the reference 	[30]
	Case Study Dataset		
Simulation data for train schedule	<ul style="list-style-type: none"> • considered a railway terminal station with four railroads, each with an attached platform • there are 5 train services • considered type 4 railway capacity: maximization of the number of trains that can be scheduled at a railway station 	[29]	
VRP	Benchmark Dataset		
	Christofides N, Eilon S. (1969)	<ul style="list-style-type: none"> • the same 3 problems used in the research • C1 with 50 customers, C3 with 100 customers and C4 with 150 customers 	[31]
	Vehicle Routing Dataset (branchandcut.org)	<ul style="list-style-type: none"> • Contains variants of VRP dataset • R101 – R107 and RC208 datasets used in the reference 	[32]
	OR-library (Beasley, 1990)	<ul style="list-style-type: none"> • Contains variants of VRP dataset • 14 problems dataset used in the reference • Size data (customer) from 50 – 199 and capacity range from 140 – 200 	[33]
CVRP	Benchmark Dataset		
	Christofides, Mingoizzi and Toth (1979)	<ul style="list-style-type: none"> • 14 instances (denoted by C1 – C14) with 50 customers to 199 customers for different instances • C1 – C10: customers with random location • C11 – C14: customers are clustered • conditions for C1 – C5 are similar to C6 – C10 • C6 – C10: limited routing path length, each vehicle • C13 – C14 have the routing path length constraints • instances with length limitation also include the service time cost considerations on all the customers 	[14] [20] [35] [43]
	Set M (Christofides, Mingoizzi & Toth, (1979))	<ul style="list-style-type: none"> • used 3 open instances in the M series, namely M-n151-k12, M-n200-k16 and M-n200k17 • customer are in range of 150 and 199 	[20]
	Golden, Wasil, Kelly and Chao (1998)	<ul style="list-style-type: none"> • composed of 20 large-scale instances for CVRP • customer are in the range of 200 to 480 • some instances have restrictions on the maximum length of every route 	[20]
	Toth and Vigo (2003)	<ul style="list-style-type: none"> • considered several Euclidean VRP and DVRP instances from the literature with up to about 500 customers • 14 classic Euclidean VRP and DVRP instances described in Christofides and Eilon (1969) and Christofides et al. (1979) • 3 Euclidean VRP instances proposed by Fisher (1994) • 20 large scale Euclidean VRP and DVRP by Golden et al. (1998) 	[38]



	Case Study		
	Transportation of gas cylinders in Greater Athens Area	<ul style="list-style-type: none"> • more or less 10000 roads with 300 customers • the network is divided into regions of variable risk with 3 contour areas presented: areas of high-risk (yellow), medium-risk (green), low-risk (red) 	[7]
	Italian Postal Delivery System	<ul style="list-style-type: none"> • postal network described as directed graph • 1 Post Automation Center (depot) to distribute mail to 48 Postal Delivery Centers (customers) • vehicle capacity 550kg • weight of mail not mentioned • used the Decision Support System Approach 	[12]
	Virtual environment	<ul style="list-style-type: none"> • created a virtual environment • a centrally located depot with 15 customers • then calculate the route length 	[36]
	Coca-Cola Distribution in Rajshahi, Bangladesh	<ul style="list-style-type: none"> • a distribution center in Rajshahi city supplies coca-cola to 15 places • used 4 vehicles in 2 days to supply 350 Coca-Cola cases 	[37]
ACVRP	Benchmark Dataset		
	Fischetti, Toth and Vigo	<ul style="list-style-type: none"> • instances number used is 24 • vehicle capacity used is same, 1000 • customer number used is 33 to 70 • vehicle number used is 2 to 12 	[20]
	Pessoa et al.	<ul style="list-style-type: none"> • considered the same dataset of Fischetti, Toth, and Vigo, but different capacities (150, 250, and 500) • but the reference do not consider instances with 150 capacity as they can be easily solved 	[20]
	ACVRP_Depot	<ul style="list-style-type: none"> • 540 location files, for different number of nodes on several territories and depot locations • 540 distance matrix files (real asymmetric) • 360 demand and maximum capacity files 	[23]
	Case Study Dataset		
	randomly generated test problem	<ul style="list-style-type: none"> • several classes of test problem are randomly generated and used as ACVRP dataset • up to 300 customers 	[39]
	Pharmaceutical and herbalist product delivery in Bologna	<ul style="list-style-type: none"> • vehicle is 3 • capacity is 1000 • customer is 70 • delivery must be made in 4 hours, no time window 	[39]
	Real-life mail delivery network problem	<ul style="list-style-type: none"> • the mail delivery base selected consists of 13 vehicles and covers around 3000 homes and buildings • all the nodes are clustered into small clusters • based on the result of all the clusters, a VRP is formed comprising all the clusters • then, the actual distance data is derived from a commercial GIS software 	[14]
VRPTW	Benchmark Dataset		
	Solomon	<ul style="list-style-type: none"> • 56 problem instances, classified as 6 different sets • each set contains, 8 and 12, 100-node problems • R1 and R2: random dataset • C1 and C2: clustered • RC1 and RC2: semi-clustered • can be used directly for OVRPTW 	[40] [41]
	Case Study		
	Cash distribution of bank in Bangkok, Thailand	<ul style="list-style-type: none"> • 377 branches and has 3 distribution centers • Hours of operation of each branch depends on where are it located • If located at department store; 11 am until 8 pm. • If located elsewhere; 8.30 a.m. - 3.30 p.m. • Each depot/distribution center (DC) – A, B, and C – has different processing capacity at the proportion of 50: 30: 20 • Each DC's operating time is from 8.00 a.m. to 5 p.m. 	[3]



	Morning newspaper delivery in Bangkok, Thailand	<ul style="list-style-type: none"> • newspaper distribution from Distribution Center (DC) to drop points, not end customer • vehicle is 7, vehicle capacity is 2000 • 118 nodes with different demands (22 – 235) time window is 200 minutes 	[4]
	Postal express mail network in Shandong, China	<ul style="list-style-type: none"> • express mail distributed from 10 postal central offices to 7 cantonal offices, with 257 post roads • time window is next morning arrival (8.30 a.m.) 	[13]
CVRPTW	Benchmark Dataset Solomon Dataset	<ul style="list-style-type: none"> • used 2 instances from the Solomon dataset (C1 & C2) • C1: customers: 200, service time: 90, vehicle capacity is 200 • C2: customers 100, service time 90, vehicle capacity is 700 	[42]
	Case Study Dataset Newspaper delivery for 26 districts in Ashanti, Ghana	<ul style="list-style-type: none"> • distribution from regional capital to districts capital not to end users • 27 nodes with 1 depot • vehicle is 6 • time window is 180 minutes 	[5]
VRPSD	Benchmark Dataset Christiansen and Lysgaard 2007	<ul style="list-style-type: none"> • dataset made up of 40 instances • nodes from 16 to 60 • vehicles from 2 to 15 	[43]
VRPSDTW	Benchmark Dataset Modified from Ak and Ereira (2007)	<ul style="list-style-type: none"> • single depot • 4 customers • time window is 60 minutes 	[11]
	Case Study Dataset Delivery of perishable, temperature sensitive food, from a distribution center, using a vehicle with frozen storage equipment	<ul style="list-style-type: none"> • rectangular grid network that covers 50 square kilometers with random node locations • 1 depot as distribution center • 50 customers • deliver lunch box items to local retail customers • customer time window duration, half hour • customer demand ranged, ten items to items • customers' time-windows randomly generated between 6:20 – 11:00 a.m. • service times for customers: demand-dependent temperature 24 hours and 8 °C 	[10]
MDVRPTW	Case Study Dataset Newspaper publication company in Korea, Hankuk-ilbo	<ul style="list-style-type: none"> • 3 main distribution centers (depot) • 250 local distribution centers (customer) • newspaper should delivered by truck to the local distribution centers by 4.00 a.m. • assign local centers to main centers 	[44]
MDOVRP	Case Study Dataset Seafood product delivery in Dalian, China	<ul style="list-style-type: none"> • seafood product depots send seafood product to supermarkets • a method is used to reduce the complexity of the problem by changing the MDOVRP into an OVRP with a dummy central depot vehicle capacity is 200 	[9]
HFFVRP	Case Study Dataset Fresh milk distribution for a dense populated area of the Greek capital	<ul style="list-style-type: none"> • dairy company distributed milk to 299 customers • use heterogeneous vehicle: 3 types of vehicle • total load 6120 • total demand 4644 	[8]