A Comparative Study of Local Search Techniques Addressing an Electric Vehicle Routing Problem with Time Windows

Dhekra Rezgui
ECSTRA Laboratory
ISG, Université de Tunis
Tunis, Tunisia
dhekra.rezgui@live.fr

Hend Bouziri
LARODEC Laboratory,
ESSECT, Université de Tunis
Tunis, Tunisia
hend.bouziri@gmail.com

Wassila Aggoune-Mtalaa
ITIS department
Luxembourg Institute of Science and Technology
wassila.mtalaa@list.lu

Jouhaina Chaouachi Siala
ECSTRA Laboratory
IHEC, Université de Carthage
Tunis, Tunisia
siala.jouhaina@gmail.com

***Abstract*—This paper addresses an electric routing problem (e-VRP) of last-mile delivery operated by innovative electric vehicles. In fact the studied vehicles are modular. It means that they consist of an innovative system with one cabin for the driver and one or more modules for the goods. Local search techniques and their combination with evolutionary schema are proposed. Experimental testing from this study was performed to demonstrate the relevance of the evolutionary variable neighborhood descent method.**

***Index Terms*—Evolutionary Algorithm, Variable Neighborhood Descent, Modular Electric Vehicles, Charging Policy, VNS**

I. Introduction

To achieve the objectives drawn by the Paris agreement in the COP21 adopted in 2015, initiaties were launched by various stakeholders, including a tender for cheaper electric cars, less than 7,000 USD (per car) and an initiative for cities to develop sustainable mobility plans [2], [15] . Consequently, a huge research and development work is dedicated to propose practical and sustainable technological solutions for transportation of goods. Indeed, by adding electric and sustainable vehicle constraints, we study a new variant of the e-VRP in which the vehicles are modular.

Hence, in this problem, we have a set of electric vehicles V where each vehicle consists of a set of modules (including the cabin of the driver). Each module has a battery that could be charged separately. We assume that we are in the case of problem of distribution of goods to customers who have charging stations. Thus, if the vehicule charge falls below a certain threshold, the vehicle can detach and leave a module in a client to be recharged and it ends its path. Optionally, the vehicle can recover another module already charged in another customer to benefit from its additional energy. In this work, we consider only releasing modules for recharging. But this idea of modularity can also be used for example to treat the problem of congestion. Several types of modular electric vehicles already exist as prototypes. We can cite basically those developped in the German Research Center for Artificial Intelligence (DFKI) [19].

To show the relevance and effectiveness of our approach, we carried out extensive experiments comparing the proposed method called EVND (Evolutionary Variable Neighborhood Descent) against the VNS technique. In addition, the relevance of the EVND method was emphasized compared to an evolutionary local search. Subsequently a detailed comparison with existing methods was detailed.

The paper provides in section 2, the description of our problem, and we present in section 3 some related works dealing with hybrids and VNS techniques for routing problems. Section 4 discusses the application of the enhanced evolutionary algorithm to tackle it. The next section is dedicated to the testing and comparison of the different algorithms. Section 6 presents the conclusion of the paper and gives some perspectives for further researches.

II. Problem description

In this paper, we consider the routing problem of modular electric vehicles with time windows. This problem has been formulated as a Mixed Integer Linear Programming (MILP) in [10]. Several constraints have been added compared to the standard Vehicle Routing Problem with Time Windows (VRPTW) with a heterogeneous fleet, notably the constraints related to the modules and their battery charging. These constraints constitute the recharging policy adopted in the studied problem.

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A. Recharging policy

As detailed above, each vehicle is composed of a set of modules that can be detached for energy reloading purposes, see [11]. The following assumptions are retained during the routing of this type of electric vehicles.

- All the vehicles, with their modules are fully charged when they leave the depot.
- The charge of the battery of a vehicle is equal to the sum of the charges of batteries of the modules attached including the charge of the cabin.
- A charging threshold is set for each vehicle bellow it the module with the lowest charge is detached to recharge its battery.
- Each customer is provided with an electric charging station by which modules and vehicles can be recharged. The recharging time depends on the level of charge when arriving at the recharging station and should not exceed the time window constraint.
- The cabin module can not be detached. If the charge of its battery falls below a certain threshold, the vehicle is forced to stop to recharge in electricity, this by respecting the predefined time window.

III. Related works

A wide variety of methods has been proposed for the VRPTW problem and its variants which are classified NP-hard. Since our problem is a variant of the VRPTW, our interest has focused on the methods dedicated to this problem and its electric variants. Three major findings can be identified from the study of these methods. First, we can note the great tendency to use metaheuristics with its different types to overcome the difficult nature of the problem. We can cite as example, the work of Schneider et al. [13]. Secondly, the study of the related work has shown the need to adopt methods with diversification mechanisms to visit areas scattered in the research space, which avoids being trapped in local optima. This could explain the use of evolutionary schemas in several methods dedicated to the VRPTW with its different variants as noticed by Bräysy and Gendreau [4]. We can cite for example the work of Ursani et al. [18]. Finally, we noticed in our study of related literature, the effectiveness of the VNS (Variable Neighborhood Search) method which also contains a component of diversification of the search but its strength lies in its component called VND (Variable Neighborhood Descent) which alters its moves locally between several neighborhood operators to intensify research in promising areas. Several variants have been used in the VRPTW, such as the work of Chen et al. [5] which suggests an adapatation of the VNS, called VNS-C.

The literature review reported previously highlights the relevance of hybridising approaches to deal with the proposed variant of the e-VRPTW problem. More precisely, we are intersted with a method that marries a diversification component and an elaborated intensification component. Hence, the main contribution of this work is to suggest a variable neighborhood descent procedure within an evolutionary to solve the presented problem of VRPTW using a fleet of electric modular vehicles. This idea of hybridizing evolutionary algorithm with a variant of the VNS was also followed by Baniamerian et al. [1] in their method called MVNS (Modified Variable Neighborhood Search).

IV. An Evolutionary Variable Neighborhood Desent Method

In order to guide a search algorithm efficiently in a solution space, it would be necessary to properly define move operators to be used, but also an appropriate objective function that should reflect the properties of the problem being addressed. Indeed, since it concerns the routing of electric vehicles, it is important to minimize as much as possible the number of vehicles used as well as the time allocated for recharging the batteries of the cabin modules (since the vehicle is forced to stop in this case).

A. Objective function

To ensure efficient routing in the context of our specific VRPTW problem using modular and electric vehicles, we opt for an objective function comprising three terms. The first provides the purchase cost of the vehicles used in the routing. The second term corresponds to the distance traveled to serve all customers and the third term penalizes vehicle stops for reloading cabins modules. More formaly, consider a set of vehicles V and C a set of customers. A binary decision variable x_{ij}^v is assigned to each route between two customers i and j, x_{ij}^v is equal to 1 if the vehicle crosses the road from i to j. Further, a transportation cost c_{ij}, which is obtained by multiplying the distance d_{ij} by the variable cost p_k, is also assigned to the road from i to j. Hence, the objective function is determined as follows:

$$\sum_{v\in V}\sum_{j\in C} a^v x_{0j}^v + \sum_{v\in V}\sum_{i,j\in C, i\neq j} c_{ij} x_{ij}^v + \sum_{v\in V}\sum_{i\in C} c_r r_i^v, \quad (1)$$

where a^v is the purchasing cost of a vehicle v, x_{0j}^v indicates if a vehicle v leaves the depot 0 to reach the customer j. The binary variable r_i^v denotes if the vehicle v is recharged at customer i at recharge cost c_r of a cabin module. For the detailed mathematical formulation reflecting all the constraints, please refer to [10].

B. The algorithm

The algorithm of the EVND method is presented in Algorithm 1. An initial population Pop of size S_p is generated, then the individual are ranked according to their cost value calculated by the function f in equation (1). At each generation, a tournament selection procedure is performed to choose two parents $Parent_1$ and $Parent_2$. These routings will be combined within a crossover procedure to generate a $Child$. The VND procedure is then applied on the child to be improved and we have a new routing called $Local$ that will substitute the worst routing in the population Pop. The algorithm is stopped when a prefixed number of generations is reached.

Algorithm 1 Eolutionary Variable Neighborhood Descent Method.

Input: C: Customers, d_{ij}: distance from customer i to j; S_p population size.
Output: Feasible routing
$Pop \leftarrow$ Initial population (S_p) ;
$best \leftarrow$ Ranking(Pop);
Do while Stopping criterion is not satisfied
  $Parent_1$,$Parent_2 \leftarrow$ Select(Pop);
  $Child \leftarrow$ Crossover $(Parent_1, Parent_2)$;
  $Local \leftarrow$ VND($Child$);
  $Pop \leftarrow$ Replacement $(Pop, Local)$;
  If f $(Local < best)$ **Then** $best \leftarrow Local$
Return Best individual in Pop;

a) ***Routing representation :*** A vehicle routing is represented by an integer array of length N (number of nodes) where vehicle tours are separated by zeros. Furthermore, for each customer, we report its time service as in classical VRPTW problems. Besides, for our eletric variant, we report for each vehicle, its cost, its recharging stations and the number of attached modules when it visits a customer.

b) ***Initial population generation:*** A greedy algorithm is used to provide a feasible routing, where at each time, the nearest customer is served by respecting all constraints related to the recharging constraints reported above. The rest of individuals in the population Pop are generated by using a 2-opt move and adding vehicles when recharging and time windows constraints are violated.

c) ***Crossover operator:*** In this work, we choose the Best Cost Route Crossover (BCRC) firstly proposed by Ombuki et al. [9]. Basically, BCRC provides as offspring, the best combination of tours from each parent that satisfies all the constraints. Routings are valuated according to objective function reported in equation (1).

d) ***The Variable Neighborhood Descent procedure:*** It replaces the classical mutation and tries to improve the child quality by applying local moves. The VND heuristic applies alternatively the neighborhood operators until no improvement is possible. Four neighborhood operators are applied successively on each routing provided by the crossover operator. The sequence of movements retained in this adaptation of VND is: 2-opt, swap, insert and exchange. Approximately, the same order is used for other VRP problems [6] [12]. If the VND can't improve the routing provided as input, i.e. $Child$, VND will return this routing as $Local$.

V. Experimental setup

To test the EVND algorithm, we have used a laptop PC equipped with an Intel Core i3-3217U Processor clocked at 1.8 GHz with 4 GB RAM, running Windows 8.2 Professional. Further, the tests are performed on Solomon instances [16] classified as C1, C2, R1, R2, RCl and RC2 classes, each with 8 to 12 problems. We excecuted for each instance, 10 independent runs of the EVND method. In the experiments we try to show these main issues:

- the comparision between the EVND and the VNS method, since these two algorithms share the same intensification technique and differ in the diversification tool,
- the relevance of the EVND procedure compared to ELS method,
- the performance of our method to treat the electric vehicles routing problem regarding best state of the art methods basically hybrid metaheuristics.

A. Comparison of the EVND with the VNS heuristic

The Variable Neighborhood Search (VNS) is an elaborated search method that showed its performance in solving several optimisation problems including the VRPTW and its variants [7]. Its basic principle is to vary the neighborhood structure over the search process. This is performed by its component called the Variable Neighborhood Descent (VND). To diversify the search, VNS used the so-called shaking procedure. However, EVND replaces this routine of shaking by being population-based. In this part of experiments, we try to compare the performance of the proposed EVND regarding a classical VNS that uses a shaking technique. More specifically, we conducted experiments on all the instances stemmed from Solomon benchmark. In these experiments, we have noted that the EVND is more competitive than the VNS. Table I summarizes the results of the comparison between VNS and EVND. The columns represent the results obtained for each algorithm whereas the lines show the average of the total traveled distance and the average number of vehicles for each class.

TABLE I
Average number of vehicles used and total traveled distance of EVND against VNS.

Benchmark	VNS	EVND
C1	828.78	**825.89**
	9.44	10
C2	585.37	**585.27**
	3	**3**
R1	1189.48	**1183.92**
	11.08	**11**
R2	935.17	**934.52**
	2.72	**2.63**
RC1	1354.84	1357.13
	11.12	11.25
RC2	1050.54	1107.30
	3.12	**3.12**

As shown in Table I, the obtained results indicate that the proposed EVND gives promising results as compared VNS, regarding the decreased numbers of vehicles as in R1 and R2. It is worth noting, that for the group RC1 and RC2, the distances obtained by the VNS are better than the ones obtained with EVND. In the set of instances C1 and C2, EVND provides, in average, a better feasible solution than the one detected by the VNS in terms of distances.

B. Relevance of the EVND procedure compared to the ELS method

Here, we try to assess our theoretical assumptions that the VND could give efficient results by exploring the local neighborhood using the four operators defined before. For this reason, we experiment an Evolutionary Local Search (ELS) procedure that works similarly to the EVND, but replaces the VND procedure by a local descent procedure that iteratively applies the 2-opt move on the child until an improvement is recorded.

Table II summarizes the results of the comparison between ELS and EVND. The columns represent the results obtained for each algorithm whereas the lines show the average of the total traveled distance and the average number of vehicles for each class.

TABLE II
AVERAGE NUMBER OF VEHICLES USED AND TOTAL TRAVELED DISTANCE OF EVND AGAINST ELS.

Benchmark	ELS	EVND
C1	869.62	**825.89**
	8.22	10
C2	592.73	**585.27**
	3	**3**
R1	1186.23	**1183.92**
	11	**11**
R2	940.58	**934.52**
	2.63	**2.63**
RC1	1393.24	**1357.13**
	11.37	**11.25**
RC2	1136.73	**1107.30**
	3.25	**3.12**

As shown in Table II, the obtained results indicate in almost all cases that the proposed EVND gives promising results as compared with the ELS.

C. Comparaison of the results with the historical best local search methods

In this section, we report the experimental results generated by the proposed EVND. The experimental study was conducted as a comparison of different algorithms on the famous 100 customers' instances from Solomon [16]. In order to assess the EVND, its performance is compared to three approaches: the Tabu Search (TS) [14], the Localized Genetic Algorithm (LGA) [18] and the VNS-C [5].

TABLE III
COMPARISON BETWEEN OUR BEST RESULTS AND RELATED METHODS ON THE SOLOMON INSTANCES.

Problem	TS		LGA		VNS-C		EVND	
	NV	TD	NV	TD	NV	TD	NV	TD
C101	10	828.94	10	827.3	10	828.94	**10**	**820.66**
C102	10	828.94	10	827.3	10	828.94	**10**	**823.05**
C103	10	828.07	10	827.3	10	828.94	**10**	**827.54**
C104	10	824.78	10	827.3	10	825.65	**10**	**824.12**
C105	10	828.94	10	827.3	10	898.94	**10**	**828.48**
C106	10	828.94	10	827.3	10	898.94	**10**	**826.35**
C107	10	828.94	10	827.3	10	898.94	**10**	**827.47**
C108	10	828.94	10	827.3	10	898.94	**10**	**827.31**
C109	10	828.94	10	827.3	10	898.94	**10**	**827.99**
C201	3	591.56	3	589.1	3	591.56	**3**	**583.50**
C202	3	591.56	3	589.1	3	591.56	**3**	**591.56**
C203	3	588.49	3	588.7	3	591.17	**3**	**586.45**
C204	3	587.71	3	588.1	3	590.6	**3**	**581.83**
C205	3	588.49	3	586.4	3	588.88	**3**	**581.44**
C206	3	588.49	3	586.0	3	588.49	**3**	**585.43**
C207	3	588.29	3	585.8	3	588.29	**3**	**583.89**
C208	3	588.32	3	585.8	3	588.32	**3**	**588.05**
R101	18	1606.07	20	1640.1	19	1652.47	**13**	**1653.80**
R102	17	1447.36	18	1467.5	18	1476.06	**14**	**1479.22**
R103	13	1257.49	14	1214.0	14	1219.89	**13**	**1248.64**
R104	9	1007.39	11	992.6	11	994.85	**10**	**986.42**
R105	13	1462.39	16	1362.3	14	1381.88	**12**	**1354.98**
R106	12	1263.29	13	1243.3	13	1243.72	***11***	***1250.08***
R107	10	1080.89	11	1069.5	11	1077.24	10	1102.42
R108	9	957.04	10	943.5	10	956.22	**9**	**945.75**
R109	11	1205.27	13	1152.4	13	1157.61	**11**	**1102.68**
R110	10	1128.61	12	1070.6	12	1081.88	**10**	**1118**
R111	10	1102.07	12	1057.3	11	1087.5	10	1064.95
R112	9	1003.76	10	960.8	10	958.7	**9**	**900.05**
R201	4	1248.49	10	1152.7	5	1190.52	**3**	1249.77
R202	3	1177.11	7	1045.4	4	1098.06	**3**	**1164.58**
R203	3	939.54	6	871.2	4	905	3	940.95
R204	2	822.66	5	731.3	3	766.91	2	827.27
R205	3	1005.05	7	965.1	4	964.02	**3**	**969.13**
R206	2	1076.74	5	887.6	3	931.01	**3**	**889.17**
R207	2	883.502	5	807.0	3	855.37	2	894.35
R208	2	730.62	4	703.4	3	708.9	**2**	**725.054**
R209	3	915.07	6	867.0	3	983.75	**3**	**908.48**
R210	3	949.52	6	944.7	4	935.01	**3**	**848.81**
R211	2	864.83	5	754.6	3	794.04	**2**	**862.17**
RC101	14	1685.39	18	1662.5	15	1624.97	**14**	**1607.48**
RC102	12	1503.25	15	1480.6	13	1497.43	**12**	**1502.27**
RC103	10	1305.20	12	1286.7	11	1265.86	**11**	**1255.57**
RC104	10	1118.42	10	1136.1	10	1136.49	10	1135.52
RC105	13	1626.49	16	1549.8	14	1642.81	**13**	**1555.63**
RC106	11	1366.86	13	1382.7	12	1396.59	***10***	***1427.95***
RC107	10	1312.23	12	1215.8	11	1254.68	**10**	**1238.22**
RC108	10	1132.60	11	1115.5	11	1131.23	10	1134.41
RC201	4	1394.81	10	828.93	5	1310.44	***3***	***1417.36***
RC202	3	1326.40	8	828.93	4	1219.49	3	1367.42
RC203	3	1066.66	6	828.93	4	957.1	**3**	**1051.20**
RC204	2	945.44	4	828.93	3	829.13	**3**	**792.11**
RC205	3	1566.16	8	828.93	5	1233.46	4	1243.81
RC206	3	1140.98	7	828.93	4	1107.4	3	1144.37
RC207	3	1055.42	6	828.93	4	1032.78	**3**	**1020.11**
RC208	3	827.58	5	827.52	3	830.06	**3**	**822**

Table III compares the results obtained for the three algorithms in terms of total distance travelled (TD) and number of vehicles required (NV). In average, the EVND procedure performs better against the solutions of the 56 instances, when compared to the other historical best methods, according to the total distance (underlined distances show an improvement with a competitive number of vehicles).

Results highlight clearly that for the group of instances C1 and C2, our approach is able to minimize the TD for all the instances with the same number of vehicles. However, for the R1 and R2 classes, EVND is less performant but it is still very competitive on the two criteria NV and TD. Concerning the classes RC1 and RC2, the EVND results are very competitive especially on the number of vehicles and outperforms the other methods in some cases, namely; RC101, RC203 and RC208, where the TD and the NV are the best. All the most interesting performances of the EVND are in bold in Table III.

The results also show that our method has managed to provide routings using the least number of vehicles compared to other existing methods without significantly degrading the total distance traveled. This is more clear for the results underlined in Table III. Indeed, for example, the R205 instance is solved by a routing distance equal to 969,13 using 3 vehicles against VNS-C heuristic whose distance traveled is equal to 964,02 using 4 vehicles. This kind of improvement is suited for our variant of e-VRP since the vehicles are assumed to be expensive. Further, for 13 instances (with results in italic), EVND has succeeded in reducing the number of vehicles compared to state-of-the-art methods.

This performance can be explained by the hybridation mecanism followed by EVND that explores the search space using a population of routings and an effective intensification VND method. In addition, we can note the ability of our method to lead for good tradoffs (NV,TD) suitable for the electric specifity of the problem treated. Indeed, the objective function chosen penalizes the use of added vehicles and the recharging of batteries while looking for routing with minimal distance.

VI. Conclusion

This paper proposed an enhanced evolutionary method for the VRP using electric modules. It consists in a combination of the evolutionary schema with local search procedures. Experimental analyses carried out on a set of problems clearly show the advantages of combining the evolutionary approaches with local search techniques. This work can be extended to other VRP variants especially those handling electric constraints in emerging freight delivery distribution problems. Moreover, we intend to enhance the variable neighborhood descent procedure by exploring other move operators.

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