

## Vehicle Routing Problem with Simultaneous Pickup and Delivery

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**Abstract**—This paper focuses on the Vehicle Routing Problem with Simultaneous Pickup and Delivery (VRPSPD) issue. VRPSPD is one of the extended problems related to the usual Vehicle Routing Problem (VRP). VRPSPD consists of both linehaul customers and backhaul customers with known demand. In VRPSPD, only a single depot can receive and supply the loads. The vehicles can only visit each customer once and can serve all customers simultaneously by delivering or picking up the loads within a limited capacity. VRPSPD is an NP-hard problem. The considerable data size has increased the difficulty for it to be solved by using mathematical programming or combinatorial optimization. A heuristic approach based on the Variable Neighborhood Search (VNS) is proposed. Heuristic-based solutions offer feasible solutions that are approximately accurate to the exact solution. It is one of the most popular solutions to solve a complex problem. In this research, the algorithm solution consists of two main phases. A simple heuristic is used to generate the initial solution in the first phase. Then, the feasible solution obtained in the first phase will become the initial input for the improvement phase, which applied the VNS algorithm. The proposed algorithm is tested using a list of benchmark datasets. The result obtained is compared with the best solution that can be found in literature research. The comparison result shows that the heuristic algorithm is favorable to be used for this kind of vehicle routing problem.

**Keywords**— vehicle routing problem; heuristic algorithm; delivery pickup customers; variable neighborhood search.

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### I. INTRODUCTION

The Vehicle Routing Problem (VRP) is a significant logistics problem with a wide range of applicability. VRP aims to come up with suitable routes for a fleet of homogeneous vehicles that can serve a group of customers that start and end at a depot by minimizing the traveling distance. Each customer can only be served once by one vehicle at a time. VRP was first introduced by Dantzig and Ramser [1] in the research, which targets to provide an optimum routing solution with minimum travel distance between a fleet of gasoline delivery trucks and a list of terminals with various service stations supplied. In the year 1964, Clarke and Wright [2] introduced a new variant of VRP that will commonly occur in logistics and transport fields, such as considerably more than one vehicle in the problem formulation, mode to serve the customer or vehicle with varying capacities. This is since the source of the problem is attributed to the numerous modes used to serve the customer and the varying capacities handled by more than one vehicle.

On that note, research was commenced to apply or combine VRP with different constraints and parameters. VRP is one of the most popular research topics. For example, VRP with time window [3], VRP with a capacity [4], VRP with multiple depots [5], VRP with pickup and delivery [6], and vehicle routing with split deliveries [7]. Green vehicle

routing [8] are some of the joint research topics related to regular VRP that were conducted in the past few years. During the last few decades, VRP had begun to be applied in solving various kinds of real-life logistics problems. Different methodologies and techniques were investigated to solve the VRP problem. There are a considerable number of methods and solutions that can be found in published academic literature.

Furthermore, the development of VRP software and applications displayed rapid growth in the industry and logistics fields. Thousands of companies have started to implement this technology into the logistics management process, such as the support system used by an oil downstream company, which was proposed by Gayialis and Tatiopoulos in the year 2004 [9]. Likewise, the scheduling model was used by a sales company for flight tickets to arranging their free pickup and delivery services [10]. Moreover, literature research has proven that the optimized routing solution reduces transportation cost [11], amount of resources required, fuel consumption [12], and the emissions of greenhouse gas, such as carbon dioxide, especially in urban areas [13], [14].

Vehicle Routing Problem with Simultaneous Pickups and Deliveries (VRPSPD) is one of the additional problems that stem from the usual VRP. VRPSPD consists of both linehaul customers and backhaul customers with known demand. According to Pinto, Alves, and Carvalho [15], linehaul

customers can be categorized as the source of demand, while backhaul customers are the suppliers in daily life. Meanwhile, the customers involved in this problem will require a delivery or pickup service, but not both. In VRSPD, only a single depot can receive and supply the loads. The vehicles can only visit each customer once and can serve all customers simultaneously by delivering or picking up the loads within a limited capacity.

The fluctuating loads on vehicles are determined by the strategy, which can serve linehaul and backhaul customers simultaneously. The strategy has advanced in complexity in comparison to the classical VRP. On the other hand, VRSPD is an NP-hard problem [1]. The huge data size of NP-hard issues has increased the difficulty of solving it by using any form of mathematical programming or combinatorial optimization.

VRSPD consists of a set of customers with two different characteristics and has proven to be of value to the research in the industry. However, it should be noted that Breakers, Ramaekers, and Nieuwenhuys [16] conducted and published a research in 2016. The study was about the tendency of a total of 277 VRP articles, which was recorded between 2009 and mid-year of 2015. Most of the literature research involved the capacitated vehicle problem. Only 18.65% of the recorded articles considered VRP with backhauls. Thus, this research will focus on VRSPD. The objective function of this research is to minimize the travel distance by maximizing the use of the offered vehicle's capacity. A heuristic algorithm is proposed, and the final solution is compared against a list of benchmark solutions.

## II. MATERIALS AND METHOD

There is, presumably, a depot and some customers that are divided into linehaul and backhaul customers with either request for pickup or delivery services and a known demand. The customers are in a transportation network with different coordinates and locations. There are multiple vehicles. Each vehicle, with a limited capacity, will leave the depot with some loads, which needs to be delivered to the customer and collect some loads from the customer. When the maximum capacity is reached, the vehicle travels back to the depot to perform its necessary function once more. Moreover, one customer can only be served once by one vehicle at a time. Therefore, loads of a customer cannot be spilled. The objective of this project is to minimize the total travel distance and optimize the use of the limited capacity of a vehicle.

### A. Hard Constraints

- The vehicle will depart and return to the origin for every route
- Each customer can only be served once
- Customer is visited by exactly one vehicle only
- The demand must be fulfilled for all customers
- All vehicles will have the same predefined capacity
- The total capacity cannot exceed the maximum capacity of the vehicle

### B. Soft Constraints

The usage of the vehicle capacity for every route should be optimized.

### NOTATION

$I$	Set of customers
$I_0$	Set of all customers and depot (origin)
$n$	Number of customers
$c_{ij}$	Distance between customer $i$ and customer $j$ ; $i, j = 1, 2, 3, \dots, n$
$c_{0j}$	Distance between depot, 0 and customer $j$ ; $j = 1, 2, 3, \dots, n$
$m$	Number of vehicles
$K$	Set of vehicles $K = \{1, 2, \dots, m\}$
$Q_k$	Maximum capacity of vehicle $k$
$p_i$	Pickup demand of customer $i$ ; $i = 1, 2, 3, \dots, n$
$d_i$	Delivery demand of customer $i$ ; $i = 1, 2, 3, \dots, n$
$y_{ij}^k$	Load pickup by vehicle $k$ while traveling from customer $i$ to customer $j$ , $i \neq j$
$z_{ij}^k$	Load to be delivered by vehicle $k$ while traveling from customer $i$ to customer $j$ , $i \neq j$

Decision variable

$$x_{ij}^k = \begin{cases} 1, & \text{If vehicle from } i \text{ to } j \text{ by vehicle } k \\ 0, & \text{Otherwise} \end{cases}$$

The corresponding model is building as below

$$\text{Minimize } \sum_{k=1}^m \sum_{i=1}^n \sum_{j=1}^n C_{ij}^k x_{ij}^k$$

Subject to

$$\sum_{k=1}^m x_{ij}^k \leq 1, \quad i, j = 1, 2, 3, \dots, n \quad (1)$$

$$\sum_{k=1}^m \sum_{i=1}^n \sum_{j=1}^n x_{ij}^k = 1 \quad (2)$$

$$\sum_{i=1}^n x_{ij}^k = \sum_{i=1}^n x_{ji}^k, \quad k = 1, 2, 3, \dots, m \quad (3)$$

$$\sum_{k=1}^m \sum_{j=1}^n y_j^k = \sum_{k=1}^m \sum_{j=1}^n p_j^k, \quad i = 1 \quad (4)$$

$$\sum_{k=1}^m \sum_{j=1}^n z_j^k = \sum_{k=1}^m \sum_{j=1}^n d_j^k, \quad i = 1 \quad (5)$$

$$\sum_{k=1}^m \sum_{i=1}^n y_{ji}^k x_{ji}^k - \sum_{k=1}^m \sum_{i=1}^n y_{ij}^k x_{ij}^k = p_j, \quad j \neq 0 \quad (6)$$

$$\sum_{k=1}^m \sum_{i=1}^n z_{ji}^k x_{ji}^k - \sum_{k=1}^m \sum_{i=1}^n z_{ij}^k x_{ij}^k = d_j, \quad j \neq 0 \quad (7)$$

$$\sum_{k=1}^m x_{ij}^k (y_{ij}^k + z_{ij}^k) \leq Q_k, \quad i = 1, j = 1, 2, 3, \dots, n \quad (8)$$

$$y_{0j} = 0, \quad j = 1, 2, 3, \dots, n \quad (9)$$

$$z_{j0} = 0, \quad j = 1, 2, 3, \dots, n \quad (10)$$

The mathematical model above represents the problem statement of VRPSPD that this research focus. The objective function is to minimize the total travel distance. (1) and (2) guarantee that every vehicle can only have one route, and each customer is served by exactly one vehicle. (3) guarantees that the vehicle that arrived at and departed from the customer is the same vehicle. (4) guarantees that the total load picked up is the same as the sum of the total pickup demand in a route. (5) guarantees that the sum of the load on the vehicles from the depot amounts up to the total delivery demand in that route. (6) and (7) are the flow equations that are regarding the amount of pickup and delivery loads. (8) is to ensure the vehicle's maximum capacity is not exceeded. (9) means the amount of pick up and loads on the vehicle at the start from the depot is zero, and (10) means the total amount of delivery loads when the vehicle returns to the depot must equal to zero.

VPRSPD is an NP-hard problem [1]. The considerable data size has increased the difficulty for it to be solved by using mathematical programming or combinatorial optimization. From the literature research, most researchers tend to solve the NP-hard problem by using a heuristic-based solution. A heuristic solution enables there to be multiple constraints and handles the issue of having a large number and size of data. It is one of the most popular solutions to solve a complex problem. Moreover, heuristic-based solutions offer feasible solutions that are approximately accurate to the exact solution within a reasonable, computable performance [17]. Thus, a heuristic-based algorithm is proposed in this project to solve the VRPSPD model. The algorithm solution consists of two main phases. In the first phase, a simple heuristic is used to generate the initial solution. Then, the feasible solution obtained in the first phase will become the initial input for the improvement phase of the Variable Neighborhood Search (VNS) algorithm.

### C. Initial Solution

Firstly, the distance between each customer and the depot and distance between customer to customer is calculated. Then, each customer was arranged in order based on the distance between the two knobs. For example, starting from the depot, Customer A with the shortest distance will precede customer B, who has the shortest distance from customer A.

Once the customer with the shortest path is determined, the capacity of all loads is summed up based on the demand and type of customer. If the vehicle has struck a capacity violation, the customer will be skipped, and the following customer will be taken into consideration. This is to ensure (8) in the model is fulfilled. The fluctuating loads on the vehicle is the most challenging part of this step. To ensure the accuracy of the model constraints (3), (4) and (5), customer demands need to complete in whole individual load. Hence, the load demand should be considered along with every customer needs to be served next.

In addition to that, for backhaul customers who require a pickup service, the vehicle will keep the loads for the entire way and deliver them back to the depot whereas, for linehaul customer, the loads are stored in the vehicle from the starting point at the depot. Based on the constraints (9), the very

beginning includes delivery loads that will be kept on the vehicle and the number of loads to be picked up at the start from the depot is always zero.

This step will be repeated until the maximum capacity is reached, or all the customers have been served at least once as in accordance to the constraint (2) in the model. When a limited capacity is reached, the vehicle will return to the depot, and a new route will be started to serve the remaining customers. In this research, every new route, as a new vehicle departs from the origin, is calculated to make sure that the constraint (1) in the model is followed. The process will be terminated if all customers have been served exactly once. In conclusion, the initial solution proposed can fulfill all the constraints in the mathematical model from (1) until (10). The data flow diagram for the initial solution is shown in Fig. 1.

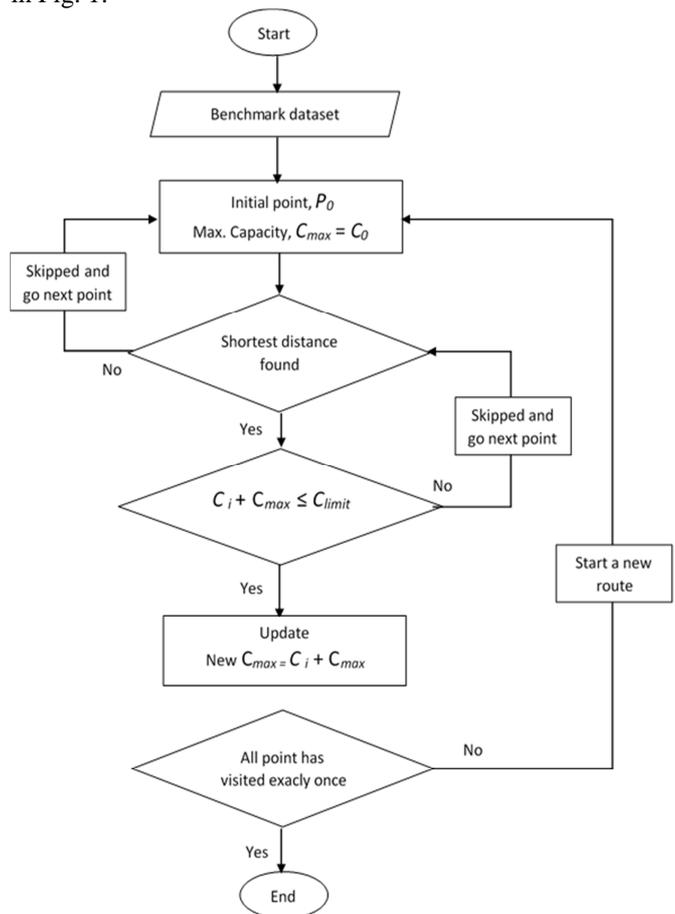


Fig. 1 Flowchart Diagram for Initial Solution

### D. Improvement Method

The Variable Neighborhood Search (VNS) algorithm aims to improve the solution through a systematic exploration of some neighborhood structures in a local search [4]. The principle of VNS is that the first local findings should not limit a solution because it may not provide an accurate local optimum. The local optimum of one neighborhood structure is not necessarily a local optimum for others. Once VNS reaches the local minimum, the shaking step will be used to increase the chances of finding a global minimum solution by getting out of local optima using a list of random selection strategies. If there

has been an improvement throughout the structure, the current solution will be updated.

VNS is a metaheuristic method [18]. Based on the research by Braekers, Ramaekers, and Nieuwenhuys [16], metaheuristic methods are often used by researchers to solve VRP in comparison to the exact method or classical heuristic. According to them, this trend is due to the computationally expensive incurred when using the exact solution to solve complex and large instances, as well as the high risks to get stuck in local optima when applying the heuristic method.

Multiple research aimed to compare the efficiency and accuracy of various heuristics methods in solving VRP. According to Bianchessi and Righini [19], the local search algorithm with complex and variable neighborhood yielded a better solution after comparing its result to a constructive algorithm and tabu search algorithm. In their experiment, the local search algorithm can generate a high degree of accuracy within a short computing time. Therefore, local search is applied iteratively in VNS to retrieve a local optimum of the neighborhood structure. Hence, VNS is proposed in this research to improve the solution generated by the initial solution. The algorithm structure of VNS is shown in Fig.2.

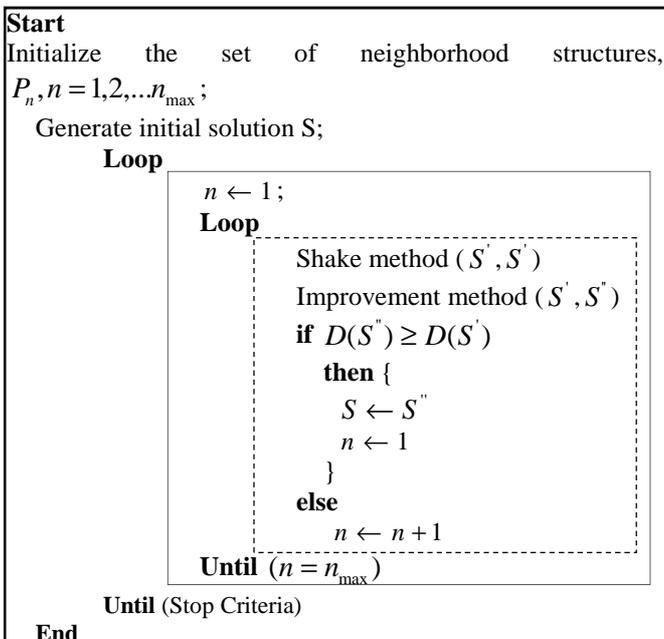


Fig. 2 General algorithm structure of VNS

In this research, the neighborhood structure is set up by three types of shaking methods and three types of iterated improvement methods. At each iteration, a feasible solution is randomly generated through the shaking method. Each of the shake method contains a stopping criterion. If a feasible solution is failed to be generated until the stopping criteria reached, the other two shake methods will be applied. The random shake iteration steps will be repeated until a feasible solution is obtained. If no feasible solution is unearthed after all shake methods tried, the shaking process will be skipped. In this condition the last improvement solution will be treated as the new feasible solution and applied to the local search process.

Local search is applied repeatedly until a local optimum is reached. In this research, all the improvement methods will be run exactly once in each iteration. The current solution will always be updated when an improvement is met. A new cycle of looping will start if all the possible neighborhood structures have been tested. The VNS process ended when no improvement solution is found in any neighborhood structure or the maximum stopping criterion is met. The shaking methods proposed are show in Fig.3 until Fig.5. Fig.6 until Fig.8 are the improvement methods used in this research.

### 1) Shake Methods

- Random 1-to-0 swap: One customer is selected at random and shifted to an alternative random selected route.

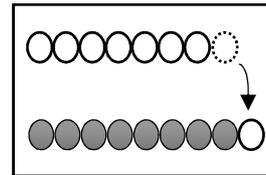


Fig. 3 Random 1-to-0 swapping process

- Random 2-to-2 swap: Swapping the randomly picked customers (linehaul or backhaul) from the same randomly selected route with another two randomly picked customers from a different route (customers can select from the different routes).

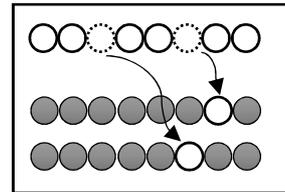


Fig. 4 Random 2-to-2 swapping process

- Extra route: One randomly chosen customer is moved to a new extra route.

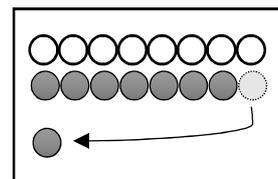


Fig. 5 Random extra route adding process

### 2) Improvement Methods (Local search)

- Local 1-to-1 swap: The location of a customer is swapped iteratively with another customer from a differ route until all feasible structures are tested.

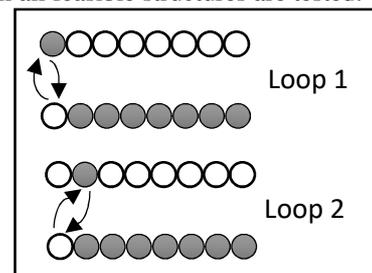


Fig. 6 1-to-1 local iteration swapping process

- Local 2-to-1 swap: Two consecutively arranged customers in a certain location are swapped iteratively with a customer from a different route until all feasible structures are tested.

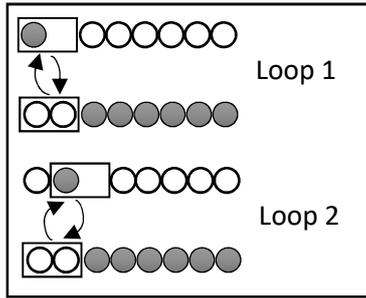


Fig. 7 2-to-1 local iteration swapping process

- Local 1-to-Many swap: The location of a customer is swapped iteratively with another  $n$  customer that is arranged consecutively from a different route with a cumulative capacity, which does not exceed the maximum capacity range provided. The process is repeated iteratively until all feasible structures are tested.

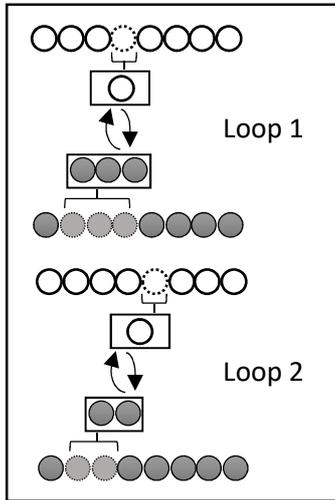


Fig. 8 1-to-Many local iteration swapping process

### III. RESULTS AND DISCUSSION

In this research, the benchmark data on VRP with backhauls introduced by Goetschalckx and Jacobs-Blecha which is proposed in the paper, “The Vehicle Routing Problem with Backhauls” in 1989 [20], is used to validate the efficiency of the proposed algorithm. The benchmark data involved a depot with a group of linehaul and backhaul customers. The benchmark datasets consist of different ratios of linehaul customers to backhaul customers, which are 50:50, 33:67 and 20:80 respectively, with differing demands. The depot for all these problems is located at the fixed coordinate [12000,16000]. On top of that, the x-coordinate of customers are randomly distributed within the interval [0.24000] whereas the y-coordinates are generated within the interval [0.32000].

In this research, 15 sets of benchmark problems with different total numbers of customers from 25 to 45 with different customer demands are considered. The 15 sets of benchmark data used in this research are shown in Table I. Moreover, even though the benchmark provided the fixed

fleet number along with each set of data, it will not be considered in this research. We do not restrict the number of vehicles at the beginning to test the capability and dynamic efficiency of the proposed algorithm in solving the problem to simulate a dynamic, real-life situation. Although the number of vehicles is not fixed, it must not exceed a number 5 vehicles of the fixed fleet that is set to each set of benchmark data.

TABLE I  
BENCHMARK DATASET

Dataset	Customer Size	Fixed Fleet	Capacity Size
A1	25	8	1550
A2	25	5	2550
A3	25	4	4050
B1	30	7	1600
B2	30	5	2600
B3	30	3	4000
C1	40	7	1800
C2	40	5	2600
C3	40	5	4150
D1	38	12	4400
D3	38	7	5000
D4	38	5	6000
E1	45	7	2650
E2	45	4	4300
E3	45	4	5225

#### A. Computational Result

Table II and Table III below reported the computational results of the proposed algorithm. There are two sets of total distances shown in Table II. The initial solution was the total distance travelled initially in this research, which was calculated by using the simple heuristic. However, the optimum solution is the total distance travelled that was obtained after using the improvement method and the variable neighbor search algorithm. The improvement percentage  $IMP$  is calculated by using the formula shown in (11). There is a significant improvement to the results when one compares them before and after the VNS is applied. The highest improvement rate is 54.11% and the lowest rate obtained is 10.08%. The result has shown that proposed method managed to provide the increment of at least 10% compare to the initial solution.

TABLE II  
RESULT OBTAINED BY PROPOSED ALGORITHM

Dataset	Total Distance		IMP (%)
	Initial Solution	Optimum Solution	
A1	372089	222819	-40.12
A2	253802	191118	-24.70
A3	279088	180137	-35.46
B1	426989	233392	-45.34
B2	375324	204501	-45.51
B3	372115	182269	-51.02
C1	590547	271029	-54.11
C2	302608	234360	-22.55
C3	215303	193607	-10.08
D1	442356	330263	-25.34
D3	356245	246987	-30.67
D4	374832	251191	-32.99
E1	387683	279779	-27.83
E2	456167	241653	-47.03
E3	402027	272943	-32.11

TABLE III  
COMPARISON OF CURRENT BEST RESULT AND OBTAINED RESULT

Data set	Best Known Solution		Result Obtained		RD (%)
	Travel Distance	Fixed fleet	Travel Distance	No. of Vehicle	
A1	229886	8	222819	7	-3.07
A2	180119	5	191118	5	6.11
A3	163405	4	180137	3	10.24
B1	239080	7	233392	7	-2.38
B2	198048	5	204501	5	3.26
B3	169372	3	182269	3	7.61
C1	250557	7	271029	7	8.17
C2	215020	5	234360	5	8.99
C3	199346	5	193607	4	-2.88
D1	322530	12	330263	10	2.39
D3	239479	7	246987	6	3.13
D4	205832	5	251191	4	22.03
E1	238880	7	279779	7	17.12
E2	212263	4	241653	4	13.85
E3	206659	4	254768	3	32.07

$$IMP = \frac{(\text{Optimum solution} - \text{Initial solution})}{\text{Initial solution}} \times 100 \quad (11)$$

The final results reflect that the total distance travelled can be minimized in the shake and implement steps. The optimum solution has a much shorter total of distance travelled compared to that of the initial solution. This is caused by the repeated local search process which occurred in the variable neighborhood search structure, which can ensure a local minimum is reached. The outcome in Table II shows that VNS can help simple heuristic to escape from the trap at the local optimum.

Table III shows the comparison result between the optimum solution obtained in this research and the best-known solution. The best-known solution is obtained from previous research papers [8], [21], [22]. To evaluate the proposed methodology, the Relative Percentage Deviation, *RD* (12) is computed for each solution obtained [1]. It shows that the total travel distance obtained in this research for benchmark datasets, A1, B1, B2, C3, D1 and D3 are very close to the best known published solution. It only has a difference of around less than 4%. Besides, for dataset A1, B1 and C3, the total distance travelled obtained is slightly shorter than the best-known solution. Although the number of vehicle used are different with the fixed fleet provided, but the overall solution has shown that the proposed method is able to compete with other methods.

$$RD = \frac{(\text{Heuristic solution} - \text{Best known solution})}{\text{Best known solution}} \times 100 \quad (12)$$

Furthermore, based on the experimental results, the proposed algorithm proved that it could complete each route by using a total vehicle number equal to or not exceeding five from the fixed fleet. The number of vehicles for dataset A2, B1, B2, B3, C1, C2, E1 and E2 are the same as the fixed fleet that are set in the benchmark even though it was not restricted in the algorithm. Moreover, dataset A1, A3, C3, D1, D3, D4 and E3 shows that all customer can be served by using fewer vehicles. Although the total travel distance of it is lengthy, this solution may be suitable for the area which

there is a shortage of human resource or when the transport charge is higher than the fuel oil cost. In short, the proposed algorithm can minimize the total travel distance or reduce the number of vehicles.

#### IV. CONCLUSION

This project deals with the Vehicle Routing Problem with Simultaneous Pickups and Deliveries (VRPSPD). A heuristic based algorithm is proposed to obtain the initial solution. The heuristic method can easily initiate the initial solution based on the model of VPRSPD. Then, the Variable Neighborhood Search (VNS) mechanism along with some improvement procedures is then applied to improve the initial solutions. From the optimum solution obtained, it has been proven that the proposed algorithm is as effective as other methods. Although some of the results obtained are not good enough compared to the current best research result, the proposed method is able to improve the initial solution. The solution can be improved in the future by applying more effective and varied improvement procedures. In addition to that, a larger data size proves more effective in order to test the enhanced algorithm for future research.

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