OPERATIONS AND SUPPLY CHAIN MANAGEMENT
Vol. 10, No. 3, 2017, pp. 161 - 169
ISSN 1979-3561 | EISSN 2759-9363

A Time-dependent Vehicle Routing Algorithms for Medical Supplies Distribution Under Emergency

Tsai-Yun Liao
Department of Business Administration,
National Chiayi University, Chiayi City, Taiwan, R.O.C.
Email: tyliao@mail.ncyu.edu.tw

Ta-Yin Hu
Department of Transportation and Communication Management Science,
National Cheng Kung University, Tainan, Taiwan, R.O.C.
Email: tayinhu@gmail.com (*Corresponding Author*)

Yu-Wen Wu
Department of Transportation and Communication Management Science,
National Cheng Kung University, Tainan, Taiwan, R.O.C.
Email: anie0610@gmail.com

ABSTRACT

On 27 June 2015, flammable starch-based powder exploded at Formosa Fun Coast, a recreational water park in Bali, New Taipei, Taiwan, injuring 508 people, with 199 in critical condition. During the emergency medical distribution, two processes, casualty transportation and relief distribution, are poorly coordinated and performed. The medical relief distribution process can be described as vehicle routing problems with pickup and delivery under time-windows (VRPPDTW). Under Intelligent Transportation Systems (ITS), information can be gathered from roadside surveillance systems to design efficient and effective routes for medical relief distribution. In this study, a time-dependent VRPPDTW formulation is constructed based on the concept of step function and a solution algorithm is proposed to solve the VRPPDTW problem. Numerical experiments based on a city network with three hospitals are used to illustrate the proposed algorithms under different levels of traffic conditions.

Keywords: *vehicle routing problems with pickup and delivery under time-windows (VRPPDTW), time-dependent travel time, DynaTAIWAN, medical relief distribution*

1. INTRODUCTION

On 27 June 2015, flammable starch-based powder exploded at Formosa Fun Coast, a recreational water park in Bali, New Taipei, Taiwan. The incident caused 508 injuries, among which there were 199 persons in critical condition. The dust explosion, is the "worst incident of mass injury ever in Taiwan". The injuries were treated in over 50 hospitals across Taiwan. As of 29 November 2015, 15 had died, 44 victims remained hospitalized. Due to the hot weather (36.6°C), many victims were lightly covered with clothes; as a result, they suffered burns over large portions of their bodies and some victims suffered burns to 80-90% of their skin.

Two important processes, casualty transportation and relief distribution, in the emergency medical distribution are poorly performed and coordinated. Casualty transportation sends wounded people to medical centers; whereas, relief distribution normally consists of bringing medical supplies to medical centers (hospitals). Some observations during the incident regarding relief distribution and casualty transportation are summarized as follows:

1. The number of injured is about 500 persons and half of the injured need to be sent to Intensive Care Units (ICU). The number of injured is beyond the total capacity of hospitals in Taipei areas.
2. The number of ambulance is insufficient to support 500 injured patients at the same time. Most of the emergency rooms were full of the patients, for example, one of the hospitals took in 65 patients at one time.
3. During the first week, injured patients are re-distributed among medical centers in the northern part of Taiwan and serious burned patients are re-distributed among ICU among major medical centers in Taiwan.
4. All the injured persons suffer similar burn wounds from contamination sources and they require similar treatments with the same medical supplies. However, only a limited stock can be found in these hospitals and emergency relief distribution need to be performed.
5. Medical supplies for burn treatments are insufficient and emergency medical relief are poorly planned and coordinated. There were urgent needs for cadaver skin, which is limited. Other medical supplies, such as burn treatment, gauze, bandages, etc., are insufficient for the amount of patients since they need to be replaced several times a day.

The observations indicate that medical-related logistics, such as casualty transportation, ambulance dispatch, and medical supply distribution, are not well-planned. Urgent needs are required for efficient and effective medical logistics. Medical logistics can be defined as the logistics of pharmaceuticals, medical and surgical supplies, medical devices and equipment, and other products needed to support doctors, nurses, and other health care providers.

The medical relief distribution process can be described as vehicle routing problems with pickup and delivery under time-windows (VRPPDTW). Due to the urgent characteristics of medical supply distribution, medical logistics is different from VRP, and thus it tends to seek to optimize effectiveness rather than efficiency. In general, constraints in medical logistics include vehicle capacity, time window, fleet size, and precedence, and these constraints need to be satisfied when designing efficient vehicle routes.

Most of the VRP algorithms treat travel times as static and constant; however, travel time might change due to traffic conditions, such as congestions and/or incidents. Ignoring such travel time variations, traditional algorithms might not be able to generate efficient routes. Although VRPPDTW have been discussed for several decades, only a few studies consider how variations in travel time might affect the vehicle routes for VRPPDTW. Under Intelligent Transportation Systems (ITS), road information can be gathered from roadside surveillance systems and/or vehicles in terms of probes to generate useful and meaningful travel time information for designing efficient and effective routes.

This research aims to construct a mathematical formulation to describe the VRPPDTW for medical relief distribution problems. With given demands (pick-up and delivery) and time-dependent travel times, the VRPPDTW is solved through a solution algorithm based on the branch-and-price algorithm. The Dantzig-Wolfe decomposition technique is applied to decompose the time-dependent VRPPDTW formulation into the master problem and sub-problems. The master problem is Set Partitioning Problems and solved through CPLEX under the column generation solution framework. The sub-problem is Constrained Shortest Path Problems and large neighborhood search (LNS) is used to find possible columns, i.e. routes, with negative reduced costs to add to the master problem.

The paper is structured as follows. Related literatures are briefly described in the next Section. Then, a mathematical model is presented, followed by a solution algorithm. Next, a real-world application is provided to illustrate the proposed algorithm, followed by a brief summary.

2. LITERATURE REVIEW

Some literature related to VRPPDTW is reviewed, followed by brief discussions on exact algorithms, heuristic approaches and meta-heuristic approaches.

2.1 VRPPDTW Problems

Traditional Vehicle Routing Problems (VRP) design vehicle routes for a vehicle fleet to meet customer requests under different constraints, such as pick-up and/or delivery, time-windows, multiple depots, heterogeneous vehicles. A comprehensive overview of the VRP can be found in Laporte (1992).

Three different types of pickup and delivery problems identified by Berbeglia et al. (2007) include: many-to-many problems, one-to-many-to-one problems and one-to-one problems. Berbeglia et al. (2010) presented a survey on the dynamic one-to-one pickup and delivery problems (PDPs) including the dynamic stacker crane problem, the dynamic vehicle routing problem with pickup and delivery, and the dynamic dial-a-ride problem.

Travel times are usually used in the VRP as travel costs; however, time-dependent travel costs due to traffic congestion could affect the results of vehicle routes and scheduling. Different techniques are applied to capture such fluctuations in travel times. For example, the concept of step functions is used by Malandraki and Daskin (1992) to deal with time-dependent travel time. Haghani and Jung (2005) extended the Malandraki and Daskin's work and adopted a continuous function to describe the variation of travel times. Jabali et al. (2012) adopted tabu search algorithm to study CO2 emission for time-dependent VRP. Stepwise speed functions are used to describe the time-dependent travel times. Dabia et al. (2013) proposed the Branch-and-Price algorithm based on the study by Jabali et al. (2012) for time-dependent VRP with time windows.

2.2 Exact Algorithm

Ropke and Cordeau (2009) proposed a branch-and-cut-and-price algorithm for the pickup and delivery problems with time windows. The problem is decomposed into a set partitioning formulation and constrained shortest path problem. Hu and Chang (2011) extended Ropke and Cordeau (2009)'s works by introducing time-dependent travel time and the results showed that the time windows can affect the computational time and objective value.

2.3 Heuristic Approach

Fabri and Recht (2006) developed a heuristic solution algorithm for dynamic pickup and delivery vehicle routing problems with time windows. Ropke and Pisinger (2006) proposed an adaptive large neighborhood search heuristic (LNS) for solving the pickup and delivery problem with time windows. Xiang et al. (2008) presented a fast heuristic solution algorithm to consider different stochastic situations, such as travel time fluctuations, new requests, cancelled requests, vehicle status, and traffic congestion. Luo and Schonfeld (2011) introduced the on-line rejected-reinsertion heuristic for dynamic dial-a-ride problems (DARP), a variant of VRP. Kim and Haghani (2011) developed a mixed integer programming approach for static DARP with time-varying travel time.

2.4 Meta-Heuristic Approach

Cortes et al. (2009) proposed a hybrid adaptive predictive control approach to solve the dynamic pickup and delivery problem, and the numerical results showed that the PSO can be successfully applied to in this context. Berbeglia et al. (2011) combined an exact constraint programming algorithm and a tabu search to build a hybrid tabu search for dynamic DARP. Kirchler and Calvo (2013) proposed a Granular Tabu search algorithm for static

DARP with a fixed fleet of vehicles. Schilde et al. (2014) proposed four meta-heuristic methods including the dynamic VNS, the dynamic stochastic VNS, the multiple plan approach and the multiple scenario approach for dynamic DARP with consideration of the time-dependent travel speed. The numerical results indicated that the dynamic stochastic VNS can obtain better solutions with 45% to 90% dynamic requests.

3. MATHEMATICAL FORMULATION

In the VRPPDTW problems, deployed vehicles need to pick-up medical supplies then deliver the supplied to the hospitals as well as medical institutes. Under emergency conditions, some important factors are summarized as follows:

1. Uncertainty of demands. Requests and quantities of medical supplies change dynamically as patients are treated and re-distributed among hospitals. Although the best way is to describe the problem in real-time context, the problem then becomes very complicate and difficult to solve. In this study, we assume requests are known in advance.
2. Extra ambulance and/or vehicle fleet. In addition to normal vehicle dispatching operations, additional vehicles and/or ambulances might be needed under emergency conditions. We assume vehicles are available to fulfill all the constraints. In the worst case, each medical request is served by a vehicle and it means that the vehicles pick up medical supplies and then directly deliver to the hospitals.
3. Travel time fluctuations. Travel times might change dramatically due to congestions, especially near the incidents. Road traffic conditions can be monitored and the information can be utilized by the center to design efficient routes.
4. Depots. Vehicles might need to be dispatched to multiple depots and/or pickup nodes before the delivery.

In the VRPPDTW problems, possible objectives include (1) to minimize the cost for demands; (2) to maximize the demand based on a fixed size of fleet; (3) maximize the quality of service (Psaraftis, 1980; Jaw et al., 1986; Cordeau and Laporte, 2007). There are different ways to evaluate operator cost. The operator cost typically can be evaluated by minimizing the vehicle used or travel time/distance. The customer satisfaction can be described through customer's pick-up waiting time or delivery delay time.

The objective in the formulation is to minimize the vehicle fleet and/or the sum of travel time, with the restriction that the vehicle must have enough capacity for transporting the commodities to be delivered and those ones picked-up at customers for returning them to the depot.

Assume a directed graph $\mathbf{G} = (N, A)$ with a set of nodes N and a set of arcs A. The set of nodes $(N = P \cup D \cup \{0\} \cup \{2n+1\})$ is comprised of four different kinds: source nodes "$\{0\}$", sink nodes "$\{2n+1\}$", pickup nodes "$\mathbf{P} = \{1, \dots, n\}$" and delivery nodes "$\mathbf{D} = \{n+1, \dots, 2n\}$". The depot nodes include two different kinds of nodes, source $\{0\}$ and sink $\{2n+1\}$. A medical relief distribution request (i) can be represented by a medical supply pickup node $\{i\}$ and delivery node $\{n+i\}$. The load at node q_i must comply with $q_0 = q_{2n+1} = 0$ and $q_i = -q_{n+i}, \forall i \in \mathbf{P}$. The set of vehicles is defined as $\mathbf{V} = \{1, \dots, V\}$. A vehicle capacity limitation (Q) is imposed on each vehicle. The c_{ij}^m is defined as the travel cost (time) for the arc (i, j) at the time interval m. The definition of $\mathbf{T}_{ij}^{m}$ represents the starting time of interval m for arc (i,j).

Although different models have been proposed to model time-dependent travel time in VRPPDTW problems, these models represent different explanations of travel time fluctuations. This study adopts the concept of the step function for modeling travel time fluctuations because the step function can capture traffic flow congestion phenomenon without complicated details for traffic flows. The time-dependent travel time performance function is discretized into different intervals and travel time is constant in the same time interval.

During the medical relief distribution, medical supply need to be delivered on time, and thus all requests are delivery-specified. For each medical supply delivery, the vehicle arrival time at the delivery node must be within the earliest delivery time (EDT) and the latest delivery time (LDT). The direct ride time (DRT) for each customer is defined as the shortest travel time between the pickup node and the delivery node. Notations are summarized in in **Table 1**. The formulation and constraints are discussed hereafter.

Table 1 The notations used in the time-dependent VRPPDTW formulation

Notation	Contents
N	Node set (n = 0, 2n+1:Depot; n=1,…,n: Pick-up nodes; n=n+1,…,2n: Delivery nodes),
P	Pick-up nodes, P={1,…,n},
D	Delivery nodes, D={n+1,…,2n},
V	Vehicle set,
m	Number of time intervals,
B	A large number,
c_{ij}^m	Travel time from node i to node j at the time interval m,
S_i	The service time at node i,
CAP	The vehicle capacity,
q_i	The load at node i,
T_{ij}^m	Upper bound for time interval m for link (i, j),
e_i	Earliest time that the vehicle can arrive at node i,
l_i	Latest time that the vehicle can arrive at node i,
t_i	The time starts service at node i,
w_i	The load of the vehicle upon leaving node i,
DPT_i	Desired pickup time at node i $(i \in P)$,

Table 1 The notations used in the time-dependent VRPPDTW formulation (Con't)

DDT_i	Desired delivery time at node i $(i \in D)$,
DRT_i	Direct ride time ($DRT_i = t_{i+n} - t_i - S_i$),
MRT_i	Maximum ride time,
$x^m_{i,j,v}$	If any vehicle v travels from node i to node j during the time interval m, the variable is equal to 1. Otherwise is equal to 0.
R	The set of all feasible routes satisfying constraints (2)~(19),
c_r	The cost of the route r,
a_{ir}	The number of times a node is visited by route r $(i \in P)$,
y_r	If route r is used in the solution, the variable is equal to 1. Otherwise is equal to 0.
π_i	The dual variables associated with the set partitioning problem constraint (20).

Minimize

$$\sum_{i\in N}\sum_{j\in N}\sum_{m\in M}\sum_{v\in V} c^m_{i,j} x^m_{i,j,v} \quad (1)$$

subjectto

$$\sum_{j\in N}\sum_{m\in M}\sum_{v\in V} x^m_{i,j,v} = 1 \quad (\forall i \in P) \quad (2)$$

$$\sum_{i\in P}\sum_{m\in M} x^m_{0,i,v} = 1 \quad (\forall v \in V) \quad (3)$$

$$\sum_{j\in D}\sum_{m\in M} x^m_{j,2n+1,v} = 1 \quad (\forall v \in V) \quad (4)$$

$$\sum_{j\in N}\sum_{m\in M} x^m_{i,j,v} - \sum_{j\in N}\sum_{m\in M} x^m_{n+1,j,v} = 0 \quad (\forall i \in P, v \in V) \quad (5)$$

$$\sum_{j\in N}\sum_{m\in M} x^m_{j,i,v} - \sum_{j\in N}\sum_{m\in M} x^m_{i,j,v} = 0 \quad (\forall i \in P \cup D, v \in V) \quad (6)$$

$$t_j \ge t_i + S_i + C^m_{i,j} - B\left(1 - x^m_{i,j,v}\right) \quad (\forall i,j \in N, m \in M, v \in V) \quad (7)$$

$$t_i - T^{m-1}_{i,j} x^m_{i,j,v} \ge 0 \quad (\forall i,j \in N, m \in M, v \in V) \quad (8)$$

$$t_i + B x^m_{i,j,v} \le T^m_{i,j} + B \quad (\forall i,j \in N, m \in M, v \in V) \quad (9)$$

$$e_i \le t_i \le l_i \quad (\forall i \in N, v \in V) \quad (10)$$

$$w_j \ge w_i + q_j - B\left(1 - \sum_{m\in M} x^m_{i,j,v}\right) \quad (\forall i,j \in N, v \in V) \quad (11)$$

$$w_i \le CAP \quad (\forall i \in N, v \in V) \quad (12)$$

$$x^m_{i,j,v} \in \{0,1\} \quad (13)$$

$$m \in M \quad (14)$$

$$v \in V \quad (15)$$

$$t_i \ge 0 \quad (16)$$

$$w_i \ge 0 \quad (17)$$

$$N \in \{\{0\} \cup \{2n+1\} \cup P \cup D\} \quad (18)$$

The objective function (1) is to minimize the total travel costs and the objective is achieved under the constraint of no delay for medical supply delivery. Constraint (2) guarantees that each demand has to be served once, and each demand is only allowed to be visited by one vehicle. Constraints (3) and (4) ensure that all vehicles must start from the depot and return to the depot. Constraint (5) ensures that each customer must be picked up first and then delivered in the same vehicle. Constraint (6) is the flow conservation equations. Constraint (7) calculates the departure time to node j. Constraints (8) and (9) are the temporal constraints. If the vehicle travels from node i to node j during time interval m, the departure time of the vehicle from node i is between the upper bound for time interval m-1 and upper bound for time interval m. Constraint (10) imposes the time windows restrictions. Constraints (11) and (12) impose the capacity constraints. Constraint (11) is the sub-tour elimination constraints. Constraint (12) ensures that the vehicles do not exceed the vehicle capacity limitation.

A solution algorithm based on the branch-and-price approach is proposed to solve the time-dependent VRPPDTW problems. Three main steps in the branch-and-price approach include decomposition, column generation and branch-and-bound. In the decomposition, the Dantzig-Wolfe algorithm is used to decompose the time-dependent formulation into a master problem and a set of sub-problems. The master problem becomes the set partitioning problems and the sub-problem becomes the constrained shortest path problem. The master problem determines the optimal feasible vehicle routes based on the meaningful subset of the feasible vehicle routes (columns). The time-dependent VRPPDTW formulation can be reformulated by using path flows instead of link flows. Each route $\mathbf{r}$ means one vehicle-route ($\mathbf{v}$) in the time-dependent VRPPDTW formulation. The notation, a_{ir} can be defined by, $x^m_{i,j,v}$. The a_{ir} is expressed as follow:

$$a_{ir} = \sum_{m\in M}\sum_{j\in N} x^m_{i,j,v}\ (\forall i \in P, r \in R, v \in V) \quad (19)$$

Then, the set partitioning problem is solved based on the given set of routes, $R_{Given} \subseteq R$. If all feasible vehicle routes can be identified (i.e. $R_{Given} = R$), the set partitioning problem can solve for optimal solutions. However, the feasible vehicle routes (columns) are hard to enumerate when there are a large number of instances. To overcome this difficulty, the sub-problem needs to be capable of generating a promising column, and then can be added to the master problem. In the sub-problem, the heuristic approach can reduce the computational time for finding the promising column. The route cost for each vehicle can be expressed as follows:

$$c_r = \sum_{i\in N}\sum_{j\in N}\sum_{m\in M} c^m_{ij}\, x^m_{i,j,v} \quad (\forall r \in R, v \in V) \quad (20)$$

The mathematical formulation for the master problem is constructed as follows:

Minimize

$$\sum_{r\in R} c_r y_r \quad (21)$$

subjectto

$$\sum_{r\in R} a_{ir}\, y_r = 1 \quad (\forall i \in P) \quad (22)$$

$$y_r \in \{0,1\} \quad (\forall r \in R) \quad (23)$$

The objective function (21) is to minimize the total cost of the selected route. Constraint (22) guarantees that each request is visited by one vehicle. In order to solve the set partitioning problem polynomially, the binary constraint is relaxed to be linear constrain, as follows:

$$y_r \geq 0 \quad \forall r \in R \quad (24)$$

The Lagrangian relaxation technique is applied and the problem can be expressed as follows:

Minimize

$$L = \sum_{r\in R} c_r y_r + \pi_i\left(1 - \sum_{r\in R} a_{ir}\, y_r\right), \forall i \in P \quad (25)$$

subjectto

$$y_r \geq 0 \quad \forall r \in R \quad (26)$$

The first-order condition for minimizing the above formulation can be stated as follows:

$$y_r * \frac{\partial L}{\partial y_r} = y_r\left[c_r - \sum_{r\in R} a_{ir}\, \pi_i\right] = 0, \forall i \in P \quad (27)$$

$$\frac{\partial L}{\partial y_r} = c_r - \sum_{r\in R} a_{ir}\, \pi_i \geq 0, \forall i \in P \quad (28)$$

$$\frac{\partial L}{\partial \pi_i} = 1 - \sum_{r\in R} a_{ir}\, y_r = 0, \forall i \in P \quad (29)$$

Based on the problem, optimality conditions can be found by taking derivatives with respect to decision variables. The optimality conditions are expressed in Equations (24), (27), (28) and (29). In equation (27), the term $c_r - \sum_{r\in R} a_{ir}\, \pi_i$ means the reduced cost for node i. Equation (28) shows that the reduced cost for each node i must be greater than or equal to zero in the optimality condition. Equation (29) ensures that each request is served by one vehicle. If y_r is not equal to zero, the reduced cost, $c_r - \sum_{r\in R} a_{ir}\, \pi_i$ is equal to zero. If y_r is equal to zero, the reduced cost, $c_r - \sum_{r\in R} a_{ir}\, \pi_i$ must be greater than zero.

Based on the optimality condition, if any vehicle route is found with negative reduced cost, this route is added into the master problem in order to improve the objective value. Following the optimality condition for minimizing the master problem, the mathematical formulation for the sub-problem is constructed as follows:

Minimize

$$\sum_{i,j\in N}\left(c_{ij} - \pi_i\right) x_{ij} \quad (30)$$

Subject to constraints (2)~(18).

The objective of the sub-problem is to minimize the total reduced cost for the constrained shortest path problem. A more detailed discussion on the formulation can be found in Hu and Chang (2015).

4. SOLUTION ALGORITHM

As shown in **Figure 1**, the solution algorithm includes six main parts: Input data, VRPPDTW formulation, Decomposition, Column generation, Branch-and-bound and Output. Detailed descriptions for each step are presented as follows:

1. Input Data: Several data items are required in solving the problem. Basic data for DynaTAIWAN include network geographic data and traffic-related data, such as traffic control data. Based on given demand and traffic network, DynaTAIWAN simulates traffic flow patterns and outputs time-dependent travel time matrices.
2. Time-dependent VRPPDTW Formulation. The input data for the formulation include time-dependent travel times, vehicle fleet data and medical supply requests.
3. Decomposition: After the decomposition, a master problem and a set of sub-problems are obtained.
4. Column Generation: The master problem is solved by CPLEX. Large Neighborhood Search (LNS) is used to find the column with the minimum reduced cost. If the reduced cost is less than 0, this column as dual variables are added into the master problem. If not, the solution process will proceed to the next step.
5. Branch and bound: If the final solution is not an integer, the branch and bound method is used.
6. Stop criteria: The algorithm stops when the algorithm cannot find any column solution with negative reduced cost.
7. Output. Major outputs include service sequences, route costs, and vehicle routes.

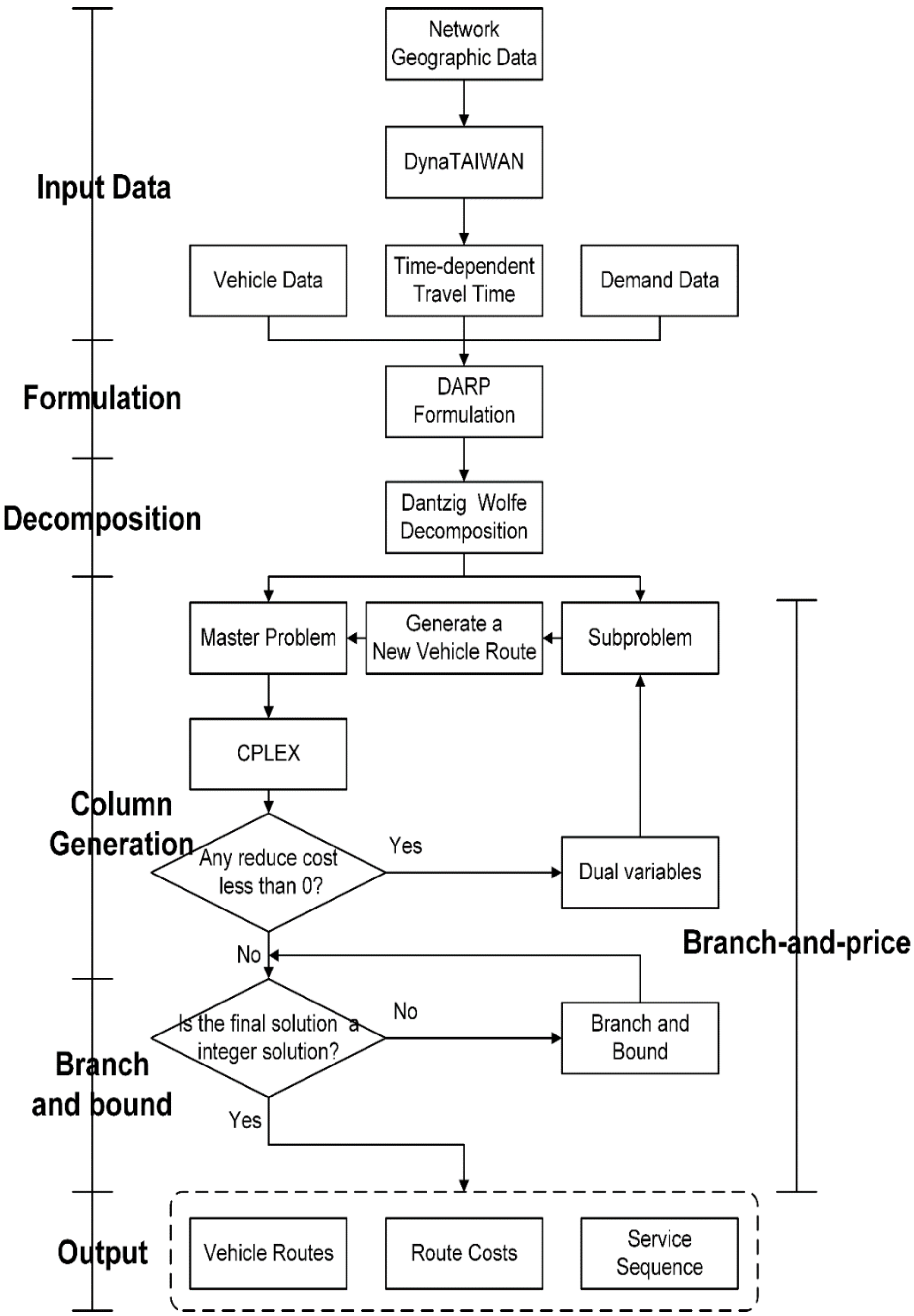

Figure 1 The overall procedure of the proposed solution algorithm

5. NUMERICAL EXPERIMENTS

The A network based on the Kaohsiung City, Taiwan, is coded for numerical analysis, as shown in **Figure 2**. There are 132 nodes and 363 links. The depot, medical supply pick-up and delivery nodes are chosen from the Kaohsiung city network to represent hospitals and medical centers. The desired pickup time for each customer is generated randomly. The time interval in the step function is assumed to be 5 minutes. The service time for each customer is set to be 5 minutes. The maximum ride time (MRT) is defined as follows:

$$\boldsymbol{MRT_i = a + b * DRT_i} \quad (31)$$

In the numerical experiments, the coefficients a and b in equation (31) are set as 5 and 1.5, respectively. The maximum number of iterations that are run in the Large Neighborhood Search is set as 1,000.

Although experimental factors, such as time-windows, service time, and size of vehicle fleet, could be experimented to observe how medical supply distribution performs under different assumptions, the study focuses on illustrating the proposed algorithm and how time-dependent travel times might affect vehicle sequence as well as vehicle routes. Simulation experiments are designed to observe how vehicle paths vary with respect to traffic conditions. The analysis reflects the importance of temporal traffic conditions in designing vehicle routes for medical supply distributions. Basic experiments and results are presented in this section. Due to the limitation of paper length, other experiments, including parameter setting and sensitivity analysis, are reported elsewhere.

Three traffic patterns are simulated to explore the impact of different traffic conditions, including light traffic, medium traffic, and heavy traffic, and these patterns are represented by demand multipliers. The simulation results are summarized in **Table 2**. The average travel times are 8.36 mins, 17.23 mins, and 70.62 mins, respectively. Similar patterns for the average stopped time can be observed. It indicates more congestion for heavy traffic scenario.

Table 2 Summary of traffic network performance under different demand levels

Traffic Conditions (Demand level)	Number of Vehicles	Average Travel Time (min)	Average Stopped Time (min)	Average Speed (m/min)
Light (0.1)	4347	8.36	1.75	679.54
Medium (1.0)	85567	17.23	8.96	341.23
Heavy (2.0)	174726	70.62	39.5	94.74

As shown in **Figure 2**, there are one depot (3052), 3 pick-up warehouses (128,122,130), and 3 hospitals (3049, 2618, 5177). The number of vehicles are not considered in the experiments and at most three vehicles can be deployed and service times are assumed to be 5 minutes. The time windows are randomly generated and the data is listed in **Table 3**.

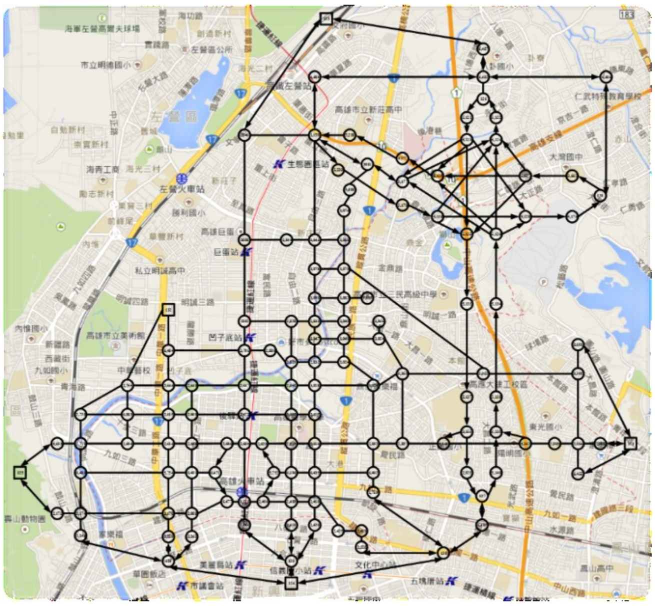

Figure 2 A Kaohsiung City Network

Table 3 Assumptions Time Windows on Medical Supply Pick-up and Delivery Points

Node ID	0.1		1.0		2.0	
0	0	10000	0	10000	0	10000
1	39.35	47.9	38.42	47.28	37.28	46.52
2	42.685	50.79	42.355	50.57	41.425	49.95
3	24.95	33.3	24.44	32.96	24.23	32.82
4	50	60	50	60	50	60
5	52	62	52	62	52	62
6	35	45	35	45	35	45
7	0	10000	0	10000	0	10000

The results are summarized in **Table 4**. The travel paths for these three scenarios are illustrated in **Figure 3**. In the light traffic scenario, the total vehicle travel time is 84.38 mins and two vehicles are dispatched and travel times are 33.16 mins and 51.22 mins, respectively. In the medium traffic scenario, the total vehicle travel time is 105.16 mins and three vehicles are dispatched and travel times are 33.95 mins, 35.12 mins, and 35.09 mins, respectively. In the heavy traffic scenario, the total vehicle travel time is 113.69 mins and three vehicles are dispatched and travel times are 38.51 mins, 39.08 mins, and 36.10 mins, respectively.

Table 4 Assumptions Time Windows on Medical Supply Pick-up and Delivery Points

Traffic Conditions	solutions	Travel time (min)
0.1 Total travel time: 84.38 min	[0 1 4 7]	33.16
	[0 3 6 2 5 7]	51.22

Table 4 Assumptions Time Windows on Medical Supply Pick-up and Delivery Points (Con't)

Traffic Conditions	solutions	Travel time (min)
1.0 Total travel time:105.16 min	[0 1 4 7]	34.95
	[0 2 5 7]	35.12
	[0 3 6 7]	35.09
2.0 Total travel time:113.69 min	[0 1 4 7]	38.51
	[0 2 5 7]	39.08
	[0 3 6 7]	36.10

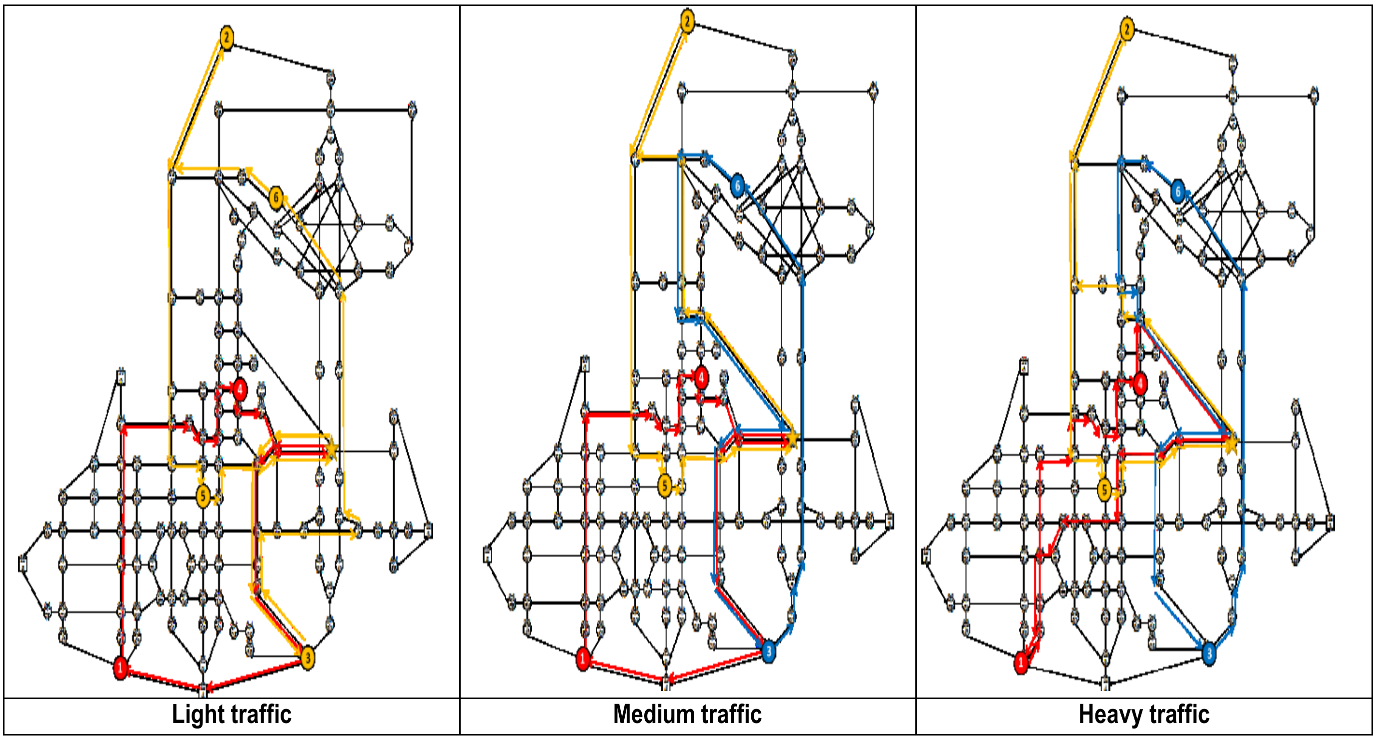

Figure 3 Detailed Paths Taken for Each Vehicle

Some observations are summarized as follows:

1. In the light traffic condition, two vehicles are dispatched and the delivery can meet the requirement. Under free-flow traffic conditions, vehicles can be utilized more efficiently. However, three vehicles need to be dispatched in the medium and heavy traffic conditions in order to meet delivery deadlines. With pre-planning, system operators can arrange vehicle fleet in advance to reduce possible delays and costs.
2. As expected, vehicle travel times increase with respect to the level of congestion in traffic networks, and vehicle paths are different in three traffic conditions, as illustrated in **Figure 3**. The result indicates that route sequence and paths taken need to be considered simultaneously to achieve optimal performance.
3. Although objectives in these experiments are mainly travel time, no delay is observed in the experiments. However, time-windows in practice might generate delivery delays. Therefore, the limited results can only illustrate the possible benefits and advantages from the proposed models.

6. CONCLUDING REMARKS

A time-dependent VRPPDTW formulation is formulated and the branch-and-price algorithm is proposed for medical supply distribution problems. Numerical analysis is performed to illustrate the algorithm. The solution algorithms shows its flexibility and sensitivity to a variety of assumptions on location, vehicle, and demand, and provides a useful environment for emergency management strategies prior to field experiments.

In these limited experiments, the results suggest that appropriate coordination can provide more efficient and reliable medical relief distributions. It can also be expected that more significant benefit can be obtained by simultaneously optimizing vehicle sequences and paths taken between demand nodes.

Medical distribution process, part of bio-logistics, should be integrated with other processes of bio-logistics to achieve efficient and effective logistical solutions.

ACKNOWLEDGEMENTS

This paper is based on work partially supported by the Ministry of Science and Technology, ROC. Of course, the writers are solely responsible for the contents of this paper.

REFERENCES

Berbeglia, G., Cordeau, J. F., Gribkovskaia, I., & Laporte, G. (2007). Static pickup and delivery problems: a classification scheme and survey. *Top*, 15(1), pp. 1-31.

Berbeglia, G., Cordeau, J. F., & Laporte, G. (2012). A hybrid tabu search and constraint programming algorithm for the dynamic dial-a-ride problem. *INFORMS Journal on Computing*, 24(3), pp. 343-355.

Cordeau, J. F., & Laporte, G. (2007). The dial-a-ride problem: models and algorithms. *Annals of Operations Research, 153(1)*, pp. 29-46.

Cortés, C. E., Sáez, D., Núñez, A., & Muñoz-Carpintero, D. (2009). Hybrid adaptive predictive control for a dynamic pickup and delivery problem. *Transportation Science*, 43(1), pp. 27-42.

Dabia, S., Ropke, S., Van Woensel, T., & De Kok, T. (2013). Branch and price for the time-dependent vehicle routing problem with time windows. *Transportation Science*, 47(3), pp. 380-396.

Fabri, A., & Recht, P. (2006). On dynamic pickup and delivery vehicle routing with several time windows and waiting times. *Transportation Research Part B: Methodological*, 40(4), pp. 335-350.

Haghani, A., & Jung, S. (2005). A dynamic vehicle routing problem with time-dependent travel times. *Computers & operations research*, 32(11), pp. 2959-2986.

Hu, T. Y., & Chang, C. P. (2011). Time-Dependent Dial-a-Ride Problems: Formulation Development and Numerical Experiments. *Journal of the Eastern Asia Society for Transportation Studies*, 9, pp. 690-701.

Hu, T. Y., & Chang, C. P. (2015). A revised branch-and-price algorithm for dial-a-ride problems with the consideration of time-dependent travel cost. *Journal of Advanced Transportation*, 49(6), pp. 700-723.

Jabali, O., Woensel, T., & de Kok, A. G. (2012). Analysis of travel times and CO2 emissions in time-dependent vehicle routing. *Production and Operations Management*, 21(6), pp. 1060-1074.

Jaw, J. J., Odoni, A. R., Psaraftis, H. N., & Wilson, N. H. (1986). A heuristic algorithm for the multi-vehicle advance request dial-a-ride problem with time windows. *Transportation Research Part B: Methodological*, 20(3), pp. 243-257.

Kim, T., & Haghani, A. (2011). Model and Algorithm Considering Time-Varying Travel Times to Solve Static Multidepot Dial-a-Ride Problem. *Transportation Research Record: Journal of the Transportation Research Board*, (2218), pp. 68-77.

Kirchler, D., & Calvo, R. W. (2013). A granular tabu search algorithm for the dial-a-ride problem. *Transportation Research Part B: Methodological*, 56, pp. 120-135.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, 59(3), pp. 345-358.

Liao, T. Y., Hu, T. Y., Chen, L. W., & Ho, W. M. (2010). Development and empirical study of real-time simulation-based dynamic traffic assignment model. *Journal of Transportation Engineering*, 136(11), pp. 1008-1020.

Luo, Y., & Schonfeld, P. (2011). Online rejected-reinsertion heuristics for dynamic multivehicle dial-a-ride problem. *Transportation Research Record: Journal of the Transportation Research Board*, (2218), pp. 59-67.

Malandraki, C., & Daskin, M. S. (1992). Time dependent vehicle routing problems: Formulations, properties and heuristic algorithms. *Transportation science*, 26(3), pp. 185-200.

Psaraftis, H. N. (1980). A dynamic programming solution to the single vehicle many-to-many immediate request dial-a-ride problem. *Transportation Science*, 14(2), pp. 130-154.

Ropke, S., & Pisinger, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation science*, 40(4), pp. 455-472.

Ropke, S., & Cordeau, J. F. (2009). Branch and cut and price for the pickup and delivery problem with time windows. *Transportation Science*, 43(3), pp. 267-286.

Schilde, M., Doerner, K. F., & Hartl, R. F. (2014). Integrating stochastic time-dependent travel speed in solution methods for the dynamic dial-a-ride problem. *European journal of operational research*, 238(1), pp. 18-30.

Xiang, Z., Chu, C., & Chen, H. (2008). The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments. *European Journal of Operational Research*, *185*(2), pp. 534-551.

Tsai-Yun Liao received the Ph.D. degree in Civil Engineering (Transportation Engineering), the University of Texas at Austin, in May1997. She is an associate professor with the Department of Business Administration, National Chiayi University, Chiayi, Taiwan, R.O.C. She specializes in decision analysis, Intelligent Transportation Systems, and logistics management.

Ta-Yin Hu received the Ph.D. degree in Civil Engineering (Transportation Engineering), the University of Texas at Austin, in May1995. He is a professor with the Department of Transportation and Communication Management Science, National Cheng Kung University, Taiwan, R.O.C.He specializes in Intelligent Transportation Systems (ITS), dynamic network analysis, simulation analysis, and transportation planning.

Yu-Wen Wu is a master student in the Department of Transportation and Communication Management Science, National Cheng Kung University, Taiwan, R.O.C. The current research interests include: ITS and transportation planning.