Constructive Heuristics for Periodic Electric Vehicle Routing Problem

Tayeb Oulad Kouider, Wahiba Ramdane Cherif-Khettaf and Ammar Oulamara
Université de Lorraine, Lorraine Research Laboratory in Computer Science and its Applications - LORIA (UMR 7503), Campus Scientifique, 615 Rue du Jardin botanique, 54506 Vandœuvre-les-Nancy, France

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Abstract: This paper introduces a new variant of the electric vehicle routing problem, named PEVRP for Periodic Electric Vehicles Routing Problem, in which the routing and charging are planned over a multi-period horizon, subject to frequency constraints, limited fleet of electric vehicles available at the depot, intermediate facilities for charging during the trips, and partial charging. The objective of the PEVRP is to minimize the total cost of routing and charging over the time horizon, such that each vehicle could be charged nightly at the deport, and during the day at charging stations if refuelling is necessary. We propose two constructive heuristics. The first one is based on clustering technique that aims at allocating customers per vehicle and per period, and then constructs tour for each vehicle visiting customers and charging stations for refuelling. The second one is based on best insertion strategy, in which each customer is allocated to its best position that minimizes charging and routing cost. Using several parameters setting, we compared and analysed the results of the two proposed approaches on 50 new instances derived from EVRP instances of the literature.

1 INTRODUCTION

Several urban centers encounter to mobility and goods transportation problems. As they become larger, traffic congestion, energy consumption, and carbon emissions are increasing, imposing many adverse consequences in terms of environment. In order to cope with these environmental problems, public institutions have restricted access to these urban centers, by imposing public policies. However, these public policies have limited impact on the problems generated by transport activities. Others alternatives are focused on the development of clean vehicles, such as electric or hydrogen vehicles.

Thanks to technological progress, especially the storage capacity of batteries, electric vehicle becomes a promising tool to meet the challenge of decarbonising transport activities. Services using electric vehicles are already deployed to meet the demand of mobility through several cities, especially for daily commuting such as Autolib in Paris. However, there are some factors that prevent massive use of vehicles in all transport activities. These factors are mainly, limited to electric vehicle driving range, long charging time of electric vehicle batteries, and the availability of a charging infrastructure. However, to ensure a successful deployment of electric vehicles in the short-term, it is significant to target development towards (i) specific usage categories where the electric vehicle is the most suitable (e.g. urban transport, urban logistic, business fleet) in terms of the driving range, load capacity, and operating cost, and (ii) manage operations of a complex landscape of ecosystem of EVs (vehicles - chargers - electricity grid - fleet management) with a focus on the new optimization challenges aiming to develop efficient models and decision tools to manage the ecosystem of electric vehicles. In fact, to plan their activities, several fleet managers use decision software tools either at tactical (sizing of the fleet, etc.) or operational (route optimization, performance monitoring, tracking of vehicles, etc.) level. However, the existing route planning software are not suitable for planning routing of electric vehicles, since they do not take into account the specificities of the ecosystem of electric vehicles (autonomy, charging time, charging rate of batteries, type and the availability of charging stations, capacity of the electricity grid, the cost of energy, etc.), and these tools need to be upgraded in order to consider the ecosystem of electric vehicle. This upgrade requires the development of new and efficient optimization models and decision tools to manage the whole ecosystem of the electric vehicles.

In this paper, we focus our study on a specific usage in which electric vehicles are most suitable such as parcel or mail delivery in which agents distribute

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commodities to clients. More precisely, we consider the periodic electric vehicle routing problem, in which a set of customers require visits on one or more days within a planning period, and there is a set of feasible visit options for each customer. Customers must be assigned to a feasible visit option. The typical objective is to minimize the total cost including charging and traveling costs over the planning period, more details of the problem are provided in section 3. The rest of the paper is organized as follows. Section 2 provides a selective review on the studied problem. Section 3 gives more details on the constraints and characteristics of our problem. Section 4 proposes solving approaches based on constructive heuristics. Section 5 presents experimental results. Section 6 concludes this study with a short summary and provides an outlook on future research.

2 RELATED WORK

The design of weekly transportation plans arises in diverse applications in urban logistics, such as the collection of recyclables or mails, the routing of healthcare nurses, the transportation of elderly or disabled persons, etc. This gives rise to a so-called pe- riodic vehicle routing problems (PVRP), which has been introduced in (Christofides and Beasley, 1984). The objective of the PVRP is to find a set of routes over time horizon of h periods of days that minimizes total travel time while satisfying vehicle capacity, predetermined visit frequency for each client, and spacing constraints. For a client, the spacing constraints can be defined either by minimum and maximum periods between consecutive visits, or by a set of allowed period combinations. The periodic vehicle routing problem consists of selecting for each client a day combinations (tactical decisions), and then of constructing routes for clients assigned to each day (operational decisions). Several objective functions can be considered, such as minimizing the traveled distance, intra-days load balancing, or total transportation cost. Since the PVRP is NP-Hard problem, most of works in literature presents heuristic and metaheuristic approaches (Mancini, 2016), (Dayarian et al., 2016), (Baldacci et al., 2011). A survey on the PVRP can be found in (Francis et al., 2008).

Electric vehicle routing problems have attracted close attention from researchers and business organizations in recent years. Several variants of electric vehicle routing problems have been studied in the literature. (Schneider et al., 2014) introduced the Electric Vehicle Routing Problem with Time Windows and Recharging Stations. The EVRP problem with mixed fleet is addressed in (Goeke and Schneider, 2015). Authors consider a fleet of electric and conventional vehicles with time windows constraints. (Hiermann et al., 2016) consider a heterogeneous fleet of vehicles that differ in their capacity, battery size and acquisition cost. In (Felipe et al., 2014), the authors present a variation of the electric vehicle routing problem in which different charging technologies are considered and partial EV charging is allowed. (Schiffer and Walther, 2017) proposed an electric location routing problem with time windows and partial recharging. The papers consider routing of electric vehicles and siting decisions for charging stations simultaneously in order to support strategic decisions of logistics fleet operators. In (Sassi et al., 2015b), (Sassi et al., 2015a) a rich variant of Electric Vehicles Routing Problem related to a real application is proposed. This variant considers a Mixed fleet of conventional and heterogeneous electric vehicles and includes different charging technologies, partial EV charging, compatibility between vehicles. The charging stations could propose different charging costs even if they propose the same charging technology and they are subject to operating time windows constraints The only study in the literature that addressed the multi-periodic aspect for electric vehicles could be found in (Zhang et al., 2017), but the routing and the charging over the period is not considered. This study deals with the multi-period planning of the charger location problem for EVs considering facilities capacity and dynamic demands. The aim is to determine the locations of chargers as well as the number of charging modules at each station over multiple time periods. In summary, the current EVRP literature is limited to daily or strategic planning. Although EVs routing problems have attracted close attention from researchers and business organizations in recent years, the periodic extension of electric vehicles routing problem has never been studied. In our study to be presented below, we propose a new variant named PEVRP (Periodic Electric Vehicle Routing Problem), which deals with tactical and operational decisions level for electric vehicles routing and charging. The aim is to define a routing and a charging plan for each vehicle over a planning horizon. Two constructive heuristics are proposed. The first one is based on clustering technique that aims at allocating customers per vehicle and per period, and then constructs tours for each vehicle visiting customers and charging stations for refuelling. The second one is based on best insertion strategy, in which each customer is allocated to it best position that minimizes charging and routing cost.

3 PROBLEM DEFINITION

The Periodic Electric Vehicle Routing Problem (PEVRP) is defined on complete directed graph $G = (V, A)$. V denotes the set of vertices composed of the set C of n customers, a depot denoted by 0, and the set B of ns external charging stations. The set of arcs is denoted by $A = \{(i, j) \mid i, j \in V\}$.

Each arc (i, j) of A is described by distance $d_{i,j}$, travel time $t_{i,j}$, and travel cost $c_{i,j}$. When an arc (i, j) is travelled by an electric Vehicle (EV), it consumes an amount of energy $e_{i,j} = r \times d_{i,j}$, where r denotes a constant energy consumption rate. Each customer i has a demand q_i, and a service time s_i. We consider a time horizon H of np periods typically "days", in which each customer i has a frequency $f(i) = 1$, and a set of allowed visit days $D(i) \in H$. This means that customer i must be serviced one time in $D(i)$, but at most once in the chosen day.

The set B is defined by ns external charging stations that can be visited during each day of the planning horizon. In most studies of the literature on routing with electric vehicles, the charging cost depends either on the amount of powers delivered by the chargers or on the total time spent for charging the vehicles. In this paper, we consider a fixed charging cost Cc, that neither depends on the amount of the delivered energy nor on the time needed to charge the vehicle. This assumption is more realistic since charging service providers are energy operators and law prohibits companies that offer charging services from reselling the energy, as they sell services, prices do not depend on the amount of energy, but depends on the quality of service (fast or slow charging) (Sassi et al., 2015b) (Sassi et al., 2015a).The depot contains charging points, allowing free charging at night and during the day. The amount of power delivered to each vehicle k at the night of day h is a decision variable $P_{h,0,k}$, defining the vehicle's initial state of charge at the beginning of the trip of the vehicle k for the day $h+1$, $h \in 1...np$ ($P_{np,0,k}$ defines the charging at night for day 1 for the vehicle k). A feasible solution to our problem is composed of a set of routes and a charging planning for each vehicle over the planning horizon. A feasible route is a sequence of nodes that satisfies the following set of constraints:

- Each route must start and end at the depot;
- the overall amount of goods delivered along the route, given by the sum of the demands q_i for each visited customer, must not exceed the vehicle capacity Q;
- the total duration of each route, calculated as the sum of all travel durations required to visit a set of customers, the time required to charge the vehicle during the day, the service time of each customer, could not exceed T;
- no more than m electric vehicles are used;
- each customer should be visited once during the planning horizon, and the visit day must be in $D(i)$.

The PEVRP consists of assigning each client i to one service day defined by $D(i)$ to minimize the total cost of routing and charging over H. The objective function to be minimized is $f(x) = \alpha \times f_1(x) + Cc \times nbs(x)$ where: f_1 is the total distance of the solution x over the planning period H, and nbs is the total number of visits to charging stations over the planning period. α is a given weight representing the cost of one unity of distance.

4 SOLVING APPROACHES

The PEVRP is obviously NP-hard because it includes the basic (single-period) EVRP as a particular case, so large instance can hardly be solved by exact methods. The best way to tackle this problem is using heuristic approaches. In this section, we investigated extension of the best insertion heuristic, namely BIH (Best Insertion Heuristic). Another approach, based on Clustering Analysis, namely CLH (Clustering heuristic) is also proposed. In the following, we provide details of each heuristic.

4.1 Best Insertion Heuristic (BIH)

The Best Insertion Heuristic (BIH) directly builds in parallel the tours for each day. Roughly speaking, m tours, initially empty, are defined for each day. At each iteration and for each day, we consider the insertion in all available non-empty tours and in one new empty tour without exceeding m tours by day. For each customer i and for any possible day $d \in D(i)$, the algorithm simulates the insertion of i in all possible positions of all considered tours of period d. If the residual vehicle energy is not enough to add i in a given position k of a considered tour tr, the algorithm simulates the insertion of i and a charging station $b \in B \cup \{0\}$ simultaneously. For the insertion of b, we choose the less costly charging station that allow satisfying the energy constraint. The total cost variation of $f(x)$ is computed for each insertion simulation. The customer (and eventually the charging station) with the minimum insertion cost is inserted at the end of each iteration at its best position. The best position is given by a day $h \in D(i)$, the tour tr in the considered tours of h, and a position $k \in tr$ for i

(and if needed a position $k' \in tr$ for b). The heuristic stops if all clients are inserted or when no insertion is possible.

4.2 Clustering Heuristic (CLH)

The proposed CLH algorithm proceeds in four steps. The first step aims at creating m initial clusters in each day, one for each available vehicle. In the second step, for each day d, the algorithm CLH tries to dispatch the maximum number of remaining customers in the m available clusters of the day d, without inserting any charging station, and using as criterion the smoothing of $Distance(cl_d)$ overs all clusters of the day d. In step 3, the customers not inserted in step 2 due to energy constraint, will be considered. In this step, the insertion objective is the minimization of the additional energy consumption for each cluster. Finally, in the fourth step, a best insertion TSP heuristic is used to find a feasible route in each cluster for each day. More precisely, for each cluster cl_d, we compute an estimation of 1) the distance $Distance(cl_d)$, 2) the energy consumption $Energy(cl_d)$, and 3) the Time $Time(cl_d)$ needed to perform an electric TSP tour, starting from depot, visiting once all nodes in cl_d, and charging stations if necessary, and returning to the depot. We also compute the $Load(cl_d)$ that represents the total quantity to be served in the cluster cl_d. Details of the CLH steps are given bellow.

$Distance(cl_d)$ is an estimation of the length of the tour starting at the depot, visiting all customers in cl_d and ends at the depot. It is computed according to (1) (2) (3).

$$Distance(cl_d) = \min(Distance_1(cl_d), Distance_2(cl_d)) \quad (1)$$

$Distance_1(cl_d)$ is an overestimation computed according to the costly arc in cl_d.

$Distance_2(cl_d)$ uses an approximation based on the distance of each customers to the center of the cluster.

$$Distance_1(cl_d) = |cl_d - 1| \times \max_{i,j \in cl_d} d_{i,j} + 2 \times \max_{i \in cl_d} d_{i,0} \quad (2)$$

$$Distance_2(cl_d) = 2 \times \sum_{i \in cl_d} d_{center(cl_d),i} + 2 \times d_{center(cl_d),0} \quad (3)$$

$$Energy(cl_d) = r \times Distance(cl_d)$$

$$Time(cl_d) = \min(Time_1(cl_d), Time_2(cl_d))$$

$Time_1(cl_d)$ (respectively $Time_2(cl_d)$) is computed as $Distance_1(cl_d)$(respectively $Distance_2(cl_d)$) by replacing $d_{i,j}$ by $t_{i,j}$.

$$Load(cl_d) = \sum_{i \in cl_d} q_i$$

$Check - Energy - Feasibility(cl_d)$: this function check the energy feasibility of the solution that will be obtained in cl_d and return true if $Energy(cl_d) \leq E$. $Check - Constraints - Feasibility(cl_d)$: this function check the feasibility of the solution that will be obtained in cl_d and return true If $Load(cl_d) \leq Q$ and $Time(cl_d) \leq T$.

Step 1. Cluster Initialization

The cluster initialization starts by assigning all customers having one allowed day visit (all $i \in V$, with $|D(i)| = 1$), because these clients will be the most difficult to insert in the tours. Let L_d be the list of customers of the day d, and $ListE_d$ the list of the exclusive clients i for day d, such that $D(i) = \{d\}$. The cluster initialization algorithms is given bellow :

1. $d := 1$
2. $ListE_d = \{i \in V, |D(i)| = 1$ and $D(i) = \{d\}\}$, $Nbcluster_d = |ListE_d|$
3. If $Nbcluster_d \geq m$ go to step 4, Else go to step 7
4. Initialization: for each given client $i \in ListE_d$, one cluster $cl_{d,a} = \{i\}$ is created
5. While $Nbcluster_d \geq m$ do search for the closest clusters a and b, such that $Check - Constraints - Feasibility(a \cup b) = true$, merge a and b in one new cluster a and delete b.
6. $d = d + 1$, if $d = np + 1$ stop else go to 2
7. For each given customer $i \in ListE_d$, a cluster $cl_{d,a}$ = {i} is created. As we need to have m initial clusters, we must add $m - Nbcluster_d$ clusters. Let be $L(z)$ a list of the customers not considered in the available clusters ($d \in D(i)$ and $|D(i)| = z$, $z \in 2..np$). Choose randomly $m - Nbcluster_d$ customers such as each customer form a new cluster considering at first $L(2)$, then $L(3)$, and so $L(z+1)$ until m clusters are formed.

Step 2. Customer's Insertion without Additional Energy

Let $list_{cl}$ be the list of available clusters over all the planning horizon, and L be the list of customers i not assigned to any cluster, sorted in increasing order according to the value $|D(i)|$. The algorithm repeats the following two steps until $L = \varnothing$. In the first step, the algorithm selects i from the head of L, and scans all feasible insertions in each day $d \in D(i)$ and in each cluster of day d, using $Check - Constraints - Feasibility(cl_d \cup \{i\})$. In the second step, the cluster a (see formula (4)) that minimizes the distance increases over all clusters is selected (if $Check - Constraints - Feasibility(cl_d \cup \{i\})$= false for each d then put $a := \varnothing$). If $a \neq \varnothing$, and if $Check-Energy-Feasibility(cl_d \cup \{i\})$ = true, insert i in a and delete i from L, else insert i in L_2. If $a = \varnothing$, delete i from L and insert i in L_1.

$$a = \arg \min_{\substack{\forall i \in L \\ \forall cl_d \in list_{cl}}} \{Distance(cl_d \cup \{i\}) - Distance(cl_d)\} \quad (4)$$

At the end of this algorithm, the list L_1 will contain all customers ejected due to the violation of capacity and time constraint. The list L_2 will contain the clients ejected due to the violation of the energy constraint. All customers in L_2 will be introduced in the next step.

Step 3. Customer's Insertion with Additional Energy

This step aims to insert all customers from L_2 while minimizing the increase of the energy consumption. We know that all customers in L_2 verify the capacity and the time constraints for at least one cluster. At first, L_2 is sorted according to the value of $|D(i)|$, then we select the cluster a that verifies $Check-Constraints-Feasibility(a \cup \{i\})$ and minimizes the energy increase according to the following formula.

$$a = \arg \min_{\substack{\forall i \in L \\ \forall cl_d \in list_{cl}}} \{Energy(cl_d \cup \{i\}) - Energy(cl_d)\} \quad (5)$$

Step 4. Route Construction

In this step, each cluster will be considered to construct a tour using the best insertion method. This method builds a tour, starting by an empty tour composed by a loop in the depot, and extends the tour customer per customer. At each iteration, for each customer i, the algorithm simulates the insertion of i in each position in the tour. If the residual vehicle energy is not enough to add i, the algorithm simulates simultaneously the insertion of i and a charging station $b \in B \cup \{0\}$. The total cost variation of $f(x)$ is computed for each insertion simulation. The customer i with the minimum insertion cost is inserted at it best position at the end of each iteration.The cost of inserting a customer includes the cost of inserting charging stations if necessary.

5 COMPUTATIONAL EXPERIMENTS

5.1 Data Sets

Our methods are implemented using C++. All computations are carried out on an Intel Core (TM) i7-5600U CPU, 2.60 GHz processor, with 8GB RAM memory. In this paper, we proposed a new PEVRP instances inspired by the data instances provided by (Felipe et al., 2014). These instances are divided on two types: in instances of type A, the depot is centrally located and there are nine charging stations, and in instances of type B, the depot is at a corner and there are only five charging stations (including charging at the depot).

We considered a limited homogeneous fleet of vehicles and we adjust parameters of cited above article to our problem. We consider the following settings:

- Number of customers: n=100 and n=200
- Number of vehicles: in the interval $[\frac{\sqrt{n}}{4}, \frac{\sqrt{n}}{2}]$
- Battery capacity: 20 kWh (equivalent to a range of 160 km).
- Energy consumption: 0.125 kWh/km.
- Average speed: 80 km/h.
- Vehicle capacity: 20000 Kg.
- Maximum route duration: 8 h.
- Recharging power: 10kWh and a fixed cost of charging service of 2.5 €

Furthermore, we randomly generated visit days for each client respecting the following rule: in each day, the exclusive clients are selected randomly, then for the rest of clients we randomly generate the visiting days.

As the generation of visiting days being influential on the toughness of the problem, we generate 10 instances for each setting parameters by varying the visiting days for each customer.

5.2 Comparative Analysis

In this section, we analyse the performance of the proposed methods on the PEVRP generated instances.

Our first computation are on instances with 100 clients and 2 vehicles and we allow only two visiting days. Table 1 provides results of heuristics CLH and BIH on five setting parameters for each type-instance (A and B). For each setting we generate 10 random instances.Thus, we have 100 tested instances in table 1. The average CPU time in seconds (CPU), the average

Table 1: Instances with 100 clients and 2 vehicles.

	CLH			BIH		
	CPU	$f(x)$	***N.V.C***	***CPU***	$f(x)$	***N.V.C***
A1	0,44	90,47	0,00 %	4,10	87,56	0,00%
A2	0,56	104,69	0,00 %	4,42	88,01	0,00%
A3	0,61	102,25	0,00 %	3,85	83,73	0,00%
A4	0,56	106,49	0,00 %	4,14	91,61	0,00%
A5	0,65	105,31	0,40%	4,51	97,98	0,00%
B1	0,46	61,13	0,00%	4,71	45,09	0,00%
B2	0,63	65,45	0,00%	5,37	48,36	0,00%
B3	0,65	65,91	0,00%	5,24	47,68	0,00%
B4	0,59	68,34	0,00%	5,11	50,47	0,00%
B5	0,62	66,74	0,00%	4,86	47,87	0,00%
Average	**0,58**	**83,68**	**0,04%**	**4,63**	**68,84**	**0,00%**

cost of the solution (f(x)) and the average number of non serviced clients (NVC) over all 10 instances are reported in table 1 as results of computation. The CPU time is indicated in the first column, the cost of solution and the number of non serviced clients are reported in the second and third columns, respectively, for each solving method.

Regarding results of table 1, clearly CLH heuristic is faster than BIH heuristic, however, CLH fails to visit all clients, whereas heuristic BIH is able to visit all clients in all instances. BIH heuristic performs better than CLH even if it's slower. Furthermore, the heuristic CLH is more suitable for instances of type B than instances of type A.

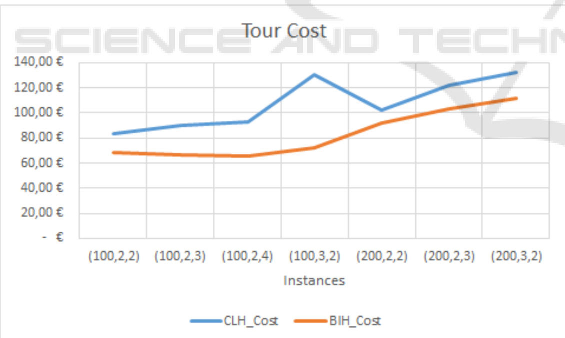

Figure 1: Evaluation of the cost variation.

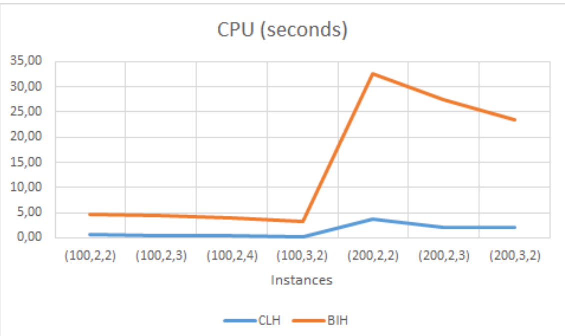

Figure 2: Evaluation of the CPU variation.

Table 2: Instances with 200 clients and 2 days.

v=2						
	CLH			BIH		
Inst	CPU	N.V.C	$f(x)$	CPU	N.V.C	$f(x)$
A1	2,96	0,30%	104,03 €	28,41	0,00%	107,47 €
A2	3,18	0,00%	105,12 €	27,70	0,00%	112,27 €
A3	3,38	0,70%	108,31 €	28,70	0,20%	111,27 €
A4	2,84	0,00%	109,56 €	28,84	0,00%	110,40 €
A5	3,22	0,90%	110,19 €	26,33	0,60%	111,31 €
B1	3,85	0,00%	93,90 €	41,83	0,00%	71,30 €
B2	4,63	0,00%	98,06 €	38,35	0,00%	74,84 €
B3	4,56	0,00%	97,08 €	36,12	0,00%	73,72 €
B4	4,31	0,00%	98,86 €	35,98	0,00%	74,01 €
B5	4,29	0,00%	98,01 €	35,00	0,00%	74,82 €
Average	**3,72**	**0,19%**	**102,31 €**	**32,73**	**0,08%**	**92,14 €**
v=3						
	CLH			BIH		
Inst	CPU	N.V.C	$f(x)$	CPU	N.V.C	$f(x)$
A1	1,78	0,30%	140,22 €	26,13	0,00%	138,49 €
A2	2,03	0,20%	137,27 €	24,99	0,00%	128,64 €
A3	1,83	0,60%	142,81 €	25,73	0,00%	138,62 €
A4	1,77	0,00%	144,24 €	25,39	0,00%	134,73 €
A5	1,89	0,60%	138,42 €	25,07	0,10%	135,77 €
B1	1,81	0,10%	97,09 €	30,26	0,00%	68,64 €
B2	2,48	0,00%	104,55 €	30,00	0,00%	70,40 €
B3	2,38	0,00%	104,44 €	27,83	0,00%	69,47 €
B4	2,45	0,00%	105,91 €	31,37	0,00%	73,64 €
B5	2,45	0,00%	104,40 €	29,02	0,00%	71,48 €
Average	**2,09**	**0,18%**	**121,93 €**	**27,58**	**0,01%**	**102,99 €**

For a better performance study of the two heuristics, we considered several settings of parameters. In the following we will use the notation (n,d,v) to describe a setting parameters, n being the number of customers, d the number of available days and v the number of vehicles. As before, each type-instance has 5 setting parameters, and for each setting parameters, we generate 10 instances. Thus, for each setting we have 50 instances.

Firstly, we set the number of customers to 100, the number of available days to 2, and the number of vehicles to 3 and 4. Then we increase the number of available days to 3, while setting v to 2. Finally, we took the 200 customers instances, and varying d and v between 2 and 3. The results given in tables 1 to 5 show that BIH remains better than CLH in terms of solution cost for all instances. The BIH method successfully inserted all customers except for two instances.The average percentage of non-inserted clients remains very low for BIH, whereas CLH can-

Table 3: Instances with 100clients and 2 days.

v=2						
	CLH			*BIH*		
Instance	*CPU*	*N.V.C*	$f(x)$	*CPU*	*N.V.C*	$f(x)$
A1	0,44	0,00%	90,47 €	4,10	0,00%	87,56 €
A2	0,56	0,00%	104,69 €	4,42	0,00%	88,01 €
A3	0,61	0,00%	102,25 €	3,85	0,00%	83,73 €
A4	0,56	0,00%	106,49 €	4,14	0,00%	91,61 €
A5	0,65	0,40%	105,31 €	4,51	0,00%	97,98 €
B1	0,46	0,00%	61,13 €	4,71	0,00%	45,09 €
B2	0,63	0,00%	65,45 €	5,37	0,00%	48,36 €
B3	0,65	0,00%	65,91 €	5,24	0,00%	47,68 €
B4	0,59	0,00%	68,34 €	5,11	0,00%	50,47 €
B5	0,62	0,00%	66,74 €	4,86	0,00%	47,87 €
Average	**0,58**	**0,04%**	**83,68 €**	**4,63**	**0,00%**	**68,84 €**
v=3						
	CLH			*BIH*		
Instance	*CPU*	*N.V.C*	$f(x)$	*CPU*	*N.V.C*	$f(x)$
A1	0,38	0,00%	107,63 €	3,92	0,00%	80,95 €
A2	0,46	0,00%	108,85 €	4,77	0,00%	81,97 €
A3	0,49	0,00%	104,18 €	3,83	0,00%	83,40 €
A4	0,33	0,00%	113,88 €	3,47	0,00%	89,08 €
A5	0,36	0,30%	111,09 €	3,59	0,00%	91,80 €
B1	0,45	0,00%	65,99 €	5,80	0,00%	45,84 €
B2	0,42	0,00%	72,25 €	5,38	0,00%	48,55 €
B3	0,50	0,00%	72,32 €	5,61	0,00%	47,36 €
B4	0,36	0,00%	74,01 €	4,52	0,00%	48,75 €
B5	0,42	0,00%	72,78 €	4,15	0,00%	48,32 €
Average	**0,42**	**0,03%**	**90,30 €**	**4,50**	**0,00%**	**66,60 €**
v=4						
	CLH			*BIH*		
Instance	*CPU*	*N.V.C*	$f(x)$	*CPU*	*N.V.C*	$f(x)$
A1	0,31	0,00%	106,07 €	3,56	0,00%	82,41 €
A2	0,32	0,00%	109,17 €	3,52	0,00%	82,82 €
A3	0,41	0,00%	108,48 €	3,45	0,00%	80,83 €
A4	0,33	0,20%	118,76 €	3,73	0,00%	86,98 €
A5	0,35	0,30%	113,57 €	3,72	0,00%	88,83 €
B1	0,33	0,00%	70,62 €	4,80	0,00%	45,84 €
B2	0,31	0,00%	74,37 €	4,39	0,00%	48,55 €
B3	0,36	0,00%	75,86 €	4,16	0,00%	47,36 €
B4	0,33	0,00%	76,72 €	4,31	0,00%	48,75 €
B5	0,34	0,00%	77,20 €	3,67	0,00%	48,32 €
Average	**0,34**	**0,05%**	**93,08 €**	**3,93**	**0,00%**	**66,07 €**

not manage to insert all clients in most instances. The computing time of BIH remains higher than the computing time of CLH, but this computing time of BIH is always reasonable (it reaches at maximum 32,73 seconds).

In the following two figures, we compare the average CPU and the average cost of the solutions obtained by the two heuristics in the different settings of instances.

Table 4: Instances with 100 clients and 3 days.

v=2						
	CLH			BIH		
Inst	CPU	N.V.C	$f(x)$	CPU	N.V.C	$f(x)$
A1	0,25	0,00%	123,55 €	3,40	0,00%	95,86 €
A2	0,25	0,00%	134,72 €	3,40	0,00%	94,98 €
A3	0,25	0,00%	127,15 €	3,20	0,00%	92,56 €
A4	0,25	0,00%	135,92 €	3,13	0,00%	98,83 €
A5	0,26	0,00%	130,60 €	3,36	0,00%	98,90 €
B1	0,18	0,00%	123,55 €	3,56	0,00%	45,84 €
B2	0,18	0,00%	134,72 €	3,38	0,00%	48,55 €
B3	0,18	0,00%	127,15 €	3,17	0,00%	47,36 €
B4	0,18	0,00%	135,92 €	3,46	0,00%	48,75 €
B5	0,19	0,00%	130,60 €	3,26	0,00%	48,32 €
Average	**0,22**	**0,00%**	**130,39 €**	**3,33**	**0,00%**	**71,99 €**

Table 5: Instances with n=200 and day=3.

v=2						
	CLH			BIH		
Inst	CPU	N.V.C	$f(x)$	CPU	N.V.C	$f(x)$
A1	1,63	0,10%	153,76 €	20,83	0,00%	148,40 €
A2	1,47	0,00%	162,50 €	20,28	0,00%	136,95 €
A3	1,50	0,20%	162,69 €	21,01	0,00%	146,32 €
A4	1,69	0,00%	162,47 €	19,93	0,00%	149,88 €
A5	1,70	0,40%	164,34 €	21,87	0,00%	147,28 €
B1	1,81	0,10%	97,09 €	25,21	0,00%	74,81 €
B2	2,48	0,00%	104,55 €	25,57	0,00%	77,17 €
B3	2,38	0,00%	104,44 €	24,31	0,00%	79,56 €
B4	2,45	0,00%	105,91 €	28,36	0,00%	77,54 €
B5	2,45	0,00%	104,40 €	28,01	0,00%	78,89 €
Average	**1,96**	**0,08%**	**132,21 €**	**23,54**	**0,00%**	**111,68 €**

If we compare the two heuristics for the 100 customers and 2 days instances in terms of cost, we could see that the BIH heuristic performance is improved by the increase of v, which is explained by the more possibilities given to insert the customers and the less needs to visit charging stations. In the other hand, the cost of solutions given by the CLH heuristic is increasing, which is due to the fact that the heuristic use inevitably all the vehicles every day. We predicate that there is an optimal number of vehicles for the CLH and that a smaller or even bigger fleet increases the cost. BIH being not constrained to use all the vehicles.

6 CONCLUSION

This paper addresses a new extension of the EVRP, named PEVRP (Periodic Electric VRP), in which the routing and charging are planned over a multi-period horizon, subject to frequency constraints, limited fleet of electric vehicles available at the depot, intermediate facilities for charging during the trips, and partial charging. We have proposed two constructive heuristics, Best Insertion Heuristic (BIH) and Clustering Method (CLH). These methods are tested on instances derived from EVRP instances with up to 200 customers. Computational experiments show the effectiveness of the BIH approach. In further researches, we aim to improve the CLH method by a post optimisation step, and to propose a metaheuristic approach.It will also be interesting to develop more efficient lower bounds. Another perspective is to generalize the PEVRP model considering that $f(i) \geq 1$.

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