Modeling and Algorithm Design for Driver Assignment Problems Considering Drivers States and Capacity

Rizki Basuki and Rully Cahyono and Andi Cakravastia
Department of Industrial Engineering
Institut Teknologi Bandung
Jalan Ganesa 10 Bandung 4013, INDONESIA
rizkibasuki1@gmail.com, rully@mail.ti.itb.ac.id, andi@mail.ti.itb.ac.id

Abstract

This paper aims to model a driver assignment problem which considers drivers states and capacity. The problem can be classified as a capacitated vehicle routing problem (CVRP). In the current literature, CVRP is a topic which has the most papers devoted to solving the problem. In this research, a comprehensive cost function is considered, and the driver can always have sufficient amount goods to deliver, and the variety of drivers is enlarged. These three factors are the improvement of the CVRP when compared to the state-of-the art research. We develop a mathematical model using linear programming approach. The complexity of the models makes the analytical solution is difficult to solve the problem. We develop a modified version of genetic algorithm to suit the problem in this research. We apply the model and algorithm to a e-commerce delivery problem of agricultural products. Based on a simulation from an actual dataset, the objective function from the algorithm differs 1.15% from the global optimal solution, which give the algorithm a promising future to be applied in other sets of problem.

Keywords
CVRP, genetics algorithm, sweep algorithm, driver states and capacity

1. Introduction
Driver assignment problem can be classified as vehicle routing problems (VRP). The objective of VRP is to assign drivers to tasks which gives efficient operations, which is usually represented by time and minimization (Braekers et al., 2016). One branch of VRP is the capacitated vehicle routing problem (CVRP), where the problem usually tries to optimize the capacity delivered by each courier (driver). In Brakers, et al., (2016), CVRP is the topic which has the most papers. In this type of problem, the capacity of the drivers used is considered in solving the problem. In this case, there is a depot/center that has a certain capacity that will serve requests by a number of customers (Saraswati et al., 2017).

We focus the CVRP to a specific case of agricultural products delivery. Agricultural products are generally sent by suppliers and received at company's main warehouse. The product then undergoes a series of activities which include quality inspection, storage, collection, and packaging in the main warehouse. The finished product is then sent to the distribution center according to the location of the request. In each distribution center (DC) requests are taken by drivers who use two-wheeled motor drivers to be sent according to the request address.

In the delivery of demand products, the company has two driver status, namely partners and third-party logistics (3PL) service providers. Mitra is the status of an individual driver who works at the company, while the driver status of a logistics service provider is the status of an outsourced driver. The company currently has three different logistics service providers from three different companies. Therefore, in one delivery from a DC, the company can use the status of a third partner driver or service provider. In addition, the two driver status both send requests according to the assignments made by the company. Furthermore, the term driver category is used.
In sending requests, each driver knows the requests that will be sent through the company's information system. The driver is given a notification via the respective driver's device regarding any requests that need to be delivered. In addition, if the drivers have finished sending all their requests, they do not have to come back to the distribution center. Driver assignments are managed by logistics operators. Prior to the assignment, the logistics operator will receive a list of requests that need to be delivered from the company's information system. From the list received, the operator

will assign the available drivers in each distribution center to send the received requests. The assignment process is usually completed one day before delivery so that the driver can find out which requests will be sent the next day.

In carrying out assignments, logistics operators have several rules for each driver. Firstly, a driver has a minimum and maximum driver capacity. Secondly, a driver has a volume driver. Thirdly, a driver has his/her respective service areas. Lastly, a driver has different delivery fee schemes (based on distance, number of requests, or a combination of distance and number of requests and with distance restrictions). Symptoms of problems that are considered critical are the assignment of drivers which are considered long and inefficient from the cost. The calculation of shipping costs becomes quite complex by the operator manually because it is necessary to calculate the distance traveled and the number of requests as well as each category of drivers. In addition, the operator also needs to check the area where the customer lives and the category of drivers who serve that area. In addition, the operator's speed in the assignment is considered limited due to the ability and number of operators in carrying out the task. We would like to develop a mathematical model of this problem. The complexity of the model makes algorithm is necessary to solve the models.

1.1 Objectives

The types of problems encountered can be classified as the CVRP. The reference mathematical model for this problem is the model proposed by Altabeeb et al. (2019) with modifications to make it more relevant to the problems at hand. The reference algorithm used is the sweep algorithm proposed by Akhand et al. (2017) and the genetic algorithm proposed by Baker and Ayechew (2003). The objective function determined is to minimize shipping costs with an acceptable computation time. The purpose of this study is to develop models and algorithms to determine the allocation of drivers and delivery routes of requests to customers that minimizes shipping costs, considers the capacity and volume of drivers as well as the cost scheme and accessibility of the driver category with the accepted duration.

2. Literature Review

VRP is one of the problems related to determining the optimal route that involves more than one driver considering the constraints (Braeckers et al., 2016). VRP is a combinatorial optimization problem to provide services to a collection of customers using a fleet of drivers (Na et al., 2011) with one or more depots (Toth and Vigo, 2002). VRP is a variation of m-TSP, that is, in each city only one salesman needs to visit from m-salesmen who need to visit a collection of cities. VRP problems are widely studied and developed because they are relevant to real problems. The development is based on various constraints that can occur in real practice and then identifies the characteristics of the problem scenario, the characteristics of the physical problem, the characteristics of the information, and the characteristics of the data (Eksioglu et al., 2009).

The CVRP problem can be solved using exact, heuristic and metaheuristic methods. The exact method guarantees that the global optimal solution is found. An example of this algorithm is the robust branch-and-cut-and-price (Fukasawa et al., 2005). The most effective exact method can solve CVRP problems consistently with the largest number of customers being 50 customers (Toth and Vigo, 2002). In real cases, the number of customers that need to be served can be greater as in this study so that heuristic and metaheuristic methods can be an alternative choice to solve operational problems. One reason is because this method usually has lower computation time. The reference mathematical model used is the model proposed by Altabeeb et al. (2019). The proposed model relates to the VRPHETW (Vehicle Routing Problem with Heterogenous Fleet and Time Windows) problem.

Many heuristic and metaheuristic algorithms have been developed, one of which is for the sake of solving practical problems. Some of the reasons for choosing heuristic and metaheuristic algorithms are that apart from the computational time required to solve the CVRP problem is shorter, the completion steps can be simpler and can produce sub-optimum solutions. Several algorithms that have been developed are simulated annealing (Lin et al., 2006), artificial bee colony algorithm (Szeto et al., 2011), ant colony algorithm (Mazzeo and Loiseau, 2004), variable neighborhood search algorithm (Amousa et al., 2017), hybrid discrete particle swarm optimization algorithm (Ai-ling, Gen-ke and Zhi-ming, 2006), solomon's insertion algorithms, genetic algorithm (Baker and Ayechew, 2003) sweep, and Clarke and Wright's savings (Na et al., 2011). Solution algorithms can also be combined such as a combination of simulated annealing and tabu search with local search (Lin et al., 2009).

3. Mathematical Model and Algorithm Design

The mathematical model in this case is a modification of the Altabeeb et al. (2019) and Widagdo (2014) model. This model is used because it has several similarities, namely the accessibility limitations and different cost schemes for the types of drivers available. The type of driver in the model is analogous to the driver category in this study. The modification is intended to make the model more relevant to the problems faced by the company.

The objective function in this research is performance measures which depends on the route taken, the number of customers visited, the cost of the distance traveled, the cost of the number of requests delivered and special fees. The driver category always has enough number to send request. Accessibility limiters for some types of drivers are needed later in the model. In research, the type of driver is referred to as the driver category.

The decision variable is x_{ijk} which is a decision to assign the *k* driver from point *i* to point *j*. The variable is 1 is the path (*i*, *j*) passed by a vehicle *k*, and 0, vice versely. The parameters are shown in Table 1.

Table 1. Parameters of the model

Notasi	Keterangan
q_{max}	Driver maximum capacity, with $0 \le q_{min} \le q_{max}$
q_{min}	Driver minimum capacity, with $0 < q_{min} \le q_{max}$
r_{max}	Driver volume, with $0 < r_{max} \le q_{max}$
n	The number of customers that need to be visited
t_{ij}	Distance of path *ij*, with $t_{ii} = +\infty, t_{ij} > 0, t_{i0} = 0, \forall i \in V, \forall j \in N$ which relates to another path $(i,j) \in A$, dan $t_{ij} = t_{ji}$. In km.
d_i	The number of demand in *customer i* with $0 < d_i \le q_{max}$ (deterministic demand), $\forall i \in V$, with $d_0 = 0$
b_i	The number of demand in *box* type with index i with $0 \le b_i \le r_{max}$ (deterministic box demand), $\forall i \in V$, with $b_0 = 0$
u_j	The number of accumulated demand carried by driver when arrives at point *j* with $\forall j \in V$, and $u_0 = 0$
v_j	The number of accumulated box demand carried by driver when arrives at point *j* with $\forall j \in V$, and $v_0 = 0$
m	Number of *driver* with driver c category which can be assigned , with $m_c = \left\lfloor \frac{n}{q_{min}} \right\rfloor, c \in C$
w_0	Distance threshold for category *driver c*=0 to make special price h_0 applies
h_0	D*river c*=0 category special cost when used in the traveled distance of *driver* with category *driver c* = 0 does not exceed w_0
a_c	Cost per traveled distance for category *driver* c in Rp/km
f_c	Cost per demand for category *driver* c for each delivered demand.

The objective function is given in (1)

$$Min \sum_{c\in C, c\neq 0} a_c \sum_{k\in S_c, c\neq 0} \sum_{(i,j)\in V} t_{ij}x_{ijk} + \sum_{c\in C} f_c \sum_{k\in S_c} \sum_{(i,j)\in V} x_{ijk} + (h_0 \sum_{k\in S_0} x_{0jk} + a_0 Y) \quad (1)$$

$$Y = \max(0, \sum_{(i,j)\in V} t_{ij}x_{ij1} - w_0) + \max(0, \sum_{(i,j)\in V} t_{ij}x_{ij1} - w_0) + \cdots + + \max(0, \sum_{(i,j)\in V} t_{ij}x_{ijm_0} - w_0)$$

The objective function in equation (1) is a modified objective function. The objective function consists of cost per mileage, cost per request delivered and special cost. Special costs are only for the driver category $c = 0$. In the calculation of special costs, there are two components, namely the component when the driver category is used, and the costs incurred if the driver with the driver category $c = 0$ travels a distance exceeding w_0.

$$\sum_{j\in N} x_{0jk} \le 1 \qquad \forall k \in K \tag{2}$$

$$\sum_{i\in N} x_{i0k} \le 1 \qquad \forall k \in K \tag{3}$$

$$\sum_{i\in V} x_{ijk} = \sum_{i\in V} x_{jik} \qquad \forall j \in V, \forall k \in K \tag{4}$$

$$\sum_{k\in K}\sum_{j\in V} x_{ijk} = 1 \qquad \forall i \in N \tag{5}$$

$$\sum_{k\in K}\sum_{i\in V} x_{ijk} = 1 \qquad \forall j \in N \tag{6}$$

$$\sum_{j\in N_l} x_{ijk} = 0 \qquad \forall k \in K_l, \forall i \in V, l \in L \tag{7}$$

$$\sum_{j=i} x_{ijk} = 0 \qquad \forall i \in V, \forall k \in K \tag{8}$$

$$d_i \le u_i \le q_{max} \qquad \forall k \in K, \forall i \in N \tag{9}$$

$$u_j \ge u_i + d_j - q_{max} + q_{max}\left(x_{jik} + x_{ijk}\right) - \left(d_j + d_i\right) x_{jik}$$
$$\forall j \in N, \forall i \in N, i \ne j, \forall k \in K \tag{10}$$

$$u_j \le d_j + M\left(1 - x_{0jk}\right) \qquad \forall k \in K, \forall j \in N, i = 0 \tag{11}$$

$$b_i \le v_i \le r_{max} \qquad \forall k \in K, \forall i \in N \tag{12}$$

$$v_j \ge v_i + b_j - r_{max} + r_{max}\left(x_{jik} + x_{ijk}\right) - \left(b_j + b_i\right) x_{jik}$$
$$\forall j \in N, \forall i \in N, i \ne j, \forall k \in K \tag{13}$$

$$v_j \le b_j + M\left(1 - x_{0jk}\right) \qquad \forall j \in V\backslash\{0\}, i = 0, \forall k \in K \tag{14}$$

$$\sum_{i\in V}\sum_{j\in N, j\ne i} d_j x_{ijk} \ge q_{min} - M(1 - \sum_{j\in N} x_{0jk})$$
$$\forall k \in K \tag{15}$$

$$\sum_{i\in V}\sum_{j\in N, j\ne i} d_j x_{ijk} \ge (-M) \sum_{j\in N} x_{0jk}$$
$$\forall k \in K \tag{16}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall (i, j) \in A, \forall k \in M \tag{17}$$

Constraints (2), (3) and (4) guarantee that each customer is only served by one driver. Equations (5) and (6) are constraints that guarantee that drivers entering a customer location are the same as drivers leaving that customer. Equation (7) is a constraint that ensures that no customer $j \in N_l$ receives requests from $k \in K_l$ (drivers that do not serve area *l*). Constraint (8) ensures that no driver does not leave the customer *i*. Constraints (9), (10) and (11) guarantee that the number of requests carried by the driver (including customer *i* requests) does not exceed the q_{max} limit and must be greater than d_i. The constraints (12), (13) and (14) guarantee that the number of boxes carried by the driver (including customer requests *i*) does not exceed the limit of r_{max} and must be greater than b_i. The constraints (15) and (16) ensure that the number of requests carried at least corresponds to the minimum capacity of the driver. Both of these functions are if functions which guarantee that each driver will carry more requests than the minimum capacity limit of each driver. Finally, constraint (17) ensures that the decision variables are binary.

The next step is developing the algorithm to solve the models. The solution search algorithm follows the genetic algorithm of Baker and Ayechew (2003) in solving the problem. There have been several modifications made. The genetic algorithm that is carried out in outline is shown in the following pseudo-code.

Create an initial population of structured solutions
Evaluation of the fitness of each individual in the population
Repeat
    Choose two random individuals from the population to be parents
    Generate two offspring from parents (do a crossover)
    Mutations in both offspring
    Check the eligibility of the offspring
    Evaluate the suitability value of offspring
    If there are eligible offspring:
        Select individuals from the existing population to be replaced using the ranking replacement method
        Offspring enter the population and selected individuals are removed
    End if
Until the number of generations is 10000 or there is no improvement after 200 generations

4. Results

The results are presented in Table 2. In the summary of the test results, *n* is the number of customers and the *id* column is a variation of the customer parameters (having different locations). Different locations affect the distance between the customer and the depot and accessibility (the customer's area).

Table 2. Results of the algorithm testing

n	*id*	Mean of difference from agorithm *Sweep*	Mean of difference from genetic agorithm	Minimum cost difference algorithm *Sweep*	Minimum cost difference genetic algorithm
3	1	11.54%	0.00%	0.00%	0.00%
3	2	0.00%	0.00%	0.00%	0.00%
3	3	5.88%	5.88%	5.88%	5.88%
Sub-mean		**5.81%**	**1.96%**	**1.96%**	**1.96%**
5	1	3.45%	1.03%	3.45%	0.00%
5	2	15.45%	2.45%	4.08%	0.00%
5	3	3.90%	0.00%	0.00%	0.00%
Sub-mean		**7.60%**	**1.16%**	**2.51%**	**0.00%**

Based on the data in Table 2, it can be seen that for minimal cost differences, genetic algorithm always gives better results for all number of customers. This also applies to the average cost difference. It can be concluded that genetic algorithm is able to improve the results of the Sweep algorithm which becomes a better construction algorithm. In addition, it can be concluded that the algorithm can provide a solution that is close to optimum for small datasets. After knowing the performance of the algorithm against a small dataset, the test is continued with customer parameters that resemble the original dataset.

5. Conclusion

In this study, the development of models and algorithms for the problem of assigning drivers to delivery of agricultural products has been carried out. The mathematical model developed has been verified and validated. The algorithm is tested with a dataset resembling the original dataset. Compared to manual assignment, the assignment speed is faster (manual assignment has a speed of 0.0833 customers/sec). The algorithm has been verified and validated and provides a feasible solution and at a faster speed than the initial conditions. One of the suggestions that can be given to the company is to improve the accuracy of the longitude and latitude coordinates of the customer. One way that might be used is to ask the customer to place a point on a map application service (such as Google Maps) so that the resulting distance matrix is more accurate.

Acknowledgement
This research is funded by Basic Research Grant, Ministry of Education, Culture, Research and Technology, Republic of Indonesia.

References
Ai-ing, C., Gen-ke, Y. and Zhi-ming, W., Hybrid discrete particle swarm optimization algorithm for capacitated vehicle routing problem, *Journal of Zhejiang University SCIENCE A*, vol. 7(4), pp. 607–614, 2006.
Akhand, M. A. H. et al., Solving capacitated vehicle routing problem using variant sweep and swarm intelligence, *Journal of Applied Science and Engineering*, vol. 20 (4), pp. 511–524, 2017.
Amousa, M. et al., A variable neighborhood search algorithm for the capacitated vehicle routing problem, *Electronic Notes in Discrete Mathematics*, vol. 58, pp. 231–238, 2017.
Altabeeb, A.M., Mohsen, A.M., and Ghallab, A., An improved hybrid firefly algorithm for capacitated vehicle routing problem, *Applied Soft Computing*, vol. 84, 2019.
Baker, B. M., and Ayechew, M. A., A genetic algorithm for the vehicle routing problem, *Computers & Operations Research*, vol. (30), pp. 787–800, 2003.
Braekers, K., Ramaekers, K., and van Nieuwenhuyse, I., The vehicle routing problem: state of the art classification and review, *Computers & Industrial Engineering*, vol. 99, pp. 300-313, 2016.
Eksioglu, B., Vural, A. V. and Reisman, A., The vehicle routing problem: A taxonomic review, *Computers & Industrial Engineering*, vol. 57(4), pp. 1472–1483, 2009.
Fukasawa, R. et al. (2005), Robust Branch-and-Cut-and-Price for the Capacitated Vehicle Routing Problem, Mathematical Programming, vol. 106(3), pp. 491–511, 2005.
Lin, S.-W. et al, Applying Simulated Annealing Approach for Capacitated Vehicle Routing Problems, *2006 IEEE International Conference on Systems, Man and Cybernetics*, vol. 7 (2), pp. 383–392, 2006.
Mazzeo, S. and Loiseau, I., An Ant Colony Algorithm for the Capacitated Vehicle Routing, *Electronic Notes in Discrete Mathematics*, vol. 18, pp. 181–186, 2004.
Na, B., Jun, Y. and Kim, B. I., Some extensions to the sweep algorithm, *International Journal of Advanced Manufacturing Technology*, vol. 56(9–12), pp. 1057–1067, 2011.
Saraswati, R., Sutopo, W. dan Hisjam, M., Penyelesaian Capacitated Vechile Routing Problem Dengan Menggunakan Algoritma Sweep Untuk Penentuan Rute Distribusi Koran: Studi Kasus, *Jurnal Manajemen Pemasaran*, 11(2), hal. 41–44, 2017.
Szeto, W. Y., Wu, Y. and Ho, S. C., An artificial bee colony algorithm for the capacitated vehicle routing problem, *European Journal of Operational Research*, vol. 215 (1), pp. 126–135, 2011.
Toth, P. and Vigo, D., Models, relaxations and exact approaches for the capacitated vehicle routing problem, *Discrete Applied Mathematics*, vol. 123(1–3), pp. 487–512, 2002.
Widagdo, J. S., *Penentuan Rute Driver dengan Mempertimbangkan Jendela Waktu, Driver Heterogen, dan Akses Driver Menggunakan Algoritma Tabu Search*, Thesis series, Institut Teknologi Bandung, 2014.

Biographies
Rizki Basuki earns his bachelor's degree from Department of Industrial Engineering, Institut Teknologi Bandung, Indonesia, in 2020. His bachelor thesis is on model and algorithm design of capacitated vehicle routing problem. He is now working as a supply chain specialist at one of the biggest paint company in Indonesia.

Rully Tri Cahyono received the B.Sc. degree in industrial engineering, in 2009, and the M.Sc. degree in industrial engineering and management, in 2011, from Institut Teknologi Bandung, Bandung, Indonesia. He obtained a Ph.D in 2021 from the research group of Discrete Technology and Production Automation, Faculty of Science and Engineering, University of Groningen, Groningen, The Netherlands. He is also a lecturer in Department of Industrial Engineering, Institut Teknologi Bandung. His research interests are on the mathematical modeling for complex systems, for examples are seaport operations, logistics and supply chain systems, and industrial systems.

Andi Cakravastia is an Associate Professor in Industrial Engineering Program, Faculty of Industrial Technology, Bandung Institute of Technology - Indonesia. He completed his doctoral program from Graduate School of Engineering, Hiroshima University – Japan. Dr. Andi Cakravastia has published numerous publications in various international peer-reviewed journals and presented scientific papers in many international conferences. Dr. Andi

Cakravastia research and teaching interests include Supply Chain System Integration, Operation Research and Decision Science.