A Framework for Modeling Freight Railcar Routing Problems with a Time Window

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by

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ABSTRACT

The Vehicle Routing Problems (VRPs) have been extensively studied over the last two decades due to their applications in many logistics, supply-chain, and freight operations. Various extensions of VRPs, such as problems dealing with probabilistic demand, time-window constraint, and multi-depots have been solved in previous works. In this paper we study a special class of VRPs for efficient port shipment operations. We call that problem Freight Railcar Routing Problems with a Time Window (FRRPTW). The FRRPTW s formulated as a mixed-integer programming and constraint programming problem in which the objective function is to minimize the total travel cost and the total delay cost with the constraints of time windows, freight car capacity and demand for ships. A heuristic approach based on Genetic Algorithms (GAs) is presented to solve the problem of obtaining optimal transportation routes that minimizes the total transportation cost. Within the GAs, two modification operators namely, crossover and mutation, are designed specially to solve the optimization problem. An example study is presented using the real-world case of shipping metallurgic coal from the Baltimore harbor to some high demand Asian countries. While the results are quite promising, a sensitivity analysis needs to be conducted in future works to investigate the performance of the algorithm as the problem size grows.

Key-words: vehicle routing problem, genetic algorithm, optimization, vehicle routing problem with time window.

INTRODUCTION

The Vehicle Routing Problems (VRPs) have been extensively studied over the last two decades due to their applications in many logistics, supply-chain, and freight operations. Various extensions of VRPs, such as problems dealing with probabilistic demand, time-window constraint, and multi-depots have been solved in previous works (see for example, Samanta and Jha 2011). In this paper we study a special class of VRPs for efficient port shipment operations. We call that problem Freight Railcar Routing Problems with a Time Window (FRRPTW). The problem is motivated by the recent surge in the coal export through the port of Baltimore due to higher demands for coal in China, India, and other Asian countries. Demand from those countries for high-priced metallurgic coal to fuel steel production has grown so strong that ships are generally backed up south of the Chesapeake bay bridge waiting to gain a berth at one of Baltimore's two privately owned coal terminals, Consol Energy's CNX Marine Terminal in Southeast Baltimore and the CSX facility on Curtis Bay. Last year, consistently, the port exported more than double of its total recorded in 2009. The coals are shipped to the port of Baltimore in freight railcars from neighboring mines in Ohio, Pennsylvania, Virginia, West Virginia and Western Maryland. The shipment has to be quickly loaded up in the queued up ships in order to minimize both the loading delay costs and ship queuing delay cost.

The problem of transporting coal to the Port of Baltimore can be formulated as a Vehicle Routing Problem with Time Window (VRPTW) since coals are shipped from multiple mines via freight railcars to the two port terminals. The real life vehicle routing problem with a larger network primarily has various issues. First, the demands at the customer nodes vary due to various factors, such as locational and temporal seasonal factors. Second, the imperative criterion for any logistics system is to provide the service within a specified time period. Hence, the time window concept is associated with the VRPs. This paper attempts to address the aforementioned pragmatic issues of ports and proposes a novel approach by means of a Genetic Algorithm (GA)-based optimization algorithm as a decision making tool.

The paper is organized as follows: a literature review is presented followed by the methodology, example problem, results and discussion, and conclusions and future works.

LITERATURE REVIEW

(Lin 2001) studied the freight routing problem of time-definite common carriers to minimize the sum of handling and transportation costs, while meeting service commitments and operational restrictions. There are two types of operational restrictions, capacity and directed in-tree rooted at each destination. Directed in-tree implicitly implies that there is a singular path for each origin–destination pair. The routing problem is an integrality constrained multi-commodity problem with side constraints. In addition, two major shortcomings of the LR approach are shown: it may fail to find any feasible solutions even though they exist, and it cannot determine whether the feasible set is empty or not.

(Hall 1987) developed a procedure for deciding whether to route a shipment through an intermediate transportation terminal or route it directly to its destination. The procedure applies to networks with many origins (e.g. 2000) and few destinations (e.g. 20, or vice versa), where each origin is served by exactly one terminal. This decision is difficult because of economies-to-scale in transportation, which cause the cost of routing a shipment through a terminal to depend on the routes chosen for other shipments. The optimization procedure developed here finds the optimal routes graphically with a one-dimensional search, and is sufficiently efficient to be programmed on a hand calculator or personal computer. The procedure also provides insights as to the sensitivity of the optimal solution to changes in model parameters.

(Aykin 1995) considered a hub location and routing problem in which the hub locations and the service types for the routes between demand points are determined together. Rather than aggregating the demand for the services, flows from an origin to different destination points are considered separately. For each origin-destination pair, one-hub-stop, two-hub-stop and, when permitted, direct services are considered. In the system considered, the hubs interact with each other and the level of interaction between them is determined by the two-hub-stop service routes. A mathematical formulation of the problem and an algorithm solving the hub location and the routing subproblems separately in an iterative manner are presented. Computational experience with four versions of the proposed algorithm differing in the method used for finding starting solutions is reported.

(Crainic and Rousseau 1986) examined the freight transportation problem which occurs when the same authority controls and plans both the supply of transportation services (modes, routes, frequencies for the services and classification, consolidation, transfer policies for terminals) and the routing of freight. We present a general modeling framework, based on a network optimization model, which may be used to assist and enhance the tactical and strategic planning process for such a system. The problem is solved by means of an algorithm, described in some detail, based on decomposition and column generation principles. We also present detailed results on the behaviour and performance of the algorithm, as observed during experimentation with a specific rail application.

(M. Gendreau, G. Laporte, and Séguin 1996) proposed a stochastic vehicle routing problem where customers are present at locations with some probabilities and have random demands. A tabu search heuristic is developed for this problem. Comparisons with known optimal solutions on problems whose sizes vary from 6 to 46 customers indicate that the heuristic produces an optimal solution in 89.45% of cases, with an average deviation of 0.38% from optimality.

(Huntley et al. 1995) described fundamental tactical operations along its rails and scheduling trains necessary to service the routes. The computer-aided routing and scheduling system (CARS) bridges the gap between these day-to-day operations and strategic planning. By investigating low-cost routes and schedules in a controlled environment under various cost scenarios, CSX Transportation's strategic planners can better account for these tactical operations in their long-range policies.

(Crainic 2000) explained Tactical planning of operations on a set of interrelated decisions that aim to ensure an optimal allocation and utilization of resources to achieve the economic and customer service goals of the company. Tactical planning is particularly vital for intercity freight carriers that make intensive use of consolidation operations. Railways and less-than-truckload motor carriers are typical examples of such systems. Service Network Design is increasingly used to designate the main tactical issues for this type of carriers: selection and scheduling of services, specification of terminal operations, routing of freight. The corresponding models usually take the form of network design formulations that are difficult to solve, except in the simplest of cases. The paper presents a state-of-the-art review of service network design modeling efforts and mathematical programming developments for network design. A new classification of service network design problems and formulations is also introduced.

(Goetschalckx and Jacobs-Blecha 1989) The Vehicle Routing Problem with Backhauls is a pickup/delivery problem where on each route all deliveries must be made before any pickups. A two-phased solution methodology is proposed. In the first phase, a high quality initial feasible solution is generated based on spacefilling curves. In the second phase, this solution is improved based on optimization of the subproblems identified in a mathematical model of the problem. An extensive computational analysis of several initial solution algorithms is presented, which identifies the tradeoffs between solution quality and computational requirements. The class of greedy algorithms is capacity oriented, while K-median algorithms focus on distance. It is concluded that the greedy and K-median algorithms generate equivalent tour lengths, but that the greedy procedure reduces the required number of trucks and increases the truck utilization. The effect of exchange improvement procedures as well as optimal procedures on solution quality and run time is demonstrated. Comparisons with the Clark—Wright method adapted to backhauls are also given.

(G. Laporte et al. 2000) surveyed heuristics for the *Vehicle Routing Problem*. It is divided into two parts: classical and modern heuristics. The first part contains well-known schemes such as, the savings method, the sweep algorithm and various two-phase approaches. The second part is devoted to tabu search heuristics which have proved to be the most successful metaheuristic approach. Comparative computational results are presented.

(Secomandi 2000) considered a vehicle routing problem where customers' demands are uncertain. The focus is on dynamically routing a single vehicle to serve the demands of a known set of geographically dispersed customers during real-time operations. The goal consists of minimizing the expected distance traveled in order to serve all customers' demands. Since actual demand is revealed upon arrival of the vehicle at the location of each customer, fully exploiting this feature requires a dynamic approach. This work studies the suitability of the emerging field of neuro-dynamic programming (NDP) in providing approximate solutions to this difficult stochastic combinatorial optimization problem. The paper compares the performance of two NDP algorithms: optimistic approximate policy iteration and a rollout policy. While the former improves the performance of a nearest-neighbor policy by 2.3%, the computational results indicate that the rollout policy generates higher quality solutions. The implication for the practitioner is that the rollout policy is a promising candidate for vehicle routing applications where a dynamic approach is required.

(Kleywegt, Nori, and Savelsbergh 2002) studied an inventory routing problem that addresses the coordination of inventory management and transportation. The ability to solve the inventory routing problem contributes to the realization of the potential savings in inventory and transportation costs brought about by vendor managed inventory replenishment. The inventory routing problem is hard, especially if a large number of customers are involved. We formulate the inventory routing problem as a Markov decision process, and we propose approximation methods to find good solutions with reasonable computational effort. Computational results are presented for the inventory routing problem with direct deliveries.

(Fukasawa et al. 2006) presented an algorithm that combines both approaches: it works over the intersection of two polytopes, one associated with a traditional Lagrangean relaxation over q-routes, the other defined by bound, degree and capacity constraints. This is equivalent to a linear program with exponentially many variables and constraints that can lead to lower bounds that are superior to those given by previous methods. The resulting branch-and-cut-and-price algorithm can solve to optimality all instances from the literature with up to 135 vertices. This more than doubles the size of the instances that can be consistently solved.

(Roy and Crainic 1992) pointed out that routing decisions play an important role in managing the operations of LTL motor carriers. They strongly interact with service and terminal operation policy choices and are particularly sensitive to variations in demand. We conducted several studies with large Canadian carriers, using a network optimization based methodology for tactical planning of freight transportation that we developed. We obtained results that illustrate the complexity of the routing decisions and the importance of tactical analysis and planning for the efficiency of intercity freight transportation.

(Alvarenga, Mateus, and De Tomi 2007) studied the Vehicle Routing Problem with Time Windows (VRPTW). This is a well-known and complex combinatorial problem, which has received considerable attention in recent years. This problem has been addressed using many different techniques including both exact and heuristic methods. The VRPTW benchmark problems of Solomon [Algorithms for the vehicle routing and scheduling problems with time window constraints, Operations Research 1987; 35(2): 254–65] have been most commonly chosen to evaluate and compare all algorithms. Results from exact methods have been improved considerably because of parallel implementations and modern branch-and-cut techniques. However, 24 out of the 56 high order instances from Solomon's original test set still remain unsolved. Additionally, in many cases a prohibitive time is needed to find the exact solution. Many of the heuristic methods developed have proved to be efficient in identifying good solutions in reasonable amounts of time. Unfortunately, whilst the research efforts based on exact methods have been focused on the total travel distance, the focus of almost all heuristic attempts has been on the number of vehicles. Consequently, it is more difficult to compare and take advantage of the strong points from each approach. This paper proposes a robust heuristic approach for the VRPTW using travel distance as the main objective through an efficient genetic algorithm and a set partitioning formulation. The tests were produced using real numbers and truncated data type, allowing a direct comparison of its results against previously published heuristic and exact methods. Furthermore, computational results show that the proposed heuristic approach outperforms all previously known and published heuristic methods in terms of the minimal travel distance.

(Fu, Eglese, and Li 2004) studied the open vehicle routing problem (OVRP) is studied, in which the vehicles are not required to return to the depot, but if they do, it must be by revisiting the customers assigned to them in the reverse order. By exploiting the special structure of this type of problem, we present a new tabu search heuristic for finding the routes that minimize two objectives while satisfying three constraints. The computational results are provided and compared with two other methods in the literature.

(M. Iori, Salazar-González, and Vigo 2007) considered a special case of the symmetric capacitated vehicle routing problem, in which a fleet of K identical vehicles must serve n customers, each with a given demand consisting in a set of rectangular two-dimensional weighted items. The vehicles have a two-dimensional loading surface and a maximum weight capacity. The aim is to find a partition of the customers into routes of minimum total cost and such that, for each vehicle, the weight capacity is taken into account and a feasible two-dimensional allocation of the items into the loading surface exists.

(Doerner et al. 2002) proposed a hybrid approach for solving vehicle routing problems. The main idea is to combine an Ant System (AS) with a problem specific constructive heuristic, namely the well known Savings algorithm. This differs from previous approaches, where the subordinate heuristic was the Nearest Neighbor algorithm initially proposed for the TSP. We compare our approach with some other classic, powerful meta-heuristics and show that our results are competitive.

(Kwon, Martland, and Sussman 1998) proposed a freight car scheduling that is taking on a more important role in rail operating plans as more shippers demand trip plan information for their procurement, production and distribution plans, and as railroads pursue operations that are better scheduled and planned. This paper presents several ways to improve current freight car scheduling practices and describes a dynamic freight car routing and scheduling model that can produce more achievable and market-sensitive car schedules. A time–space network representation technique was used to represent car moves on possible sequences of car-to-block and block-to-train assignments on a general-merchandise rail service network. The problem was formulated as a linear multicommodity flow problem; the column generation technique was used as a solution approach. The model was tested on a hypothetical rail network based on the sub-network of a major U.S. railroad.

(Bräysy, Dullaert, and M. Gendreau 2004) surveyed the research on evolutionary algorithms for the Vehicle Routing Problem with Time Windows (VRPTW). The VRPTW can be described as the problem of designing least cost routes from a single depot to a set of geographically scattered points. The routes must be designed in such a way that each point is visited only once by exactly one vehicle within a given time interval. All routes start and end at the depot, and the total demands of all points on one particular route must not exceed the capacity of the vehicle. The main types of evolutionary algorithms for the VRPTW are genetic algorithms and evolution strategies. In addition to describing the basic features of each method, experimental results for the benchmark test problems of Solomon (1987) and Gehring and Homberger (1999) are presented and analyzed.

(Michel Gendreau et al. 2008) addressed the Capacitated Vehicle Routing Problem (CVRP), in the special case where the demand of a customer consists of a certain number of two-dimensional weighted items. The problem calls for the minimization of the cost of transportation needed for the delivery of the goods demanded by the customers, and carried out by a fleet of vehicles based at a central depot. In order to accommodate all items on the vehicles, a feasibility check of the two-dimensional packing (2L) must be executed on each vehicle. The overall problem, denoted as 2L-CVRP, is NP-hard and particularly difficult to solve in practice. We propose a Tabu Search algorithm, in which the loading component of the problem is solved through heuristics, lower bounds, and a truncated branch-and-bound procedure.

(Bräysy and M. Gendreau 2002) surveyed the research on the Tabu Search heuristics for the Vehicle Routing Problem with Time Windows (VRPTW). The VRPTW can be described as the problem of designing least cost routes for a fleet of vehicles from one depot to a set of geographically scattered points. The routes must be designed in such a way that each point is visited only once by exactly one vehicle within a given time interval; all routes start and end at the depot, and the total demands of all points on one particular route must not exceed the capacity of the vehicle. In addition to describing basic features of each method, experimental results for Solomon's benchmark test problems are presented and analyzed.

(Samanta and Jha 2006), and (Samanta and Jha 2011) formulated and solved a Multi Depot Probabilistic Vehicle Routing Problem with Time Window (MDPVRPTW). According to them, previous researchers had approached various components of FRRPTWseparately. The stochasticity in demand, the time window constraint, and the multi-depot scenario were either addressed individually or in the combination of two in most of the cases. As the number of variants increase with the introduction of each component, it becomes difficult to devise an analytical approach to obtain an optimal solution. This might be the reason for the FRRPTW to be unsolved, to date. The earlier works in the area did not address all the three components of the vehicle routing problem together, but in real life problems, they exist together in most cases. Sutapa and Jha (2011) developed an innovative algorithm, which was capable of handling those three components simultaneously and produced reasonable results. The algorithm could be modified and improved further in a future scope of study, but provided a good start to handle the unique problem in vehicle routing problem area at this stage.

Methodology

We formulate the FRRPTW as an extension of the Vehicle Routing Problem with Time Window (VRPTW). It is assumed that the freight railcars start from a common terminus, travel through various mines to pickup the goods from the mines and reach to the final terminus, which is a port, to fill up the ships. There are three logistical parts to this problem. Firstly, the capacities of the freight cars have to be validated during all pickups and the pickup times have to be within certain time windows while minimizing the routing cost or shipment cost. The second part is to minimize the loading delay cost by minimizing the delay time in arrival of the freight cars to the port and the delay time in loading operation. The third part is to meet the demand for each ship within a certain time window so that the waiting time of ships can be minimized. Thus, the methodology consists of developing an optimization model to jointly minimize the shipment cost, loading and ship queuing delay costs. The data for the study is collected from the Port of Baltimore.

The problem is formulated as a mixed-integer programming and constraint programming problem. The objective function is to minimize the total travel cost and the total delay cost with the constraints of time windows, freight car capacity and demand for ships. The notations are given as follows:

Notations for parameters:
$N = \{1,2,\cdots n\}$ set of mines
$M = \{1,2,\cdots m\}$ set of vehicles or freight cars
$K = \{1,2,\cdots k\}$ set of ships
$(a_{i,} b_i) =$ Time window for mine i
$(al_{k,} bl_k) =$ Time window for shipk for loading
$(aq_{k,} bq_k) =$ Time window for ship k for queuing
$q_i =$ Demand of mine i
$q_m =$ Capacity of freight car m
$c_{ij} =$ Cost per unit travel distance
$D_{max} =$ Maximum distance which the vehicles may cover in a tour

Notations for decision variables:
$$x_{ijr} = \begin{cases} 1, \text{if arc ij is part of route r} \\ 0, \text{otherwise} \end{cases}$$
$d_{ij} =$ Distance between customer i and j
$C_w =$ Penalty for the early arriving at the mine
$C_d =$ Penalty for late arriving at the mine

t_i = Actual arrival time at node i
tl_k = Actual loading time of ship k
tq_k = Actual departure time of ship k
w_i = Waiting time at the mine i
d_i = Delay time at the mine i
r = number of routes
q(m) = Total demand picked up by freight car m
C_{load} = Unit cost for loading delay for the ship
C_{queu} = Unit cost for queuing delay for the ship
DT_k = Loading delay time for the ship k
QT_i = Queuing delay for the ship
The total expected cost of the routes formed from multiple depot is calculated considering factors, such as time window, and shortest routes.

Travel time cost

The shortest route set is developed using the GA-based heuristic discussed later this section. The travel time cost is calculated by multiplying the total travel time by the unit travel time cost for each route formed. Total travel time cost is estimated for all the routes

$$T_{total} = \sum_{\forall i} \sum_{\forall j} C_{ij} \cdot d_{ij} \cdot x_{ij} \tag{1}$$

The cost incurred due to the early arrival or delay at i^{th} node is given by

$$C(T_x) = C_w \times w_i \quad or, \quad = C_d \times d_i \tag{2}$$

The loading delay cost for the ship is given by

$$C(DT) = \sum_{k} C_{load} \cdot DT_k \tag{3}$$

The queuing delay cost for the ship is given by

$$C(Q) = \sum_{k} C_{queu} \cdot QT_k \tag{4}$$

The objective function and constraints are given as follows:

$$Minimize\ Z = \sum_{\forall i} \sum_{\forall j} C_{ij} \cdot d_{ij} \cdot x_{ij} + C_w \times \sum_{i} w_i + C_d \times \sum_{i} d_i + \sum_{k} C_{load} \cdot DT_k + \sum_{k} C_{queu} \cdot QT_k \tag{5}$$

subject to

$$q(m) \leq Q_m \quad (m \in M) \tag{6}$$

$$q(m) \leq Q_k \quad (k \in K) \tag{7}$$

$$\sum_i \sum_j d_{ij} \cdot x_{ij} \leq D_{max} \tag{8}$$

$$\sum_i \sum_j x_{ijr} = 1 \quad (j \in N) \tag{9}$$

$$\sum_i \sum_j x_{ijr} \geq 1 \tag{10}$$

$$\sum_i x_{ijr} = \sum_j x_{ijr} \quad (j \in N \cup r, r \in M) \tag{11}$$

$$w_i \geq a_i - t_i \quad (i \in N) \tag{12}$$

$$d_i \geq t_i - b_i \quad (i \in N) \tag{13}$$

$$ld_k \geq al_k - tl_k \quad (k \in K) \tag{14}$$

$$ld_k \geq tl_k - bl_k \quad (k \in K) \tag{15}$$

$$qd_k \geq aq_k - tq_k \quad (k \in K) \tag{16}$$

$$qd_k \geq tq_k - bq_k \quad (k \in K) \tag{17}$$

The objective (Eq. 5) is to minimize the total travel cost embedded with the penalty for the delay and waiting at the node. Constraints (6) and (7) are the maximum capacity of the freight cars and ships (Secomandi 2000), respectively. Equation (8) represents the total demand which consists of capacity of the freight cars. Constraints (9) and (10) impose that every customer belongs to one and only one route or vehicle. Constraint (11) implies that every customer is serviced by the same vehicle. Constraints (12) and (13) are the time window constraints (Jung and Haghani, 2001) for the freight cars. Constraints (14) and (15) are the time window constraints for loading time for the ships .Constraints (16) and (17) are the time window constraints for queuing time for the ships.

A heuristic approach based on Genetic Algorithms is presented to solve the problem of obtaining optimal transportation routes that minimizes the total transportation cost. Within the GAs, two modification operators namely, crossover and mutation, are designed specially to solve the optimization problem. The overview of the GA methodology is shown in Figure 1.

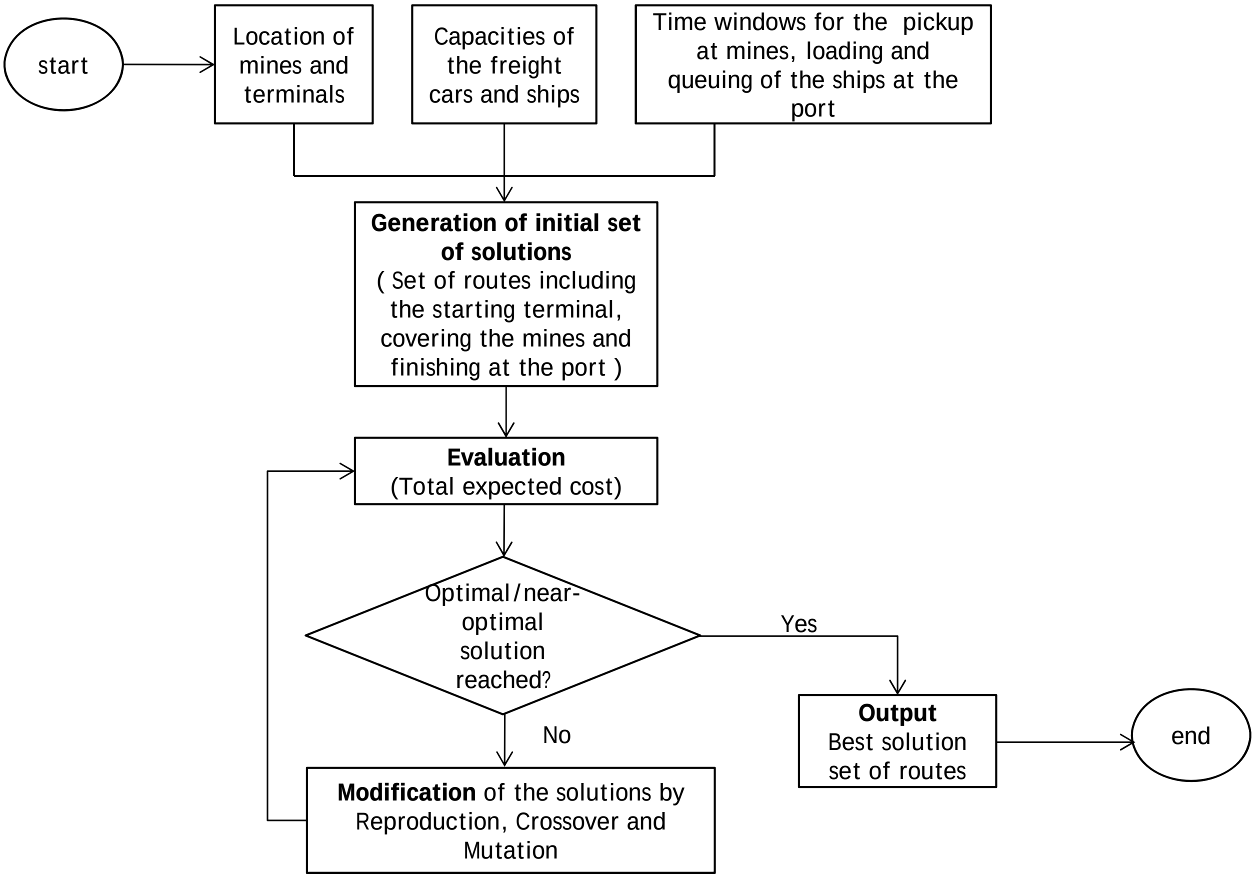

Figure 1: Overview of the proposed methodology

The steps of the algorithm can be summarized as:

I. Generation of initial set of solutions
II. Evaluation
III. Modification

Two special modification operators, namely *Crossover-mutation* and *Mutation-crossover* are developed for the modification scheme, to suit the nature of the problem.

I. Generation of initial set of solutions: The first step presents the procedure for generating the initial solutions. The steps for constructing the initial feasible solution are given below:

Step1. Initial feasible solution set will consist of the routes formed by the freight cars from the starting terminal. Freight cars of varying capacities are assigned to pick up the demands from the mines. Different sets of solutions are generated.

Step 2. Each car starts from the same terminal. It picks up the mine nodes one by one following a nearest neighborhood method.

Nearest Neighborhood method:

The nearest neighborhood method is the simplest method used to order the nodes. In this method, once a node is selected, the node which has the minimum travel time from the previously selected node is selected as the next node from the set of unselected nodes.

As for example, if there are 4 nodes and node 2 is selected randomly as the first node to form a route. The travel times from node 2 to node 1, node 3 and node 4 have to be evaluated. The node with the least travel time is node 4 and will be selected as the next node. The ravel time from node 4 to node 1 and node 3 will be evaluated and the least time is for mode 3 and will be chosen to be the next node. Hence the route formed by Nearest Neighborhood method will be 2-4-3-1.

Step 3. As a vehicle keeps on adding the nodes, the capacity of the car gets exhausted gradually by adding up the demands of the picked up mine nodes.

Step 4. Once the capacity of the car is reached, i.e., it can no longer serve any more nodes, it travels to the port terminal. The time window constraint has to be validated while forming these routes. If the total time for the route set does not fall within the time window, the total delay time or waiting times are calculated and associated with the evaluation of the solution set.

By following the above steps, one initial set of solution is generated. Similarly, *k* initial set of solutions are generated randomly, given by:

$S_i\colon \{mx_{i1}\mathrm{D}_1\mathrm{A}_i\mathrm{B}_i\mathrm{C}_i\mathrm{D}_2\mathrm{x}_{i2}\mathrm{D}_1\mathrm{E}_i\mathrm{F}_i\mathrm{D}_2\mathrm{x}_{i3}\mathrm{D}_1\mathrm{G}_i\mathrm{H}_i\mathrm{I}_i\mathrm{D}_2\}$

$S_j\colon \{mx_{j1}\mathrm{D}_1\mathrm{A}_j\mathrm{B}_j\mathrm{C}_j\mathrm{D}_2\mathrm{x}_{j2}\mathrm{D}_1\mathrm{E}_j\mathrm{F}_j\mathrm{D}_2\mathrm{x}_{j3}\mathrm{D}_1\mathrm{G}_j\mathrm{H}_j\mathrm{I}_j\mathrm{D}_2\}$

:

:

$S_k\colon \{mx_{k1}\mathrm{D}_1\mathrm{A}_k\mathrm{B}_k\mathrm{C}_k\mathrm{D}_2\mathrm{x}_{k2}\mathrm{D}_1\mathrm{E}_k\mathrm{F}_k\mathrm{D}_2\mathrm{x}_{k3}\mathrm{D}_1\mathrm{G}_k\mathrm{H}_k\mathrm{I}_k\mathrm{D}_2\}$

The initial set of solutions is represented by:

$I\colon \{S_i, S_j \cdots S_k\}$

II. Evaluation: After generation of the initial solution sets, the fitness values of the solutions are determined. Fitness value is calculated by the total travel time cost and the penalty values incurred due to the waiting and delay time while picking up the deliveries at the mine nodes, loading and queuing delay costs of the ships at the port. The fitness function is given by Eq. (5).

$$Z = \sum_{\forall i}\sum_{\forall j} C_{ij}\cdot d_{ij}\cdot x_{ij} + C_w \times \sum_i w_i + C_d \times \sum_i d_i + \sum_k C_{load}\cdot DT_k + \sum_k C_{queu}\cdot QT_k$$

III. Modification: The initial set of solutions is modified to result into improved solutions. Various modification schemes such as, Reproduction, Crossover and Mutation are used for this purpose. Two unique operators are designed specially in accordance with the nature of the problem. The operators are i) *Crossover-mutation*, which is applied at the end of the crossover and ii) *Mutation-crossover,* which is applied during mutation.

a) *Reproduction*: Tournament Selection is applied for the reproduction operation. The intent of this operation is to duplicate good solutions and eliminate bad ones from the population. The steps to apply this operator are given below:

Step 1. The value of the tournament selection of size is assumed to be *p* for this purpose.

Step2. The *m* better solutions are chosen from the initial set of solutions based on the fitness ***Step*** function values. The *m* selected solutions are copied n times to develop the mating pool of population size $m \times n$

Step 3. From $m \times n$ population size, *p* solutions are selected.

Step 4. The best of *p* solutions are selected and copied *p* times and kept in the mating pool. Thus, the new mating pool will consist of $\left(\frac{m \times n}{p}\right)$ sets of solutions, each of which contain *p* number of solution sets.

b) *Crossover:* Crossover takes place in a set of two solutions. New solutions are created by exchanging the segments of any two solutions from the mating pool. So, there will be $p/2$ number of crossover operations in a mating pool of *p* solutions. The steps to apply the crossover operator are given below:

Step 1. Two solutions are picked up randomly.

Step 2. A few nodes of one route of one solution set are selected randomly and interchanged with the same number of nodes of a route of another solution. The exchange takes place between the randomly chosen sub routes of two route sets.

Step 3. The selected segments are exchanged provided the constraint of vehicle capacity does not get violated in either case.

Crossover-mutation operator: A new operator called *Crossover-Mutation operator* is designed for the modification scheme while solving the FRRPTW with the GA heuristic. It is a post-crossover operator. After the nodes of the sub routes of two solutions get exchanged in the crossover process, the sub routes except the participating sub routes in the crossover get mutated in order to satisfy the constraint that each node can be visited only once. The already existing nodes which become identical with the newly imported nodes due to crossover are eliminated and the exported nodes are appended to the same sub route. Thus, a modified sub route is generated due to the sudden change made after the crossover.

Mutation**:** Application of the mutation operator is an occasional phenomenon where random modification takes place within the solution. A few of the nodes of one route are exchanged with some other nodes of another route in the same solution set. A completely new route set is developed by this process.

Mutation-crossover operator:

The mutation takes place through intra-solution crossover, hence the name of the operator is proposed as mutation-crossover. The nodes of two sub routes within a solution are exchanged to give rise to two new sub routes. The exchange of information does not take place between two solutions; rather it remains restricted within the same solution. The assignment of the nodes to the depots changes within the same solution. So, the operator can be presented as a special type of mutation operator.

Results and Discussion

A hypothetical example problem is used in this section to demonstrate the concept of the proposed algorithm. Figure 2 shows the sketch of layout and location of the starting point, mines, and port. The problem includes one starting point, eight mines, and one port. Table 1 shows the coordinates of the individual node types. Distance from the nodes, and time needed to traverse is also shown in Table 1. Time to traverse is estimated based on assumed speed of freight rail cars as 60 miles per hour (mph). Time windows for the mines are shown in Table 1. The assumed values of time windows suggest that the freight rail cars are required to reach to the mines in the specified time windows to minimize the delays in loading and queuing. The optimization problem requires in obtaining the optimal value of the objective function (also finding the corresponding decision variables), in such a manner that all the constraints are satisfied.

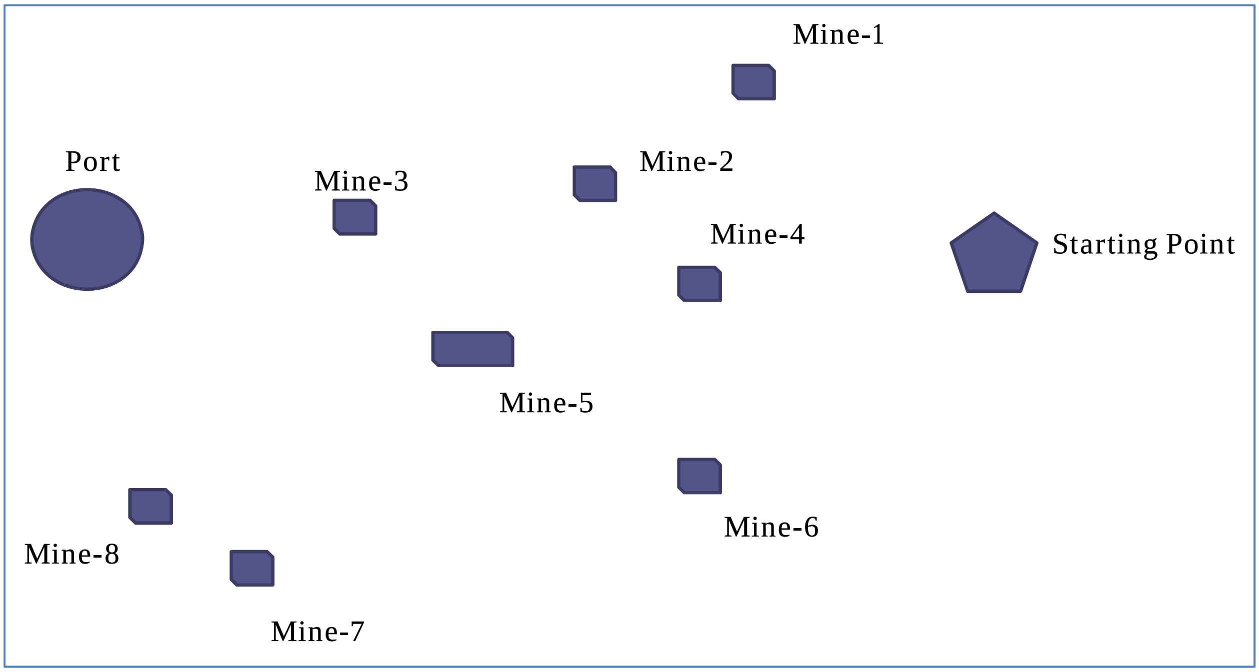

Figure 2: Example Problem

The task was to determine the shortest path from the mine to the port in such a manner that the five components of the objective function should be minimized. The five components consists of minimizing (1) shortest path cost, (2) early arrival penalty, (3) late arrival penalty, (4) loading delay cost, and (5) queuing delay cost satisfying the capacity and time window constraints. Each of the cost terms are shown in equation (5), and described in the methodology section. Other assumed parameters needed for the optimization problem is shown in Table 2.

Table1: Input Data

Node No.	Node	X	Y	Distance From Node (miles)	Time to Traverse (min)	Time Window
1	Port	10.0	60.00			
2	Mine-1	80.0	85.0	28.3	28.3	9:25 - 9:35
3	Mine-2	60.0	75.0	22.4	22.45	10:00 -10:10
4	Mine-3	40.0	65.0	22.4	22.4	9:55 - 10:05
5	Mine-4	70.0	55.0	31.6	31.6	9:15 - 9:25
6	Mine-5	50.0	45.0	22.4	22.4	10:00-10:10
7	Mine-6	70.0	20.0	54.1	54.1	9:45 - 9:55
8	Mine-7	30.0	10.0	41.2	41.2	10:35 - 10:45
9	Mine-8	20.0	20.0	14.1	14.1	10:40 - 10:50
10	Starting Point	100.0	65.0			

Table 2 shows two components in the optimization problem. First, the number of units of freight cars, ships; second, unit values of distance cost, loading, queuing, waiting, and delay cost. Each of the items is described in the methodology section. It should be noted that, the assumed values of the parameters are only used to demonstrate the concept of MDPVRPTW. However, the values may change in a specific case study. For example, the cost for the unit distance traveled (C_{ij}) is $20/mile. Similarly, other parameters C_{load}, C_{que}, C_w, and C_d are shown in Table 2.

Table 2: Parameters for Analysis

Assumption	Numerical Value
# of Ports	1
# of Mines	8
# of Starting points	1
# of freight cars	3
# of ships	2
Speed of freight cars (mph)	40
C_{ij} ($/mile)	20
C_{load} ($/min)	2.50
C_{que} ($/min)	5.00
C_w ($/min)	5.00
C_d ($/min)	1.67

A population size of 10x2, and 1000 generations are used in the genetic algorithm.

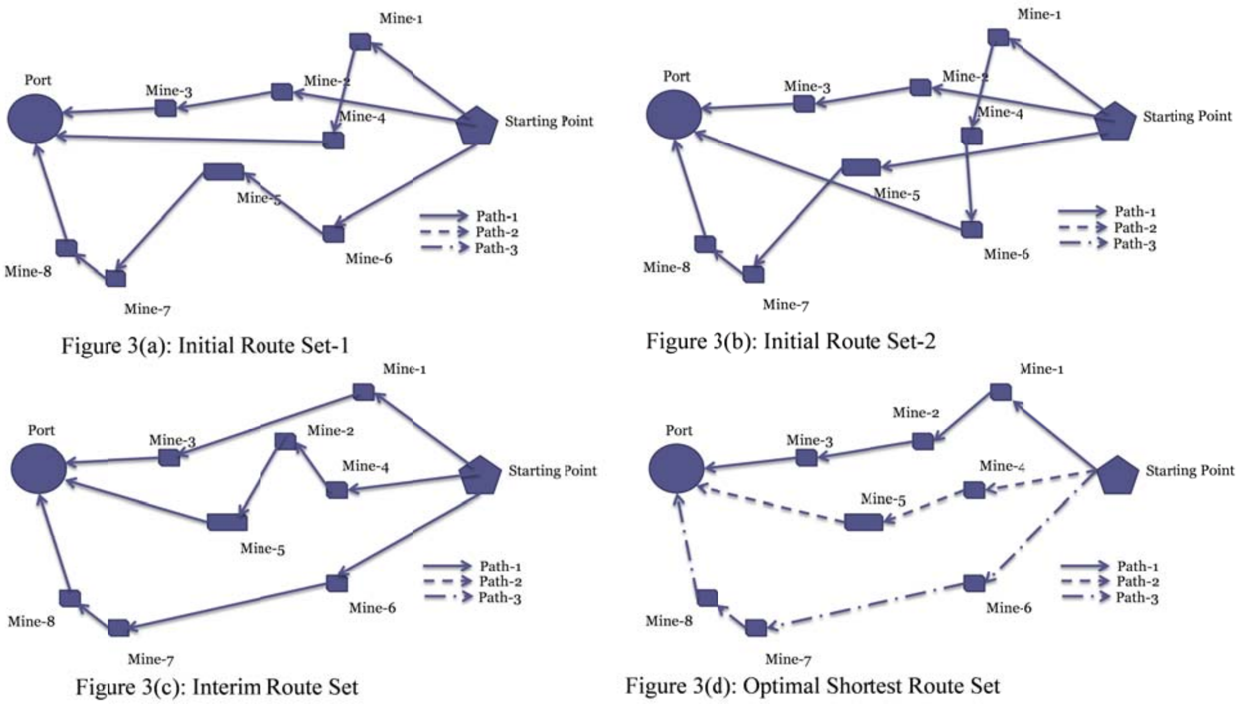

Figure 3(a): Initial Route Set-1

Figure 3(b): Initial Route Set-2

Figure 3(c): Interim Route Set

Figure 3(d): Optimal Shortest Route Set

Figure 3: Different Path Generations

Figure 3 shows different paths generated in the genetic algorithm steps. For example, Figure 3(a), 3(b), and 3(c) shows initial paths generated in the search of optimal value of the objective function. Total costs for route set are shown in Table 3. The first and second column shows route set and path details of the example problem. Path details describe the nodes traversed by the freight railcar from the starting point to the port. The total cost is shown in the last column. For example, the path generation type-1 resulted in total cost of $7, 633.66. Similarly it can be seen that three examples types of path generation sets resulted in higher cost values than the optimal total cost, $7353.71. Only for demonstration purpose, results of three example type sets are presented in Table 3.

Table 3: Path Generation and Total Cost

Example Problem	Path	Path Details	Total Cost ($)
	Path-1	S->1->4->P	
	Path-2	S->2->3->P	
Route Set-1	Path-3	S->6->5->7->8->P	7633.66
	Path-1	S->1->4->6->P	
	Path-2	S->2->3->P	
Route Set -2	Path-3	S->5->7->8->P	8548.70
	Path-1	S->1->3->P	
	Path-2	S->4->2->5->P	
Route Set -3	Path-3	S->6->7->8->P	7490.23
.	.	.	.
.	.	.	.
.	.	.	.
	Path-1	S->1->2->3->P	
	Path-2	S->4->5->P	
Optimal Route Set	Path-3	S->6->7->8->P	7353.71

Note: "S" is the starting point, "P" is the port, numerical values 1 through 8 represent nodes, and "->" represents the forward direction of the path.

The objective function values over all iterations are plotted in Figure 4. The objective values are sorted for plotting purposes and presented to view the decreasing trend. The algorithm searches for the best route in such a manner that the selection of path from the starting point to the port. In the intermediate steps optimization algorithm searches the shortest paths in such a way that the demand for the rail cars are met while minimizing costs involved in loading, queuing, early and late arrival times. The results of the example problem are used to demonstrate the concept of FRRPTW and can be further applied to large real world case study.

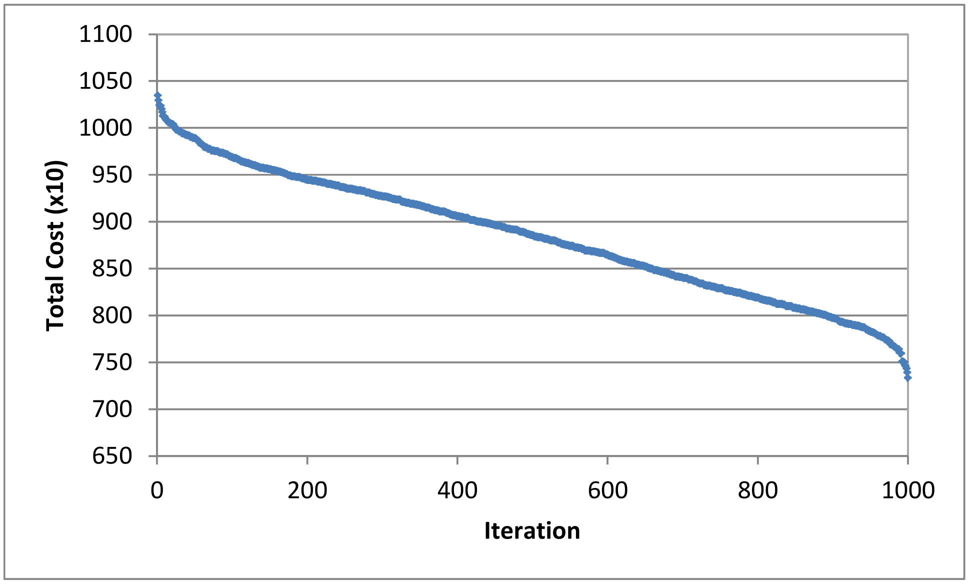

Figure 4: Objective Function Value over all iterations

Conclusions and Future Works

This paper presented is a special class of VRP known as Freight Railcar Routing Problems with a Time Window (FRRPTW). The methodology presented attempts to optimize the transportation and shipment problems simultaneously. The underlying attributes of the FRRPTW were examined and a mathematical formulation of the problem was proposed. A genetic-algorithms based solution framework was presented which seemed promising for the hypothetical case study example presented. The example problem presented in this paper can be considered as a proof of concept of the FRRPTW. I the example problem, various path generation sets and the corresponding total cost results were presented. The heuristic algorithm proposed appears robust in addressing FRRPTW problems. The preliminary results indicate that there may be significant cost savings if adequate paths are selected in such a way that the arrival, loading, and queuing delays are minimized. Adequate planning and optimization techniques are needed to minimize system level delays where time window plays a significant role. The example problem shows large savings when analyzed with the proposed algorithm. The proposed framework can be used for large scale problems of freight railcars when with time windows.

Larger size real-world problems can be studied in future works. Also, various sensitivity analyses can be performed in future works to examine the effects of tighter and more relaxed time windows for loading on the quality of the solution. The values of the coefficients and the parameters can be fine-tuned through further sensitivity analysis.

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