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A Hybrid Solution Approach for Electric Vehicle Routing Problem with Soft Time-Windows

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Abstract: An electric vehicle routing problem (EVRP) with time windows is carried out using a hybrid algorithm. Through the modeling of problem, not only the energy consumptions and the charging durations of the EDVs, but also the conventional vehicle flow formulations and the soft time window constraints are taken into account. A hybrid solution method is proposed to solve EVRP. The proposed method combined genetic algorithm and simulated annealing algorithm to complement each other. In order to demonstrate the effectiveness of the proposed approach, simulations are carried out on a case study with 25 customers, 2 charging stations, a depot and 3 identical EDVs. The performance of the proposed method has been compared with the standalone genetic algorithm. It is resulted that the hybrid algorithm outperforms the genetic algorithm in terms of both solution accuracy and computational time.

Keywords: Electric Vehicle Routing Problem, Hybrid Algorithm, Genetic Algorithm

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Yumuşak Zaman Pencereli Elektrikli Araç Rotalama Problemi için Hibrit Çözüm Yaklaşımı

Öz: Bu çalışmada elektrikli araç rotalama problemi zaman pencereleri göz önünde bulundurularak ve hibrit bir algoritma kullanılarak ele alınmaktadır. Problemin modellenmesi aşamasında sadece elektrikli araçların enerji tüketimleri ve şarj süreleri değil aynı zamanda geleneksel araç akış formülasyonları ve yumuşak zaman pencereleri kısıtları da hesaba katılmaktadır. Elektrikli araç rotalama probleminin çözümü için bir hibrit yaklaşım önerilmektedir. Önerilen yöntem birbirlerinin eksikliklerini kapatacak şekilde Genetik Algoritma ve Benzetilmiş Tavlama Algoritmalarını birleştirmektedir. Önerilen yaklaşımın etkinliğini gösterebilmek için, 25 müşteri, 2 şarj istasyonu, bir depo ve 3 aynı özelliklere sahip elektrikli araç ile bir durum çalışması benzetimi yapılmaktadır. Performans olarak, önerilen hibrit yaklaşım, yalın Genetik Algoritma ile karşılaştırılmaktadır. Sonuçlar, hibrit algoritmanın hem çözüm hassasiyeti hem de hesaplama süresi açısından daha iyi sonuç verdiğini göstermektedir.

Anahtar Kelimeler: Elektrikli Araç Rotalama Problemi, Hibrit Algoritma, Genetik Algoritma

1. Introduction

The increase in the rate of greenhouse gas emitted into the atmosphere is becoming a substantial concern for global warming which has a negative effect on natural environment and society. One of the major contributors to greenhouse gas emissions is transportation. Since the vehicles with internal combustion engines (ICE) emit carbon and nitrogen oxides. Commercial vehicles draw more attention considering the size of energy consumption and the gas emissions. The environmental awareness and the cost of energy have impelled the commercial firms to employ

electric drive vehicles instead of conventional commercial vehicles with ICE. Electric vehicles (EVs) has no emission and they are obviously energy efficient, however, most EVs are equipped with batteries and thereby they have a short driving range. Furthermore, position of charging stations are critical while charging time is relatively long.

Vehicle routing problem (VRP) is one of the most effective methods to not only decrease energy consumption but also increase time efficiency of fleet of commercial vehicles. Various approaches were applied to solve VRP over the years such as: [1-4]. It is obvious that analytical approaches are convenient for small size problems. Heuristic approaches yield optimum solutions for large scale problems, however, they do not guarantee the optimal solution. Considering the EV perspective, VRP turns into an extended form: electric vehicle routing problem (EVRP).

In recent years, developments in electric vehicles have increased researchers' interest in electric vehicle routing problem. It is clear that the size of problem affects the computational complexity of EVRP. In this sense, Felipe et al. proposed mathematical programming approach for small size problem and heuristic approach for medium and large scale EVRP. According to their simulation results, exhaustive local search algorithm was outperformed when the problem is medium size and simulated annealing (SA) performed better as the problem size increased [5]. Certain types of EVs are required to exchange their batteries at the battery exchange stations while plug-in EVs need to charge in recharging stations. Determining the locations of the battery exchange stations or recharging stations could be a part of EVRP. Yang and Sun developed an integer programming model in order to handle location of battery exchange stations and routing problem. As a solution approach, extended tabu search (ETS) algorithm and adaptive large neighborhood search (ALNS) with four-level were employed. Test environment was defined in small, medium and large scales. The authors found ALNS performed better than ETS for all scale of problem [6]. Also, column generation based algorithms [7] and local search algorithms [8] were employed for the same concept of problem.

VRP was also addressed for a fleet with both conventional (with ICE) vehicles and EVs. Sassi et al. created a fleet which consists of one-of-a-kind conventional vehicles and EVs with different battery capacities and energy consumptions. They aimed to reduce the number of used vehicles and their operating costs [9]. Iterated tabu search which is based on large neighborhood search (LNS) was chosen as a solution method. Similarly, Goeke and Schneider presented an EVRP model based on time windows considering a fleet with EVs and conventional vehicles. They proposed a real-like energy consumption model which was the part that distinguished this study from other studies. The new model for energy consumption was a function of vehicle's speed, slope of the road, and the amount of load carried by the vehicles [10]. An ALNS algorithm based on linear search was employed to solve problem. Hiermann et al. formulated an EVRP which consists of a fleet with a combination of EV, hybrid and conventional vehicles. The reason behind employing hybrid vehicles was that these vehicles had both ICE and electric motors [11]. So changing the driving mode of hybrid vehicles could give the advantage of passing by the recharging stations, however, this causes the increase in fuel consumption. The problem was formulated as a combination of genetic algorithm (GA) and LNS. It was resulted that employing mixed fleet could help to reduce operational costs. In another study, Zhen et al. modeled the routing problem of hybrid electric vehicles (HEVs). The model selected an appropriate mode of HEV considering the various road conditions to reduce fuel consumption. An extended particle swarm optimization (EPSO) method was utilized to solve EVRP [12]. Due to the heuristic nature of the algorithm, results of problem even for large scales was reasonable. Furthermore, Zuo et al. proposed the mixed fleet EVRP by using AMPL/CPLEX. In some studies, EVRP was handled by changing vehicle configuration instead of vehicle type [13]. For instance, Hiermann et al. proposed an EVRP which consisting of a fleet of EVs with different capacity, battery size and operating cost. They applied ALNS algorithm

to solve problem. Time and energy efficiency are the two most significant goals of EVRP [14]. There are various approaches applied to EVRP which considered time and energy efficiency in recent years. Bozorgi et al. proposed a routing algorithm in consideration of not only time and energy efficiency but also battery lifespan and driving range. A speed profile were constituted based on past driving data using data mining methods [15]. Regenerative braking were taken into account as a negative weight on search graph by [16]. They used the PSO algorithm to obtain a solution. Dijkstra algorithm is a well-known shortest path algorithm and it was employed to solve EVRP by [17-18]. Similarly some other popular methods were applied to solve EVRP such as: Mixed integer linear programming (MILP) by [19-21]; iterated local search (ILS) by [22-23]; Ant colony optimization (ACO) by [24-26].

In addition to existing studies mentioned above, this manuscript take into account charging time of EVs at recharging stations as a constraint. Also the main contribution is the hybrid solution algorithm that increases the efficiency in the manner of time and energy consumption. This paper is organized as follows: In Section 2, the mathematical model of problem is given. In Section 3, the solution approaches are introduced. A sample EVRP is formulated and obtained results are discussed in Section 4. Finally, the conclusion is presented in Section 5.

2. Mathematical Model

The nomenclature used in this manuscript is given below:

R	: Fictional monetary unit.
$cost_{EV}$	: Unit transport cost of electric drive vehicles (*R/h*).
V	: The set includes all electric drive vehicles.
A	: The set includes all nodes.
N	: The set includes all customers.
C	: The set includes all charging stations.
O	: The set includes all depots.
d_{ij}	: Euclidean distance between node i and node j (*km*).
p_i	: Punishment cost for time window violation of ith customer, $i \in N$, (*R*).
veh	: Total number of electric drive vehicles.
cus	: Total number of customers.
chg	: Total number of charging stations.
q_i	: Demand of ith customer, $i \in N$, (*tons*).
cap_{EV}	: Loading capacity of electric drive vehicles (*tons*).
t_i^{arrive}	: Arriving time of electric drive vehicles at node i, $i \in A$, (*hours*).
t_i^{leave}	: Leaving time of electric drive vehicles from node i, $i \in A$, (*hours*).
t_{ij}	: Time elapsed to travel between node i and node j (*hours*).
$speed_{EV}$	: Driving speed of electric drive vehicles (*km/h*).
t_{si}, t_{wi}	: Service time and waiting time of electric drive vehicles at node i,i, respectively. $i \in N \cup C$, (*hours*).
e_i, l_i	: Lower limit and upper limit for time window of ith customer, respectively. $i \in N$, (*hours*).
e_p, l_p	: Punishment cost for arriving early and lately according to time window, (R/h).
SOC_{ik}^{arrive}	: Battery SOC value of kth vehicle while arriving node i.
SOC_{ik}^{leave}	: Battery SOC value of kth vehicle while leaving node i.
SOC^{max}	: Maximum battery SOC value of electric vehicles.

The electric vehicle routing problem considered in this manuscript is NP-hard problem and can be mathematically modeled as given below:

$$\min F_{obj} = cost_{EV} \sum_{k \in V} \sum_{i \in A} \sum_{j \in A, i \neq j} x_{ijk} d_{ij} + \sum_{i \in N} p_i \tag{1}$$

Subject to

$$\sum_{k \in V} \sum_{j \in N} x_{0jk} - \sum_{k \in V} \sum_{i \in N} x_{i0k} = 0 \tag{2}$$

$$\sum_{i \in N, i \neq j} x_{ijk} = 1, \quad \forall j \in A, \forall k \in V \tag{3}$$

$$\sum_{k \in V} \sum_{i \in A, i \neq 0} x_{0jk} \leq veh \tag{4}$$

$$\sum_{i \in N} \sum_{j \in N, i \neq j} x_{ijk} \leq cus, \quad \forall k \in V \tag{5}$$

$$\sum_{i \in N} y_{ki} q_i \leq cap_{EV}, \quad \forall k \in V \tag{6}$$

$$t_0^{leave} = 0 \tag{7}$$

$$t_{ij} = d_{ij}/speed_{EV}, \quad \forall i, j \in A \tag{8}$$

$$t_i^{leave} = t_i^{arrive} + ts_i + tw_i, \quad i \in N \cup C \tag{9}$$

$$t_j^{arrive} = \sum_{i \in A} \sum_{j \in A, i \neq j} x_{ijk}(t_i^{leave} + t_{ij}), \quad \forall k \in V \tag{10}$$

$$tw_i = \max[0, (e_i - t_i^{arrive})], \quad \forall i \in N \tag{11}$$

$$p_i = e_p \times \max[0, (e_i - t_i^{arrive})] + l_p \times \max[0, (t_i^{arrive} - l_i)], \quad \forall i \in N \tag{12}$$

$$SOC_{ik}^{arrive} = SOC_{ik}^{leave}, \quad \forall i \in N, \forall k \in V \tag{13}$$

$$SOC_{ik}^{leave} = SOC^{max}, \quad \forall i \in O \cup C, \forall k \in V \tag{14}$$

$$SOC_{ik}^{arrive} \geq 0, \quad \forall i \in A, \forall k \in V \tag{15}$$

$$x_{ijk}, y_{ki} \in \{0,1\}, \quad \forall i, j \in A, \forall k \in V \tag{16}$$

As it is given in Equation (1), the objective function is formulated as the sum of the total operation cost of all EDVs during their routes and the total penalty cost of failure to satisfy the time window constraints for each customer. Vehicle flow formulations are given by Equations (2)-(6). Equation (2) guarantees that the route of each electrical drive vehicle starts and ends on the depot. Equation (3) makes sure that every customer should be visited by any electrical drive vehicle once. Equation (4) ensures that the total number of electrical drive vehicles that deliver goods to customers should never exceed the number of available vehicles while Equation (5) guarantees that an electrical drive vehicle should never serve more customers than defined customer number. Equation (6) restricts that the amount of goods delivered should never exceed loading capacity for any vehicle.

The soft time windows constraints are represented by Equations (7)-(11). Equation (7) constitutes the departure time from the depot to zero for each vehicle. In Equation (8), the time elapsed to travel between the nodes is calculated. Equation (9) represents that the leaving time of a vehicle from a node can be calculated by considering the arriving time of the vehicle plus the service time and the waiting time at this node. As it is given by Equation (10), the arriving time of a vehicle to a node is equal to the summation of the leaving time from the previous node and the travel time

between the nodes. The waiting time of a vehicle at any node is calculated by Equation (11). It is obvious that the waiting time on any node takes place if a vehicle arrived at a node earlier than its time window. Equation (12) indicates the cost penalty for time window violation. Constraints related to energy consumption of electric vehicles are given by Equations (13)-(15). Equation (13) ensures that vehicles do not consume any energy at customer nodes while serving or waiting. Equation (14) guarantees that vehicles leave both charging stations and depots with fully charged batteries. Besides Equation (15) makes sure that the remaining battery SOC values is not negative on any node.

Equation (16) represents the binary decision variables for the given mathematical model, x_{ijk} and y_{ki}. Here x_{ijk} takes value of 1 if and only if the kth vehicle visits node j right after node i. Similarly, y_{ki} becomes 1 if and only if the kth vehicle visits node i.

3. Solution Methods

In this section, two solution approaches, Genetic Algorithm and the hybrid algorithm which is a consecutive combination of GA and SA, are briefly reviewed. Also detailed structure of hybrid algorithm for EVRP is presented later in section.

3.1. Genetic Algorithm

Genetic algorithm is a population based meta-heuristic search algorithm which takes its power from the laws of natural selection and theory of evolution [27]. The smallest part of the algorithm is gene and a number of genes somehow come together to form chromosomes. A population can be considered as an array of chromosomes which refer to individual solutions of addressed problem. The algorithm starts seeking from initial population first. A score is assigned to each chromosome by computing its fitness value which is the value of the fitness function (or objective function) for that individual. The algorithm then generates a sequence of new populations based on survival of the fittest genes. At each generation, the algorithm randomly selects two individuals as parents from the current population. The next generation is created by applying generic operators - such as crossover and mutation - to these parents. The algorithm continues to generate new populations in this way until the stopping criterion is met. As soon as the stopping criterion is reached, the algorithm terminates and the chromosome with best fitness value is accepted as optimal solution. A pseudo code, represents the main steps of genetic algorithm, is given in Algorithm 1.

Algorithm 1: Pseudo code of GA

begin
    $k \leftarrow 0$;
    initialize $P_1(k)$;
    evaluate $P_1(k)$;
    while *not satisfy stopping criteria* **do**
        recombine $P_1(k) \rightarrow P_2(k)$;
        evaluate $P_2(k)$;
        select $P_1(k)$ and $P_2(k) \rightarrow P_1(k+1)$;
        $k \longleftarrow k+1$;

3.2 Hybrid Algorithm

GA and SA are two well-known algorithms used to solve wide spread global optimization problems. Although they have similar features, they vary from each other in algorithm structure and

operation as well. The theory of evolution is substantial part of GA. The new individual generated from parents with fairly well fitness values will have a better fitness value. Briefly, good solutions could generate better solutions. Although GA is preferable method for most optimization problems due to its large scale searching capability, it performs poorly in avoiding local minimums [26]. SA is a nature-inspired algorithm which is analogous to annealing process. The procedure of SA initializes an initial point first, and then new solutions are generated arbitrarily by reducing temperature. Since algorithm accepts a few worse solutions besides better solutions with a probability, it is capable of avoiding local minimum. On the other hand simulated annealing is a robust and general technique which deals with highly nonlinear problems and has ability of solving global optimization problems. However the solution quality and the computational time considerably depend on the selected initial point [29]. Thus inaccurate initial points may result infeasible solutions and affect badly on time efficiency of algorithm. The combination of GA and SA can improve the solution quality since it eliminates the weaknesses of both algorithms. In this manuscript, we propose a hybrid algorithm which uses genetic algorithm first to provide feasible solution and then initialize simulated annealing with this solution. Flowchart of this proposed hybrid algorithm is shown in Figure 1.
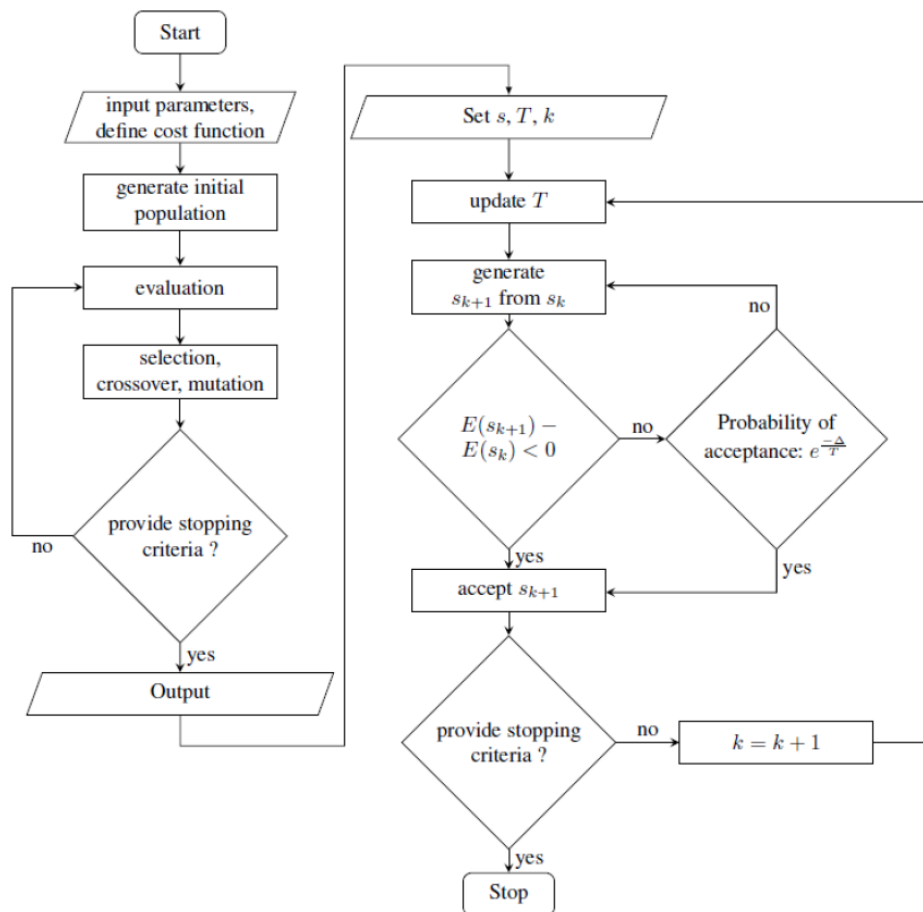

Figure 1. Flowchart of Hybrid Algorithm

3.3. Chromosome Structure and Encoding

Modelling EVRP with a proper chromosome structure is one of the most important point that heavily effects the solution quality and solution time. The chromosome used in this manuscript has total number of $(cus + chg + veh - 1)$ genes where each gene has a value of real number between zero and one. All the operations of GA and SA are applied over this mentioned chromosome. However, routes assigned to each vehicle should be known in order to calculate the fitness values.

To do that, first the indices of genes are sorted in ascending order according to their values. Hereby we have a chromosome that consist of all integers from 1 to $(cus + chg + veh - 1)$. The chromosome encodes the customers (integers from 1 to cus), charging stations (integers from $cus + 1$ to $cus + chg$) and separation points (integers from $cus + chg + 1$ to $cus + chg + veh - 1$) by an integer. These separation points are used to form the routes and assign these routes to vehicles.

Consider a problem with 7 customers, 2 charging stations and 3 vehicles. In this case, chromosomes consist of 11 genes and is formed as given in Figure 2(a). If the indices of genes are sorted in ascending order according to their values, a string of integers can be obtained as given in Figure 2(b). In this string, integers from 1 to 7 represent customers, 8 and 9 represent charging stations and 10 and 11 represent separation points. Hence, the routes assigned to vehicles can be determined as given in Figure 2(c). Figure 2(c) expresses a chromosome which encodes three routes for three vehicles. Electric drive vehicle 1 starts its journey from the depot and stop by customer 2 and then travels to charging station 8. After recharging it returns to the depot. Similarly electric drive vehicle 2 starts its journey from the depot and drop by customer 6 and 3 and then travels to charging station 9. After recharging it returns to the depot. Likewise electric drive vehicle 3 starts from the depot and visits customer 7, 5, 1 and 4 and then returns to the depot without charging battery.
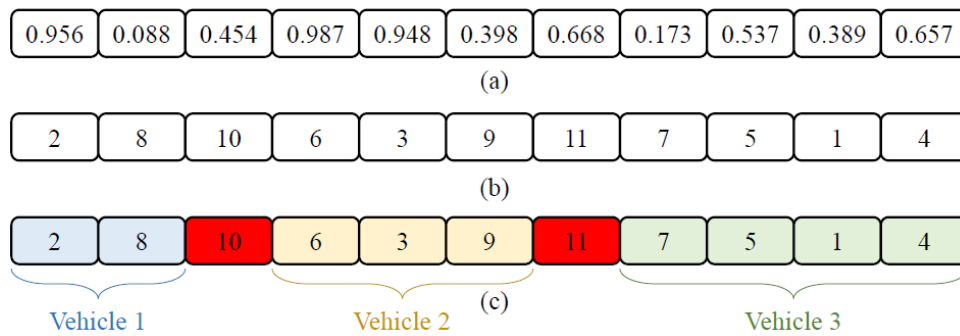

Figure 2. Sample chromosome representation

3.4. Constraint Handling

In this manuscript, the constraints of the considered problem are implemented by using two different techniques. The constraints represented by Equation (2) – (5) are mainly related to vehicle flow formulations and are handled directly by the chromosome structure. However Equation (6) and (15) refers to vehicle loading capacity and energy consumption constraints, respectively, and they cannot be realized by the chromosome structure. Instead, penalty functions are defined for the above mentioned constraints as given below:

$$pen_i = \begin{cases} 25000, & if\ i^{th}\ constraint\ is\ not\ satisfied \\ 0, & otherwise \end{cases} \tag{17}$$

Therefore, the fitness function of the considered problem is formed by adding the penalties regarding to vehicle loading capacity and energy consumption constraint to the objective function as given by Equation (18) and Equation (19).

$$F_{fitness} = F_{obj} + pen_6 + pen_{15} \tag{18}$$

$$F_{fitness} = \left(cost_{EV} \sum_{k \in V} \sum_{i \in A} \sum_{j \in A, i \neq j} x_{ijk} d_{ij} + \sum_{i \in N} p_i\right) + pen_6 + pen_{15} \tag{19}$$

It is obvious that $F_{fitness}$ and F_{obj} become equal to each other for any solution that satisfies all the constraints. Thus feasible solutions are evaluated with the proposed algorithm.

4. Simulation Results

The proposed method is tested on a vehicle routing problem that consists of 25 customers, 2 charging stations, 1 depot and 3 identical EDVs. Vehicle parameters are given in Table 1, it is assumed that the speed of each vehicle is constant, and it is 40 *km/h* and has a maximum travel distance of 200 *km* when the batteries are fully charged. It is also accepted that the battery SOC values are reduced directly proportional to the distance traveled.

Table 1. EDV Characteristics

Parameter	Value
Maximum Carrying Capacity	5 *tons*
Charging Time of EDV	4 *hours*
Transport Cost of EDV	10 *R/km*
Penalty Cost for Early Arrival	20 *R/h*
Penalty Cost for Late Arrival	30 *R/h*

Customer demands and service times, upper and lower bounds of soft time windows constraints and node coordinates are given in Table 2 [29].

Table 2. Parameters related to customers, depot and charging stations

Node	Load Demand (*tons*)	Service Time (*h*)	Time Window (*h*)	Coordinates
Depot	-	-	-	(56,56)
C1	0.2	0.2	[0,1]	(66,78)
C2	0.3	0.3	[1,2]	(56,27)
C3	0.3	0.3	[2,4]	(88,72)
C4	0.3	0.3	[7,8]	(88,32)
C5	0.3	0.3	[5,6]	(24,48)
C6	0.5	0.5	[3,5]	(40,48)
C7	0.8	0.8	[0,2]	(32,80)
C8	0.4	0.4	[7,8]	(16,69)
C9	0.5	0.5	[1,3]	(88,96)
C10	0.7	0.7	[4,5]	(48,96)
C11	0.7	0.7	[1,2]	(32,104)
C12	0.6	0.6	[3,4]	(80,56)
C13	0.2	0.2	[0,1]	(48,40)
C14	0.2	0.2	[2,4]	(24,16)
C15	0.4	0.4	[2,3]	(48,8)
C16	0.1	0.1	[7,8]	(16,32)
C17	0.1	0.1	[6,8]	(8,48)
C18	0.2	0.2	[7,9]	(32,64)
C19	0.5	0.5	[1,3]	(24,96)
C20	0.2	0.2	[1,3]	(72,104)
C21	0.7	0.7	[8,10]	(72,32)
C22	0.2	0.2	[6,10]	(72,16)
C23	0.7	0.7	[7,8]	(88,8)
C24	0.1	0.1	[6,7]	(104,56)
C25	0.5	0.5	[4,6]	(104,32)
CS1	-	-	-	(83,45)
CS2	-	-	-	(32,40)

The proposed method is applied to the considered problem with the parameters given in Table 3. 25 trials are performed and the obtained results are established. Simulations are carried out in MATLAB environment on a personal computer with dual core i5 processor and 2 GB memory.

Table 3. Hybrid algorithm parameters.

Hybrid Algorithm Section	Parameter	Value
Genetic Algorithm	Population Size	350
	Number of Generations	35
	Crossover Ratio	0.95
	Mutation Ratio	0.05
Simulated Annealing	Temperature	500
	Minimum Temperature	0.5
	Number of İterations	50

For the best solution achieved among those 25 trials, optimal routes, cost of each vehicle that also includes the time window violation punishments and the vehicle loads are given in Table 4. The total cost value of the best solution is obtained as 7370.92 R. As it can be seen from Table 4, all the routes are started and ended on the depot and every customer is visited by a vehicle once. Besides the amount of goods carried by the vehicles does not exceed the vehicle loading capacities. The demonstration of the optimal routes of EDVs in the $x - y$ coordinate plane is given in Figure 3.

Table 4. Optimal routes of three EDVs

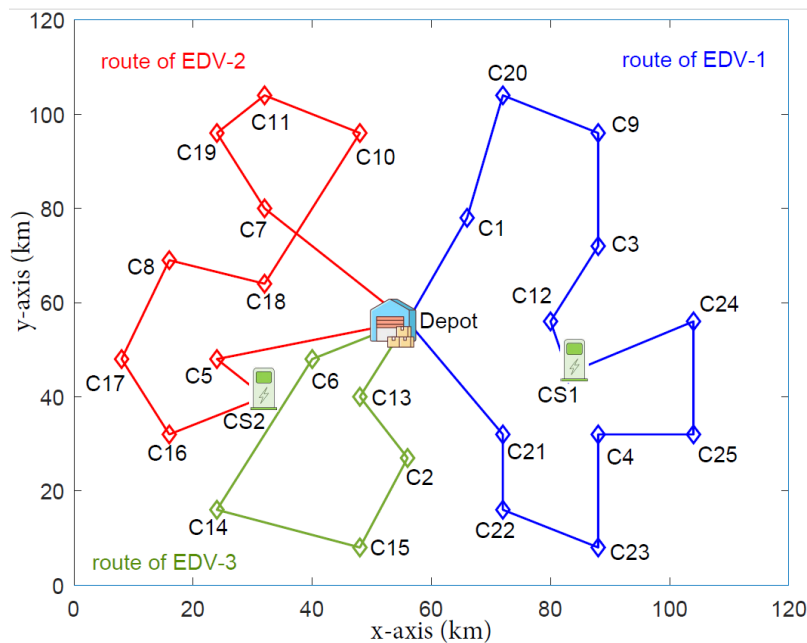| Vehicles	Routes of vehicles	Operation cost (R)	Vehicle load (ton)
EDV-1	Depot→C1→C20→C9→C3→C12→CS1→C24 →C25→C4→C23→C22→C21→Depot	3335.32	4.70
EDV-2	Depot→C7→C19→C11→C10→C18→C8→C17 →C16→CS2→C5→ Depot	2705.16	4.20
EDV-3	Depot→C13→C2→C15→C14→C6→Depot	1330.44	1.60
	TOTAL	**7370.92**	**10.50**

Figure 3. Optimal routes of all EDVs in the x − y coordinate plane.

During the routes of each vehicle, battery SOC values are given in Figure 4. As demonstrated in Figure 4, all vehicles leave the depot and start their routes with fully charged batteries. Energy consumption takes place while only traveling between nodes thus SOC values are dropped away

with this transportation period. However, when the customers are served, there is not any battery depletion exist and SOC values remain same. On the other hand, EDV-1 and EDV-2 visit charging stations, CS1 and CS2 respectively, when their SOC values reached a critical level. In the charging stations, EDV-1 and EDV-2 are recharged to maximum capacity with n the predefined charging durations and the SOC values become 100%. Moreover, battery SOC values never drop down below 2.5% and therefore the energy consumption constraints are also satisfied.
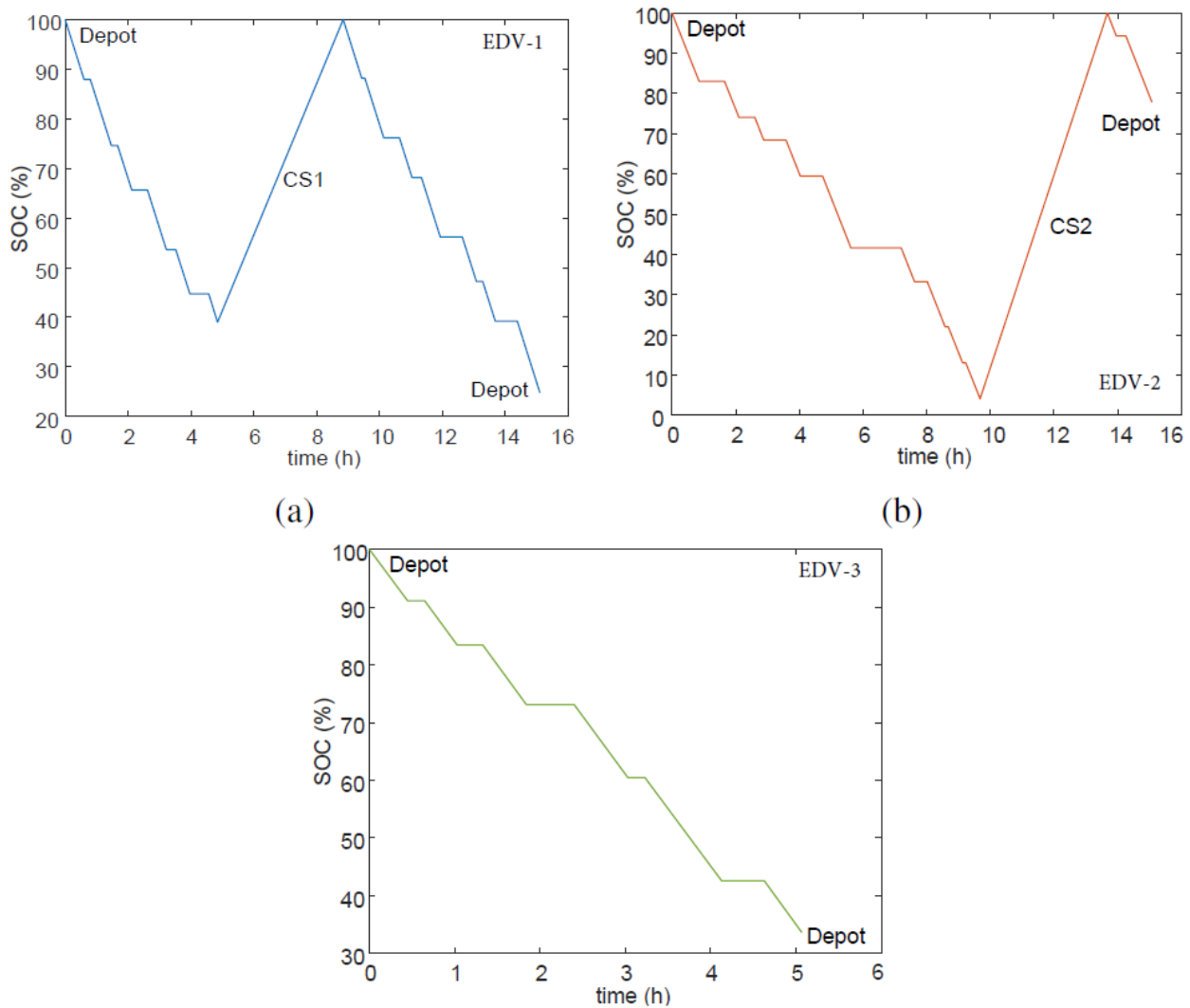

Figure 4. Battery SOC values of (a) EDV-1 (b) EDV-2 (c) EDV-3 vs. time.

In order to demonstrate the efficiency of the proposed algorithm, same problem is solved by using genetic algorithm only. Since the optimal solution is searched this time, population size and the number of generations are increased to 500 and 100, respectively. Other parameters are remained same as used in the hybrid method. Once again 25 trials with genetic algorithm are performed. The best solution, the average solution, the worst solution and the average solution times obtained with hybrid method and genetic algorithm are given in Table 5. It is apparent that proposed hybrid method results better solutions in a short span of time. Proposed hybrid method leads genetic algorithm by 20.81 % in best solutions, by 16.15 % in average solutions and by 19.35 % in average solution times.

Table 5. Comparison of results.

Method	Best Solution (R)	Average Solution (R)	Worst Solution (R)	Average Solution Time (S)
Hybrid algorithm	7370.92	8873.73	13063.89	20.59
Genetic algorithm	9308.18	10582.29	12522.85	25.53

5. Conclusions

In this manuscript, a hybrid method based on genetic algorithm and simulated annealing has been proposed to solve electric vehicle routing problem. The proposed method is tested on a vehicle routing problem which consists of 25 customers, 2 charging stations, 1 depot and 3 identical EDVs. Among 25 trials, the best solution is achieved with a total operation cost of 7370.92 R. At this optimal solution all the constraints related to vehicle flow formulations and energy consumption are perfectly satisfied. So, it is obvious that both the used chromosome structure and the applied penalty functions serve the purpose. However, the total punishment cost of failure to satisfy the time window constraints becomes 957.72R which is 13% of the total operation cost. This is because EDVs arrive at 4 customers before their time windows and deliver goods after a waiting time and visit 6 customers beyond their time windows. These mentioned customers are mostly placed after the charging stations in the obtained routes. Since the battery charging durations are selected much longer than the service time of customers, the time windows violations and so the punishment costs are occurred. Therefore, it can be concluded that battery charging durations highly effect on EVRP and should be shortened for customer satisfaction in terms of servicing times. The performance of the proposed method has been compared with the results obtained by using genetic algorithm. The results show that proposed methods outperform the genetic algorithm not only in terms of best solution, but also the computational time.

Acknowledgments

Authors' Contributions

Burak Urazel and Kemal Keskin designed the structure. Problem definition has been made by Kemal Keskin according to the studies in the literature, while mathematical model has been clarified by Burak Urazel. The setting of test environment and experimental work were done by Burak Urazel and Kemal Keskin, and both authors wrote up the article.

Both authors read and approved the final manuscript.

Competing Interests

The authors declare that they have no competing interests.

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