



## A Time-Dependent Vehicle Routing Problem for Disaster Response Phase in A Multi-Graph-Based Network

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### KEYWORDS

Time-dependent vehicle -  
routing problem,  
Multi-graph,  
FIFO property,  
Disaster relief,  
Emergency time

### ABSTRACT

*Logistics planning in the disaster response phase involves dispatching commodities, such as medical materials, personnel, food, etc., to affected areas as soon as possible to accelerate the relief operations. Since transportation vehicles in disaster situations can be considered as scarce resources, their efficient application is substantially important. In this study, we provide a dynamic vehicle routing model for emergency logistics operations in case natural disasters. The aim of the model is to find optimal routes for a fleet of vehicles to give emergency commodities to a set of affected areas by considering the existence of more than one arc between each of two nodes in the network (multi-graph network). The proposed model considers FIFO property and focuses on minimization of waiting time and total number of vehicles. Various problem instances have been provided to indicate the efficiency of the model. Finally, a sensitivity analysis is carried out to investigate the impact of different parameters on the obtained solutions.*

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### 1. Introduction

Natural disasters, such as droughts, earthquakes, hurricanes, and floods, have proven to be a global challenge due to their unpredictable nature and potential scale of impact represented by fatalities and social, environmental, and economic costs. On the other hand, Supply chain and logistics management are an important key in humanitarian relief context. Emergency logistics is the process of planning, managing, and controlling the flow of resources to provide relief to people affected by disasters [1]. It relies on a

given number of strategically located vehicles over affected area. Transportation is one of the most crucial processes in the supply chain network. Vehicle routing problem (VRP) is one of the famous problems in transportation optimization. It aims to determine the least cost routes from a depot to a wide range of customers. The routes have to satisfy the following set of constraints [2]:

- Each customer is visited exactly once
- All routes start and end at the depot
- Sum of all demands on a route must be less than capacity of a vehicle
- A subset of arcs must be traversed by only one vehicle

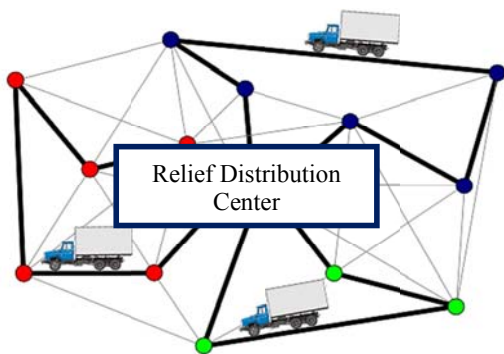
The Vehicle Routing Problem (VRP) in disaster situations is applied to design an optimal route

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for a fleet of vehicles and to service a set of affected areas given a set of constraints such as delivering the commodities in a specifically restricted time. The VRP is used in supply chain management in the physical delivery of goods and services. There are various versions of VRP modeled based on the nature of the transported goods, the quality of service required, and the characteristics of the customers and the vehicles. The vehicle routing problem is shown in Figure 1. As seen in Figure 1, the vehicle's tour starts at the depot and visits all the nodes once. Models in emergency logistics are employed to manage inventory prepositioning and vehicle routing which are considered as two of the most important operations in disaster risk management, separately. The main differences between humanitarian logistics and business logistics include the object of minimization (minimizing time of response or maximizing fairness of distribution) and maximizing profit or minimizing costs and the circumstances in which operations are to be performed (known resources and infrastructure in contrast to uncertainty regarding supplies, available vehicles, and the condition of the road network. Their demands go at the nodes and then return to the depot again [3].



**Fig. 1. An example solution to a vehicle routing problem**

One of the most important disasters is an earthquake, which often causes huge property damage, human injuries and casualties. The increase of this type of disaster over the last years [4] along with growth of population congestion in areas sensitive to earthquakes creates a growing need for designing emergency response procedures prior to an earthquake disaster. These emergency procedures guide a set of actions taken during the initial phase of this emergency situation, the so-called “Earthquake Response Phase” [5].

Oh and Haghani analyzed the transportation of different disaster relief commodities, such as medical, clothing, food, medicine, machinery, and personnel, to minimize the loss of life and maximize the efficiency of the rescue operations. The authors modeled a multi-commodity, multi-modal network flow models for generic disaster-relief operations [6,7]. Other commodity logistic planning models are provided by Barbarosoglu et al. [8], Ozdamar et al. [9], Tzenget al. [10], Sheu [1,11], and Nolz et al. [12]. Barbarosoglu et al. concentrated on the use of helicopters for aid delivery and rescue missions during natural disasters. Lin et al. proposed a multi-item, multi-vehicle, multi-period and multi-objective model for delivery of prioritized items in disaster-relief operations [13]. This model includes two objective functions, which minimize the total unsatisfied demands and the total travel time for all tours and all vehicles. Mohamadi and Yaghoubi proposed a bi-objective stochastic optimization model for location of medical supplies distribution centers (MSDCs) and transfer points. they also utilized backup MSDCs for enhancing efficiency of services during such events [14].

Mguis et al. decomposed the problem into two parts: the first one concerns the vehicle routing planning to serve several requests, while the second one concerns the treatment of an eventual event including the arrival of a new demand and the appearance of a disturbance [15].

Time-dependent vehicle routing problems have received significantly little attention among researchers. Variations in travel time common in disaster-affected areas are as due to poor-quality roads, security, and weather hostile condition. Therefore, the assumption of constant travel times is unrealistic [5]. One of the first approaches using the later interpretation was the approach of Malandraki and Daskin [16], where the objective is minimization of the total travel time. Nevertheless, time-dependent problems might produce sub-optimal solutions if there are high uncertainties in the assumed travel times. The approach presented in this article differs from papers, which do not ensure the “first-in-first-out” property correctly, because the objective is to guarantee that the FIFO property is realized as what done by Ichoua et al. [17]. We will completely explain the problem in Section 2. Setak et al. [18] proposed a new extension of the time-dependent vehicle routing problem with the existence of more than one arc between two nodes. They modeled the problem as the time-dependent vehicle routing problem in multi-graph which provided the FIFO property. Alinaghian and Naderipour presented a model to calculate fuel consumption in time-dependent vehicle

routing problem with consideration of multi-alternative graph in their network. They also considered fuel consumption factors such as vehicle speed, road gradient and urban traffic in their study [19]. Lai et al. formulated a mixed-integer linear programming model by considering the time-constrained heterogeneity on a multigraph where parallel arcs between two points represent different travel options based on the criteria such as time, cost, and distance. They also developed a Tabu Search heuristic in their study [20]. Mancini proposed the Time-Dependent Travel Times as a vehicle routing model with service times at nodes and limit on the maximum route duration. A Multi-start Random Constructive Heuristic, (MRCH), in which congestion level is considered, was proposed in that study [21]. Thus, the possible existence of more than one arc between two specified nodes has not been considered in the Time-dependent Relief Vehicle Routing Problem (TDRVRP) in the literature.

The studied problems are limited to the existence of only one edge between two disaster regions or between distribution center and disaster region. Although it is reasonable to assume that there is only one arc with a minimum travel time between different points in humanitarian transportation, it is not very acceptable in a large disaster-stricken situation according to the complexities of humanitarian logistic and traffic restriction in the first hours after earthquake. Urban areas in disaster situation usually have a complicated structure, which provides accessibility to different nodes by more than one edge. In this condition, traffic rules for arcs (e.g., determining maximum allowable speed and vehicle traffic constraints) affect arc selection. Choosing suitable edges is an important humanitarian transportation due to time reduction. The problem is called the time-dependent relief vehicle routing problem in multi-graph (TDRVRPM) which allows for considering more than one arc between two points.

According to the literature review, the research innovations are as follows:

- The concept of multigraphs in post-disaster conditions covers the gap in the analysis of relief routing problems in urban areas.
- Presentation of the mixed integer linear programming model for time-dependent problem in relief routing problems with considering different speeds at different hours after disaster.
- There is no limitation at the starting time of relief vehicles and the FIFO property is considered, which is one of the most

important features in time-dependent problems.

- Existence of emergency time will better address the sensitivity of relief logistics and timely relief to damaged areas.

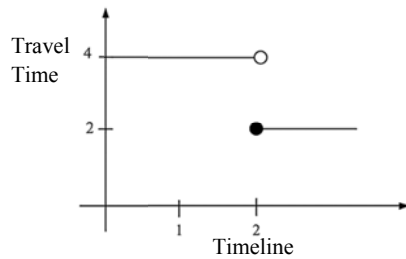
In Section 2, TDRVRPM is described. In Section 3, TDRVRP is modeled using mixed integer linear programming. Computational results are presented in section 4. Finally, the results are summarized in conclusions and future works.

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## 2. Problem Definition

An important property for time-dependent problems is the First In-First Out (FIFO) property proposed by Ichoua et al. [17]. In this paper, the FIFO property was assumed. In TDVRP, FIFO guarantees the following assumption:

when vehicle “A” overpasses the distance from Affected Region (AR)  $i$  to region  $j$  and a similar vehicle “C” starts to move from AR  $i$  to AR  $j$  after “A”, vehicle “C” will reach AR  $j$  later than “A” [17]. The early papers related to TDVRP have a main shortcoming: they have modeled travel time as a discrete function of time [8]. For instance, Figure2 indicates this function as it pertains to an arc with the length of 1. So, if vehicle 1 leaves the Relief Distribution Center (RDC) node at time  $t_1=1.5$ , then it reaches the destination node (AR) at  $t_2=3.5$ . Nonetheless, when vehicle 2 leaves the RDC at time  $t_3=2(>t_1)$ , it will reach the destination at  $t_4 = 3(<t_2)$ , which means that, despite the fact that vehicle 2 leaves the origin node later than vehicle 1, it reaches the destination node earlier. Thus, the result does not satisfy the FIFO property. Currently, researchers apply continuous travel time functions over the time horizon, instead of discrete travel time functions. In order to do so, travel speed function is applied, as shown in Figure3. In this paper, a process was provided to transform a travel speed function into a continuous travel time function according to the represented approach by Ichoua et al. [17].



**Fig. 1. A discrete travel time function**

In the aftermath of a large disaster, the routing of vehicles carrying critical supplies can greatly affect the arrival times to those in need. Since it is critical that the deliveries are both fast and fair to those being served, it is not clear that the classic cost-minimizing routing problems properly reflect the priorities relevant in disaster relief.

Thus far, TDVRP papers have been based on this assumption: arc  $(i,j)$  is the only shortest distance between two locations  $i$  and  $j$ . Accordingly, the transportation network is based on a simple graph in which there is only one edge between two specific nodes. In static problems, this assumption is suitable with the consideration of fixed travel time. However, in the real-world, particularly in the urban transportation networks, there is more than one edge between two locations, in which their travel time is different according to the daytime. Thus, choosing the edge for traveling depends on the specific time of the day. Multi-graph can be used for this type of problems. In contrast with the simple graph, multi-graph allows the model to establish more than one edge (or parallel edges) between two nodes. In the multi-graph, the edge is shown by  $(i,j,m)$ , in which  $m$  shows the  $m^{\text{th}}$  parallel edge between nodes  $i$  and  $j$ . Figure 4 demonstrates an example of the multi-graph vs. simple graph. In basic TDVRP, the problem is defined on a simple graph such as Figure 4(a), in which the travel speed changes in each time interval with 8.

congestion. However, the network with the lowest travel time is fixed. In contrast, TDVRPM employs a multi-graph-based network, in which the network with the lowest travel time edges is not fixed. In fact, this network usually changes in each time interval. For additional explanations, see Figure 5, which implies a simple multi-graph-based network. It shows the network of edge with the lowest travel time in three time intervals by bold continuous lines. Based on Figure 5(a), in time interval number 1, travel time throughout the edge  $(i,j,1)$  is less than  $(i,j,2)$ . Consequently, this edge is selected for the network that includes the lowest travel time edges. The same explanation is used to determine other edges of the network. In this paper, the minimum travel time of humanitarian aid is aimed to be determined in the transportation networks based on multi-graph.

### 3. Model Formulation

The main purpose of this paper is to minimize the total travel time to serve the affected areas and the number of vehicles in multi-graph transportation network. There are the following assumptions in this model:

1. It is possible to get from a location to another with more than one arc (multi-graph).
2. The shortest edge between two locations is different according to the crisis situation after disaster
3. All vehicles leave the Crisis Management Headquarters or local aid Location (depot) simultaneously.
4. All vehicles return to the depot after finishing the product delivery of relief goods in case of disasters.
5. The demand of aid packages in all case of disaster is given and fixed.
6. Capacity of each vehicle is given and fixed.
7. The first purpose of this model is to minimize travel time route.

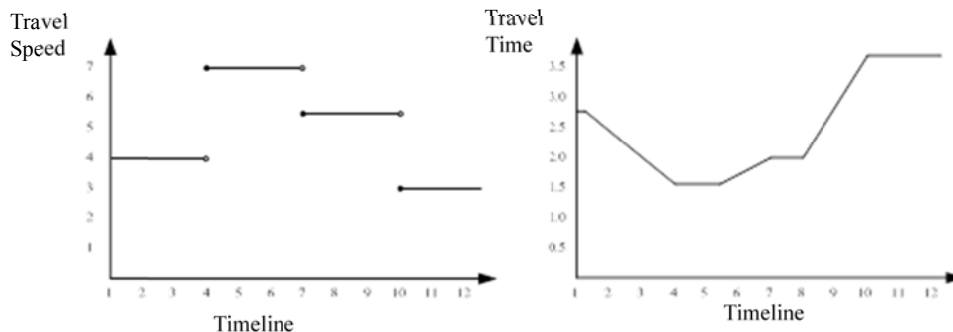


Fig. 3. A travel speed function and its travel time function

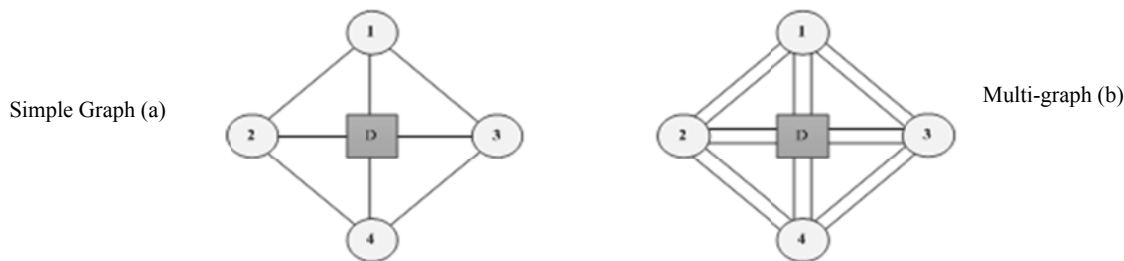


Fig. 4. Representation of multi-graph vs. simple graph

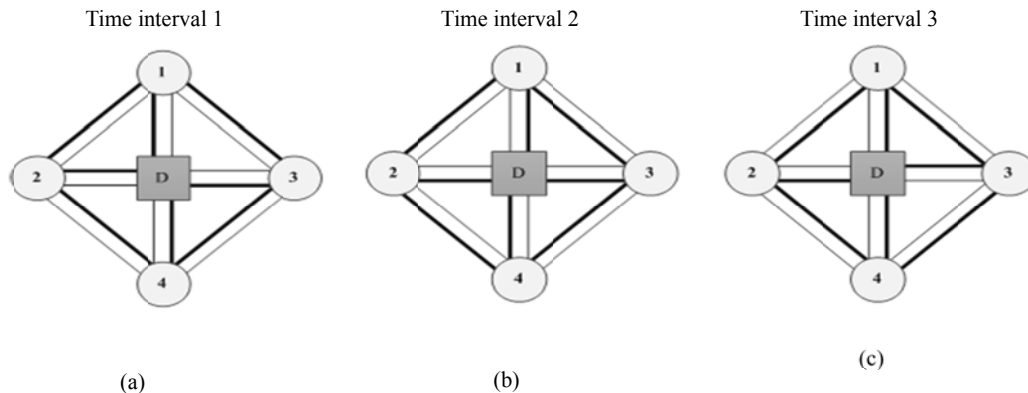


Fig. 5. Network of edges with less travel time in multi-graph network transportation

In order to model TDRVRPM problem, notations are described as:

Suppose  $G = (V, E)$  is a complete graph, in which  $V$  and  $E$  are the set of nodes and arcs, respectively. Each arc can be defined by a regular triplex as  $(i, j, m_{ij})$  in which  $i, j$ , and  $m_{ij}$  represent Relief distribution center (first node of link),

destination node or case of disaster (second node of link), and the  $m^{\text{th}}$  arc between those two nodes, respectively. In this model,  $H$  and  $Tnew_{m_{ij}}^h$  are the number of new time intervals and the head point of new time intervals, respectively. Other notations are as follows:

- N: A Set of relief distribution center (depot), case of crisis places and copied from the distribution center
- $Ps = \{0, N + 1\}$  Relief distribution center and its Copy
- $Ns = \{1, \dots, N\}$  Set of disaster areas

$N = [Ns \cup Bs]$	
$C_t$	Transportation cost per unit of travel time of relief operations
$C_k$	Fixed cost for vehicles
$E_1, E_2, E_3$	Large numbers
$k$	Number of available vehicles
$s_i$	The time required for relieving the affected people in the $i^{\text{th}}$ node
$Q$	Capacity of vehicle
$M_{ij}$	The number of arc between affected regions $i$ and $j$ ;
$q_i$	The demand of necessary disaster relief commodities relief for location $i$
$e_i$	Emergency relief time for affected region $i$

There are two decision variables in this formulation which are as follows:

$$x_{ijm_{ij}}^{h_{m_{ij}}k} = \begin{cases} 1 \\ 0 \end{cases}$$

$$y_i^k \quad \text{Departure time of vehicle } k \text{ from node } i$$

The formulation of TDVRPM model is presented as follows:

$$\text{Min} \quad C_k \sum_{k \in K} \sum_{m \in M_{ij}} \sum_{h \in H_{m_{ij}}} \sum_{j \in N_s} x_{0jm}^{hk} + C_t \left( \sum_{k \in K} y_{N+1}^k - \sum_{k \in K} y_0^k \right) \tag{1}$$

$$\sum_{i \in (0 \cup N_s)} \sum_{m \in M_{ij}} \sum_{h \in H_{m_{ij}}} \sum_{k \in K} x_{ijm}^{hk} = 1 \quad \forall j \in N_s, \quad i \neq j \tag{2}$$

$$\sum_{j \in (N_s \cup N + 1)} \sum_{m \in M_{ij}} \sum_{h \in H_{m_{ij}}} \sum_{k \in K} x_{ijm}^{hk} = 1 \quad \forall i \in N_s, \quad i \neq j \tag{3}$$

$$\sum_{i \in (0 \cup N_s)} \sum_{m \in M_{ij}} \sum_{h \in H_{m_{ij}}} x_{im}^{hk} = \sum_{j \in (N_s \cup N + 1)} \sum_{m \in M_{ij}} \sum_{h \in H_{m_{ij}}} x_{ijm}^{hk} \quad \forall r \in N_s, \quad \forall k \in K \tag{4}$$

$$y_j^k - y_i^k - E_1 x_{ijm}^{hk} \geq a_{ijm}^h + b_{ijm}^h y_i^k + s_j - E_1 \quad \forall k \in K; \quad \forall m \in M_{ij} \tag{5}$$

$$\forall h \in H_{m_{ij}}; \quad i \neq j$$

$$y_i^k + E_2 x_{ijm}^{hk} \leq Tnew_{ijm}^h + E_2 \quad \forall i \in (0 \cup N_s); \quad \forall j \in (N_s \cup N + 1); \quad \forall k \in K \tag{6}$$

$$\forall h \in H_{m_{ij}}; \quad i \neq j; \quad \forall m \in M_{ij}$$

$$y_i^k - Tnew_{ijm}^{h-1} x_{ijm}^{hk} \geq 0 \quad \forall i \in (0 \cup N_s); \quad \forall j \in (N_s \cup N + 1); \quad \forall k \in K \tag{7}$$

$$\forall h \in H_{m_{ij}}; \quad i \neq j; \quad \forall m \in M_{ij}$$

$$y_j^k \leq E_3 \sum_{i \in N} \sum_{m \in M_{ij}} \sum_{h \in H_{ij}} x_{ijm}^{hk} \quad \forall k \in K; \forall j \in N \tag{8}$$

$$y_i^k - s_i \leq e_i \sum_{j \in (Ns \cup N+1)} \sum_{m \in M_{ij}} \sum_{h \in H_{ij}} x_{ijm}^{hk} \quad \forall i \in Ns; \quad \forall k \in K \tag{9}$$

$$\sum_{i \in Ns} q_i \sum_{j \in (Ns \cup N+1)} \sum_{m \in M_{ij}} \sum_{h \in H_{mij}} x_{ijm}^{hk} \leq Q \quad \forall k \in K \tag{10}$$

$$x_{iim}^{hk} = 0 \quad \forall i \in N; \quad \forall m \in M_{ij}; \quad \forall h \in H_{mij}; \quad \forall k \in K \tag{11}$$

$$x_{i0m}^{hk} = 0 \quad \forall i \in N; \quad \forall m \in M_{ij}; \quad \forall h \in H_{mij}; \quad \forall k \in K \tag{12}$$

$$x_{(N+1)jm}^{hk} = 0 \quad ; \forall j \in N; \forall m \in M_{ij}; \quad \forall h \in H_{mij}; \quad \forall k \in K \tag{13}$$

$$x_{ijm}^h = \{0,1\} \quad \begin{matrix} \forall i, j \in N; \quad \forall m \in M_{ij} \\ \forall h \in H_{mij}; \quad \forall k \in K \end{matrix} \tag{14}$$

$$y_i^k \geq 0 \quad \forall i \in N; \quad k \in K \tag{15}$$

The objective function minimizes the total travel time and the number of vehicles, because often available vehicles are rarely sufficient in disaster relief situations. Without minimizing the number of vehicles, the model would probably use more vehicles to minimize the total travel time. The constraints are defined as follows:

Constraints (2) and (3) show that all the disaster-affected areas must be served just once. Constraint (4) guarantees that the routes must be finished in the depots. In fact, a vehicle must leave the node which entered before. Constraint (5) shows the departure time from disaster areas. This constraint also prevents the creation of sub tour. Constraints (6) and (7) determine the appropriate time interval according to the vehicle departure time from the relief distribution center. An inequality auxiliary (8) is provided in order to estimate the time of finishing the travel. Constraints (9) imply that the exit time from each affected area must be less than the related emergency time of that node. Constraints (10) reflect the vehicle capacity limitations. It exerts that the mass of any load being carried on a vehicle must not exceed the maximum load capacity. Constraints (11-13) are used to ensure that the achieved solutions are accurate and practical. Decision variables types and domains are shown in (14) and (15). In the next section,

the problem has been modeled in General Algebraic Modeling System (GAMS).

#### 4. Experimental Study

In this section, we produce different examples, and the related results are presented. The commercial software GAMS and the MIP solver GAMS/OSL are employed to solve the proposed MIP problem. All tests were executed on a personal computer equipped with a 3.2 GHz Intel Pentium 4 CPU and 1 GB RAM, using the Microsoft Windows 7 as the operating system. The results are represented in Tables 1 and 2. In Table 1, the second column shows the number of parallel edges. The third column indicates the number of available vehicles. The obtained number of required vehicles for each sample problem is represented in column 4. The next two columns are related to CPLEX results which are optimal solution. Also, a number of sample problems were designed to examine the impact of changing the number of available relief points available in Table 2. The second column relates to the number of affected areas and the third column shows the number of parallel edges. Moreover, the fourth and fifth columns are related to the available relief vehicle and used vehicle after solving the model, respectively. The sixth and seventh columns show the objective function value and computational time. As can be seen from these tables, the achieved solution is

affected by various parameters such as the number of relief points, parallel edges, and number of vehicles. In order to investigate the impact of different parameters on the objective function and computational time, a brief sensitivity analysis is provided in the next section.

### 5. Sensitivity Analysis

In this section, we analyzed the impact of size of parameter on the computational time. First, we investigated the impact of parallel edge transportation on the computational time in the proposed model. Figure 6 shows the computational time resulting from Table 1. Based on Fig. 6, by increasing the number of parallel edges, computational time of the model will increase. This trend intensifies with increasing the number of available relief vehicle. The changes in the number of parallel edges and available relief vehicle have an increasingly direct impact on the computational resolution time. As mentioned, we also have solved several examples to investigate the effect number of

node, parallel edge and vehicle on computational time. as shown in Table 2. Figure 7 is extracted from results of Table 2. Figure 7 indicates the impact of three parameters, such as relief nodes, parallel edges, and the number of available vehicle. According to Figure 7, by increasing the number of relief locations, the required time for solving the model will increase. It shows that due to the NP hardness of the problem, computational time of model will increase by enhancing the number of available vehicle. Furthermore, an increase in the number of parallel edge leads to growth of the rate of the required solution time. Generally, any increase in the dimensions of the problem (i.e., number of nodes, number of parallel edges and number of vehicles) will enhance the computational time exponentially. The analysis implies that all arcs in the network are not equally valuable. In fact, due to the variation of travel time between parallel arcs, some of them are more desirable to be utilized in transferring the injured people.

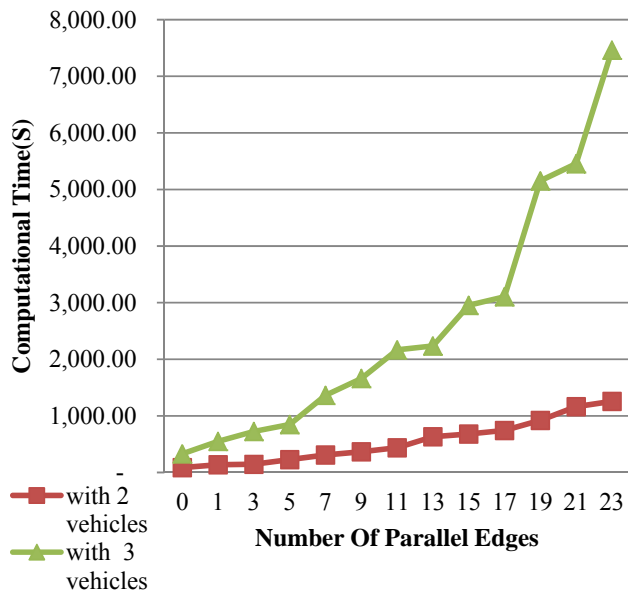
**Tab. 1. Structures of the sample problems and the Results of CPLEX for first dataset**

Example	Number Of parallel Edges	Number Of vehicle	Number Of used Vehicle	Result of examples	Computational time
E01	0	2	2	23.08	84.7
E02		3	2	23.08	327.9
E03	1	2	2	23.08	137.2
E04		3	2	23.08	548.9
E05	3	2	2	23.08	144.1
E06		3	2	23.08	723.9
E07	5	2	2	22.53	225.6
E08		3	2	22.53	845.8
E09	7	2	2	22.53	309.9
E10		3	2	22.53	1361.5
E11	9	2	2	22.53	364.1
E12		3	2	22.53	1661.5
E13	11	2	2	22.53	436.1
E14		3	3	22.53	2166.9
E15	13	2	2	22.53	629.687
E16		3	2	22.53	2235.31
E17	15	2	2	22.53	679.45
E18		3	2	22.53	2951.686
E19	17	2	2	22.53	742.911
E20		3	2	22.53	3105.16
E21	19	2	2	21.97	920.243
E22		3	2	21.97	5152.446
E23	21	2	2	21.97	1162.516
E24		3	2	21.97	5454.434
E25	23	2	2	21.77	1255.857
E26		3	2	21.77	7459.98



**Tab. 2. Structures of the sample problems and the Results of CPLEX for second dataset**

Example	Number of Nodes	Number Of parallel Edges	Number Of vehicle	Number Of used Vehicle	Result of examples	Computational time
E27		0	2	2	17.7	25.67
E28	6	0	3	2	17.7	83.56
E29		5	2	2	17.0	55.67
E30		5	3	2	17.0	185.56
E31		0	2	2	20.1	80.43
E32	7	0	3	2	20.1	317.16
E33		5	2	2	20.1	214.67
E34		5	3	2	20.1	790.34
E35		0	2	2	21.9	296.8
E36	8	0	3	2	21.9	1960.92
E37		5	2	2	20.6	787.88
E38		5	3	2	20.6	5158.39
E39		0	2	2	25.9	4624.08
E40	9	0	3	3	25.9	21908.32
E41		5	2	2	25.2	5787.09
E42		5	3	2	25.2	63453.67



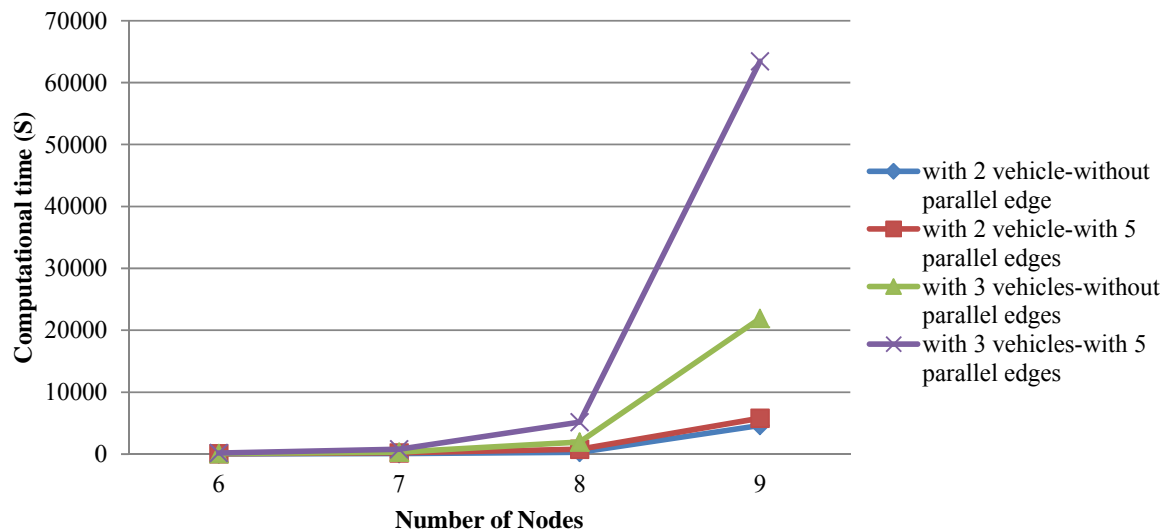


Fig. 7. Computational time for different instances with various numbers of nodes and vehicles.

## 6. Conclusions and Future Works

In emergencies, humanitarian logistics management is applied to improve the efficiency of scarce resources. In this paper, we studied a time-dependent vehicle routing problem in disaster relief efforts where more than one edge exists between the nodes. Such problems can be demonstrated in urban areas with different traffic conditions. Therefore, vehicle routing problem is utilized to assign routes to a fleet of vehicles in order to deliver emergency commodities to affected areas and injured people. Such decisions are significant since prompt delivery can save the

lives of many people. We provided a time-dependent vehicle routing problem by applying FIFO property in multi-graph network for the purpose of minimizing waiting time and number of vehicle. Then, we implemented the problem in GAMS (with CPLEX solver). Finally, a brief sensitivity analysis was used to examine the impact of different problem structures on the obtained solution (shown in Figures 6 and 7).

Some directions for future works can incorporate other important features of VRP problems such as a heterogeneous fleet of vehicles and consideration of demands uncertainty in the proposed model and also consideration the sustainability of vehicle assignment and vehicle switch in case of failure. Moreover, we provided an efficient meta-heuristic to solve the large-scale problems.

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