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Multi-Depot Electric Vehicle Routing Problem with Fuzzy Time Windows and Pickup/Delivery Constraints

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ABSTRACT

The use of an Electric Vehicle (EV), particularly in different operations of goods distribution is a solution for salvaging the crowded cities of the world from air and noise pollutions as well as Green House Gas (GHG) emission. This paper presents a Multi-Depot Electric Vehicle Routing Problem (MD-EVRP) with recharging stations by considering the expected penalty of fuzzy time windows in pickup/delivery. Since the MD-EVRP with Fuzzy Time Windows and Pickup/Delivery (MD-EVRP-FTW-PD) constraints is an NP-hard problem, three meta-heuristics (i.e., Simulated Annealing (SA), Variable Neighborhood Search (VNS) and a hybrid of SA and VNS (VNS-SA)) are used to solve such a hard problem. The parameters of these algorithms are measured by the Taguchi experimental design method. The proposed hybrid VNS-SA algorithm is more efficient in comparison with other algorithms.

1. Introduction

Air pollution is the main problem of general health in developing countries. The causes of the many such pollutions are rooted in the energy section. It is the fourth and the greatest threat to human health after high blood pressure, unhealthy date, and smoking [1]. Almost 6.5 million people's annual death are assigned to the low quality of the air.

Earth warming caused by the emission of a lot of greenhouse gas is a global concern [2]. The second participation in Green House Gas (GHG) with 23% of CO_2 emission in 2014 is a transportation section [3]. This section depends severely on the combustion of oil so improving and changing the energy consumption in this industry is one of the national aims of many countries. Countries as India, England, and Germany declared that they will not sell and use the vehicle with inner combustion to 2030 [4].

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European Union obligates to reduce CO_2 in 2050 in comparison with 1990 between 80 and 90%. To reduce GHG emission and keep the global warming increase under 2 centigrade [5].

An electric vehicle is a helpful approach to solve the climate problem [6]. Among vehicles, electric trucks with a medium-size in comparison with a diesel truck produce less CO_2, 300 tons on average [7]. Although, most of the scientific and technological achievements related to the private and general electric vehicles, in recent years, a large virtue of research is concerning by using electric vehicles in the distribution of goods. In the same portion, the share of the electric vehicle market is increasing. For example, in China, the sale of these vehicles has reached 331000 per year to more than 50% between 2015 and 2017, which is 777000 set [8]. Also, in the world, 1.26 milliard electric vehicles in 2015 are used that are 100% more than 2010 [9]. This increase is due to features with an environment as a lack of GHG emission, less noise pollution, and high random energy that could provide logistic companies with a green picture for increasing social consciousness and environmental awareness [8]. However, this share of the market for vehicles is not satisfied. Then with financial incurring politics to finance the cost of buying a car, road toll exemption, and priorities of reaching the city center that some of the countries use it, can help to use these vehicles widely [10-13].

An electric vehicle challenges a limitation of movement ranges, and longings of complete charge time. Movement ranges limitation of these vehicles, that is, reaching to customers and returning to depot needs to recharge the battery, then the place of recharge station is important. Because of the long duration of charging time, it uses a changing battery technique instead of charging the battery, to spend less time. In the way vehicles to complete a route, faced trouble because of lack of suitable and enough under structures for changing the battery and lack of similar standards. For this reason, logistics companies prefer to provide these facilities by themselves. Thus, the place of the recharging stations plays an important role in optimization.

A fuzzy optimization method is widely used in Vehicle Routing Problems (VRPs); however, a very limited uncertain problem is proposed for electric vehicles. To deal with unknown parameters, some researchers have used an incidental optimization method. However, in practical applications, it is difficult to describe these parameters as incidental variations for the lack of enough historical data for analyzing. In return, it can be used fuzzy variations to deal with these unknown parameters [14].

The model proposed in this paper for the Multi-Depot Electric Vehicle Routing Problem with Fuzzy Time Windows and Pickup/Delivery (MD-EVRP-FTW-PD) is time windows of fuzzy service time. Then, the model is first solved by GAMS software for small-sized problems and by three meta-heuristic algorithms (i.e., Simulated Annealing (SA), Variable Neighborhood Search (VNS) and a hybrid of SA and VNS (VNS-SA)) coded in MATLAB software for large-sized problems. Finally, the efficiency of the algorithms and solution time is reported and compared. Experimental results show that the proposed algorithm is effective for solving the MD-EVRP-FTW-PD.

This paper is organized as follows. Section 2 considers the related work concerns with this investigation. Section 3 presents the MD-EVRP-FTW-PD model. Section 4 proposes meta-heuristic algorithms for solving this model. Section 5 reports the findings and result analyses. Finally, Section 6 provides the conclusion and some future studies.

2. Literature Review

The wishes of the countries to use electric vehicles not only in cities with high crowded population and pollution but also in logistic distribution networks are increasing. Although in an electric vehicle section, there are many mathematical models, in commercial electric vehicles and trucks, there are many fields to investigate. First, a brief literature review of VRPs with Pickup and Delivery (VRP-PD) and fuzzy theory in VRPs is presented. Then, the papers related to EVRPs are reviewed to find the research gap.

Çatay [15] studied on the VRP-PD. Fan [16] presented the VRP-PD and time windows to increase customer satisfaction. Wang and Qiu [17] studied the VRP-PD and probable demand and solved their model by a meta-heuristic algorithm. Setak et al. [18] presented a multi-depot capacitated Location-Routing Problem (LRP) with simultaneous pickup and delivery and split loads. They used heterogeneous vehicles in their model and solved the problem with a generic algorithm. Wang and Chen [19] studied the VRP-PD and time windows and solved their problem by a generic algorithm. Several papers in the VRP-PD and time windows or multi-depot can be found in [20-24]. The fuzzy theory has also been used widely in VRPs, such as LRP [25], multi-depot VRP for hazardous material [26], fuzzy multi-depot VRP-PD [27]. Other related VRPs can be found in [28-30].

Although, the purpose of the VRP and EVRP is to find an optimal routing to cover all of the customers' demands. As mentioned before, in contrast to classical vehicles, the domain of driving electric vehicles is short and the limits will be more due to battery capacities.

Artmeier et al. [31] used a graph theory concept and suggested a routing optimization problem with alternative fuel vehicles. They presented the shortest path algorithm by considering vehicle limitations. Other studies can be mentioned in the literature, such as a study on the battery capacity by Lin et al. [32], concentration on variable policies, such as type of charges by Mart´ınez-Lao et al. [33], partial recharge station electric vehicle with time windows by Keskin and Çatay [34] and the possibility of battery swapping by Yang and Sun [35].

The other studies concerning an EV location and routing problem are also presented. Schiffer and Walther [36] and Li et al. [37] studied the charge station LRP. Hof et al. [38] presented swapping battery and charge station LRP. Paz et al. [39] considered multi-depot LRP in three models. The first model has only a partial charge station in the route. The second model has only a battery-swapping station and the third one has partial charge station and battery swapping in the route. The results of their model show that partial charge and battery swapping are more efficient. Keskin and Çatay [40] represented the EVRP with time windows and fast chargers and proposed the ALNS algorithm to solve the model. For further studies in this field, the reader can refer to [41].

The point is this that the above-mentioned studies have been done in a certain environment and the unknown factors affecting the effects have been ignored suggested to these unknown factors. In fact, in addition to unknown factors relating to vehicles, many of the city and intercity logistic applied programs are the cases out of the atmosphere, traffic condition, road conditions, the existence of recharging stations, or battery changing, and unknown demands of customers. Although Zhang et al. [9] regarded three parameters of time service, energy consumption, and travel time as fuzzy, their model was one depot.

The model presented in this paper has a multi-depot, a set of customers with certain demand, the possibility of pickup/delivery, charge stations, and homogenous fleet with a fixed capacity of the EV. In this model, time windows of fuzzy service time for customer satisfaction. This model is very suitable for the decision-maker considering a multi-depot distribution and determining the route with the minimum cost under uncertainty.

The contributions of this paper are to develop the EVRP-TW-PD model to a multi-depot model and use the expected penalty of time windows with a fuzzy approach for salsify customers. The model is solved for small and large sizes with GAMS software and also three algorithms of SA, VNS, and combination of SA and VNS algorithm.

3. MD-EVRP-FTW-PD Model

In this section, the important assumptions for formulating the model is first presented, and then, it concerns with notations and a description of the model.

3.1. Assumptions Model

The main assumptions about the proposed model are as follows:

- The numbers of depots and vehicles in each inventory are specified.
- Electric vehicles have the same capacity loading and battery as well as move with constant speed a limitation for driving.
- The electrical energy consumption multiple is constant and is adjusted to the distance.
- Recharging time in the station is fixed.
- EVs move from distribution depots or recharging stations with a complete charge and do not consume energy in a customer service process.
- Each customer has only one specific demand (delivery or pickup), and services to each customer are provident only one time.
- EVs exit each disturbing depot, then provide service to customers continuously and finally return to the same depot from where it had started to move.
- To satisfy customers, the time windows of a fuzzy number are considered to pick up or delivery.

3.2. Notations

The following notations are used in the proposed MD-EVRP-FTW-PD shown in (e.g., *Table 1*):

Table 1. *Definitions of sets, parameters, and variables.*

Notations	Definition
Sets and Indices	
O	*Set of all depots; denoted by index o.*
NC	*Set of customers.*
NE	*Set of recharging stations.*
NT	*Set of all nodes,* $O \cup NC \cup NE$, $i, j = \{1,2,3,\ldots,n\}$.
NK	*Set of electric vehicles; denoted by index k.*

Notations	Definition
Parameters	
$\mathbf{Dis_{ij}}$	*Distance between nodes i and j.*
$\mathbf{Dem_i}$	*Demand of node i.*
$\mathbf{Cap_k}$	*Capacity of electric vehicle k.*
$\mathbf{[LT_i, UT_i]}$	*Fuzzy interval: lower and upper bounds of acceptable time windows of node i.*
$\mathbf{[LE_i, UE_i]}$	*Fuzzy interval lower and upper bounds of expected time windows of node i.*
$\mathbf{ST_i}$	*Service time in node i.*
$\mathbf{TT_{ij}}$	*Travel time between nodes i and j.*
BC	*Battery capacity of electric vehicle k of node i.*
EC	*Electricity consumption coefficient.*
CU	*Cost of unit transportation.*
CW	*Cost of unit time for waiting.*
CL	*Cost of unit time cost for late.*
$\mathbf{K_o}$	*Number of electric vehicle k of depot o.*
LN	*An arbitrarily large number.*
Variables	
$\mathbf{X_{ijk}}$	*1 if the route between nodes i and j is traveled by electric vehicle k; 0, otherwise.*
$\mathbf{Y_{ik}}$	*1 if node i is served by electric vehicle k; 0, otherwise.*
$\mathbf{W_{ok}}$	*1 if electric vehicle k travels from depot o; 0, otherwise.*
$\mathbf{A_{ijk}}$	*Amount of pickup or delivery electric vehicle k on board on nodes i and j.*
$\mathbf{TA_{ik}}$	*Time of vehicle k arrives at node i.*
$\mathbf{TL_{ik}}$	*Time of vehicle k leaves node i.*
$\mathbf{TS_{ik}}$	*Service start time of vehicle k at node i.*
$\mathbf{RCA_{ik}}$	*Remaining charge when vehicle k arrives at node i.*
$\mathbf{RCL_{ik}}$	*Remaining charge when vehicle k leaves node i.*
$\mathbf{Sub_{ik}}$	*Variable used for elimination of sub-tours.*

3.3. Determination of the Objective Function and Constraints

In this paper, the minimization objective function is divided into two sections: Transporting cost and penalty cost of time windows. These sections are the total cost of transportation and the penalty cost of violating of soft and hard time windows, respectively. Since it is very important to rank the fuzzy subsets [42] in the transportation problem, the service time windows are assumed to be fuzzy. Different methods for ranking of fuzzy subsets are proposed in the literature. In this paper, the developed method of Liou and Wang [43] is used. Based on this method, the total integral value is a convex combination of the right and left integral values through an index of optimism, $\beta \in [0, 1]$. The left and right integrals show the optimistic and pessimistic points of view of the customers, respectively. The total integral value is reached by a convex combination of the right and left integral values. This value is used to rank fuzzy numbers.

In this model, uncertain parameters, the pattern sets of the fuzzy number $F= (a, m, b)$, where a, m and b are estimated as the pessimistic value and most likely, and optimistic values, respectively *Eq. (1)*. If F is a triangular fuzzy number, the membership function S_F will be defined as follows [42, 44-46].

$$S_F(x)=\begin{cases} f_n(x)=\dfrac{x-a}{m-a} & \text{if } (a\le x\le m) \\ 1 & \text{if } (x=m) \\ g_n(x)=\dfrac{b-x}{b-m} & \text{if } (m\le x\le b) \\ 0 & \text{if } (x\le a, x\ge b) \end{cases} \tag{1}$$

Then, the Expected Interval (EI) and the Expected Value (EV) of *F* are calculable by:

$$EI(F)=[E_1^{\,n},E_2^{\,n}]=[\int_0^1 f_n^{-1}(x)dx,\int_0^1 g_n^{-1}(x)dx]=[\frac{1}{2}(a+m),\frac{1}{2}(m+b)]. \tag{2}$$

$$EV(F)=\frac{E_1^{\,n}+E_2^{\,n}}{2}=\frac{a+2m+b}{4}. \tag{3}$$

Therefore, for each of the parameters *LTi*, *UTi*, *LEi*, and *UEi*, three *Pessimistic (A)*, *probabilistic (m)*, and *Optimistic (b)* times are assumed. For example, *LTi*: *LT (a)i*, *LT (m)i*, *LT (b)i*. Then, we calculate the penalty cost of the mixed time windows if the vehicle arrives earlier or later than these intervals. The other limitation of this model is the limitation of a vehicle if the vehicle is not charged to reach the customer, it should be returned to the recharge station if not, it should be returned to the depot from which the vehicle had started to move.

3.4. Mathematical Model

In this subsection, the presented model is as follows:

$$\text{Minimize } Z=CU(\sum_{i\in NT}\sum_{\substack{i\in NT\\ j\neq i}}\sum_{k\in NK} Dis_{ij}X_{ijk})+\sum_{i\in NC}\sum_{k\in NK} Y_{ik}(CW.LL_{ik}+CL.UL_{ik}) \tag{4}$$

$$\text{subject to } \sum_{i\in NT,i\neq j}\sum_{k\in NK} X_{ijk}=1, \qquad \forall j\in NC, \tag{5}$$

$$\sum_{i\in NT,i\neq j}\sum_{k\in NK} X_{jik}=1, \qquad \forall j\in NC, \tag{6}$$

$$\sum_{j\in NC\cup NE} X_{ojk}=\sum_{j\in NC\cup NE} X_{jok}\le W_{ok}, \qquad \forall k\in NK, o\in O, \tag{7}$$

$$\sum_{i\in NT,i\neq j} X_{ijk}=\sum_{i\in NT,i\neq j} X_{jik}=Y_{jk}, \qquad \forall j\in NC\cup NE, k\in NK, \tag{8}$$

$$X_{ojk}=0 \qquad \forall j\in O\cup NE, k\in NK, o\in O, \tag{9}$$

$$0\le A_{ijk}\le Cap_k.X_{ijk} \qquad \forall i,j\in NT, j\neq i, k\in NK, \tag{10}$$

$$\sum_{i\in NT,i\neq j}\sum_{k\in NK} A_{ijk}-Dem_j=\sum_{i\in NT,i\neq j}\sum_{k\in NK} A_{jik} \qquad \forall j\in NC, \tag{11}$$

$$TL_{ok}=0 \qquad \forall k\in NK, o\in O, \tag{12}$$

$$TA_{jk}=\sum_{i\in NT,i\neq j} X_{ijk}.(TL_{ik}+TT_{ij}) \qquad \forall j\in NC\cup NE, k\in NK, \tag{13}$$

$$TL_{ik}=Y_{ik}.(SST_{ik}+ST_i) \qquad \forall j\in NC\cup NE, k\in NK, \tag{14}$$

$$SST_{ik}=Y_{ik}.(TA_{ik}+LL_{ik}) \qquad \forall j\in NC\cup NE, k\in NK, \tag{15}$$

$$RCA_{ik} \geq 0 \qquad \forall j \in NT, k \in NK, \qquad (16)$$

$$RCA_{jk} = \sum_{i \in NT, i \neq j} X_{ijk}.(RCL_{ik} - EC.Dis_{ij}) \qquad \forall j \in NT, k \in NK, \qquad (17)$$

$$RCL_{ik} = BC \qquad \forall i \in O \bigcup NE, k \in NK, \qquad (18)$$

$$RCL_{ik} = RCA_{ik} \qquad \forall j \in NC, k \in NK, \qquad (19)$$

$$Sub_{ik} - Sub_{jk} + LN.X_{ijk} \leq LN - 1 \qquad \forall j \in NT, j \in NC, j \neq i, k \in NK, \qquad (20)$$

$$\sum_{j \in NC \bigcup NE} \sum_{k \in NK} X_{ijk} \leq K_o \qquad \forall i \in O, \qquad (21)$$

$$TA_{ik} \geq LT_i \qquad \forall i \in NC \bigcup NE, k \in NK, \qquad (22)$$

$$TA_{ik} \leq UT_i \qquad \forall i \in NC \bigcup NE, k \in NK, \qquad (23)$$

$$X_{ijk} \in \{0,1\} \qquad \forall i, j \in NT, i \neq j, k \in NK, \qquad (24)$$

$$Y_{ik} \in \{0,1\} \qquad \forall j \in NT, k \in NK, \qquad (25)$$

$$W_{ok} \in \{0,1\} \qquad \forall o \in O, k \in NK, \qquad (26)$$

$$Sub_{ik} \geq 0, LN \geq 0 \qquad \forall i \in NT, k \in NK. \qquad (27)$$

Constraint (4) illustrates the objective function representing the total cost, including transportation costs and the costs for violating time windows. *Constraints (5)* & *(6)* ensure that every customer is served exactly once. *Constraint (7)* guarantees that each vehicle moved from each depot should be returned to the same depot. *Constraint (8)* represents the vehicle flow-conservation equation, that is, the number of times vehicle k enters into a point *i* is equal to the number of times it leaves point *i*. *Constraint (9)* guarantees the vehicle do not go to recharge stations from depots directly. *Constraint (10)* imposes the maximum vehicle capacity constraint. *Constraint (11)* ensures the vehicle load variation on a route. *Constraint (12)* imposes the departure time of a vehicle from each depot. *Constraints (13) - (15)* are to calculate the time that vehicle *k* arrives at and departs from the point *i* and the time starting service at point *i*. *Constraint (16)* ensures that the vehicles are fully charged after departing from the distribution center or the recharging stations. *Constraints (17) - (19)* represent the electricity constraint. *Constraint (20)* guarantees the elimination of the sub-tour. *Constraint (21)* represents the number of vehicles that cannot exceed m_o. *Constraints (22)* & *(23)* represent time windows (according to what is said, fuzzy numbers). *Constraints (24)* & *(26)* are binary variables. *Constraint (27)* guarantees Sub_{ik}, where *LN* is a non-negative auxiliary variable.

3.5. Model Linearization

Considering the nature of the problem, the model is formulated in nonlinear form. By considering that nonlinear models are time-consuming in comparison with their solving linear models and there is not available an algorithm for ensuring a comprehensive optimal answer. The presented mathematical model is a Mixed-Integer Nonlinear Programming (MINLP) model due to some nonlinear equations. The multiple variables in *Eqs. (4), (13)-(15)* & *(17)*. Linearization methods are now applied to obtain an equivalent linear mathematical model. Linear Programming (LP) as a very multi-functional technique is used to making the design and solving a variety of problems [47]. This method was proposed by McCormick [48].

In the second term of the objective function, two variables change *Eqs. (28)* and *(29)* are occurring. Some equations are non-linear that will be changed in linear equations. Then, the model is solved in an MIP form.

$$LL_{ik} = \max\left[\left(LE_i - TA_{ik}\right), 0\right] \qquad \forall i \in NT, k \in NK. \tag{28}$$

$$UL_{ik} = \max\left[\left(TA_{ik} - UE_i\right), 0\right] \qquad \forall i \in NT, k \in NK. \tag{29}$$

4. Proposed Method

A reason for using the meta-heuristic algorithm is the history and complexity of the MD-EVRP-FTW-PD model for its optimization. This section represents a solution representation method, neighborhood structure, solution initialization, operators to deal with the infeasible solutions, and adjusted method of parameters and parameters of each algorithm. Then, three meta-heuristic algorithms (i.e., SA, VNS, and a hybrid of SA and VNS) are proposed to solve the presented model.

4.1. Solution Representation Method

To write the computer programs for the proposed algorithms, we first need the representation structure method of solutions. The structure must be in a manner that can be observed and studied performing a solution. The structure design of the representation method has an important role in the fitness function. The solution representation is a solution string that includes several cell customers, depots, and charge stations. Vehicle order of visit between nodes is determined in this representation. The (e.g., *Fig. 1*) shows a small problem with four customers and two depots and one recharge station are shown. In this figure, the places of 1 and 2 are depots, and 3, 4, 5, and 6 are nodes of customers, and 7 is the charge station showing an electric vehicle movement tour. To assign customers to electric vehicles, all the cells from the beginning of the string will be assigned to the first vehicle until we reach a zero value.

1	3	4	5	6	1	0	7	2

Fig. 1. *Example of a solution representation*.

4.2. Neighborhood Structure

The main purpose of the neighborhood structure in the algorithms is to construct a neighborhood solution out of an available solution by changing them [49]. The SA algorithm uses temperature changes to make neighborhood structures. The VNS algorithm uses three moving actors to make a new neighborhood for current solutions. The hybrid VNS-SA algorithm uses the combination of these structures presented separating in describing each algorithm.

4.3. Solution Initialization Algorithm

To begin the algorithm, it needs to initialize the suitable and quality solution. After recalling the main parameters out of initializing the solutions based on the demand limitation (for delivery and pickup), the maximum limit of the loading capacity (the algebraic sum of delivery and pickup should not exceed the vehicle capacity) and the charge limitation of EVs should have enough charge. Breach of limitations may result in an infeasible solution thus the strategy of the punishment extent suitable with the extent of a limitation breach in the algorithm should be added to the fitness function. These parameters (i.e.,

Sol.demand, Sol.charge, and Sol.cap) are equal to the extent of punishment for the demand limitation breach of per unit, charge, and the extent of the loading capacity. This results in a feasible solution with the β coefficient.

4.4. Simulated Annealing Algorithm

SA is a simple and effective meta-heuristic algorithm for solving optimization problems proposed by Metropolis in 1953. It was first used in optimization by Kirkpatrick et al. (1983). SA has been used successfully in various types of VRPs and shown good performance [50].

SA is an algorithm based on slowly annealing technique, which is based on local searching in solution space and accepts probabilistic and non-standard solutions to escape from local optimization to reach for better answers. By decreasing the annealing condition for each given temperature, the level of energy is calculated according to the Boltzmann distribution. Algorithm parameters are included in initial temperature, final temperature, the number of iterations in the fixed temperature, and the number of iterations in the case of lack of any solution improvement. The algorithm by establishing one of two conditions: reaching to final temperature or several important solution iterations is concluded. To escape of local optimization, SA uses a function for accepting the worse solution.

In this probable function, the current situational situation, a situation in the neighborhood, Boltzmann consonant, and current temperature are determined. In *Eq. (30)*, Δ means the deviation of energy (i.e., objective) function values.

$$R = \exp\ [-\Delta/(K * T)]. \tag{30}$$

It is necessary to mention that the initial solution of the SA algorithm is presented by using the method of producing the initial solution in the next section.

In SA, one of neighborhood search methods is used in each repetition, until the best solution results; however, there is not any specific procedure for using the neighborhood search method. This neighborhood search process will be continued until the number of repetition reach to determined quantity, then the system temperature will be reduced and this process will be continued to reach the stopping criterion.

4.5. Variable Neighborhood Search Algorithm

VNS is a meta-heuristic algorithm used to solve hybrid and global optimization problems. In 1997, Mladenović and Hansen [51] first developed a VNS algorithm. The main idea of this algorithm is the systematic neighboring change by using a local searching method. The general structure of this method is as follows. First, several neighboring structures and a primary answer are determined, then the algorithm using the primary neighboring structure, based on two first improvement selection approaches or best improvement selection starts to search. In the case of observing any improvement in solution, the better solution is replaced by the current solution, and the neighboring structure returns to the first start. After several iterations and in a case of not observing any improvement in answer, it enters the next neighboring structure. The stopping condition of this algorithm is included in the case as a limitation in the number of iterations, the computational time, the number of iterations between two consequent improvements in answering as well finding a locally optimal solution in the whole

neighboring structure. The VNS algorithm has a more meta-heuristic algorithm structure and its advantage is fewer parameters, consequently, it has high speed.

The suggested VNS algorithm to the given problem has four main phases, namely the generate solution initialization, shaking, local search phase, and altimetry stop.

- Generating the initial solutions: The solution initialization is made with generating a line matrix. It is necessary to point out that this phase will be continued to find a solution.
- Shaking: The aim of this phase is to make a shake in the existing solution. In this phase, several making neighbor structures are used and the neighborhood structure is changed.
- Local search: This phase aims to find the local optimal solution. After making the neighborhood in this phase, the local search method is applied to the changed solution. Swap, Insertion, and Reversion are used in this paper. The first operator (insertion) first selects two elements of *i* and *j* as a sample, and then take the *i*-th element from its place and locate it in the place of $j+1$ (one cell after *j*). The second operator (i.e., reversion) first selects the elements of *i* and *j* as a sample and then ordering of their arrangements, and all of the elements between them are reversed. The third move operator (i.e., swap) select two elements of *i* and *j* accidently and then change the place of their elements with each other.
- Stopping criterion: In each algorithm in the neighborhood, if in the number of repetitions *MaxIt2*, a better answer than the current answer will not be found, the neighborhood will be increased and if the algorithm in the neighborhood will be L_{max}, the neighborhood will be returned to l_1. The algorithm will be stopped if the number of repetitions reaches to *MaxIt*.

4.6. Hybrid SA and VNS Algorithm

The concept of the SA algorithm into VNS, it guarantees the effectiveness of VNS and alleviates the potential weakness of VNS (intensification) [42]. The reason is perhaps the strategies for searching the answer space by two algorithms. In the SA algorithm in each iteration, one of the methods for searching the neighborhood is used to produce a new answer. In this algorithm, there is not a specific procedure for using the methods for the searching neighborhood. However, in the VNS algorithm, first, the methods for neighborhood searching are arranged in terms of the extent of changes that applied in solution. Then, the algorithm starts from its search by the method of neighborhood searching with the least changes in answer, and if the solution does not find any consequent repetition, it will choose the next search that causes more change in the current solution. This causes the algorithm with a few changes to follow the better solution if the current solution is good. If a better solution cannot be found, the solution will be changed more or in order words, it will continue its search in more far space from the current solution. The pseudo-code of VNS-SA used in this paper is shown in (e.g., *Fig. 2*).

The SA algorithm uses temperature changes of the neighborhood structure. The VNS algorithm has no temperature, uses three defined neighborhoods, keeps a better solution in proportionate to that neighborhood, and omits the worse solution. However, the hybrid of SA and VNS (i.e., VNS-SA algorithm) starts with finding initial solutions. It continues in addition to conventional neighborhood structures of VNS, an internal loop algorithm out of neighborhood search in temperature until $l \leq l_{max}$. Then, a geometric function is used to reduce the temperature of SA *Eq. (31)*.

$$T_{i+1} = \alpha T_i \,, \tag{31}$$

where α is temperature reducing parameter, T_i is the current temperature, and T_{i+1} is the new temperature. The algorithm will continue to reach to the determined final temperature.

```
Input : a set of neighborhood structures N_l, L = 1, 2, …, L_max
x = generate initial solution
T = T_0
While It < MaxIt
{
Until (it2 < MaxIt2)
        {
 Generate randomly Solution from neighborhood structures.
  if (xnew.cost ≤ x.cost and xnew if feasible)
            x ← xnew
                else
                        Δ = xnew.cost − x.cost;
                        r = random();
                        p = exp(Δ / T);
                        if (r < p)
                        x ← xnew
                  end
  end
       }
           T = α.T_0
}
Return the best solution found.
```

Fig. 2. *Pseudo-code of the SA algorithm into VNS (i.e., VNS-SA).*

4.7. Taguchi Parameter Design

The results of the meta-heuristics are dependent on the values of the input parameters, it has been proposed. The parameters of the effect of the meta-heuristic algorithms on their suitable function, in which the Taguchi analysis is a statistical method used to adjust parameters. In this method, a rate named *S/N* is used to study solutions. At this rate, *S* is extant of utility, and *N* is a non-utility. As a result, the is to increase the quantity of this rate as possible [52].

From the standard table of the orthogonal arrays, the *L9* is selected as the fittest orthogonal array design, which fulfills all the minimum requirements. For each algorithm, the effect parameters are determined by trial and error. For each parameter, three levels are considered. Minitab Software is used to analyze the data. By considering a number of the selected factors and selected levels for the analysis, a suitable standard table is chosen for this study. Then, three typical problems are selected accidentally. Each problem by considering the given quantities for the parameters in each line of the Taguchi table to times runes. The mean objective function values are reported to Minitab17 software [47]. Finally, for each parameter, the level with more *S/N* as the best level of that parameter is considered.

4.8. Parameter Tuning

To solve the model, the parameters of the meta-heuristic algorithms are tuned according to (e.g., *Table 2*). In this table, T is the final temperature and α is the reduction multiple of temperature in the SA algorithm. T_0 is also the initial temperature. MaxIt and MaxIt2 respectively the maximum repeated number, the repetition number in each neighborhood, and the probable selection of neighborhood structure relating to the daily visit of customers in the VNS algorithm.

Table 2. *Parameters of the meta-heuristics algorithms.*

SA		**VNS**		**VNS-SA**	
Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
T_0	100	*MaxIt*	300-500	T_0	100
α	0.98	*MaxIt2*	3	α	0.98
T	0.01			T	0.01
				MaxIt	300-500
				MaxIt2	10

5. Numerical Results and Comparison

The Solomon benchmark is a known benchmark used in VRPs. Solomon's problems are based on the features and characteristics that are classified. Each group is included in 8 to 12 problems and a maximum of customers is 100. These problems are included in three main groups (C, R, and RC), and two sub-groups (C_1, C_2, R_1, R_2, RC_1, RC_2). The problems are different in terms of four features. The quantity of demand, time windows, and service time. Also, the problems of a single depot are considered. There are two important points for using this benchmark in electric VRPs: First, this has not the possibility of specifying the place of charge stations. Second, the central depot is defined.

To produce the instance problems in small and large sizes, it is used as a combination of the Solomon benchmark and instances in the literature with a little change. The Euclidean distance of the cities from Solomon's benchmark and fuzzy time windows and time services of both points of pessimistic and optimistic values is then calculated. For each customer, a fixed quantity of pickup or delivery is considered. For each depot, the number of vehicles is allocated. The number of recharge stations candid place is specified in *([2+0.05C], [3+0.1C]*) interval.

The model for small-sized samples is solved by using of solving CPLEX in commercial software GAMS 24.1.2. The algorithms are running on the computer with specification Core i5, CPU 2.60 GHZ using software MatlabR2017a (64-bit) by Microsoft windows10 for small and large sizes.

5.1. Efficiency of the Algorithms of Small-Sized Problems

In small-sized problems, 10 problems are produced randomly and the results of an exact solution with GAMS software and CPLEX solver are compared to SA, VNS, and VNS-SA algorithms.

The results of a typical problem solving are shown in (e.g., *Tables 3* & *4*). C, D, E, K the data of the problem briefly characterize the number of customers, depots, charge stations, and the number of vehicles. Time at the table is expressed in terms of seconds and the error is expressed based on the following equation.

$$\text{Gap\%} = \frac{\text{RA} - \text{RB}}{\text{RB}} * 100. \tag{32}$$

RA and RB are solutions resulted from the algorithm and the best-resulted solutions. In this paper equation, as specified in the table, the quality of solutions resulted from three are suitable meta-heuristic algorithms. The average error rate of algorithms: SA, VNS, VNS-SA are at 0.45, 0.23, 0.12. respectively. The maximum error is SA as 0.92. In terms of time, GAMS is equal to 3.618.

Table 3. *Results of GAMS in small-sized problems.*

Instance	C-D-E-K	CPLEX	Time (s)
1	*4-2-1-3*	*194.56*	*0.1*
2	*5-2-1-3*	*293.96*	*0.3*
3	*5-2-1-4*	*304.2*	*0.2*
4	*5-2-2-4*	*342.54*	*0.27*
5	*6-2-2-4*	*312.15*	*0.38*
6	*7-2-2-4*	*367.51*	*4.81*
7	*7-2-3-4*	*325.73*	*4.14*
8	*8-2-2-3*	*547.12*	*8.45*
9	*8-2-3-3*	*603.64*	*8.2*
10	*9-2-2-4*	*714.6*	*9.33*
Average		*400.601*	*3.618*

Table 4. *Results of MATLAB in small-sized problems.*

Instance	C-D-E-K	SA	t(s)	Gap%	VNS	t(s)	Gap%	VNS-SA	t(s)	Gap%
1	*4-2-1-3*	*195.8*	*0.05*	*0.64*	*195.55*	*0.08*	*0.51*	*195.55*	*0.09*	*0.51*
2	*5-2-1-3*	*297*	*0.12*	*1.03*	*294.98*	*0.1*	*0.35*	*293.96*	*0.1*	*0.00*
3	*5-2-1-4*	*304.35*	*0.1*	*0.05*	*304.2*	*0.11*	*0.00*	*304.2*	*0.09*	*0.00*
4	*5-2-2-4*	*342.97*	*0.3*	*0.13*	*342.67*	*0.25*	*0.04*	*342.61*	*0.19*	*0.02*
5	*6-2-2-4*	*313.84*	*0.35*	*0.54*	*313.16*	*0.31*	*0.32*	*313.76*	*0.3*	*0.52*
6	*7-2-2-4*	*367.61*	*0.37*	*0.03*	*367.58*	*0.42*	*0.02*	*367.57*	*0.4*	*0.02*
7	*7-2-3-4*	*325.79*	*0.9*	*0.02*	*325.99*	*0.7*	*0.08*	*325.73*	*0.65*	*0.00*
8	*8-2-2-3*	*552.15*	*1.8*	*0.92*	*551.14*	*0.99*	*0.73*	*547.12*	*0.7*	*0.00*
9	*8-2-3-3*	*603.69*	*2.01*	*0.01*	*604.41*	*1.12*	*0.13*	*603.66*	*0.91*	*0.00*
10	*9-2-2-4*	*721.95*	*2.63*	*1.03*	*715.65*	*1.18*	*0.15*	*715.3*	*1.02*	*0.10*
Average		*402.51*	*0.86*	*0.44*	*401.53*	*0.53*	*0.23*	*400.94*	*0.45*	*0.12*

5.2. Efficiency of the Algorithms for Large-Sized Problems

In large-sized problems, groups similar to Solomon benchmark problems with the same dimension for 15-200 customer are chosen, and by considering the pickup or delivery of each customer. Then, a solving method is applied to them. The results of solving the typical problems are shown in (e.g., *Tables 5* & *6*) VNS-SA in large-sized instances is better than SA and VNS algorithms. The percent of error, the VNS-SA with 0.011 error has a very insignificant error. SA with average error 2.645 has a weaker instance than the proposed algorithm. The least time consuming is to solve the VNS-SA algorithm.

***Table 5**. Results of SA and VNS for large-sized problems.*

Instance	C-D-E-K	SA	t(s)	Gap (%)	VNS	t(s)	Gap (%)
1	*25-2-4-6*	*33073*	*12.92*	*1.122*	*32870*	*11.20*	*0.501*
2	*25-2-5-6*	*34297*	*15.56*	*1.016*	*33952*	*14.32*	*0.000*
3	*30-3-5-7*	*42398*	*26.30*	*1.150*	*42199*	*22.85*	*0.675*
4	*35-3-6-7*	*43016*	*29.41*	*1.458*	*43019*	*35.30*	*1.465*
5	*40-3-6-8*	*51202*	*40.34*	*2.027*	*51043*	*47.60*	*1.710*
6	*45-4-5-8*	*59211*	*46.26*	*2.062*	*59159*	*56.20*	*1.972*
7	*50-4-6-9*	*62726*	*50.80*	*2.121*	*61423*	*93.56*	*0.000*
8	*50-4-7-9*	*77925*	*51.22*	*2.224*	*77840*	*96.21*	*2.112*
9	*60-5-8-10*	*86390*	*67.30*	*2.545*	*86108*	*109.20*	*2.210*
10	*60-5-9-10*	*108205*	*68.12*	*2.606*	*107795*	*123.65*	*2.217*
11	*70-6-10-11*	*118603*	*80.35*	*2.897*	*117862*	*191.41*	*2.254*
12	*80-6-11-11*	*125275*	*91.65*	*2.680*	*123815*	*250.00*	*1.484*
13	*90-7-11-12*	*140154*	*109.20*	*3.123*	*138078*	*273.22*	*1.595*
14	*100-9-12-14*	*150289*	*181.60*	*3.327*	*149795*	*319.65*	*2.987*
15	*100-10-13-15*	*167568*	*319.36*	*3.185*	*166288*	*321.30*	*2.397*
16	*120-14-15-18*	*186150*	*363.30*	*3.380*	*185220*	*412.60*	*2.863*
17	*130-14-16-19*	*187150*	*420.24*	*3.873*	*185720*	*435.60*	*3.079*
18	*160-15-17-20*	*213598*	*492.51*	*3.878*	*212101*	*455.32*	*3.150*
19	*180-15-20-22*	*214048*	*539.37*	*4.097*	*213101*	*490.14*	*3.637*
20	*200-16-22-27*	*239314*	*658.00*	*4.135*	*239117*	*525.25*	*4.049*
Average		*117030*	*183.19*	*2.645*	*116325*	*214.23*	*2.018*

According to the convergence rate of the proposed hybrid VNS-SA algorithm in (e.g., *Fig. 3*), it can result that as the problem size becomes large, the algorithm has better quality in terms of objective function values. The (e.g., *Fig. 4*) depicts the objective function values with different small-sized problems.

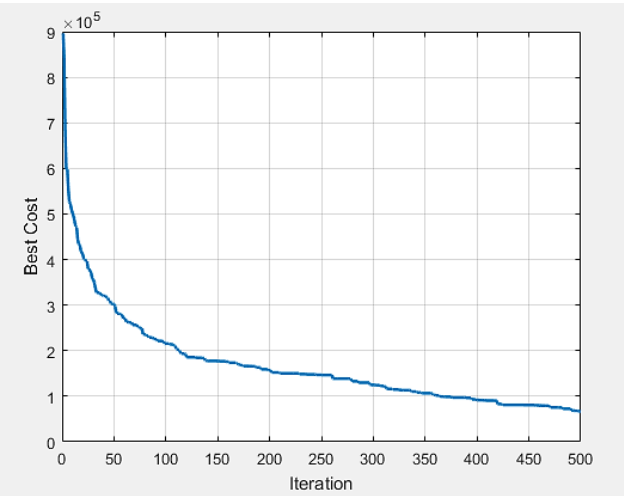

***Fig. 3.** Convergence rate of the proposed hybrid VNS-SA algorithm.*

***Table 6**. Results of VNS-SA for large-sized problems.*

Instance	C-D-E-K	VNS-SA	t(s)	Gap%
1	*25-2-4-6*	*32706*	*9.92*	*0.000*
2	*25-2-5-6*	*33975*	*11.76*	*0.068*
3	*30-3-5-7*	*41916*	*14.52*	*0.000*
4	*35-3-6-7*	*42398*	*21.03*	*0.000*
5	*40-3-6-8*	*50185*	*32.50*	*0.000*
6	*45-4-5-8*	*58015*	*45.99*	*0.000*
7	*50-4-6-9*	*61520*	*71.02*	*0.158*
8	*50-4-7-9*	*76230*	*73.15*	*0.000*
9	*60-5-8-10*	*84246*	*89.35*	*0.000*
10	*60-5-9-10*	*105457*	*92.50*	*0.000*
11	*70-6-10-11*	*115264*	*115.62*	*0.000*
12	*80-6-11-11*	*122005*	*125.48*	*0.000*
13	*90-7-11-12*	*135910*	*139.79*	*0.000*
14	*100-9-12-14*	*145450*	*150.36*	*0.000*
15	*100-10-13-15*	*162395*	*156.90*	*0.000*
16	*120-14-15-18*	*180064*	*173.10*	*0.000*
17	*130-14-16-19*	*180172*	*189.35*	*0.000*
18	*160-15-17-20*	*205623*	*232.70*	*0.000*
19	*180-15-20-22*	*205623*	*240.60*	*0.000*
20	*200-16-22-27*	*229811*	*273.09*	*0.000*
Average		*113448*	*112.94*	*0.011*

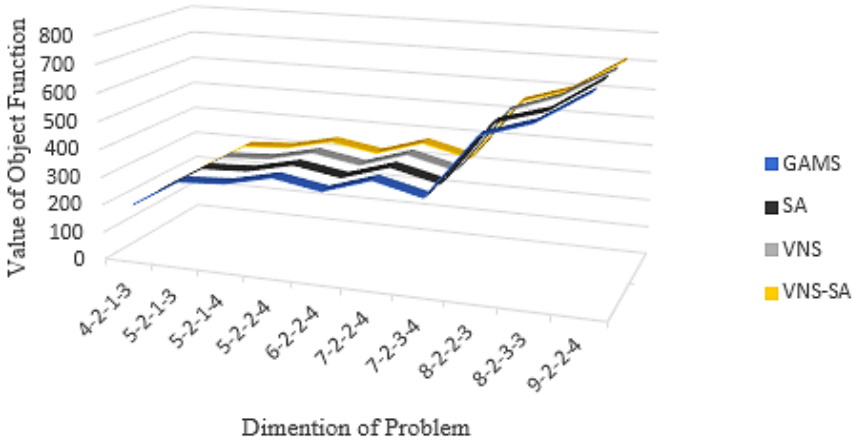

***Fig. 4.** Objective function values for small-sized problems.*

6. Conclusions and Future Research

In this paper, a new mathematical model for an Electric Vehicle Routing Problem (EVRP) with fuzzy time windows was presented. The objective function of the presented model was to minimize the cost

of the traveled distance and the penalty of time windows with a fuzzy approach. To show the efficiency of the proposed hybrid algorithm, the results were compared with the results obtained by the exact solution, Simulated Annealing (SA), and Variable Neighborhood Search (VNS) algorithms. Then, the proposed hybrid VNS-SA algorithm showed that its performance outperformed than the SA and VNS algorithms in small- and large-sizes problems. By considering the following issues that help to a deeper understanding of the effects of these factors on solutions, it is suggested to develop the model to make more practical the following future studies:

- Using a heterogeneous fleet and different speeds.
- Considering environmental factors (e.g., changing the temperature degrees), mountain routes, traffic, and queue in the battery recharge station.
- Considering the fuzzy stochastic and robust models.

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