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DINLIP: Model for Integrated Decision, Bound and Time Driven Capacitated Multi Echelon Supply Chain Network

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Abstract

One of the important extensions of the classical resource allocation problem is Integrated Resource Allocation and Routing Problem with Bound and Time Window (IRARPBWTW). The base variant of IRARPBWTW is vehicle routing problem with backhauls and time windows. IRARPBWTW problem focuses on finding the optimal allocation and routing for the vehicles with the objective of minimizing the total distance by considering the constraints on time windows and bound on resource by covering delivery service during the linehaul and the collection / pick-up service during the backhaul. We have developed a unified model Decision Support System based on Mixed Integer Linear Programming (DINLIP) to solve VRPTW and IRARPBWTW. Model DINLIP was tested for benchmark datasets of VRPTW and derived datasets of IRARPBWTW and yielded encouraging results.

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1. Introduction

One of the important extensions of the classical RA problems in the context of integrated decision, bound and time driven capacitated multi echelon supply chain network is Vehicle Routing Problem with Backhauls and Time Windows (VRPTW). The VRPTW, which simultaneously considers the operational sequence of delivery and pickup as well as the service time interval of customers, is an
extensive variant of the classical Vehicle Routing Problem (VRP). The VRPBTW involves two different subsets of customers known as linehauls and backhauls. A linehaul customer requires a given quantity of goods from a central depot, whereas a given quantity of goods is collected from a backhaul customer and brought back to the depot. Moreover, the backhauls must be visited after the linehauls in each route. Additionally, each customer must be serviced within a specified time interval (or time window). The lower and upper bounds of the time window define the earliest and latest time for the beginning of service at the customer. Hence, a vehicle is not allowed to begin service at a customer location after its time window’s upper bound. Furthermore, a waiting time is incurred if a vehicle reaches a customer before the lower bound. Each customer also has a specified maneuvering time which is the time spent by the vehicle to load or unload the goods. The total route time of a vehicle is the sum of travel time (which is proportional to the distance travelled), waiting time and maneuvering time.

The first objective of the VRPBTW is to minimize the fleet size (i.e., number of vehicles). Then, for the same fleet size, minimize the total routing time to service all customers, without violating the capacity of each vehicle and the time windows of each customer. This is addressed by very few researchers and limited solution methodologies are proposed for this variant. The variant considered in this chapter is in the context of integrated decision, bound and time driven capacitated multi echelon supply chain network and one of the classical RA problems and it is an extension of VRPBTW with the consideration of constraints on bound on resource by covering delivery service during the linehaul and the collection / pick-up service during the backhaul.

2. Literature Review

The Vehicle Routing Problem with Backhauls (VRPB), also known as the linehaul-backhaul problem, is an extension of the VRP involving both delivery and pickup points. Linehaul (delivery) points are sites that are to receive a quantity of goods from the single Distribution Centre (DC). Backhaul (pickup) points are sites that send a quantity of goods back to the DC. The critical assumption is that all deliveries must be made on each route before any pickups can be made. This arises from the fact that the vehicles are rear-loaded, and rearrangement of the loads on the trucks at the delivery points is not deemed economical or feasible. The quantities to be delivered and picked up are fixed and known in advance. The vehicle fleet is assumed to be homogeneous, each having a capacity of some weight or volume. Hence, a feasible solution to the problem consists of a set of routes where all deliveries for each route are completed before any pickups are made and the vehicle capacity is not violated by either the line haul or backhaul points assigned to the route. The objective is to find such a set of routes that minimizes the total distance traveled.

More formally, the VRPBTW involves the design of a set of pickup and delivery routes, originating and terminating at a depot, which services a set of customers. Each customer must be supplied exactly once by one vehicle route during her service time interval. The total demand of any route must not exceed the vehicle capacity. The total length of any route must not exceed a pre-specified bound. Additionally, it is required that, on each route, all linehauls have to be performed before all backhauls. The intuition for that is, that rearranging goods en route is costly and inefficient. The objective is to minimize the fleet size, and given a fleet size, to minimize operating costs. This problem is a generalization of the VRP, which is known to be NP-hard, such that exact methods like Branch and Bound work only for relatively small problems in reasonable time.

Applications of the VRPBTW arise in public and private sectors that manufacture goods requiring delivery to be made to customers and raw materials to be picked up from distributors, such as retail
distribution, airline scheduling, railway fleet routing and scheduling. The efficient routing of vehicles for both linehaul and backhaul customers can save the public and private sectors millions of dollars per year.

Thangiah et al (1996) developed a route construction heuristic for the VRPBTW, as well as different local search heuristics to improve the initial solutions. The heuristics were tested on 45 problems of size 25, 50 and 100 previously reported in the literature and whose optimum is known in most cases. In addition, the heuristic was tested on 24 newly created problems of size 250 and 500. Reimann et al (2002) presented and analyzed the application of an Ant System to the Vehicle Routing Problem with Backhauls and Time Windows (VRPBTW). At the core of the algorithm they used an Insertion procedure to construct solutions. Zhong and Cole (2005) presented a guided local search heuristic to solve a vehicle routing problem with backhauls and time windows. They considered VRPBTW both with and without customer precedence. Braysy and Gendreau (2002) presented and analyzed the experimental results for Solomon’s benchmark test problems. Raymond and Hang (2003) considered the class of vehicle routing problems with backhauls and time window constraints. They formulate the problem in the framework of label matching where the labels have multiple attributes representing the states of vehicles at customer locations or possible routes that vehicles may continue to cover. They developed two optimization-based heuristics. Dethloff (2002) investigated As a result of the analysis of the relation between both problem types the possibility of solving the VRPBM by applying an insertion heuristic based on the concept of ‘residual capacities’ originally designed for the VRPSDP.

Wade and Salhi (2002) presented a new version of the vehicle routing problem with backhauls. In this new problem backhauls are not restricted to be visited once all linehaul customers have been served, neither are backhaul customers fully mixed with linehaul customers. An insertion-type heuristic is put forward for this class of problems. An analysis of the improvement in route cost obtained by allowing a relaxation in the restriction of the mix of linehaul and backhaul customers is reported. Zachariadis and Kiranoudis (2011) deals with a practical transportation model known as the Vehicle Routing Problem with Backhauls (VRPB), which aims at designing the minimum cost route set for satisfying both delivery and pick-up demands. They proposed a local search metaheuristic which explores rich solution neighborhoods composed of exchanges of variable-length customer sequences. They tested their proposed metaheuristic on well-known VRPB benchmark instances. Jose Branda (2006) presented a new tabu search algorithm that starting from pseudo-lower bounds was able to match almost all the best published solutions and to find many new best solutions, for a large set of benchmark problems. Goetschalckx and Blecha (1989) proposed a two-phased solution methodology. In the first phase, a high quality initial feasible solution is generated based on space filling curves. In the second phase, this solution is improved based on optimization of the sub problems identified in a mathematical model of the problem. They presented an extensive computational analysis of several initial solution algorithms. 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.

Anbuudayasankar et al (2012) developed three heuristics to solve BVFB. Two heuristics are modified savings heuristics and the third heuristic is based on adapted genetic algorithm (GA). Standard data sets of VRPB of real life cases for BVFB and randomly generated datasets for BVFB are solved using all the three heuristics. Tavakkoli et al (2006) proposed a memetic algorithm (MA) which uses different local search algorithms to solve the VRPB. Exploiting power of memetic algorithm, inter and intra-route node exchanges are used as a part of this evolutionary algorithm. Extensive computational tests on some instances taken from the literature reveal the effectiveness of the proposed algorithm. Toth and Vigo (1999) considered an extension of the capacitated Vehicle Routing Problem (VRP), known as the
Vehicle Routing Problem with Backhauls (VRPB), in which the set of customers is partitioned into two subsets: Linehaul and Backhaul customers. They presented a cluster-first-route-second heuristic which uses a new clustering method and may also be used to solve problems with asymmetric cost matrix. The approach exploits the information of the normally infeasible VRPB solutions associated with a lower bound. The bound used is a Lagrangian relaxation previously proposed by the authors. The final set of feasible routes is built through a modified Traveling Salesman Problem (TSP) heuristic and inter-route and intra-route arc exchanges. Extensive computational tests on symmetric and asymmetric instances from the literature show the effectiveness of the proposed approach. Tutuncu et al (2009) presented a new visual interactive approach for the classical vehicle routing problem with backhauls (VRPB) and its extensions. The classical VRPB is the problem of designing minimum cost routes from a single depot to two type customers that are known as Backhaul (pickup) and Linehaul (delivery) customers where deliveries after pickups are not allowed. The mixed VRPB is an extension of the classical VRPB where deliveries after pickups are allowed. They developed a decision support system (DSS) in order to solve the classical VRPB, mixed VRPB and the restricted VRPB, which is a compromise problem between the classical VRPB, and the mixed VRPB. And they described the visual interactive approach that is based on Greedy Randomised Adaptive Memory Programming Search (GRAMPS). Zachariadis and Kiranoudis(2012) proposed a local search metaheuristic which explores rich solution neighborhoods composed of exchanges of variable-length customer sequences. They introduced the concept of promises, which a parameter-free mechanism is based on the regional aspiration criterion used in Tabu Search implementations.

3. Integrated Resource Allocation and Routing Problem with Bound and Time Window

This is a new variant which is not addressed by previous researchers in the literature and the variant is termed as Integrated Resource Allocation and Routing Problem with Bound and Time Window (IRARPBtw). The base variant of IRARPBtw is VRPBtw. The idea for this variant IRARPBtw is based on Figliozzi (2009). The objective of the problem is to find the optimal allocation and routing for the vehicles with the objective of minimizing the total distance by considering the constraints on time windows and bound on resource by covering delivery service during the linehaul and the collection / pick-up service during the backhaul.

The following assumptions apply.

- All routes start and end at the node of origin, also known as depot
- Each node in N is visited exactly once and served within its time window
- Demand at any node shall never exceed the vehicle capacity Q
- All vehicles have the same capacity and are stationed at the node of origin
- Split delivery is not permitted
- Each vehicle makes exactly one trip
- All delivery quantities are loaded at the depot; all quantities picked up must be unloaded at the depot
- If a node requires both delivery and pick-up, delivery precedes pick-up
- Every route should start with a pure delivery node, cover a mix of delivery and delivery and pick-up nodes and finally include pure pick-up nodes, if required
- Delivery and delivery and pick-up nodes should precede pick-up nodes in every route.
- No route shall comprise pick-up nodes exclusively

A vehicle may arrive at a node ahead of its earliest time but must not reach a node after its latest time.

4. Solution Methodology to solve IRARPBtw
A unified solution methodology is developed to solve VRPBTW and IRARPBTW.

- Decision Support System based on Mixed Integer Linear Programming (DINLIP) Model is proposed to solve VRPBTW and IRARPBTW.

### 4.1 Decision Support System Based on Mixed Integer Linear Programming (DINLIP) For VRPBTW and IRARPBTW

Decision Support System Based on Mixed Integer Linear Programming (DINLIP) is developed for IRARPBTW. The notations for this mathematical model are given below:

Notations

- \( G \) = Symmetric graph; \( G = (T, E) \)
- \( T \) = Set of node; \( T = [N \cup \{0, n + 1\}] \)
- \( E \) = Set of arcs linking any pair of node; \((i, j) \in E\)
- \( D \) = Set of delivery nodes
- \( P \) = Set of pickup nodes
- \( DP \) = Set of delivery and pick-up nodes
- \( N \) = Total number of nodes, \( = D + DP + P \)
- \( n \) = \( \{1, 2, \ldots, N\} \); \( n = 0 \), denotes depot
- \( V \) = Total number of vehicles; \( V = \{1, 2, \ldots, V\} \)
- \( c_{ij} \) = cost of travel from node i to node j
- \( d_i \) = Delivery requests of node i
- \( p_i \) = Pickup requests of node i
- \( Q \) = Capacity of vehicle
- \( e_i \) = Earliest arrival time of node i
- \( l_i \) = Latest arrival time of node i
- \( D_{iv} \) = The load remaining to be delivered by vehicle v when departing from node i
- \( P_{iv} \) = The cumulative load picked up by vehicle v when departing from node i
- \( T_{iv} \) = The starting time of the service of the vehicle v at node i
- \( Y_{iv} \) = The total load picked up along the route by vehicle v, up to and including node i, carried along arc \((i, j)\)
- \( Z_{iv} \) = The total load on vehicle v, to be delivered to nodes carried along arc \((i, j)\)

\( p_i, d_i, Q, c_{ij} \) are non-negative integers

Decision Variable

\[
X_{iv} = \begin{cases} 
1 & \text{if the vehicle v travels directly from i to j,} \\
0 & \text{otherwise;}
\end{cases}
\]

**Note:**
(i) The distance matrix $y_{ij}$ satisfies triangular inequality.

(ii) Load picked up on a route cannot be used to satisfy delivery requirements in the same route.

(iii) The sum of the loads picked up and the quantities remaining to be delivered must not exceed the vehicle capacity at any node in a path.

Formulation

Minimize $\sum_{v=1}^{V} \sum_{i=0}^{N} \sum_{j=0}^{N} y_{ij} X_{ijv}$ \hspace{1cm} (1)

Subjected to

\[ \sum_{v=1}^{V} \sum_{j=1}^{T} X_{ijv} = 1 \hspace{1cm} \forall i = 1, \ldots, N \] \hspace{1cm} (2)

\[ \sum_{i=1}^{T} X_{ipv} - \sum_{j=1}^{T} X_{pjv} = 0 \hspace{1cm} \forall p = 1, \ldots, N \text{ and } \forall v = 1, \ldots, V \] \hspace{1cm} (3)

\[ \sum_{j=1}^{N} X_{ojv} \leq 1 \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (4)

\[ \sum_{i=1}^{N} X_{iov} \leq 1 \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (5)

\[ Y_{ij} + \sum_{j=1}^{N} P_{jv} X_{ijv} = \sum_{m=1}^{N} Y_{jmv} \hspace{1cm} \forall i = 1, \ldots, N \text{ and } j = 1, \ldots, N \text{ and } \forall v = 1, \ldots, V \] \hspace{1cm} (6)

\[ Z_{ij} - \sum_{j=1}^{N} D_{jv} X_{ijv} = \sum_{m=1}^{N} Z_{jmv} \hspace{1cm} \forall i = 1, \ldots, N \text{ and } j = 1, \ldots, N \text{ and } \forall v = 1, \ldots, V \] \hspace{1cm} (7)

\[ \sum_{i=1}^{N} X_{i(v+1)} - \sum_{j=1}^{N} X_{ojv} = 0 \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (8)

\[ D_{iv} + P_{iv} \leq Q \hspace{1cm} \forall i = 1, \ldots, T \text{ and } \forall v = 1, \ldots, V \] \hspace{1cm} (9)

\[ D_{(v+1)v} = 0 \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (10)

\[ D_{ov} = \sum_{i=1}^{T} \sum_{j=1}^{N} X_{ijv} d_i \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (11)

\[ P_{(v+1)v} = \sum_{i=1}^{N} \sum_{j=1}^{N} X_{ijv} P_i \hspace{1cm} \forall v = 1, \ldots, V \] \hspace{1cm} (12)
\[ P_{ov} = 0 \quad \forall v = 1,\ldots,V \]  
\[ P_{iv} - P_{jv} + p_j + Q(X_{iv} - 1) \leq 0 \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  
\[ P_{iv} - P_{jv} + P_j + Q(X_{iv} - 1) \geq 0 \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  
\[ D_{iv} - D_{jv} + d_j + Q(X_{iv} - 1) \leq 0 \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  
\[ D_{iv} - D_{jv} + d_j + Q(X_{iv} - 1) \geq 0 \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  
\[ T_{iv} - T_{jv} + t_{ij} - (1 - X_{iv})M \geq 0 \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  
\[ Y_{iv} + Z_{iv} \leq QX_{iv} \quad \forall v = 1,\ldots,N, \quad j = 1,\ldots,N \text{ and } v = 1,\ldots,V \]  
\[ D_{iv} \geq 0 \quad \forall i = 1,\ldots,T \text{ and } v = 1,\ldots,V \]  
\[ P_{iv} \geq 0 \quad \forall i = 1,\ldots,T \text{ and } v = 1,\ldots,V \]  
\[ e_i \leq T_i \leq l_i \quad \forall i = 1,\ldots,T \text{ and } v = 1,\ldots,V \]  
\[ X_{iv} \in \{0,1\} \quad \text{and integer} \quad \forall v = 1,\ldots,V, \quad i = 1,\ldots,T \text{ and } j = 1,\ldots,T \]  

The objective function (1) seeks to minimize the total cost of travel. Constraint (2) stipulates that each node must be visited by exactly one vehicle. (3) ensures that the vehicle entering and leaving each node is the same. (4), (5) and (8) ensure that each vehicle is used, at most, once. (3), (4), (5) and (8) pertain to the flow; they require each vehicle to leave the depot (node 0), at most, once, to leave the node p only if it has been visited and to return to the depot (node n+1), at most, once. (6) and (7) and (8) restrict the fluctuations in the load on the vehicles. (9) ensures that the load on vehicle v, when departing from node i, is always lower than the vehicle capacity. (11) and (13) require that the total delivery load for a route is placed on the vehicle, embarking on each trip, at the starting node itself. They also ensure that nodes requiring pick-up alone are not visited without completing all the deliveries. (10) and (12) ensure that all the quantities to be delivered by each vehicle have been unloaded at the concerned nodes and that all loads have been picked up by every returning vehicle. (14), (15), (16) and (17) represent the following: if arc (i, j) is visited by vehicle v, then the quantity to be delivered by the vehicle has to decrease by d_j while the quantity picked-up has to increase by p_j. (18) ensures that if vehicle v travels through arc (i, j), then the time at which service started at node j, will be greater than or equal to the time at which service started at node i plus the time to travel from i to j. This constraint allows for waiting time at each node if the service time window is not open. (19) states that vehicle load must not exceed capacity. (22) sets the time window for each node i.

5. Computational Experiments and Results

The heuristics are coded in C and run on a PC Pentium IV 1.70 GHz processor. Current literature does not contain datasets or problems for IRARPB7TW. Hence all the heuristics are tested first on VRPB7TW that
are reported in VRP literature. The evaluation is then extended to data-sets derived from those available for IRARPBTW. The heuristic is tested on 9 standard VRPBTW data-sets and 25 derived IRARPBTW data-sets, size ranging from 25 to 100 nodes.

5.1 Performance of Heuristics

The number of nodes, the best-known solution value reported in the literature, the solution obtained by the construction heuristic, the solution and the CPU time for all heuristics are reported for all data-sets. A statistic called Relative percentage Deviation (RD) is calculated for each solution as follows:

\[
RD = \frac{(\text{Obtained solution} - \text{Optimal or Best known solution})}{\text{Optimal or Best known solution}} \times 100
\]

An average of the RD's is then calculated for the best solutions and presented at the end of each table. As can be seen from the Tables, computing times are low enough to allow the execution of the heuristic on a daily basis.

**VRPBTW data-sets:**

For the VRPBTW, DINLIP was tested on the data sets of Gelinas et al. (1995) who modified the first five problems of Solomon’s (Solomon, 1987) R1 data set by randomly choosing 10%, 30%, and 50% of the clients as backhaul nodes, leaving the other attributes unchanged. A total of 12 test problems were used for the VRPBTW with precedence constraints. Kontoravdis and Bard, (1995) stated the following characteristics for the data-sets:

- For R1, the nodes are scattered uniformly in two-dimensional space.
- R1 has a short scheduling horizon and a vehicle capacity of 200 units.
- The time window constraints in problem set R1 severely restrict the number of nodes that can be served by each vehicle; as a result, vehicle capacity constraints hardly have any bearing on the solution. The results reported in Table 1 for DINLIP. Three measures of performance, viz., number of vehicles, total distance traveled, and CPU time are shown in the Table 1.
Table 1. Comparison of Heuristics with Best Known Solution Value of VRPBTW Problems Derived from VRPTW R101 and R102 Data-sets

<table>
<thead>
<tr>
<th>Set</th>
<th>Number of Nodes</th>
<th>Pick-up %</th>
<th>Optimal Solution</th>
<th>Number of Vehicles</th>
<th>Solution of DINLIP</th>
<th>CPU</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>10</td>
<td>643.4</td>
<td>9</td>
<td>643.4</td>
<td>0.8</td>
</tr>
<tr>
<td>R101</td>
<td>25</td>
<td>30</td>
<td>711.1</td>
<td>9</td>
<td>711.1</td>
<td>1.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td>50</td>
<td>674.5</td>
<td>10</td>
<td>674.5</td>
<td>1.9</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>10</td>
<td>1122.3</td>
<td>13</td>
<td>1122.3</td>
<td>2.4</td>
</tr>
<tr>
<td></td>
<td></td>
<td>30</td>
<td>1191.5</td>
<td>16</td>
<td>1191.5</td>
<td>3.7</td>
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<td>16</td>
<td>1168.6</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td></td>
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<td>7</td>
<td>563.5</td>
<td>2.57</td>
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<td>622.3</td>
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<tr>
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<td></td>
<td>50</td>
<td>10</td>
<td>974.7</td>
<td>12</td>
<td>974.7</td>
<td>6.57</td>
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<td></td>
<td></td>
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<td>14</td>
<td>1024.8</td>
<td>7.62</td>
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<td>1057.2</td>
<td>14</td>
<td>1057.2</td>
<td>10.04</td>
</tr>
</tbody>
</table>

**IRARPBTW data-sets:**

Simultaneous delivery and pick up and pure pick-up on the VRPTW data-sets of Solomon, (1987) are superimposed. While the delivery quantities \( d_i, i = 1, ..., n \) given in the data-sets are used directly, the pick-up demands \( p_i, i = 1, ..., n \) are generated randomly as follows:

\[
P_i = \begin{cases} 
[(1 - \alpha) d_i] & \text{if } i \text{ is even} \\
[(1 + \alpha) d_i] & \text{if } i \text{ is even} 
\end{cases}
\]

20% of the nodes are allowed to have simultaneous delivery and pick-up nodes while 10% of nodes are permitted to have pure pick-up. Here, the best solutions reported for VRPTW are taken as lower bounds. The results are shown in Table 2.
Table 2. Comparison of DINLIP with 25 Derived Datasets of IRARPBTW from Solomon (1987) with the lower bound of Solomon (1987)

<table>
<thead>
<tr>
<th>Data-set</th>
<th>N</th>
<th>LB*</th>
<th>DINLIP</th>
<th>RD</th>
<th>CPU</th>
</tr>
</thead>
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<tr>
<td>c101</td>
<td>100</td>
<td>827.3</td>
<td>991.33</td>
<td>19.83</td>
<td>11.23</td>
</tr>
<tr>
<td>c102</td>
<td>100</td>
<td>827.3</td>
<td>997.57</td>
<td>20.58</td>
<td>11.22</td>
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<tr>
<td>c103</td>
<td>100</td>
<td>826.3</td>
<td>989.27</td>
<td>19.72</td>
<td>12.44</td>
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<tr>
<td>c104</td>
<td>100</td>
<td>822.9</td>
<td>995.91</td>
<td>21.02</td>
<td>11.17</td>
</tr>
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<td>c105</td>
<td>100</td>
<td>827.3</td>
<td>999.65</td>
<td>20.83</td>
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<td>c106</td>
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<td>827.3</td>
<td>1001.73</td>
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<td>990.29</td>
<td>19.70</td>
<td>13.56</td>
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<td>827.3</td>
<td>1005.89</td>
<td>21.59</td>
<td>13.01</td>
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<td>r101</td>
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6. Conclusion

This paper has addressed two variants VRPBTW and IRARPBTW. For this non-deterministic polynomial (NP)-hard problem, we have developed unified heuristic DINLIP as solution methodology. The DINLIP heuristic is tested for standard benchmark datasets of VRPBTW and derived datasets of IRARPBTW. The sizes of the datasets are in the range of 25 to 100 nodes. When compared with the best results reported so far for VRPBTW data sets, DINLIP has performed equally competitive both in terms of solution quality and computational time. The heuristic DINLIP was tested using publicly available sets of benchmark problem for VRPBTW and derived datasets of IRARPBTW from VRPBTW datasets.

When compared with the lower bound of VRPBTW datasets for the derived IRARPBTW data sets, DINLIP has performed with the deviation of 21.68% in terms of solution cost and equally competitive in terms of solution computational time. The average deviation for each data-set clearly indicates that DINLIP have performed well on the data-sets of VRPBTW and IRARPBTW. In fact, out of 9 cases, the
DINLIP yields equivalent solutions for all instances with reasonable computational time. The overall findings seem to justify the employment of DINLIP in general, as suitable techniques for solving the VRPB_TW and IRARP_TW. For the IRARP_TW data-sets derived from standard VRPTW sets, we evaluated the results, treating those of the latter as lower bounds.

We had also conducted a case study for IRARP_TW and the results are compared. The critical contribution of the research is the development of unified DINLIP to solve both VRPB_TW and IRARP_TW. Further research may consider constraints on precedence and time windows of nodes in both VRPB_TW and IRARP_TW. The future scope also includes development of analyst’s tool-kit for finding quick and effective solutions and can be embedded into Decision Support Systems (DSS). The incorporation of “What If” rules in a DSS along with the software for the heuristic is a potential way forward.

References


