MINIMIZING EXPOSURE RISK AND TRAVEL TIMES OF HAZARDOUS MATERIAL TRANSPORTATION IN URBAN AREAS

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1. Introduction

Industrialization and urbanization are aspiration of every country at present state of world. While substantial economic growth is a direct outcome of industrialization, accomplishment of the process is directly related with the use of huge quantity of hazardous material. Consequently, reliance on hazardous material has become a fact of life to the people living in industrialized societies and thousands of different hazardous materials are in use at present. Huge demands of hazardous material, their subsequent shipments and the potential adverse conditions related with these shipments are the main problems in hazardous material transportation. Despite the continuous effort to mitigate the adverse effects of hazardous materials, accidents do happen during their use, loading/unloading, transport and disposal[1].

Hazardous material (HAZMAT) transportation accidents are perceived as low probability-high consequence (LPHC) events[2], and this is the reason for public's increasing reaction to HAZMAT accidents than to normal traffic accidents. HAZMAT transportation has been an active area of research and a large number of literatures relating to HAZMAT in the area of risk management, operation research, and decision making has been available in literatures for last twenty years. Application of proper routing decisions is one of the efficient ways that enables decision makers to achieve safe transportation of HAZMAT, and it is this aspect of HAZMAT transportation that has been focused in this study.

The core concept in HAZMAT routing is similar to the one in Vehicle Routing Problem with Time Window (VRPTW), a common application of mathematical programming in business logistics[3]. Risk is the primary term that separates HAZMAT transportation problem from the rest of transportation problems. Moreover, HAZMAT routing is a multi-objective activity involving multiple stakeholders with often conflicting priorities. Beside risk, minimizing travel time is the main objective in any HAZMAT shipment with shipper's point of view. Numbers of HAZMAT transportation studies considering numbers of attributes are available in literatures, most of which focuses on finding shortest paths for a given origin destination pair. However, in reality, HAZMAT transportation problem particularly based on land mode like normal vehicle routing problem calls for the determination of a set of optimal routes to be traveled by a fleet of vehicles thus satisfying the demand and time window constraints of a pre-specified number of customers. Owing to this particular VRPTW aspect of HAZMAT shipment, we present a new multi-objective HAZMAT VRPTW model and subsequently a meta-heuristic approach to solve this problem. Unlike existing VRPTW studies, route choice and routing processes of transportation here have been carried out as a single step process. The requirement of consideration of multiple objectives during both route choice and routing in HAZMAT shipment calls for their simultaneous consideration for finding optimal set of paths. A meta-heuristic solution technique based on Ant Colony Systems (ACS) for solving HAZMAT vehicle routing problem is presented. The proposed algorithm is supplemented by labeling algorithm for processing route choice and routing simultaneously as a single step process.

The proposed solution approach is then used to solve a HAZMAT routing problem in a test network consisting of 12 nodes and 34 links. The pareto-optimal set obtained provides several non-dominated routing options based on varying objectives for decision making process. Alternative application of such solutions not only ensures safe and economic HAZMAT transportation but also helps to minimize accumulation of risk in particular links

* Key words: Hazardous material, VRPTW, multi-objective optimization, meta-heuristics
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of HAZMAT shipment caused by their repetitive use for multiple shipments.

2. Literature Review

The HAZMAT transportation routing is a commonly faced issue in logistical decision-making, and considerable works have been done in the areas of risk assessment, routing, combined facility location and routing, and in network design. An extensive bibliography on these topics is available in Erkut *et al.*[2)]. While large numbers of risk-related researches are available in literatures, a land-based local routing and scheduling problem relating to a particular HAZMAT type of explosive material being the major concentration of this study, we limit our search for literatures to those on local routing problems and here we provide a list of literatures in this field.

Development of appropriate mathematical models, their solution algorithms and applications for safe and economical HAZMAT shipment has been a major focus of most works in HAZMAT routing. A wide variety of studies based on both single criteria of minimizing risk (Kara *et al.*[4)], Erkut and Ingolfsson[5)]) and multiple criteria of minimizing shipment cost and various consequences of risks (List and Turnquist[6)], Chang *et al.*[7)]) have been carried out so far. With the advancement in information technology, the newer studies are even capable of reflecting stochastic and time varying nature of network information during the selection of paths for routing HAZMAT. However, most of these works in HAZMAT routing are subjected to finding shortest path for a given origin and destination pair and the practical aspect of HAZMAT transportation relating to optimal routing and scheduling of a fleet of vehicles starting from a common depot and serving to a pre-defined number of customers has been less studied.

Concept of scheduling for HAZMAT distribution has been introduced by Cox and Turnquist[8)] and several related works are available in literatures. Most of these studies are in application to routing and scheduling of HAZMAT for a given origin destination pair. So far known, Tarantilis and Kiranoudis[9)] and Zografos and Androutsopoulos[10)] are the only two relative works available in respect to this study. Both studies explicitly dealt with VRPTW prospective of HAZMAT transportation problem and solved their bi-objective VRPTW model using heuristic approaches for obtaining optimal routing of a fleet of vehicles carrying HAZMAT. Zografos and Androutsopoulos[10)] applying a weighing approach transformed their bi-objective model to single objective model. The problem was then solved using an insertion-based heuristic for routing and Dijkstra method for finding shortest path between customers. Hard time windows requirements were maintained at all customers and the depot node. On the contrary, Tarantilis and Kiranoudis[9)] maintained bi-objective modeling for routing, using a List Based Threshold Accepting (LBTA) meta-heuristic algorithm. However, they employed Dijkstra algorithm using a risk-based single objective model for route selection. Also, though they used hard time windows requirement at depot node, they did not considered time windows at customers. An extension of the model and the heuristic algorithm developed in (10) has been presented in Zografos and Androutsopoulos[11)] in application to developing a GIS-based decision support system for integrated hazardous materials routing and emergency response decisions. The survey of cargo flow (shipped base) in the urbanized part of Tokyo in 1994 shows that around 14.3% of the deliveries are time-specified, 16.5% time period-specified, 26.5% date-specified; and only around 36.6% of deliveries do not impose any time windows. This survey has been carried out for all types of cargo including HAZMAT type. Based on the survey, it can be said that in practice though some deliveries are not time-restrictive, most of the deliveries impose specified time frame. Thus we maintained strict hard time windows requirements at all customers and depot nodes in this study. To reflect a fully multi-objective nature of HAZMAT distribution problem, the consideration of non-dominated paths both in routing and route choice processes becomes necessary, which complicates the process of solving HAZMAT problem for optimal case by emphasizing the need of proceeding these processes together in single step rather than two independent steps that has been a common practice in past. In regard to this fact, we employ labeling algorithm that provides non-dominated paths based on multiple objectives for route choice and ACS to obtain pareto-optimal routing. Further the two processes have been carried out simultaneously as dependent to each other.

3. Problem Formulation

A simple definition to HAZMAT routing problem is to determine a set of safe and economical routes for a fleet of vehicles carrying HAZMAT to serve a given set of customers satisfying their requirements of demand and time windows constraints, which is more similar to that of a normal VRPTW. Route choice and routing are the two major processes of any VRPTW. While solving VRPTW in general, the two processes are completed in two separate steps. A single best path for moving vehicle from a customer to another is first determined in route choice process using some shortest path algorithms for customer-customer or customer-depot node pairs. These pre-defined paths are then used in routing process in which the order of customers to be visited for optimal case is determined. As mentioned previously, the route choice considering multiple numbers of objectives results into several non-dominated paths for each origin destination pairs, and using a pre-defined single route for proceeding routing process would cancel the possibility of numbers of other non-dominated paths to participate in routing process. This may hinder decision-makers from reaching the actual optimal solution. Keeping this in mind, we attempt to process route choice and routing as a single step process, thus providing a chance to all non-dominated paths of route choice to be part of optimal routing process.

3.1 Mathematical Modeling

HAZMAT vehicle routing problem can be formulated, similar to normal Capacitated Vehicle Routing Problem with Time Windows (C-VRPTW) that is a variant of VRPTW in day to day business logistics. In general VRPTW is mathematically formulated as a single objective problem. Given a network (V, A), where $V=\{v_1, v_2, v_3, ..., v_k\}$ is a finite set of vertices and $A=\{a_1, a_2, a_3, ..., a_k\}$, a finite set of arcs that includes all possible connections between vertices in *V*. The set of customer nodes to be visited which is subset of *V* can generally be represented by the set of $N = \{n_1, n_2, n_3, ..., n_{\hat{N}}\}$. Specifically, this paper defines as $x_l = \{n(i) \mid i = 0, \hat{N}_l\}$, where $n(i)$ is the customer to be visited by vehicle *l*. Here, $\hat{N}_l$ is the total number of customers to be visited by vehicle *l* where $\hat{N}_l$ +1 being zero. x_l is the order of customers to be visited by vehicle *l*. $X = \{x_l \mid l = 1, m\}$ is traditional decision variable representing the order of visiting customer nodes for all vehicles. Since each vehicle *l* in use has to start from depot node, it is represented as a temporary customer node $n(0)$ for all vehicles. $[e_{n(i)},\ f_{n(i)}]$ is the time window, representing earliest and latest possible service time at node $n(i)$. $D_{n(i)}$ is the demand at node $n(i)$, and $W_{c,l}$ the capacity of vehicle *l* in use, *m* being the maximum number of vehicles used for transportation process.

To carry out routing decision and route choice decision simultaneously, a new decision variable $Y = \{y_l \mid l=1, m\}$ which is the order of paths to be visited by all vehicles is introduced. Set $P = \{p_1, p_2, p_3, ..., p_{\hat{P}}\}$ represents the set of all non-dominated paths between customer-customer and customer-depot node pairs based on travel time and risk objectives. The decision variable $y_l = \{p(i) \mid i = 0, \hat{N}_l\}$ is the order of paths to be used by vehicle *l*, and $p(i)$ is the path selected by vehicle *l* while visiting customer $n(i)$ to $n(i+1)$. $p(0)$ is the path to be followed from depot node to customer node $n(1)$, and $p(\hat{N}_l)$ is the path to be used while visiting from customer node $n(\hat{N}_l)$ back to depot node.

In order to integrate multi-objective nature of HAZMAT transportation problem, the objective function is defined as a three dimensional vector [Z_1 Z_2 Z_3]: $Z_1 \rightarrow$ total number of vehicles in use, $Z_2 \rightarrow$ total scheduling time of all the vehicles in operation and $Z_3 \rightarrow$ the total risk exposure associated with transportation process. While the objective Z_3 is related with safety aspect of HAZMAT routing, the objectives Z_1 and Z_2 are associated with fixed and variable operation costs of transportation process respectively. In calculation of time objective, Z_{tl} shows the total scheduling time incurred by vehicle *l* under hard time window conditions, with the average travel time value from $n(i)$ to $n(i+1)$ that is $\overline{T}^{p(i)}_{n(i)n(i+1)}$ being dependent on both the order of customers and path used while moving from one customer node to another. Terms $t_{c,n(i)}$ and $t_{l,n(i)}$ are the service time and service start time respectively of vehicle *l* at node $n(i)$, respectively. In calculation of risk-related objective, Z_{rl} is the risk associated with vehicle *l* which is dependent on $R^{p(i)}_{n(i),n(i+1)}$ that is the risk associated with each path followed while moving from customer $n(i)$ to $n(i+1)$ of that vehicle, the detail calculation of it will be presented in Section 3.2.The formulation of the HAZMAT vehicle routing problem is shown below:

$$Min \quad Z(X,Y) = \left[Z_1(X,Y) \quad Z_2(X,Y) \quad Z_3(X,Y)\right]^T \tag{1}$$

Subjected to

$$\sum_{n(i)\in x_l} D(n(i)) \quad = \quad W_l(x_l) \quad \leq \quad W_{c,l} \tag{2}$$

$$\sum_{l=1}^{m} \hat{N}_l \quad = \quad \hat{N} \tag{3}$$

$$t_{l,n(i)} \quad \leq \quad f_{n(i)} \tag{4}$$

$$Here,\ Z_1(X,Y) \quad = \quad \sum_{l=1}^{m} \delta(x_l, y_l) \tag{5}$$

$$where \quad \delta(x_l, y_l) \ = \ \begin{cases} 1 & if\ vehicle\ l\ is\ used \\ 0 & otherwise \end{cases}$$

$$Z_2(X,Y) \quad = \quad \sum_{l=1}^{m} Z_{tl}(x_l, y_l)$$

$$= \quad \sum_{l=1}^{m} \sum_{i=0}^{\hat{N}_l} (\overline{T}_{n(i),n(i+1)}^{p(i)} + t_{c,n(i+1)} + t_{w,n(i+1)}) \tag{6}$$

$$where \quad t_{w,n(i)} \quad = \quad \begin{cases} (e_{n(i)} - t_{l,n(i)}) & if\ t_{l,n(i)} < e_{n(i)} \\ 0 & otherwise \end{cases}$$

$$Z_3(X,Y) \quad = \quad \sum_{l=1}^{m} Z_{rl}(x_l, y_l)$$

$$= \quad \sum_{l=1}^{m} \sum_{i=0}^{\hat{N}_l} R_{n(i),n(i+1)}^{p(i)} \tag{7}$$

Equation (1) represents the objective function of the model. Equations (2), (3) and (4) are the capacity constraint, customer number constraint and the time window constraint to the problem respectively. Equations (5) to (7) show the details in the calculation of each objective. It should be noted that earliest possible time has been incorporated within the calculation of second objective value of total scheduling time.

3.2 Calculation of Risk

Risk assessment has been a topic of interest studied extensively, and a number of qualitative and quantitative risk models are available in literatures. Details on this topic are available in Erkut and Verter[2]. For the purpose of calculation of risk associated with each path during route optimization in this study, we adopt the expected consequence definition of risk. This risk model is also referred as traditional risk model[5] and widely used for HAZMAT transportation optimization models because of its simplicity in explanation and justification. Moreover, the model is not data-intensive. In reference to the model, risk associated with a path R_{path} due to an undesirable HAZMAT accident event as presented in equation (8), is a measure of probability of occurrence of the event and its consequence.

$$R_{path} = \sum_{link \in path} [(HAZMAT\ accident\ probability)_{link}\ .\ (consequence\ of\ the\ accident)_{link}] \tag{8}$$

A number of consequences in relation to HAZMAT accident are possible; however, safety for human life counts for top priority. Therefore risk $R_{n(i)n(i+1)}^{p(i)}$ associated with transportation of HAZMAT from customer node $n(i)$ to $n(i+1)$ using path $p(i)$, which consists of numbers of links joining nodes $v(j)$ to $v(j+1)$, is modeled as presented in equation (9) in particular to this study. Here $AR_{v(j)v(j+1)}$ is the probability of HAZMAT accident for link connecting vertex $v(j)$ to $v(j+1)$ and $EP_{v(j)v(j+1)}$ is the exposure population of that link.

$$R_{n(i),n(i+1)}^{p(i)} = \sum_{v(j)v(j+1)\in p(i)} AR_{v(j)v(j+1)}.EP_{v(j)v(j+1)} \tag{9}$$

The exposure population of a link is the people lying within λ distance from the link segment. Details on the threshold distance λ can be referred from Batta and Chiu[12]. The value of this distance λ is dependent upon the particular HAZMAT class being under consideration and has been defined based on the assumption that all persons within this distance from the accident spot are subjected to the same consequence of life loss, while the consequences outside this distance is ignored. Event trees have been widely in use to determine the accident probability in specific to a particular event considered. A number of event trees in relation to various HAZMAT accidents, and a table showing widely-applied λ values for various HAZMAT classes have been presented by Monnier and George[13].

4. A Meta-heuristic Algorithm for HAZMAT Routing

Large numbers of heuristic and meta-heuristic approaches have been proposed in recent years for solving different variants of VRPTW. The multiple objectives involved in the HAZMAT problem and the attempt of carrying out single step routing in this study make the problem much more complicated, due to the excessive enlargement of the possible solution space. Accordingly, the use of heuristic or meta-heuristic algorithms seems indispensable for this study. A meta-heuristic algorithm for solving HAZMAT vehicle routing problem is here proposed based on Ant Colony System for multi-objective optimization. Ant algorithms have been applied to a number of combinatorial optimization problems. A complete explanation on the algorithm can be referred to Dorigo and Stutzle[14]. Bullnheimer *et al.*[15] firstly used Ant System (AS) for solving vehicle routing problems. Later, Gambardella *et al.*[16] and Baran *et al.*[17] presented Ant Colony System (ACS)-based algorithms that are MACS-VRPTW and MOACS-VRPTW, respectively, for solving VRPTW with multiple numbers of objectives. Based on our intension to use pareto-optimal approach for both route choice and routing while dealing multiple objectives in this study, the basic idea in this algorithm is similar to that of the MOACS-VRPTW. Figure 1 shows the systematic steps of proposed ACS-based meta-heuristic algorithms for HAZMAT vehicle routing.

4.1 Pheromone Initialization

The first step of initialization of trail pheromone value and setting of pareto-optimal set *S* is based on a routing solution obtained using nearest neighborhood (*nn*) heuristic. Pareto-optimal solutions are represented by (X^*, Y^*) when there is not any (X, Y) which satisfies $Z_i(X,Y) \le Z_i(X^*,Y^*)$ at $i = 1,......,k$ and $Z_j(X,Y) < Z_j(X^*,Y^*)$ at arbitrary *j*. The initial nearest neighborhood solution itself represents the first member of pareto-optimal set *S*. The initial trail pheromone value τ_0 is determined using Equation (10) that is dependent on the total scheduling time, total risk value and the average number of nodes (|*N*|) including total number of customers and average number of vehicles for the nearest neighborhood solution. This pheromone value is then used to initialize pheromone value for the set of all non dominated paths *P*. Initial pheromone values in subsequent generations are dependent upon a new pheromone value calculated based on the average objective values for pareto-optimal set used previously as shown by Step 8 in Figure 1.

$$\tau_0 = \frac{1}{(|N|)_{nn} * (Z_2)_{nn} * (Z_3)_{nn}} \tag{10}$$

Step 1: Set parameters. Initialize trail pheromone value and pareto-optimal set *S* based on initial solution using nearest neighborhood search. Iteration = 1, initialize pheromone values for all paths based on the trail pheromone value.
Step 2: Perform labeling algorithm at each customer node to find set *P*.
Step 3: For ant = 1 to number of ants, construct solution.

Construct solution:

A: depotno =1, *i* =0 and place ant at depot node, *n(i)* = depot node.

B: Identify feasible set of customer nodes from *n(i)* that is *N'* and set of non-dominated paths to these nodes *P'*. If *N'* is empty, add all non-dominated paths from *n(i)* to depot node to *P'*.

C: Select path *p(i)* from *P'*.
If exploitation, choose path with maximum heuristic and pheromone product value.
Else, choose randomly using probability of selection.

D: Local update of pheromone value of path *p(i)*.

E: If customer node corresponding to selected path *p(i)* is depot node, depotno = depotno +1, *i* = 0 and *n(i)* = depot node.
Else, *i* = *i* +1 and *n(i)* = customer node corresponding to selected *p(i)*.

F: If more customers to be served go to step B.

G: Total vehicles = depotno-1

Step 4: If ant < number of ants, ant = ant +1 and go to Step 3.
Step 5: Update *S* based on dominance rule.
Step 6: Apply Insertion local search to each solution in *S*.
Step 7: Find new trail pheromone value based on average objective values of current *S*.
Step 8: If previous trail pheromone value < new trail pheromone, trail pheromone = new trail pheromone and initialize pheromone value of all paths based on this trail pheromone value. Else, carry out global update of pheromone for all paths of solutions in *S*.
Step 9: If iteration < maximum iteration, iteration = iteration +1 and go to Step 3.

Figure 1 ACS based Meta-heuristic Algorithms for HAZMAT Vehicle Routing Problem

4.2 Solution Construction

The proposed meta-heuristic algorithm employs labeling algorithm at each customer node and depot node to find all non-dominated paths based on resource constraints of travel time and risk values to visit all other customer nodes including the depot node. Labeling algorithm used here is based on template labeling algorithm proposed by Irnish and Villenuve *et al.*[18] for shortest path problem with resource constraint. Basic knowledge on labeling algorithm is detailed described in Ahuja *et al.*[19]. The concept is to make use of information that the labels created at vertex carries to determine all non-dominated paths in the presence of multiple resource constraints. The label at a vertex generally carries information about a path leading to it by maintaining a linkage with other label at the predecessor vertex. The label in resource constrained shortest path problems are made capable of describing the state of the resources at the given node as well.

Each ant at customer node $n(i)$ then selects a path $p(i)$ among P' that is the set of all non-dominated paths from this customer node to all feasible set of customer nodes (N') based on pseudorandom proportional rule. It should be noted that this set P' is the subset of the set *P*. Selection of path $p(i)$ and thereby insertion of corresponding customer node $n(i+1)$ is based on expression in Equation (11), if $q \le q_0$. The choice otherwise is made randomly based on a probability value presented in Equation (12). q is a random number such that $0 \le q \le 1$, and q_0 is a parameter that defines relative importance of exploration and exploitation.

$$\max_{p(i)\in P'} (\tau_{p(i)} \cdot [\eta_{p(i)}]^{\beta} \cdot [\nu_{p(i)}]^{\mu}) \tag{11}$$

$$\Pr(p(i)) = \frac{\tau_{p(i)} \cdot [\eta_{p(i)}]^{\beta} \cdot [\nu_{p(i)}]^{\mu}}{\sum_{p(i)\in P'} \tau_{p(i)} \cdot [\eta_{p(i)}]^{\beta} \cdot [\nu_{p(i)}]^{\mu}} \qquad (12)$$

Here $\tau_{p(i)}, \eta_{p(i)}, \nu_{p(i)}$ are the pheromone and heuristic values relating to the scheduling time and risk value of path $p(i)$, respectively. β and μ are the parameters that define relative influence of the time and risk objectives. $\Pr(p(i))$ is the probability of path $p(i)$ to be chosen. Calculation of time-related heuristic value is similar to the one for delivery time in MOACS-VRPTW that depends on the waiting time and time window at customer node. The risk-related heuristic value depends on the risk value associated with path $p(i)$ that connects customer node $n(i)$ to $n(i+1)$ and is evaluated as given with equation (13).

$$\nu_{p(i)} = \frac{1}{R^{p(i)}_{n(i),n(i+1)}} \qquad (13)$$

4.3 Local Search

The proposed algorithm applies insertion local search that utilizing the insertion neighborhoods of a typical solution to improve the quality of the obtained solutions. All nodes of a previously obtained feasible solution are given chances to be inserted to the same vehicle route or to the route of other vehicles without violating feasibility requirements, and the newly obtained solutions are checked for improved objective values. A wide review on local search procedures including their developments, analysis and application has been presented in Hoos and Stutzle[20]. Local search being a time consuming process, in this study we apply it to only those solutions belonging to pareto-optimal set *S* which is updated at the end of each iteration. The update of pareto-optimal set *S* is carried out based on a dominance rule in which all the solutions that are dominated in terms of all objectives are discarded. For example, if ψ_1 and ψ_2 are two solutions belonging to pareto-optimal set *S* with objective values of $Z_1(1), Z_2(1), Z_3(1)$ and $Z_1(2)$, $Z_2(2)$, $Z_3(2)$, respectively, ψ_1 is said to be dominated by ψ_2 and discarded from the set *S*, if Equation (14) to (16) are satisfied.

$$Z_1(1) \leq Z_1(2) \qquad (14)$$
$$Z_2(1) \leq Z_2(2) \qquad (15)$$
$$Z_3(1) \leq Z_3(2) \qquad (16)$$

4.4 Pheromone Update

ACS employs two typical pheromone update procedures that are the local and global update of pheromone. Each path used by ant for constructing solution is subjected to the local pheromone update as given in Equation (17) where ρ is the evaporation coefficient which powers exploration process by evaporating trail pheromone values for these used paths.

$$\tau^{new}_{p(i)} = (1-\rho)\tau^{old}_{p(i)} + \rho\tau_0 \qquad (17)$$

As mentioned previously, the pareto-optimal set *S* is updated after carrying out local search process in each iteration. Global update of pheromone is carried out to each path belonging to this set based on Equation (18) before proceeding to the next iteration unless the pareto-optimal set belonging to better pheromone value in relation to initialized trail pheromone value is obtained.

$$\tau^{new}_{p(i)} = (1-\rho)\tau^{old}_{p(i)} + \rho/[(Z_2)_{\psi} . (Z_3)_{\psi}] \qquad where\ \ p(i)\in\psi \qquad (18)$$

5. Test Problem

We present an application of the HAZMAT routing model with a test network consisting of 12 nodes and 34 links for routing gasoline material. Routing results obtained from this network using the proposed ACS-based meta-heuristic algorithm will be presented in the subsequent Section 6.

Figure 2 shows the identification of various vertex nodes and their connectivity in the network through various arcs. Vertex node 4 represents the depot node and the rest of all vertices represent the customer nodes where shipments are to be made from this depot node. The demand and time windows requirements at each vertex are shown in Table 1. A uniform capacity value of 5000 liters has been assigned to each vehicle and an unloading time of 8 minutes are considered at each customer location. Each arc or link has a uniform length of 4Km and the average vehicle travel time in a link is based upon its average speed value. Two different average speed values are used in the network. All links represented by solid arrow lines have the average speed of 20Km/hr, while 15Km/hr are used for those with dotted arrow lines. For the calculation of population exposed to risk for each link, a potential impact area of 0.5Km in all direction of the link is considered, and the tentative population values within this area is determined based upon two different population density of 2212 per Km^2 and 2545 per Km^2 for the two regions represented by the region I and II whose boundaries are shown in the figure as rectangles with dotted lines. Either the value of 0.4×10^{-6} or 0.457×10^{-6} are assigned as the probability of explosive HAZMAT event for each link, based on the speed of each link. The calculation of these values are based on 2006 Japan accident and traffic data in reference to Okuda[21)]. In regard to the fact that these accident data are for the normal traffic accident, a value of 0.1 as presented in event tree for petrol tanker accident[13)] are used to estimate the probability of explosive HAZMAT event in particular to the study.

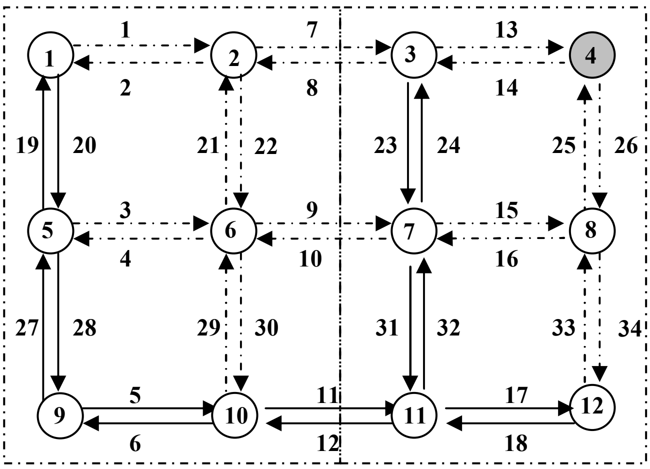

Figure 2 Test Network

Table 1 Demands and Time Windows

Vertex	Start Time Window (min)	End Time Window (min)	Demand (liters)
4	360	1440	0
11	480	600	1380
6	720	1020	1255
7	480	720	1255
9	480	600	1000
2	600	720	1500
8	480	1020	1380
10	900	1020	1135
5	480	600	1255
12	480	600	1380
1	600	720	1500
3	780	900	1135

6. Results and Discussions

The proposed meta-heuristic algorithm has been coded using Borland C and executed for solving routing of gasoline in the test network presented in Section 5 with the Core 2 Duo desktop PC of 2.67GHz with 2GB RAM. Parameters used are $m = 10,\ \beta = 1, \rho = 0.1, q_0 = 0.9$, which are the same as those used in MOACS-VRPTW and MACS-VRPTW. Ten consecutive test runs were performed in which each test run consists of 5000 numbers of iterations. The final result in each test run consists of several numbers of routing solutions representing pareto optimal set based on the three objectives. Table 2 shows the minimum and maximum time and risk values associated with pareto-optimal sets for all test runs in the case of 3 and 4 vehicles used. Computational time associated with each test run is also shown. It was observed that the minimum vehicles used are 3 for all test runs. However, minimum travel times are found to be associated with solutions using 4 vehicles for all test runs. Similar results are observed in the case of minimum risks with the exception in two test runs. The minimum risk values in these two exceptional cases however correspond to very high values of travel times. Figure 3 and Figure 4 show the range of maximum and minimum time and risk values observed correspondence to pareto-optimal solutions in the case of 3 and 4 vehicles used. The ranges are found to be small for the case using 3 vehicles in most cases with the exception of two test runs. These exceptional ranges are due to presence of a few solutions with minimized risk values while having very high time values as mentioned previously. Solutions with minimum ranges are preferable in regard to the ease they provide in decision making process.

Table 2 Minimum and Maximum Objective Values for 10 Test Runs

Test Run	Case of 3 Vehicles Used				Case of 4 Vehicles Used				Computational Time (Seconds)
	Min. Time (Minutes)	Max. Time (Minutes)	Min. Risk (x 10^{-3})	Max. Risk (x 10^{-3})	Min. Time (Minutes)	Max. Time (Minutes)	Min. Risk (x 10^{-3})	Max. Risk (x 10^{-3})	
1	580	632	139.1	154.4	552	868	130.3	154.5	21
2	604	628	145	159.6	556	868	130.3	155.1	24
3	584	632	139.8	154.3	552	868	130.3	154.4	22
4	580	616	139.1	155.1	556	868	130.3	155.1	21
5	592	612	139.8	153	552	868	130.3	154.4	20
6	584	1040	128.7	153.7	552	868	130.3	154.4	20
7	580	1032	128.7	154.4	548	868	130.3	155.1	21
8	592	620	140.5	155.2	556	872	130.9	155.1	21
9	592	620	149.2	154.4	560	872	130.9	154.3	22
10	596	620	139.8	154.4	548	868	130.3	155.1	19

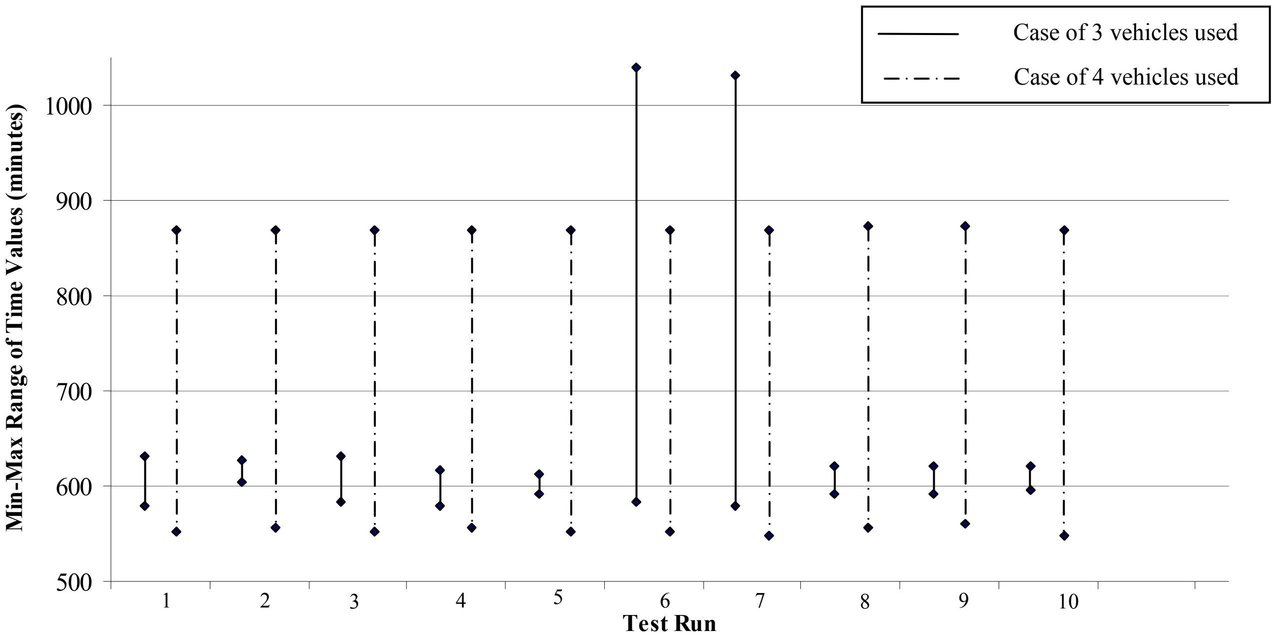

Figure 3 Minimum and Maximum Range of Time Values

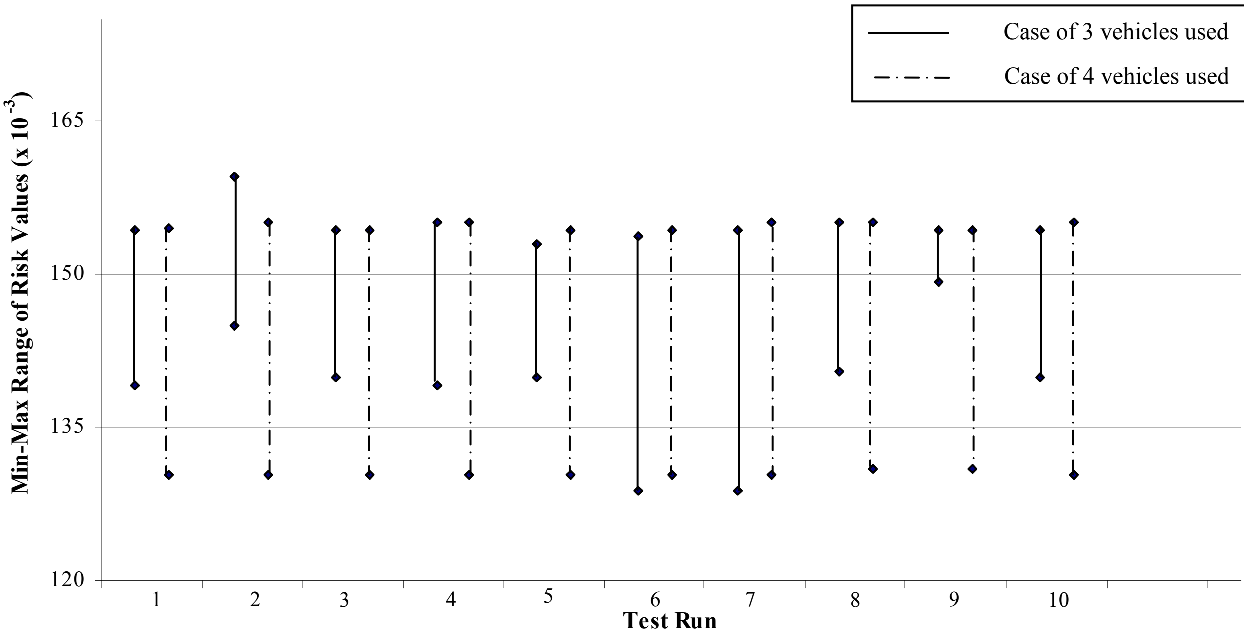

Figure 4 Minimum and Maximum Range of Risk Values

An important point to be noted is that the time and risk values being conflicting objectives, the solutions with minimum time are often associated with very high risk, and similar is the case for solutions with minimum risk. Figure 5 represents the pareto-front obtained in the first test run. The solutions located in the extreme of each axis (with 4 vehicles used) are the solution with minimum risk and time respectively; however, as clearly shown in the figure, these solutions are associated with high time and risk values, respectively. For equal consideration of all stakeholders, the solutions clustered in the central part of Figure 5 are very important. It can be observed from the figure that the time and risk values associated with solutions at central portion of pareto-front are not so different between the case of 3 and 4 vehicles used. In regard to the high cost associated with purchasing of vehicles, the central clustered solutions with 3 vehicles used provide good alternatives for routing in terms of total transportation cost.

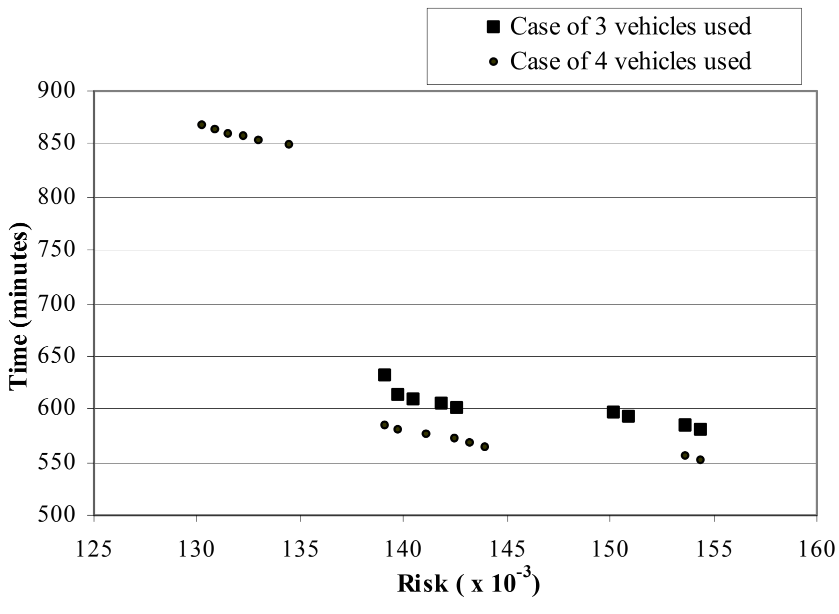

Figure 5 Pareto-front for Test Run 1

Here we would like to present some interesting results that support the idea of using route choice and routing process as a single step process in this study. Figure 6 and 7 represents the two typical pareto-optimal solutions of Solution I and Solution II in the pareto-optimal set obtained in test run 1. These solutions have time of 608 min and 604 min, respectively, and risk of 140 and 141 in 10^{-3} units, respectively. The order of customers to be visited for delivery (Vertex nodes in circle) and the paths to be followed while visiting from each customer to another (Coloured box) are shown for each vehicle. The vertex node inside the rectangular box represents the depot node. It should be noted that the order of customers to be served for both solutions are the same, however the solutions varies in terms of route choice visiting from the customer at vertex 7 back to the depot node 4 for the first vehicle and from the customer at vertex 10 to the customer at vertex 8 for the second vehicle. Both solutions obtained yet belong to pareto-optimal set. In case that the route choice were done separately for obtaining a single final route choice, the chances of obtaining one of the solution to be part of pareto-optimal set would not be possible. This clearly shows the need of simultaneous consideration of the two processes to obtain the more complete pareto-front.

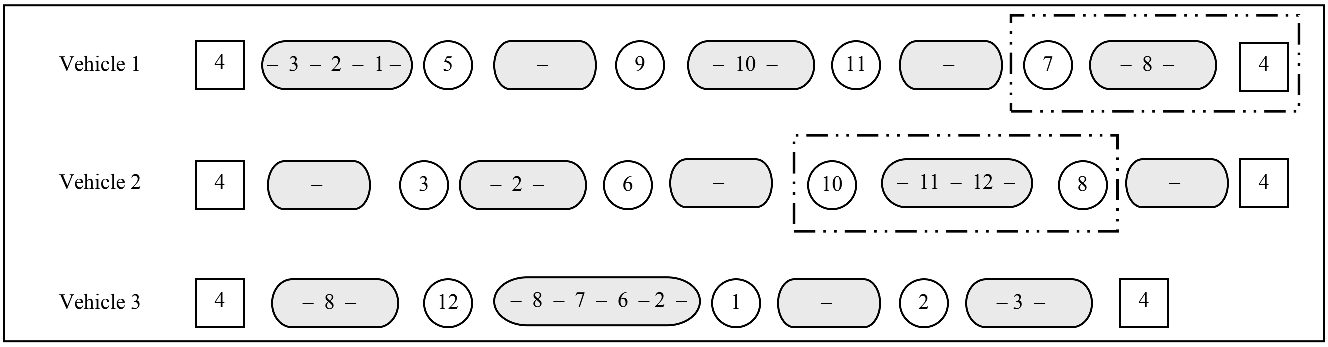

Figure 6 Vehicle Routes of Solution I

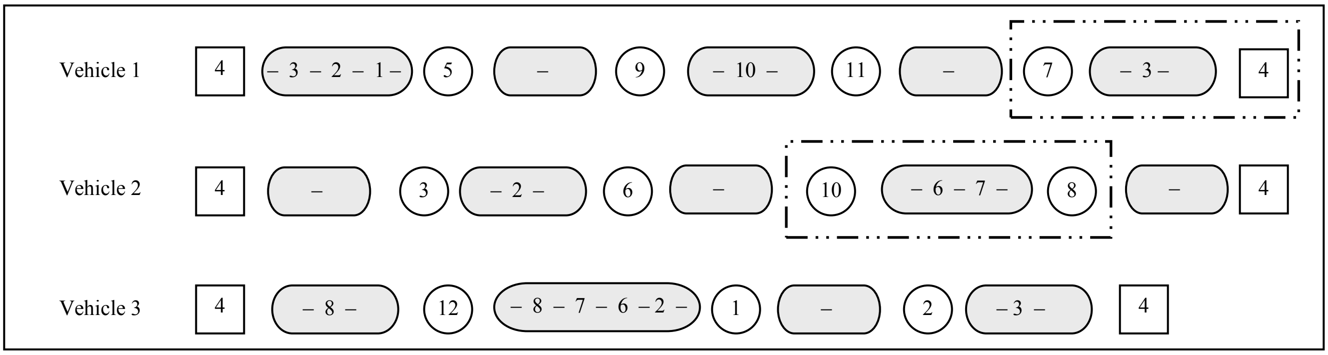

Figure 7 Vehicle Routes of Solution II

7. Conclusion and Future Work

This study presents a way to minimize the risk exposed during the transportation of Hazardous material through proper route planning yet satisfying the suppliers' need of cost minimization. Unlike the previous HAZMAT routing models, the proposed model and algorithms explicitly take into account the multi-objective requirement in HAZMAT study. The application of labeling algorithm and the consideration of pareto-front concept in the proposed ACS-based algorithms enables all the non-dominated paths between all customer-customer node pairs and customer-depot node pairs to be participated in optimal route finding process. The results obtained in the applications to the test network in this study clearly shows the requirement of consideration of all non-dominated paths both in case of route choice and routing process of VRPTW, thereby creating a need to consider these processes together as a single process.

Furthermore, the final routing solution consisting of a set of pareto-optimal solutions, in stead of a single routing solution based on a predetermined weightage values for each objective, widens the applicability of the algorithm for HAZMAT routing with the variations in decision-makers' need. The pareto-optimal solution set obtained from the test problem shows how the algorithm provides decision-makers with various pareto-optimal routing solutions with even a very slight difference of objective values. Another important point is that making the choice of alternative pareto-optimal solutions using different orders and links for multiple shipments even enables decision-makers to come up with the routing plan that eliminates the concentration of risk to typical links with repetitive use for shipment.

In order to visualize the real situation in HAZMAT vehicle routing, including those related with data requirement and size of the problem, the application of the model to a real road network is another aspect of the study. In regard to attempt of carrying out route choice and routing together, the proposed algorithm does not consider the stochastic and time varying nature of HAZMAT vehicle routing problem. However, in reality, both travel time and population terms in HAZMAT routing are not deterministic values. Extension of the work incorporating such natures of HAZMAT transportation problem would reflect more practical nature of the problem.

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Minimizing Exposure Risk and Travel Times of Hazardous Material Transportation in Urban Areas*

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A HAZMAT vehicle routing problem considering multi-objective requirements and a meta-heuristic solution algorithm is presented in this paper. In contrast to existing studies, an attempt has been made to carry out routing and route choice processes together as a single step process. Pareto-optimal concept using non-dominated paths are utilized, dealing with multiple objectives during both of these processes. An application of the proposed algorithm for solving a test HAZMAT vehicle routing problem is also presented. The set of pareto-optimal solutions obtained provides a number of economical and safe routing solutions, identifying the alternative routing choices in decision-making.
