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A Mathematical Model for the Vehicles Routing Problem with Multiple Depots, Considering the Possibility of Return Using the Tabu Search Algorithm

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Abstract. The current study examines an essential type of vehicle routing problem (VRP). This type is one where customers are served by limited-capacity vehicles from multiple depots and is known as Multi-Depot Capacitated Vehicle Routing Problem (MDCVRP). The novelty of this study is that in the present case, cars, after Leaving the Depot, can go back to any other depot. Those issues seem to occur in most real-world issues where information, messages, or news are sent electronically from somewhere. The purpose

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of the problem is to minimize the costs associated with routing. Regarding the literature on such issues, it has been proven in previous studies and research that these problems are among the hard-NP problems, and to solve them using the metaheuristic method, the exact methods justify it. After changing the basic model, this study developed a Tabu Search (TS) algorithm. The study results demonstrate that if the equipment can return to any depot, the cost is significantly reduced in contrast to the case where equipment is forced to return to their depot.

Keywords: Vehicle Routing, Metaheuristic algorithm, Possibility of vehicle return, Tabu Search Algorithm.

1. Introduction

The vehicle Routing Problem (VRP) is regarded as a complex combinatorial optimization problem that has absorbed substantial attention since its introduction over 50 years ago. VRP involves the design and optimization of a range of routes for a series of vehicles that serve a series of customers [2,3,5,24]. In general, VRP falls in the category of transportation logistics problems. In this problem, the primary aim is to define and calculate what routes vehicles should take to serve all or a particular portion of customers while traveling the minimum possible distance or in the shortest possible time [6,7,8,21]. This problem has been classified into various sub-types, each with its own vital applications in different fields [9,11,20]. The initial idea of VRP was proposed as a core issue in the transportation, distribution, and procurement field, which showed that using management and optimization methods in this field can result in significant cost savings [12,14,17,18]. According to a study by Toth and Vigo [22], the appropriate use of modern transportation methods can reduce the total production cost by 5 to 20%. Over the years, researchers have added a wide range of constraints and assumptions to VRP to extend its application to different fields, thereby creating multiple sub-types of this problem [13,23]. In this article, we also tried adding a new assumption to this problem and comparing the results with previous models in the same field. In real-world situations, vehicles that leave a given depot at the start of a tour may prefer not to return to the same depot at the end of the tour but rather go to the nearest depot or even remain at the position of the last customer when the tour ends to reduce their travel costs. This may not be of much use for the problems where humans operate vehicles. However, the same cannot be said for cases where transportation is done by self or remote-controlled vehicles (drones or robots) and in the information transfer context where the cargo is a data package (e.g., messages or news) that is sent electronically from a source and must be received at a destination after going through several customers.

2. Literature Review

The critical works carried out in the area of interest include the study of Gendreau et al. [6]. They proposed a problem formulation where a customer could be served by multiple vehicles, unlike in classic VRP, where each customer is served only once by one vehicle. In 1997, Cordeau et al. [5] proposed a problem formulation where customers are served by multiple depots instead of one, and also, the planning period is M days long instead of one day. They solved this problem by a heuristic method and showed the excellent performance of the model by several numerical examples.

Another essential work in this area is the study of Laporte and Louveaux [11], who proposed the Stochastic Vehicle Routing Problem (SVRP). In this problem, some components of the problem, such as customers, and their demand, are probabilistic and uncertain, unlike previous problems in this field where these parameters are known and given. Toth and Vigo [22] proposed the VRP with return goods, where customers can return the goods to the depot. In their problem, network nodes are divided into supply points and delivery points, the former for delivering goods from depots to customers and the latter for returning goods from customers to depots. In 2002, the vehicle routing problem with time windows (VRPTW) was formulated and solved. In this problem, each customer must be served within a predefined period; otherwise, a penalty is applied to the objective function. Pisinger and Ropke [17] proposed a general heuristic method for solving VRPs. They developed this method for solving a variety of VRPs, including those with time windows and multiple depots. After testing the method on 486 datasets in the literature, they reported that it produced optimal solutions for 183 datasets and near-optimal solutions for the rest. In a comprehensive review by Zhang et al. [24], he described the variety of algorithms that can be used to solve VRPs. As mentioned above, over the years, some assumptions were added to VRP to modify it for specific purposes. However, researchers also developed various exact, heuristic, meta-heuristic, and hybrid methods to solve these problems. Good examples of exact solution algorithms can be found in the articles of Hadjiconstantinou et al. [9] and Toth and Vigo [22]. One of the well-known exact solution methods used in this field is the branch-and-bound algorithm. Theurich et al. [21] successfully used this algorithm to solve a VRP with several customers. Singh et al. [20] also used the branch-and-bound algorithm to solve VRPTW. It should be noted that these algorithms are not suitable for larger problems, as it may take them a very long time to produce a solution. For these problems, it is better to use heuristic algorithms, which produce sufficiently accurate solutions in shorter times.

One of the simplest yet crucial heuristic algorithms used in this field is the savings algorithm of Clarke and Wright. This algorithm operates based on integrating two routes on the condition that it results in maximum cost savings. While this algorithm can be used for both directed and non-directed VRPs, Vigo [23] showed that it performs better for non-directed problems than for directed ones. There are also other algorithms for solving VRPs, such as the sequential insertion algorithm proposed, which is known for the ability to solve the problem where the number of vehicles is unknown. VRPs can also be solved by a two-step heuristic called the sweep algorithm, first proposed by Gillett and Miller [7], which has become the basis of many solution methods. This algorithm first classifies the vertices based on their geometric relations and then solves a traveling salesman problem (TSP) for each separate class. Researchers have also developed other heuristic methods such as finite branch-and-bound, petal method, and heuristic improvement for solving VRPs [13,16,19,23].

Another important group of techniques for solving VRPs is meta-heuristic methods. Compared to heuristic methods, these methods conduct deeper searches in the problem space to find higher-quality solutions. One of the metaheuristic algorithms commonly used in this field is the Simulated Annealing (SA) [7-9]. Another meta-heuristic algorithm used in this field is the Tabu Search (TS). Many researchers, including Taylard, Gendrio, Su and Kelli, Cartus, and Vigo, have worked on solving VRPs with TS. Another robust algorithm is the genetic algorithm, first proposed in 1975 [11,12,14,17,18]. This algorithm has been employed by several researchers, including Schmidt, Cross and Lin, Tan, Blanton, Wayne Wright, and Lewis, to solve a wide variety of VRPs. VRPs have also been solved by many other algorithms, such as Ant Colony Optimization (Fuller, Doller, Hart, Larry, Yu, Yang,

and Yao) and neural networks [2,3,5,6,21]. A more advanced way of using meta-heuristic algorithms is to combine them into hybrid methods. These methods have also been used in various articles for various VRPs.

In the latest studies in this field, Li et al. [12] developed an improved version of the ant colony optimization algorithm for the multi-objective multi-depot VRP. This study aimed to maximize profits while simultaneously minimizing the costs associated with greenhouse gas emissions. In another study, Sacramento et al. [18] developed an adaptive large neighborhood search algorithm for solving VRP. These researchers solved various large-scale instances of the problem with their algorithm and analyzed the results.

In an article by Asghari and Al-e [2], they comprehensively reviewed 313 articles on green VRP with a special emphasis on routing with electric vehicles and drones. Mojtahedi et al. [14] proposed a formulation for sustainable VRP for solid waste management purposes. They used the Social Engineering Optimization (SEO) algorithm to solve this problem.

One kind of VRP is one where customers are served by limited-capacity vehicles from multiple depots. This type of VRP is called Multi-Depot Capacitated Vehicle Routing Problem (MDCVRP). In these kinds of problems, if customers are concentrated around depots, this problem can be formulated and solved as a set of independent VRPs. Otherwise, the problem falls in the category of MDCVRP. In this problem, initially, customers are allocated to depots, and then the problem is solved for a limited number of vehicles stationed at depots. A substantial requirement in MDCVRP is that at the end of their tours, the vehicle must return to the depots they departed at the start [1,4].

MDCVRP can be formulated for various objectives, such as minimizing the number of vehicles, minimizing travel costs, minimizing travel time, or maximizing customer service level. One can even consider combining these objectives in a multi-objective format [10,15].

Considering relevant studies in the given arena, it can be that VRPs belong to the class of NP-hard problems. Exact methods can solve NP-hard problems, but since this could be very time-consuming, it is preferred to solve them with metaheuristic methods. While the solutions of metaheuristic methods could be sub-optimal, they tend to solve such problems much faster than exact methods. One of the metaheuristic methods that the literature has shown to be more suitable for solving MDCVRP than other such methods is TS. Therefore, throughout this study, this method was employed to solve the MDCVRP where vehicles are free to not return to their origin depot at the end of their tours (i.e., go to other depots) and compare the results with the conventional MDCVRP where they are required to do so. In both cases, the optimization objective is to minimize travel costs.

3. Methodology

The study's main objective is to minimize travel costs because of the allocation of customers to depots subject to the condition that each customer is visited only once by only one vehicle. It is assumed that the network comprises multiple depots, each with several fixed-capacity vehicles. After leaving the depot, each vehicle starts visiting customers until the tour is complete or it runs out of stock, after which it returns to any depot with the lowest return cost. Of course, it is worth mentioning that a basic assumption in our model is that at the end of each period, there will be as many vehicles in each depot as it has been at the beginning of the period.

3.1. Parameters

I: Set of depots
J: Set of customers
K: Set of vehicles
N: Number of customers
M: Number of depots
C_{ij}: Cost of travel between customers *i* and *j*
d_j: Demand of customer *j*
Q_k: capacity of vehicle *k*

3.2. Decision variable

$$x_{ijk}=\begin{cases}1 & If\ vehicle\ k\ travels\ from\ i\ to\ j\\ 0 & Otherwise\end{cases}$$

3.3. Model

$$\min \sum_{i\in I}\sum_{j\in J}\sum_{k\in K} C_{ij}\times x_{ijk} \tag{1}$$

$$\sum_{k\in K}\sum_{i\in I} x_{ijk}=1 \qquad \forall j\in J \tag{2}$$

$$\sum_{k\in K}\sum_{j\in J} x_{ijk}=1 \qquad \forall i\in I \tag{3}$$

$$\sum_{j\in I}\sum_{k\in K} x_{ijk}\le K \qquad \forall i\in J \tag{4}$$

$$\sum_{j\in J}\sum_{k\in K} x_{ijk}\le K \qquad \forall i\in I \tag{5}$$

Equation (1) is the objective function of the problem, which is to minimize costs. Constraint (2) states that only one route enters each customer, either from depots or from other customers. Constraint (3) indicates that only one route leaves each customer, either for depots or other customers. Constraint (3) limits the capacity of vehicles. Constraints (4) and (5) set the maximum number of vehicles departing from each depot or returning to the depot equal to the number of existing vehicles in order to stabilize the number of vehicles stationed at depots. In this model, the conventional constraint that makes vehicles return to their origin depot is removed. We solve this problem with a slightly modified TS. The only difference between our solution method and the conventional TS is that we generate a random number of neighbors to enhance the diversity of the search process further.

4. Results and Discussion

4.1. Solution representation

In this study, the solutions are represented as a string of integers, which show the code of customers visited by vehicles until they return to depots. An example solution is shown in Figure 1.

6	20	3	9	1	21	6	2	8	4	20	5

Figure 1. Solution representation

Initially, it is assumed that there are two depots, each with two vehicles with the same capacity, which must serve nine customers. In the above example, the first vehicle leaves the first depot, which is named Depot 20, and returns to the same depot after visiting Customer 6. The second vehicle leaves the first depot, visits Customers 3, 9, and 1, and then returns to the second depot, which is named Depot 21. The third vehicle leaves the second depot, visits Customers 6, 2, 8, and 4, and then returns to the first depot. Finally, the fourth vehicle leaves the second depot and, since the number of vehicles in the depots should remain constant, it returns to the same depot.

4.2. Generation of the initial solution

In this study, the initial solution is generated completely at random.

4.3 Neighbor generation

There are various ways to generate a neighbor solution. These include insertion, swapping, inversion, 2-opt, 3-opt, which are shown in Figures 2-4.

6	20	3	9	1	21	6	2	8	4	20	5

6	20	6	21	1	9	3	3	8	4	20	5

Figure 2. Insertion method for generating neighbor solutions

6	20	3	9	1	21	6	2	8	4	20	5

6	20	8	21	1	9	3	2	3	4	20	5

Figure 3. Swapping method for generating neighbor solutions

6	20	3	9	1	21	6	2	8	4	20	5

6	20	6	21	1	9	3	2	8	4	20	5

Figure 4. Inversion method for generating neighbor solutions

In the course of the present study, neighbor solutions are created with the aid of the swapping method demonstrated in Figure 3. In the mentioned method, two cells of the string are randomly chosen and their values are swapped.

4.4. Problem parameters

The problem parameters are as follows (Table 1).

Table1. The problem parameters

N	M		K	TABU LIST(TL)	Q
30	2		4	6	1800

4.5. Numerical Example

In order to evaluate the performance and efficiency of the model with the assumption mentioned above, an example problem with many depots and several customers was taken into consideration. In that example, the system has three depots, each with two vehicles, which are supposed to serve 30 customers scattered around the depots. After executing the model in the software MATLAB-R2011a, the following outcomes were acquired.

The cost values obtained in 100 iterations of the algorithm for the proposed model, where vehicles are allowed to return to other depots, and the conventional model, where vehicles are required to return to their origin depots, are plotted in Figures 5 and 6. By comparing these two graphs, it can be concluded that considering the proposed assumption has led to a better solution in most cases. Here, the ranking indicates the number of times the model was executed.

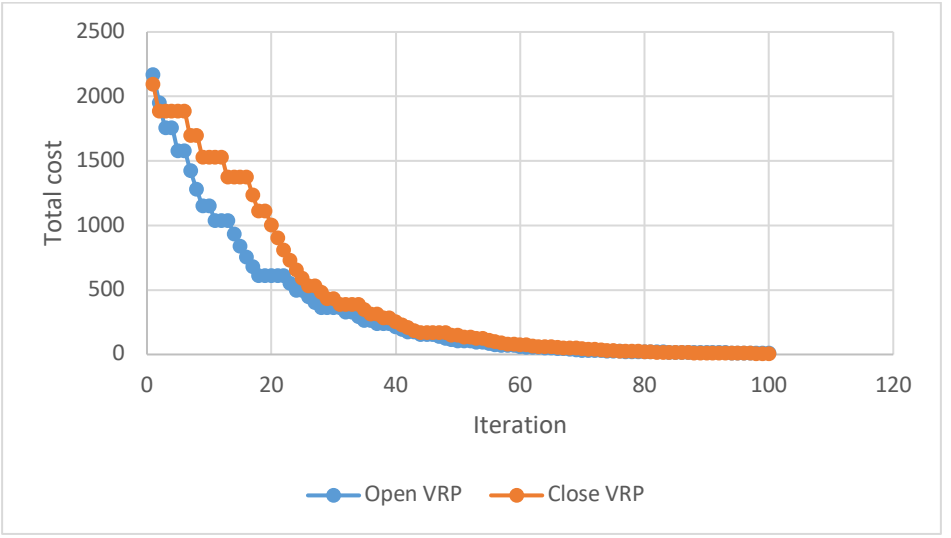


Figure 5. Comparison of the total cost of the two models in 100 iterations

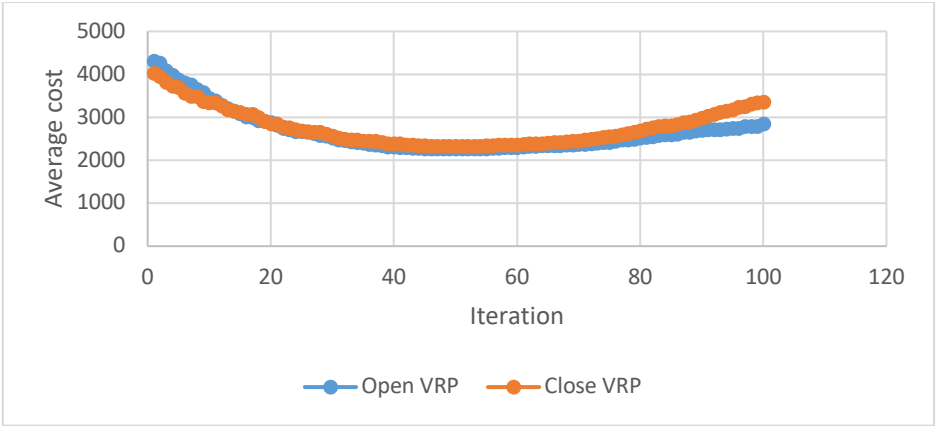


Figure 6. Comparison of the average cost of the two models in 100 iterations

Considering Figure 6, the two models are compared regarding average cost at various iteration numbers. The figure also reveals that in most iterations, the model with the suggested assumption offers more favorable solutions compared to the one without considering the assumption.

4.5.1. Numerical Examples

This study has utilized the data and information on the problems of Cordeau for multi-depot VRPs to generate numerical examples. Of course, although Cordeau has assumed that vehicles return to their origin depot, we have modeled the same problem with the assumption that vehicles are free to go to other depots [5].

As demonstrated in Table 2, the most desirable solutions acquired with the suggested assumption are, in some cases, more favorable and, in other cases, worse than Cordeau's solutions. The striking point concerning the table is that for all problems, considering the proposed assumption has resulted in a cost reduction. The results also show that our approach generates better solutions than the conventional approach (Cordeau's solutions). It is worth mentioning that the parameters of the solution process were as follows: 10,000 iterations with the Tabu list size of 100 for the model with the proposed assumption and 15,000 iterations with the Tabu list size of 100 for the model without the proposed assumption (conventional). These parameters were set offline, i.e., by trying several parameter values and selecting the best option. The average of answers was observed without assumptions.

Table 2. Comparison of the solutions of the proposed problem and the Cordeau problem

.Problem Code	Number of depots	Number of vehicles in each depot	Number of customers	Vehicle capacity	Best Cordeau solution	Best solution reached without the proposed assumption	Best solution reached with the proposed assumption	Mean of the solutions reached without the proposed assumption	Mean of the solutions reached with the proposed assumption
p01	4	4	50	80	534.65	505.64	497.54	613.65	573.26
p02	2	4	50	160	465.7	464.78	367.83	509.14	352.73
p03	3	5	75	140	626.63	584.29	373.22	649.91	590.72
p04	8	2	100	100	917.45	966.18	838.04	1078.62	861.11
p05	5	2	100	200	733.44	757.96	690.61	726.56	679.62
p06	6	3	100	100	799.6	851.13	768.51	894.2	800.78
p07	4	4	100	100	816.48	851.51	850.42	1005.17	820.44
p08	14	2	249	500	4174.08	4121.49	3969.02	4210.15	4021.54
p09	12	3	249	500	3646.09	3766.87	3288.13	3717.79	3727.7
p10	8	4	249	500	3448.06	3773.05	3074.41	3999.19	3523.13

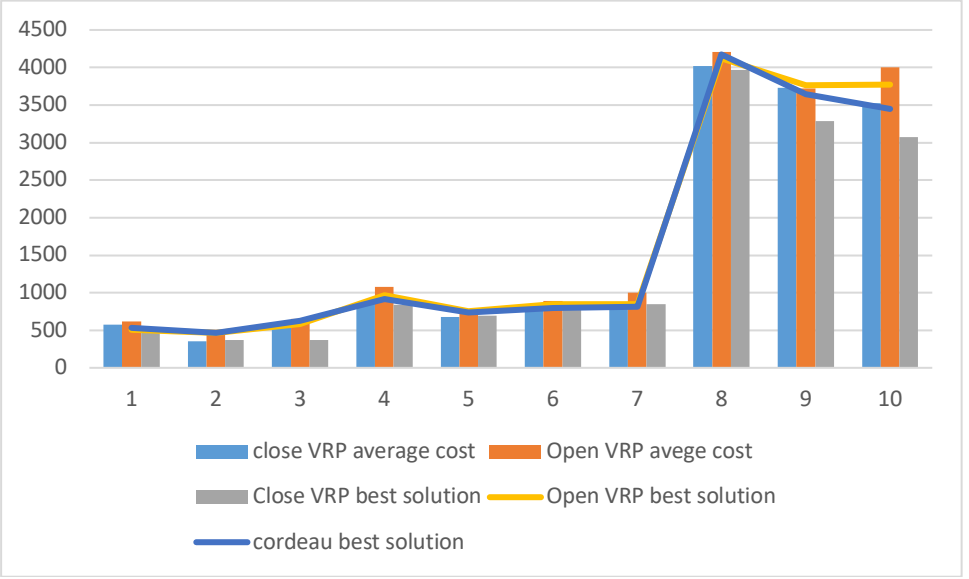


Figure 7. Comparison with the results of Cordeau [4]

As shown in Figure 7, implementing the assumption led to reaching significantly better solutions than Cordeau's. This improvement is due to a reduction in routing costs. These outcomes indicate that the considered assumption, i.e., allowing vehicles to return to any depot at the end of their tours, can notably decrease routing costs in this and other types of VRP. This can be demonstrated by comparing the results of Open VRP and Close VRP. As a consequence, overall, it can be inferred that the approach utilized in this study can enhance the solutions of VRP with several conditions and assumptions without prolonging the solution time.

5. Conclusion

Over the course of this study, it was attempted to analyze a more realistic version of the multi-depot capacitated vehicle routing problem (MDCVRP), where vehicles are not required to return to their origin depots (depots from which they start their tours). Although all of the existing articles in this field have utilized the assumptions that necessitate vehicles to return to their origin depot, this study added a new assumption to the problem formulation to eliminate this requirement. Given that this problem is NP-hard, it is better to solve it with metaheuristic methods. As a result, the Tabu Search (TS) method was utilized to solve this problem. After solving the problem, it was discovered that adding the considered assumption removes a constraint from the problem formulation and leads to cost-saving. Hence, in practice, it can be concluded that routing and delivery costs can be remarkably reduced by planning vehicle routes for customers such that they are permitted to return to any depot at the end of their tours and choose the depot that can be reached most cost-effectively from the last customer for this purpose.

Regarding future studies, applying the mentioned assumption to various other VRPs and analyzing the outcomes is recommended. Furthermore, the vehicles' distribution has a

substantial role in the efficiency of the multi-depot capacitated vehicle routing problem. In general, research on distributing vehicles among depots is regarded as highly challenging, specifically to gratify the stochastic and dynamic demand. The circumstances, whether the interaction among depots is autonomously or coordinated (competitive or collaborative), can be another compelling subject for the future outlook in this arena [10].

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