Pak. J. Statist.
2020 Vol. 36(1), 1-12

GREEN OPEN VEHICLE ROUTING (GOVR) WITH A SPECIAL TRUCK LANE TO REDUCE CONGESTION

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ABSTRACT

Effectively of transportation services plays an important role in modern industry. This study was carried out to know the transportation services that request a number of challenges of the customers; it takes from a depot center with the aim of minimizing the distance to get optimal delivery. The method or model chosen to estimate travel time on the specific route set for trucks is the Greenshield model (Banks, 2002). The Green *Open Vehicle Routing Problem* model was adapted a linear relationship between the estimated speed on the road section v_i, vehicle per meter k_i on the road route i, traffic jam k_j, the speed for the chosen truck route s_a. The data analysis showed that at the stage of optimization of the current, departures were determined from the ant system where most ants used a route that attracted ants with their pheromone deposits. Pheromone deposits were on the number of solutions of all ants. It concluded that a model of Green *Open Vehicle Routing Problem* (GOVR) to keep the sustainable transportation is more effective. It could be a special route for truck vehicles to avoid traffic congestion so that less air pollution from vehicles emits CO_2 per vehicle-mile.

KEYWORDS

Optimal delivery; congestion; transportation; green vehicle route.

1. INTRODUCTION

Transportation services now have been facing the effective handling system to meet the costumers' demand. It is concerned with the logistics, which has the process of planning, organizing, and controlling the flow of materials and services from suppliers to consumers. Logistics activities consist of transportation, storage, inventory management, material handling and all related information processing that aims to meet customer needs by minimizing costs to service providers (Crainic and Laporte, 1997). The Transportation Service Providers already focus on the accuracy of match the shipper's times such shipment times in managing the backhaul shipments and other later shipments (Jones et al., 2017).

In general, the ultimate goal of the logistics process is to optimize transportation costs related to travel distance, delivery time, route reliability, fuel use in distributing goods or services at the right location or destination so that it can provide the largest contribution to the company. Anderson (in Nair 2017) stated that in today's business world, logistics means the science of movement of goods and services from the place where raw material is sourced till the end user location where in the need and want of customer as well as the organization aims were reached. The main purpose of every logistics section is noted to make decrease the resources, and increase the deliver productivity (Nair, 2017).

One of the main challenges of transportation activities for logistics sustainability is to face a globally oriented economic system in an effective way to meet the demands of customer needs from delivery with timely delivery schedules. Ansari et al. (2017) agree that supply chain and logistics management as the integration approaches with suppliers, manufacturers, warehouses, and stores; it makes products could be distributed to locations. The transportation providers now should consider minimal cost, times and destination interactively. Even in global context, the transportation providers should consider the environment. It deals with fuel consumption, congestion, noise, and the effects caused by greenhouse gases (Knorr, 2008). Therefore transportation providers connect with the logistics and the basic infrastructure for economic growth. It should be noted transportation is the largest oil consumer; it contributes the public pollutant (Salimifard et al., 2012).

Solving the effectiveness as well as pollution problems of transportation sector, it needs to seek a new model for a better transportation system. It has been proposes the *Vehicle Routing Problem* (VRP) (Dantzig and Ramser, 1959); a vehicle would service the requests of a number of customers from a depot center with the aim of minimizing the distance to get optimal delivery. Additionally, the VRP plays a central function in the distribution management of goods or services that pay attention to services, a certain period of time by a number of trucks in every depot to destinations by applying the accurate *road network*.

The Vehicle Routing Problem (VRP) has created many logistic systems which involved routing and scheduling of vehicles from a depot to a set of customers' node (Juliandri et al. 2018). Thus, Salavati-Khoshghalb et al. (2017) argued the VRP was to create a set of routes serving all customers in a govern set at a low cost; it could be a travel cost, least number of vehicles. The routes could start and end at the depot, and were set up to be operated by a fleet of vehicles with homogeneous capacity. In the deterministic perspective of the VRP consisted of all problem parameters which had been noted precisely, every customer was only approached once by one vehicle (Salavati-Khoshghalb et al., 2017).

Additionally, the VRP variant, namely the *Open Vehicle Routing Problem* (OVRP) has become a special consideration by adding constraints and objectives that come from the real world (Vidal et al., 2013a). The OVRP was made as distribution model of VRP, in which trucks were not allowed to get back to the center of the depot after successful delivery. Some cases in industry showed that transportation providers find it difficult to entirely fulfill the demands. This was due to the limited numbers of vehicles or private fleets; thus distribution services were entrusted to users of transportation services or by renting a fleet of trucks. The OVRP's main aim is 1). Every route begins from the depot and ended at one destination; 2). Each customer was served at once with exactly one route; 3). An once-visiting costumer model and total demand was customer satisfaction, but a special delivery was not allowed; 4). Each customer visited on a route that has a total request must not exceed the vehicle's capacity; where the obstacle was the vehicle capacity did not exceed and the objective function minimized the total cost of travel.

Research was using the OVRP model and the approach used, among others, was the use of OVRP in expressed airmail distribution in the United States and resolving two route problems, namely for shipping and pickup (Bodin et al. (1983); Letchford and Lodi (2007) proposed local search met heuristic to solve OVRP, in this problem the two objective functions considered were reducing the route frequencies and expanses. Thus, Fleszar et al. (2009) proposed a semi graph based search variable (VNS) to solve the OVRP, without submitting a certain analytical models Salari et al. (2010) proposed a basic technique for completing the OVRP using *integer linear programming* (ILP). Therefore, the OVRP with heterogeneous fleets had a limited number and cost per unit of distance (Li, Leung, and Tian, 2012).

The comfort of the transportation system should make the decreased in vehicle emissions resulting in environmental pollution. In order to reduce pollution, efforts needed to be made to realize sustainable transportation by reducing environmental impacts, accelerating economic growth, and increasing social interaction between users. A sustainable transportation system was to provide transportation using renewable fuel with the aim of minimizing emissions and preventing accidents and congestion (Black, 2010).

The objectives of the sustainable transportation system that necessarily to be considered, are as follows: (1) Environmental quality. Emissions emitted from vehicles have an impact on the quality of the environment. The latest scientific research was from U.S. the Environmental Protection Agency (EPA) that on a global scale, the level of air pollution in the transportation sector has an impact on the environment by contributing more than 25% of greenhouse gas emissions (EPA, 2011), (2) Economic development. Transportation was significant for increasing productivity and economic growth; it encourages a local economy to increase regional competition for business activities. (3) Social-Equity consideration is the change in accessibility to the expected destination.

It should be noted that the growth rates and transportation activities have a greater impact and receive special attention in designing logistics policies. In addition transportation services link with environment, social and politics consequences associated with emissions due to dependency on the fuel used. It requires the policy to change the transportation schemes and shifts to sustain the distribution networks with fewer negative impacts on the environment. A green policy will be effective and efficient if the use of vehicle routes and vehicle costs reach the sustainable transportation scheme.

In sustainability and logistics transportation, the emissions control caused by vehicles aimed at minimizing economic costs, environmental costs and social costs were necessary. The integrates one of the VRP variants, namely *open vehicle routing problem* (OVRP) with *green open vehicle routing problem* (GOVRP) by optimizing routes and controlling CO_2 emissions was proposed in this study. The traffic congestion conditions were the problems. In real terms of congestion led to other problems, namely accidents and pollution (Hobbs, 1979). Congestion is one of the causes of delays in transportation activities; it has affected the fluctuating travel time (Hagnani and Jung, 2005). Decreasing the level of service and customer satisfaction is also the main thing that needs to be avoided. Transportation planning that does not pay attention to congestion problems will produce ineffective transportation routes; the planned time becomes inappropriate and late. To overcome this, special lines are used for trucks.

Therefore, in this research we put more focused on the development of distribution systems by developing a green open vehicle routing problem model which is an extension of the *Open Vehicle Routing Problem* (OVRP) and *Green Vehicle Routing Problem* (GVRP) by considering a special path for trucks to manage logistics daily operations.

2. THEORY OF LOGISTICS TRANSPORTATION

Logistics have a significant influence on costs and produce different levels of service to consumers. A transportation company should make an optimized distribution system. The *Vehicle Routing Problems* (VRP) was created to handle a number of routes for a number of vehicles that are at one or more depots which could be managed to spread geographically in getting the consumers. Optimal use of routes reduced congestion and minimized the cost and time. Usually the losses caused by dislocation are quite complicated, such as the loss of time in traveling to be longer, the vehicle operating costs bigger. The impact of congestion causes the vehicle speed getting lower, and the fuel wasteful, the distance vehicle's engine, and the resulted in vehicle exhaust, as well as air pollution.

In classic the VRP offers the vehicle routes economically impact on companies which carry out distribution services. With the consideration of broader operational objectives and constraints related to sustainable transportation issues, the vehicle route models are needed that take into account the environment, economy and social conditions so that combinatorial optimization problems become more complex. The environmental calculation impact of variously strategies for distribution, the use of energy decreasing, re-usage of waste, and management of disposal waste is part of green logistics (Sbihi & Eglese, 2007).

The VRP variant related to sustainable transportation issues from several theories concerning with; 1) Minimizing emissions while traveling. (Bektas and Laporte, 2011: 2) Considering alternative refueling (Erdoğan, S. and Miller-Hooks, 2012) *Pollution Routing Problem* (PRP) with more comprehensive objective functions related to travel distance, number of greenhouse effects, fuel, travel time and costs. Also presented are various parameters such as vehicle load, speed and total costs (Xiao et al. 2012).

For the routes of vehicle problem solving which related with the green logistics, several researchers have made some approaches. Qin et al. (2019) argued that effectiveness of green route is based on the way of controlling the carbon use of vehicles in transportation system. Ubeda et al. (2011) proposed a taboo search for completing Green-CVRP and their research results revealed that the fleet planning could balance the amount of pollution and costs total in a more effective way. Küçükoğlu et al., (2013) created a mixed integer linear programming model to complete GCVRP for assuming the calculation of fuel consumption with technical specifications of vehicles, the load and distance for the trucks. Xiao and Konak (2016) made the *Green Vehicle Routing Problem* (GVRP) with heterogeneous vehicle fleets that operate in traffic conditions in varied times using the *Mix Integer Linear Programming* (MILP) model. It is a *Heterogeneous Green Vehicle Routing* and *Scheduling Problem* (HGVRSP).

The green time-dependent VRP with time windows has an efficient model for optimization of logistics and supply chain systems by combining transportation with environmental conditions (Mirmohammadi et al., 2016). In application, a combined integer linear mathematical designed system was developed. The aim function of the design was to reduce the amount of CO_2 emissions, total travel time and total delay. Additionally, Ling Shen et al. that multi depot model should consider the low carbon system (2018).

3. MATHEMATICAL FORMULATION

The mathematical formulation for GOVRP has been expressed as a connected and non-directed $G = (V, E)$ graph, which is represented $V = \{0, 1, 2, ..., n\}$ as a set of all nodes in a graph, and also $V = V_0 \cup \{0\}$, where $V_0 = \{1, 2, ..., n\}$ a set of customers is non-negative $0 < d_i < Q$ and node 0 is represented as a depot. *E* is the side set of *G* where $E = \{(i, j);\ 0 \le i,\ j \le n,\ i \ne j \in V\}$. E with a shortest distance d_y that is connected to each side of the graph. The cost of travel from node *i* to node *j* is denoted as c_{ij}, if $i = j, c_{ij} = 0$ for $0 \le i \le n$, then it is assumed that the cost is asymmetric i.e. $c_{ij} = c_{ji}$.

3.1 Set

N Set of Costumers

N_0 Customer and depot center combined set $N_0 = \{0, n+1\} \cup N$

K Number of vehicles rented, $k \in K$

3.2 Parameter

d_i^t Request of Costumers i on the day $t \in T_i$

q_k Vehicles Capacity *k*

P_k^t The maximum route time allowed for a vehicle *k* on the day $t \in T_i$

S_{ik}^t Vehicle service time *k* from costumers i on the day $t \in T_i$

S_{jk}^t Vehicle service time *k* to costumers j on the day $t \in T$

Y_i^t Waiting time from costumers i on the day $t \in T_i$

Z_i^t Arrival time from customers i on the day $t \in T_i$

I_i^t Departure time to customers i on the day $t \in T_i$

W_{0k}^t Vehicle arrival time *k* from the depot on the day $t \in T_i$

t_{ij} Total travel time from customers i to customers j

s_{ij} Distance from customers i to customers j

t_{ij} Travel time from customers i to costumers j

n_k Number of vehicles

v_i Vehicle speed

$[u_i, v_i]$ The visit time interval that is served by any vehicle to the customer $i \in N_0$

The mathematical formulation for GOVRP requires a decision variable, which is a variable x_{ij}, $i, j \in V_0$ and y_{ij}, $i, j \in V_0$ with:

$$x_{ij}^k = \begin{cases} 1, & \text{If the trip } k \text{ vehicle from the customer } i \text{ to customer } j \text{ with rental vehicle} \\ 0, & \text{Another condition} \end{cases}$$

$$y_{ir}^k = \begin{cases} 1, & \text{If the customer } i \text{ is served via route } r \in R_k \\ 0, & \text{Another condition} \end{cases}$$

$$a_r^k = \begin{cases} 1, & \text{Route used in completion } r \in R_k \\ 0, & \text{Another condition} \end{cases}$$

3.3 Purpose Function:

Min total travel distance

$$= \sum_{i=0}^{N} \sum_{j=0}^{N} \sum_{k=1}^{K} s_{ij} x_{ij}^k + \sum_{i=1}^{N} d_i + \sum_{i=0}^{N} \sum_{j=1}^{N} \sum_{k=1}^{K} ps_{ij} M_{ij} \tag{1}$$

3.4 Constraints:

$$\sum_{i \in V} \sum_{j \in V} d_j x_{ij}^k \leq Q , \quad \forall k \in K \tag{2}$$

$$\sum_{k \in K} \sum_{j \in V} x_{ij}^k = 1 , \quad \forall i \in C \tag{3}$$

$$\sum_{i \in V} x_{il}^k - \sum_{i \in V} x_{ij}^k = 0, \quad \forall l \in C, \ \forall k \in K \tag{4}$$

$$x_{i0}^k = 0, \ x_{n+1,i}^k = 0 \qquad \forall i \in C, \ \forall k \in K \tag{5}$$

$$\sum_{i \in V} x_{ij}^k + \sum_{i \in V} y_{ij}^k = 1, \quad j \in V, \, i \neq j \tag{6}$$

$$\sum_{i \in V} x_{ij}^k + \sum_{i \in V} y_{ij}^k \leq 1, \quad j \in V, \, i \neq j \tag{7}$$

$$\sum_{j\in V} x_{oj}^{k} = 1\,, \quad \forall k \in K \tag{8}$$

$$\sum_{j\in V} x_{j,n+1}^{k} = 1\,, \quad \forall k \in K \tag{9}$$

$$s_{ik}^{t} + t_{ij} - s_{jk}^{t} \le (1 - x_{ij}^{k}) M_{ij} \qquad \forall i, j \in V \tag{10}$$

$$u_i \le s_i \le v_i \qquad \forall i \in V \tag{11}$$

$$x_{ij}^{k} \in \{0,1\} \qquad \forall (i,j) \in A, \forall k \in K \tag{12}$$

$$y_i^k \in \Re \qquad \forall i \in V, \quad \forall k \in K \tag{13}$$

$$v_i \sum_{j\in V} x_{ij}^{k} \ge y_{ir}^{k} \qquad \forall i \in V\,, \forall k \in K \tag{14}$$

$$u_i \le s_i \le v_i \qquad \forall i \in V \tag{15}$$

$$x_{ij}^{k} \in \{0,1\} \qquad \forall (i,j) \in A, \forall k \in K \tag{16}$$

$$y_i^k \in \Re \qquad \forall i \in V, \quad \forall k \in K \tag{17}$$

These constraints are defined as follows:

(Constraint 2) indicates the vehicle capacity should not exceed. (Constraint 3) ensures that each customer is visited by exactly one vehicle. (Constraint 4) if the truck reaches at the destination, it would move from the receiver. (Constraint 5) ensures the distribution quantity of each vehicle does not exceed its capacity. (Constraint 6) ensures that only one vehicle (alone or rent) enters each customer exactly once. Constraint (7) ensures that the vehicle does not need to depart from each customer, because the route of the rented vehicle ends after serving the last of the customers. Constraint (8) specifies that the vehicle chooses to remain one lane if it serves customers from node *i* to node *j*. (Constraints 9 and 10) ensure that each vehicle departs from and backs to the branch office. Constraint (11) shows a vehicle moving from *i* to *j* with a time window limitation, service to node *i* earlier than node *j*. Constraints (12) schedule of delivery should permit journey time between destinations. Constraints (13 and 14) indicate the start and end times of services that must satisfy the customer. Constraints (15) determine service start time on all nodes within the time windows limit $[u_i, v_i]$. The types of decision variables and domains are shown in (Constraints 16 and 17).

The model chosen is to estimate travel time on the specific route set for trucks is the Greenshield (Banks, 2002). This model considers a linear relationship between the estimated speed on the road section v_i, vehicle per meter k_i on the road route *i*, traffic jam k_j, the speed for the chosen truck route s_a as in Equation (18).

$$v_i = s_a\left(1 - \frac{k_i}{k_j}\right) \tag{18}$$

$$e_t = \frac{l_i}{v_i}\ . \tag{19}$$

Equation (19) shows the time estimate e_i which is the result of a comparison of the length of the trip l_i with the speed on the road section v_i.

Departure time is given by the first time visiting the customer plus service time as in Equation (19), namely:

$$I_i^t = S_{ik}^t + y_{ir}^k\ .$$

In conditions of traffic jams, the assumption of constant speed is no applicable. As a consequence, the alternative routes for vehicles to make shorter the distance of travel and the frequencies of trucks engagements; it is also to minimize the total time taken to cover the entire trip. The problem of truck routes on shipping goods to meet customer demands with a window of time that considers some vehicles with different capacities, with variations in real travel times between different nodes.

4. ALGORITHM APPROACH

The proposed approach which will later be used for the solution to the development of this model involved the heuristic method with the Ant Dispersion Routing (ADR) algorithm. Zavin et al. (2017) found an ADR algorithm to redistribute flows such that the traffic network efficiency was optimized and also to determine optimal paths for every driver in the network. The ADR is composed of two separate main steps, namely; network trimming and current optimization. Network pruning procedures load the basic ant route algorithm which finds many trajectories and the cost of travel time from the minimum trajectory, based on traffic conditions. The current optimization procedure contains the determination of the exact current distribution on the path; so that the overall traffic network conditions are optimized. The resulting solution is based on the many solutions built by ants. The value of pheromones in the solution increases until all ants use it (Alves, et al., 2009).

In the early stages of tissue pruning procedures, the value of pheromones on all routes is set with a small initial value. The probability function for selecting the path that will be passed from side r_1 to side r_2 is:

$$p_{r_1,r_2} = \begin{cases} \dfrac{\mathrm{T}_{r_2}}{\sum\limits_{j \in N_2} \mathrm{T}_j} & if\ \ r_2 \in N_{r_1} \\ 0 & for\ \ others \end{cases}$$

Which is the number of pheromones on the side of r_2, which is the set of sides connected to the side r_1 at the intersection. All ants make decisions about which road to go through. The initial value of pheromones can be determined by a formula that is:

$$"r_1; T_{r_1} = T_0 = \frac{m}{f_{\min}}$$

where $m = n_{ant}$ is the number of ants at the initial node and is the minimum travel time cost based on the route built by ants from the initial node to the destination node which is done randomly using the fastest travel time cost function.

After all ants find a route by completing the journey from node *i* to node *j*, then all routes that have been traversed are rechecked to get the fastest route that will be used in the current optimization process, that is by calculating the resulting pheromone deposits. When the pheromone value on the route is set to 0, then the sides on the route are invisible to the ants. So, trimming the network reduces the unnecessary browsing of ants on unselected routes. The pheromone deposit is updated into two strategies a positive reinforcement of the algorithm ant colony and it tends to provide the best solutions (Reed et al., 2014) and negative reinforcement strategy (pheromone evaporation, formulated as a multiplication of all pheromone values by a heuristic coefficient ($0 < \rho < 1$). Therefor, the best solution will tend to eliminate the poor ones, allowing all the ants to choose one single route and declared the best path at the end of algorithm.

It found that the solution by using ant dispersion helping the time estimation of truck lanes. Gewen argued that the Ant Colony algorithm is used to solve the minimum travel time cost (Huang et al., 2018) with an adaptive pheromone stimulation factor combined with the level of fuel consumption (MACO algorithm). Therefore, Oonsrikaw and Thammano (2018) extends the Problem of Salesman Traveling Problem (TSP) by limiting the minimum and maximum number of cities visited by each vehicle. The solution uses the Ant Colony algorithm by adding new reproduction methods and pheromone renewal strategies and four local search strategies that have the ability to avoid local optima and can be applied to transportation problems that include one vehicle or more vehicles. Thus, Ye et al. (2018) proposed an algorithm of multi-type ant system (MTAS) with an additive pheromone strategy which is a combination of ant colony system algorithms (ACS) and max-min ant (MMAS) system algorithms to solve vehicle route problems depending on time with time windows (TDVRPTW) by increasing the efficiency of insertion procedures, nearest neighbor selection (NNS) selection, insertion local search procedures and local optimization procedures that aim to find a balance of performance and rapid convergence rates. The computational results show the performance of the MTAS algorithm that is good at solving vehicle route and travel time problems (TDVRPTW).

At the stage of optimization of the current, departures are determined from the ant system where most ants use a route that attracts ants with their pheromone deposits. Pheromone deposits are not based on the number of ants using the route but on the number of solutions of all ants. The target of ants in finding the best solution is based on a probability function, namely the number of ants converted into the number of vehicles so that the density can be determined based on the traffic model used in the ADR algorithm.

5. CONCLUSION

Data analysis of the Ant Dispersion Routing (ADR) algorithm showed that the development of the Green *Open Vehicle Routing Problem* (GOVRP) model could be an alternative sustainable transportation. Data showed with an additive pheromone strategy; a mixedof ant colony system algorithms (ACS) and max-min ant (MMAS) system algorithms to solve vehicle route problems. It has a special route for truck vehicles to avoid traffic congestion; so that less air pollution from vehicles emits CO_2 per vehicle-mile. The solution was using the heuristic method with the ADR algorithm approach.

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