A Pick-up and Delivery Problem with Time Windows by Electric Vehicles

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Abstract: The Pickup and Delivery Problem with Time Windows (PDPTW) is a Vehicle Routing Problem with Time Windows (VRPTW) in which each customer, together with a demand and a time window for the service, specifies also an origin (pickup) and a destination (delivery). Our work mainly extends the PDPTW to the case in which the fleet consists of electric vehicles (E-PDPTW), in order to exploit their significant advantages in terms of energy saving and sustainability. The E-PDPTW is then modeled as a multi-objective optimization problem in order to minimize the total travel distance, the total cost due to the used electric vehicles and the penalties due to the delayed services. In addition, beyond the classical vehicle routing constraints, in order to consider the practical difficulties due to the limited battery life of the electric vehicles (EVs) and to the poor availability of the recharging stations, some additional constraints are also imposed. The problem is then formulated as a multi-objective mathematical programming model and solved by applying the Weighted Sum Method (WSM) with weights determined by an approach derived from the Analytical Hierarchical Process (AHP).

Purpose

What are the reason(s) for writing the paper or the aims of the research?

The main goal of this research is to address a problem that presents many significant and relevant impacts, among the others: a reduction of the polluting emissions thanks to the use of EVs (environmental sustainability); an optimized delivery of door-to-door transportation services to the citizens and, in particular, to the elderly and disabled people (social sustainability) and finally, significant reductions in the use of fossil-fuel and considerable energy savings (economic sustainability).

Design/methodology/approach

How are the objectives achieved? Include the main method(s) used for the research. What is the approach to the topic and what is the theoretical or subject scope of the paper?

Starting from the state-of-art, a multi-objective mixed integer linear formulation of the E-PDPTW is proposed with the aim to minimize the total travel distance, the total cost due to the used electric vehicles and due to the penalties for the delayed services. From a methodological point of view, the WSM is adopted in order to have a unique objective function, expressed as weighted sum of the above cited terms. In addition, in order to properly set the weights, a method, derived from the AHP, is proposed. Beyond the classical PDPTW constraints, additional conditions are imposed with reference to the use of EVs such as an upper bound on the total distance of each route. The final solution is then expressed in terms of both the optimal routes and the charging stations used in each of them.

Originality/value

What is new in the paper? State the value of the paper and to whom.

The originality of the work consists in introducing the use of the EVs in the context of the multi-objective PDPTW. Moreover, the paper analyzes the routing problem of the EVs taking into consideration also the recharging stations, topic recently investigated in literature by very few researchers.

Keywords: Pickup and Delivery Problem, Electric Vehicle Routing, Multi-objective Mathematical Programming, Weighted Sum Method, Analytical Hierarchical Process.
1. Introduction

The Vehicle Routing Problems (VRPs) represent one of the widely studied classes of combinatorial optimization problems and basically aim to efficiently manage the vehicles used for delivering goods/services to the customers. With that, the transportation activities of a company, that usually considerable impact on the total costs, can be optimized. In literature, several variants exist but all of them share the idea that a set of vehicles (or only one), based at the depot, have to deliver services to the customers. They are then modelled by a directed graph $G = \langle V,A \rangle$, where $V$ that denotes the nodes where the customers and the depot are placed. $A$ and $E$ are the set of arcs and edges, respectively. On the contrary of the edges, the arcs denote one-way roads. We refer the readers to Kumar and Panneerselvam (2012) for a detailed review on the VRPs. The aim is to find a set of routes, tours on $G$, each of them, assigned to one vehicle, starts/ends from/to the depot, in order to minimize an objective function (the total transportation cost, for example). The problem is solved under unique assignment constraints (i.e., each customer handled by exactly one vehicle) and flow conservation conditions for the intermediate nodes (except for the depot). If the vehicles present a limited cargo capacity, the VRP becomes a Capacitated-VRP (CVRP).

The VRPTW, instead, beyond the traditional CVRP constraints, introduces also time controls since each customer, together with a demand, establishes also a time window for receiving the service. This work addresses a variant of the CVRPTW that is the PDPTW under the assumption that the fleet consists of EVs. The PDPTW handles a set of requests, expressed in terms of couples (pickup and delivery). Let $n$ denote the number of requests to satisfy. The PDPTW is defined on a directed graph $G = \langle V,A \rangle$ where $V = \{0, \ldots, 2n+1\}$, Nodes 0 and $2n+1$ represent the depot and the dummy depot (usually introduced for modelling reasons, see Ropke and Cordeau, 2009) while subsets $P$ and $D$ denote the pickup and the delivery nodes, respectively. Thus, each pickup node $i$ is associated to a delivery node $dev_i$.

The vehicles are based at the depot ($0$) and $|P|=|D|=n$. Each pickup $p$, characterized by a demand $q_p>0$, is associated to one delivery $d$ such that $q_d = q_p$. Moreover, each request $r$ (either of picking or delivering) has a service time $s_r$ and imposes a time window $[a_r,b_r]$ within the service has to be performed (hard time window constraints). If a tolerance is accepted, the problem presents soft time window constraints. The fleet is usually homogeneous such as all the vehicles have the same cargo capacity $Q$. For each couple $(i,j)$, $i \neq j$ and $i,j \in V$, $d_{ij}$ denotes the spatial distance while $t_{ij}$, the time distance. In many realistic applications, it could be convenient to pre-process data in order to reduce the number of arcs. In particular, if a couple $(i,j)$, $i \neq j$ and $i,j \in V$ does not satisfy the condition $t_{ij} + s_i + t_{ji} \leq \tau_p$, the arc will not be included in $A$.

A solution specifies the routes, such as the service sequences for subsets of the requests. Beyond the classic VRP constraints (Toth and Vigo, 2001), the PDPTW imposes also precedence constraints, each pickup has to be handled before its delivery; pairing constraints, each couple (pickup, its delivery) has to be handled in the same route and time window constraints. It has been widely investigated in literature since it arises in many realistic contexts in which it is assumed a door-to-door service, for example. Ropke and Cordeau (2009) have modelled it as a Mixed Integer Linear Programming problem and they have solved it by a Branch-and-Cut-and-Price method. However, by increasing $n$, for example, the problem becomes computationally hard to be solved exactly. In fact, in Li and Lim (2003), a tabu-embedded simulated annealing meta-heuristic has been proposed with the aim to solve large scale instances (at least $n=50$).

Due to the relevant impacts of such problem, it has been adapted in order to use fleets of EVs. Thus, a considerable cost saving (due to the fuel) can be achieved as well as a significant reduction of the CO$_2$ emissions (environment sustainability). Moreover, the EVs allow to reach also the limited traffic zones (social sustainability).

In despite of these advantages, their use is limited by a poor availability of Recharging Stations (RSs) across the geographical areas. In addition, the limited battery life does not allow to use them across large distances. These aspects require to be properly managed during the routes optimization process. In fact, beyond the constraints of the PDPTW, the E-PDPTW takes into account also the presence of the RSs. Moreover, constraints can also be imposed for limiting the maximum spatial length of each route.

The rest of the paper is organized as in the following. In Section 2, a brief literature review is presented while Section 3 proposes a three-objective mathematical model for the E-PDPTW. In Section 4, a solution approach is outlined while in Section 5, an illustrative numerical example is described. Finally, Section 6 concludes the work.

2. Related Work

Dantzig and Ramser (1959) stated the VRP and presented a mathematical formulation for optimizing the routes of a fleet of gasoline delivery trucks. After that, a variety of VRP applications were addressed from both a modelling and methodological point of view. For example, in Bard, Kontoravdis and Yu (2002), a branch-and-cut approach is developed, while in Alvarez, Mateus and De Tomi (2007), the VRPTW is solved by a genetic and a set partitioning two steps approach. Many heuristics have been also proposed for solving VRPs with real time requests (Gandreau et al. (2006), Chen, Wan and Xu (2006)). The PDPTW (see Parragh, Doerner and Hartl (2008) for a review) has been exactly solved by both branch-and-cut and branch-and-price approaches (Barnhart et al. (1998) and Desaulniers et al. (1998), for example). In Ropke and Cordeau (2009), a branch-and-cut-and-price approach is proposed for its solution. The numerical results show that it outperforms
the branch-and-cut based algorithms. In Li and Lim (2003), a Tabu-embedded Simulated Annealing Algorithm is proposed for the multi-vehicles PDPTW, that restarts the search from the current best solution after several non-improving iterations. The computational results have showed that it is suitable to solve also large scale instances. In Hosny and Mumford (2009), a genetic algorithm is proposed for the multi-vehicles PDPTW while in Jih, Kao and Hsu (2002), the family competition genetic algorithm is designed.

In this paper, the E- PDPTW, that uses a fleet of EVs, is analyzed. In literature, some scientific contributions address the VRP with recharging vehicles is addressed as both a CVRP and CVRPTW. In Touati and Jost (2011), the VRP with recharging vehicles is addressed as both a CVRP and CVRPTW. In Conrad and Figliozzi (2011), a mathematical formulation for the Energy VRP is formulated for firstly minimizing the emissions and then the fuel consumption. In Erdogan and Hooks (2012), the Green Routing Problem such as a VRP for a fleet of alternative fuel vehicles by also considering a set of alternative fuel stations. Therefore, beyond the classic constraints imposed on the unique assignments and the flow conservation, they also consider service times for both each customer and each station, constraints on the fuel and on the cargo capacity for each vehicle. In addition, the maximum duration time of each route is limited by an upper bound. Some scientific contributions show its difficulty to properly fix them. In this paper, we describe a method derived from the AHP, a multi-criteria decision making technique introduced in literature by the mathematician Thomas L. Saaty (Saaty, 1980) and widely applied for solving a variety of applications. For example, several scientific contributions show its potentialities if applied to the Supplier Selection problem in the supply chains (see Mendoza, Santiago and Ravindran (2008), for example).

3. A three-objective mathematical model for the E-PDPTW

This section introduces a three-objective formulation for the E-PDPTW by including also the recharging stations. The output of the model consists of: the routes, each assigned to a vehicle and, the recharging stations used in each of them. Since the model aims to optimize three objective functions at the same time, each solution is characterized by the total traversed distance (TTD), the cost for using the vehicles (VC) and finally, the cost due to the penalties (PC). These penalties are due to eventual delays in delivering the service to the customers. This means that, in the proposed formulation, we model soft time window constraints.

The notation used in the paper is in the following: \( F \) is the set of \( m \) RSs, \( K \) denotes the set of EVs, \( T = PDUF \), \( T^0=TU\{0\}, \) \( T^1=Tu\{2n+m+1\} \) and \( T^2=Tu\{2n+m+1\} \), where \( 2n+m+1 \) denotes the dummy depot. The input data are: \( B \), the battery capacity; \( Q_i \), the cargo capacity of the EVs; \( \mu \), the cost for using an EV; \( \rho \), the battery recharging rate; \( r \), the battery consumption rate and \( L \) the maximum length of each route. For each customer \( i \), \( q_i \) is the demand, \( a_i \) and \( b_i \) the lower and upper bound on its time window, \( p_i \) the penalty cost for delaying its service and finally, \( s_i \) its service time. It is worth noting that the term customer is here used in order to identify either a pick-up or a delivery point. The E-PDPTW is represented by a graph \( G=(T,A) \) and it is formulated by introducing the following decision variables: \( x^k_{ij} \) equal to 1 if the vehicle \( k \) traverses the arc \((i,j)\), 0 otherwise; \( y^k_{ij} \) equal to 1 if the vehicle \( k \) is used, 0 otherwise; \( r^k_{ij} \) that denotes the arrival time of the vehicle \( k \) at the node \( i \); \( u^k_i \) that denotes the cargo capacity of the vehicle \( k \) before leaving the node \( i \); \( \Delta a_i \) and \( \Delta b_i \) that represent the delay with reference to the lower bound \( (a_i) \) and to the upper bound \( (b_i) \), respectively, imposed by the node \( i \) and finally, \( z^k_i \) that denotes the remaining autonomy of the battery of the vehicle \( k \) at the node \( i \).

The mathematical formulation is in the following:

\[
\min \sum_{i \in T} \sum_{j \in P \cup J} \sum_{k \in K} d_{ij} x^k_{ij} 
\]

\[
\min \sum_{k \in K} \mu y^k 
\]

\[
\min \sum_{i \in P \cup D} p_i (\Delta a_i + \Delta b_i) 
\]

\[
\sum_{k \in K} \sum_{j \in P \cup J} x^k_{ij} = 1 \quad \forall i \in P 
\]

\[
\sum_{j \in P \cup J} x^k_{ij} \leq 1 \quad \forall i \in F, k \in K 
\]
\[ \sum_{j \in T^j} x^k_{ij} - \sum_{j \in T^j} x^k_{ji} = 0 \quad \forall i \in P, k \in K \] (6)

\[ \sum_{j \in T^j} x^k_{ij} = y^k \quad \forall k \in K \] (7)

\[ \sum_{j \in T^j} x^k_{ij} \leq My^k \quad \forall k \in K \] (9)

\[ \sum_{j \in T^j} x^k_{ij} \geq y^k \quad \forall k \in K \] (10)

\[ \sum_{j \in T^j} x^k_{ij} - \sum_{j \in T^j} x^k_{ji} = 0 \forall k \in K, i \in T \] (11)

\[ r_i^j - r_i^j \geq (s + r_i^j)x_i^k - M(1-x_i^k) \forall i \in T, j \in T^j | i \neq j, k \in K \] (12)

\[ r_i^j + r_i^j + \rho B - c_{ij}^k \leq 0 \forall i \in P \cup D, j \in T^j | i \neq j, k \in K \] (13)

\[ r_i^j - r_i^j + I_{k(i,j)} \sum_{j \in T^j} x^k_{ij} \leq 0 \forall i \in P, k \in K \] (14)

\[ 0 \leq u_i^k \leq u_i^k - q_i^k x^k_{ji} + Q(1-x_i^k) \forall i \in T, j \in T | i \neq j, k \in K \]

\[ 0 \leq u_i^k \leq Q \forall k \in K \] (16)

\[ \max \{0,q_i\} \sum_{j \in T^j} x^k_{ij} \leq u_i^k \leq \min \{Q, q_i\} \sum_{j \in T^j} x^k_{ji} \forall i \in P \cup D, k \in K \] (17)

\[ c_{ij}^k \leq z_{ij}^k \leq r_i^j - r_i^j + B(1-x_i^k) \forall i \in P \cup D, j \in T^j | i \neq j, k \in K \] (18)

\[ z_{ij}^k \leq B - r_i^j x_i^k \forall j \in T^j | j \neq i, i \in F \cup \{0\}, k \in K \] (19)

\[ z_{ij}^k - \sum_{j \in T^j} B x^k_{ij} \leq 0 \forall i \in T, k \in K \] (20)

\[ a_i \sum_{j \in T^j} x^k_{ij} + \Delta a_i \leq r_i^j \leq b_i \sum_{j \in T^j} x^k_{ij} + \Delta b_i \forall i \in P \cup D, k \in K \] (21)

\[ \sum_{j \in T^j} d_{ij}^k x^k_{ij} \leq L \forall k \in K \] (22)

\[ x^k_{ij} \in \{0,1\} \forall i \in T^j, j \in T^j | i \neq j, k \in K \] (23)

\[ \Delta a_i, \Delta b_i \geq 0 \forall i \in P \cup D \] (24)

\[ u_i^k, c_{ij}^k, r_i^j \forall i \in T^j, k \in K \] (25)

The objective function (1) denotes TTD while (2) represents VC. The objective function (3) represents PC. The constraints (4) impose that each pick-up belongs to only one route while (5) establish that a recharging station could not be used. The constraints (6) assure the pairing conditions. The groups (7) and (8) impose that, in each route, there is exactly one arc leaving the depot and one arc entering the dummy depot, respectively. The groups (9) and (10) link the variables of type \( x \) to the ones of type \( y \) (with \( M \) a big positive number): in particular, if a vehicle is used, then it has to traverse at least one arc. If an arc is traversed by a vehicle, then the vehicle is used. The constraints (11) impose the flow conservation conditions (for both customers and recharging stations). The constraints (12) assure the time feasibility conditions for each arc leaving either a customer or the depot. While, (13) impose the time feasibility conditions for each recharging station. The precedence constraints are assured by (14). Constraints (15)—(17) impose that the remaining cargo capacity of a vehicle is never exceeded by considering that at a pickup it is decreased while it is increased at a delivery. Constraints (18)—(19) assure that the battery level of each vehicle never goes under zero. Constraints (20) logically link the \( z \) variables to the \( x \) ones. In particular, if a vehicle uses at least one arc \((i,j)\), then \( z \) has to be less or equal than the maximum capacity \( B \). Finally, (21) assure soft time windows (some eventual delays are allowed) and (22) impose an upper bound \((L)\) on the spatial length of each route. It is worth noting that (22) are necessary since the fleet consists of EVs that have a limited autonomy and that cannot be used in long distance transport. For a detailed explanation of some traditional PDPTW constraints, we refer the readers to Ropke and Cordeau (2009).

### 4. A solution approach for the E-PDPTW

This section describes the solution approach proposed for the model (1)—(25). According to the WSM, the three objective functions ((1)—(3)) are properly transformed into a unique objective function, as in the following:

\[ \min_{w_i} \sum_{i \in T^j} \sum_{j \in T^j} d_{ij}^k x^k_{ij} + w_2 \sum_{i \in T^j} b_i^k \sum_{j \in T^j} x^k_{ij} + w_3 \sum_{i \in T^j} \sum_{j \in T^j} p_i^k (\Delta a_i + \Delta b_i) \] (26)

where \( w_i \), \( w_2 \) and \( w_3 \) denote the weights of the first, the second and the third objective, respectively. To properly fix their values, a method, derived from the AHP, is proposed by imposing that the weights sum to 1. The decision maker defines the \( \eta \times \eta \) pairwise comparison matrix \( \Pi \) (with \( \eta \) the number of criteria) where each entry \( \pi_{ij} \) represents the importance of the criterion \( i \) with reference to the criterion \( j \). According to the scale proposed by Saaty (1980), \( \pi_{i,j} \) equal to 1 means that the two criteria are equally important while the values 3, 5, 7 and 9 denote that \( i \) is weakly, strongly, very and absolutely more important than \( j \), respectively. Moreover, \( \pi_{i,j} = 1 / \pi_{j,i} \) for each \( i,j = 1,...,\eta \). It is then possible to compute the normalized weights for each of the involved criteria. For this purpose, several methods have been proposed in literature. In this paper, we focus the attention on one of them, presented by Saaty, 1980 and that is outlined in the following.

1. Compute the sum of each column of \( \Pi \):

\[ \sum_j \pi_{ij} = \frac{q}{\eta} \forall j = 1,...,\eta \] (27)

2. Compute the following new entries:

\[ \overline{\pi}_{ij} = \frac{\pi_{ij}}{\sum_j \pi_{ij}} \forall i, j = 1,...,\eta \] (28)

3. Set the weights to the following values:
\[
\frac{w_i}{\sum_{j=1}^{\eta} w_{ij}} \quad \forall i = 1, \ldots, \eta \quad (29)
\]

Figure 1 shows the communication among the decision maker, the AHP module and the optimizer. The decision maker provides \( \Pi \), the AHP module computes the weights and finally, the optimizer solves the model.

Figure 1: The proposed automatic decision support system

5. Numerical Results

This section presents an illustrative numerical example that consists of 4 recharging stations (1,2,3,4) and 2 couples of pickup and delivery ((5,6);(7,8)). The detailed information is shown in Table 2 (Appendix A). Moreover, \( B \) is equal to 77.75, \( Q \) is equal to 200, \( r \) and \( \rho \) are set to 1 and \( L \) to 150. The optimal solution, found by Cplex12.4, a linear programming solver, is shown in Figure 2, in the case in which more importance is given to PC than TTD and VC. The penalty cost is set to 100 for each pickup and delivery node.

Figure 2: Numerical example: an optimal solution (Case 1)

<table>
<thead>
<tr>
<th></th>
<th>TTD</th>
<th>VC</th>
<th>PC</th>
<th>TC</th>
<th>w1</th>
<th>w2</th>
<th>w3</th>
</tr>
</thead>
<tbody>
<tr>
<td>case 1</td>
<td>201.28</td>
<td>20</td>
<td>110.72</td>
<td>195.96</td>
<td>0.474</td>
<td>0.474</td>
<td>0.052</td>
</tr>
<tr>
<td>case 2</td>
<td>201.28</td>
<td>20</td>
<td>110.72</td>
<td>194.96</td>
<td>0.174</td>
<td>0.767</td>
<td>0.059</td>
</tr>
<tr>
<td>case 3</td>
<td>213.78</td>
<td>20</td>
<td>110.72</td>
<td>197.71</td>
<td>0.767</td>
<td>0.174</td>
<td>0.059</td>
</tr>
<tr>
<td>case 4</td>
<td>213.78</td>
<td>20</td>
<td>86.98</td>
<td>114.13</td>
<td>0.059</td>
<td>0.174</td>
<td>0.767</td>
</tr>
<tr>
<td>case 5</td>
<td>213.78</td>
<td>20</td>
<td>86.98</td>
<td>115.71</td>
<td>0.174</td>
<td>0.059</td>
<td>0.767</td>
</tr>
<tr>
<td>case 6</td>
<td>213.78</td>
<td>20</td>
<td>86.98</td>
<td>190.97</td>
<td>0.091</td>
<td>0.818</td>
<td>0.091</td>
</tr>
<tr>
<td>case 7</td>
<td>209.73</td>
<td>10</td>
<td>110.72</td>
<td>110.96</td>
<td>0.091</td>
<td>0.818</td>
<td>0.091</td>
</tr>
</tbody>
</table>

Table 1: Numerical Results by varying the weights

Table 1 shows the numerical results by varying \( \Pi \), with \( \eta = 3 \). These variations, in fact, affect the determination of the weights and then, the choices of the optimizer. TC denotes the total cost of the solution (eq. (26)). The order of importance for the components of the objective function is shown in Table 1 through the weights (\( w_1 \), \( w_2 \) and \( w_3 \)). Case 1, for example, considers TTD and VC equally important and both more important than PC. Case 7, instead, imposes a longer value of \( L \) (set equal to 250) and it is here taken into consideration in order to show how this parameter can considerable influence the quality of the final solution. Indeed, it is worth noting that, in this case, the solver detects a solution that uses a lower number of vehicles.

6. Conclusions and Future Work

The VRPs represent widely studied optimization problems since they arise in a lot of realistic applications. The main contribution of this work consisted in modelling and solving a multi-objective E-PDPTW. The problem at hand was addressed from a modelling and a methodological point of view. However, beyond the scientific contribution, the work can have significant impacts: economic (cost saving), environment (reduction of the air pollution thanks to the EVs) and finally, social (improved door-to-door transportation services). A future work will consist in experimenting the model and the solution methodology on realistic scenarios and in testing how the final solutions change by varying the method for determining the weights.


### Appendix A.

<table>
<thead>
<tr>
<th>Node</th>
<th>Position</th>
<th>q0</th>
<th>s1</th>
<th>a1</th>
<th>b1</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>(40,50)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1236</td>
</tr>
<tr>
<td>1</td>
<td>(77,52)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1236</td>
</tr>
<tr>
<td>2</td>
<td>(57,82)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1236</td>
</tr>
<tr>
<td>3</td>
<td>(48,8)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1236</td>
</tr>
<tr>
<td>4</td>
<td>(93,43)</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1236</td>
</tr>
<tr>
<td>5</td>
<td>(58,75)</td>
<td>20</td>
<td>150</td>
<td>100</td>
<td>247</td>
</tr>
<tr>
<td>6</td>
<td>(88,35)</td>
<td>-20</td>
<td>90</td>
<td>100</td>
<td>250</td>
</tr>
<tr>
<td>7</td>
<td>(42,68)</td>
<td>10</td>
<td>90</td>
<td>584</td>
<td>656</td>
</tr>
<tr>
<td>8</td>
<td>(22,75)</td>
<td>-10</td>
<td>90</td>
<td>1042</td>
<td>1106</td>
</tr>
</tbody>
</table>

Table 2: Data of the numerical example