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Electric vehicle routing problem with time windows, battery swapping van, and energy consumption (EVRPTW-BSV-EC)

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Abstract

This research focuses on integrating BSVs into the Electric Vehicle Routing Problem with Time Windows (EVRPTW), aiming to minimize travel costs and energy consumption while meeting delivery time windows. This novel approach combines mathematical modeling with optimization algorithms to formulate and solve the EVRPTW-BSV-EC, addressing a gap in existing literature.

However, due to their limited range, they must recharge while delivering products to customers along their route. Long recharging times at available stations can hurt route planning, especially when considering short delivery time windows. Therefore, the authors used a swapping van instead of a recharge station. Swapping batteries can decrease recharging times by exchanging the vehicle's depleted batteries with fully charged ones. This research extends the traditional EVRPTW to address the integration of battery-swapping Vans (BSVs) and energy consumption considerations.

The objectives of this research include minimizing the total travel cost and reducing overall energy consumption within the defined time windows while considering battery-swapping vans. This research provides tools for a policy planner to measure the effectiveness of battery swaps in the presence of traditional recharging methods for commercial logistics operations

The research combines mathematical modeling techniques with optimization algorithms to formulate and solve the Electric Vehicle Routing Problem with Time Windows, Battery Swapping Van, and Energy Consumption (EVRPTW-BSV-EC). The results show that the additional choice of battery swaps at a swapping van led to better delivery routes, thereby reducing the overall costs, particularly for cases where battery swapping time and battery swapping cost are relatively lower. As far as the author knows, this issue has yet to be tackled in previous literature. Here, a model and algorithm for addressing this problem are introduced, and computational experiments are performed.

Keywords: Electric vehicles; Van battery swapping; Vehicle routing; Time windows; Energy consumption

1. Introduction

The global automotive landscape is undergoing a transformative shift driven by an unprecedented surge in the demand for electric vehicles (E.V.s). In 2022, the momentum in adopting electric cars reached a significant milestone, with over 26 million on the road. This staggering figure represents a remarkable 60% increase compared to 2021 and, more impressively, marks an exponential growth of over 500% from the stock recorded in 2018. [1]. In 2020, the worldwide

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adoption of electric vehicles witnessed a 43% increase, with over 3 million units sold. The International Energy Agency (IEA) projections indicate that approximately 30% of all vehicles will be electric by 2030 [2].

Despite the numerous advantages linked to electric vehicles (E.V.s), their integration into distribution logistics operations could have been more active, and two main factors contributed to this delay. Firstly, the cost of E.V.s is notably higher than that of conventional gasoline vehicles, with the primary contributor to this expense being the battery cost. Secondly, the distance a fully charged electric vehicle can run before the battery is out of electricity is defined as the driving range. Combustion engine vehicles have an average range of 400-600 km, whereas electric vehicles only have an average range of 350 km [3]. A traditional gasoline vehicle can be entirely refueled in 3-5 minutes. In contrast, for an E.V., even using fast charging technology, it takes half an hour to one hour to charge the vehicle entirely. [4] The average energy consumption for an electrical car battery at ground level is 195 Wh/km or 0.195 kWh/km [5], while the average battery capacity is around 40 kWh. E.V. users are required to travel to a battery swapping station for the exchange of batteries. Due to the evident limitations in location and the quantity of available battery swapping stations, queues and waiting times may persist. Thus, there is a need for a more logical and efficient architecture for E.V. battery swapping. Addressing this issue, a viable solution involves transitioning from the current passive to active battery-swapping mode. A recent advancement in this direction is the development of a rapid E.V. battery-swapping device. Patents suggest that this device can be integrated into a van, effectively converting the van into a mobile E.V. battery swapping station—removing and installing a battery takes place simultaneously. Consequently, the entire battery-swapping procedure is highly efficient, completing in just a few minutes (approximately 3 minutes in the experimental setting) [6]. While at a battery swap van (BSS), the battery of the E.V. can be swapped with a new, fully recharged battery in only about 5 minutes [7]. The savings in time achieved are crucial for efficient route planning, particularly for customers with stricter time windows. This improves the feasibility of delivery routes and, in turn, the total routing costs. The energy consumption of E.V.s has a closer relationship to the uncertain travel speed and cargo load, which must be reflected to express E.V. performance realistically. Therefore, a formula that combines a computational approach is suggested for calculating the energy consumption of Electric Vehicles (E.V.s) based on physics and theory [4]. As far as the author knows, this issue has yet to be tackled in previous literature.

2. Literature Review

The exploration of electric vehicles (E.V.s) falls within the Green Logistics field, which has garnered increased attention in recent years. Green Logistics is dedicated to mitigating the environmental impact of logistics operations, emphasizing sustainable practices in producing and distributing goods while considering environmental and social factors [8]. Distribution activities within the supply chain involve the transportation of products, and these challenges are often categorized under the Vehicle Routing Problem (VRP) in the literature. The primary goal of VRP is to optimize the selection of routes for a specified number of vehicles, originating and concluding at the depot, to minimize overall transportation costs. A notable extension of VRP is the Vehicle Routing Problem with Time Windows (VRPTW), wherein customers have designated time frames within which deliveries must be completed. Various optimization approaches have been developed from 2016 to 2023 to address different variants of the Electric Vehicle Routing Problem, including algorithms such as integer programming, adaptive large neighborhood search, genetic algorithms, bee colony optimization, iterated local search, modified clustering search-based genetic algorithm, random kernel search, simulated annealing, diversity-enhanced memetic algorithm, BAT algorithm optimization, and hybridizations thereof, aimed at improving route efficiency and addressing specific constraints such as time windows, battery swapping, and partial recharges [9]–[17]. [18] present the Modified Clustering Search-based Genetic Algorithm (MCSGA) to tackle the Electric Vehicle Routing Problem (EVRP) with time windows and travel time uncertainty. [19] focus on the time-dependent multi-depot EVRP with battery recharging and swapping, employing a multi-objective simulated annealing algorithm (SAA). [20] introduce a Diversity-Enhanced Memetic Algorithm (DEMA) for EVRP with time windows and mixed backhauls. [21] propose the Bat Algorithm Optimization for trip time and cost reduction, considering customer service requests and EV charging schedules. Additionally, [22] utilize Genetic Algorithm for EVRP with time windows and battery swapping. Finally [23] develop an improved ant colony optimization (ACO) algorithm for EVRP with Time Windows and Multiple Recharging Options. The authors conducted a search and found no existing literature reviews on the Vehicle Routing Problem with Time Windows, Battery Swapping Vans, and Energy Consumption.

3. Problem Description and Model Formulation

3.1. Problem description

This paper proposes an Electric Vehicle Routing Problem with Time Windows, Battery Swapping Van, and Energy Consumption (EVRPTW-BSV-EC), an extension of EVRPTW. The EVRPTW-BSV-EC aims to minimize the overall costs of EVRP (including fixed vehicle costs, travel costs, and swap costs).

Given a homogeneous fleet of E.V.s, EVRPTW-FC aims to determine a set of routes involving customers with known demands, delivery time windows, and service durations Vehicles with battery swap vans. The Routing Problem consists of determining a set of K vehicle trips of the minimum total cost, such that each vehicle starts and ends at the depot, and each of the C customers with service times $service\_time, i \in [1, C]$ and demands $f \ \ or, i \in [1, C]$ is visited exactly once. The total weight capacity of each vehicle is $Vehicle_{capacity}$. The VehicleRouting Problem with Time Windows is a variant of VRP with predefined customer time windows. The customer*'s service* can begin within a time window [*Ei, Li*] specified by the customer. The E.V. energy consumption formula and the constant parameter values in the energy consumption formula are taken from [4].

3.2. Mathematical model formulation

In this section, we propose a mathematical model of this problem. Concerns are customers with known demands, delivery time windows, and service durations. A homogeneous fleet of E.V.s with fixed loading capacities and limited driving ranges is used for the package delivery. ECVs and BSVs have specific roles that cannot be switched. ECVs deliver customer requests, while BSVs are only for swapping batteries when needed by an ECV and cannot be used for deliveries.

Battery swapping must happen at a customer's location and cannot be done while the ECV serves the customer. It can only be done before (if possible while waiting for customer service to start) or after the ECV finishes serving the customer. For this study, battery swapping will be done after the ECV serves the customer. It will be seen from the plan of the accompanying model that there are three limitations (customer time service limitation, route limitation, and load limitation). By looking at the limitless number of vehicles utilized (the number of vehicles utilized is additionally one of the improvement objectives), we can serve every client under load limitations. Moreover, Electric vehicles can be re-energized and require charging by battery swapping van a few times during the visit, so it has sufficient battery ability to finish the outing. Hence, the arrangement can be ensured. To clarify the model, the notations that will be used in this study are listed as follows:

Table 1 Notations used in this study

Indices and Input Parameters			
K	Number of vehicles k = 1… K	**η**	Efficiency parameter to consider all complexities of any power losses in the transmission and motor drive
C	Number of customer nodes c =1… C	Gc	Gravitational constant (m/s2)
F	Number of batteries swapping vans f =1… F	R_r	Rolling resistance coefficient
S	Start depot node	α	Angle of the road (- $(\frac{\pi}{2}) \leq \alpha \leq (\frac{\pi}{2})$)
D	End depot node	β	The percentage of the total braking energy can be applied to the electric motor ($0 \leq \beta \leq 1$).
N	Set of all types of nodes in the graph (including start node, customer, swapping vans, and end depot)	ρ_a	Air density (kg/m3)
UC_f	Per unit fixed cost/vehicle	AC_D	Aerodynamic drag coefficient
UC_{tr}	Per unit travel cost/vehicle	$Area_f$	vehicle frontal area (m2)

$U_{.C.s}$	Per unit swap cost/vehicle	DVT/ dt	Acceleration (m/s2)
v^t	Vehicle travel speed (m/s)	fw_j	The freight weight of node j will be greater than zero for customer nodes and equal zero for other nodes.
δ	Mass factor	$Vehicle_{capacity}$	Vehicle load capacity (kg)
V. M.	Vehicle mass (kg)	QB_{max}	Battery energy capacity (kWh)
E_j	Earliest start time to service node j	t_{ijk}	Travel time of vehicle k traveling from nodes i to j (min)
L_j	Latest start time to service node j	SW_t	Swapping time (min)
z_j	= 1 if node j consists a battery swapping van nodes (F); 0 otherwise	$service\_time_j$	Service time of node j
t_{ij}^{Van}	Travel time of battery swap van traveling from nodes i to j (min)	Van_b	Battery capacity of battery swapping van (kWh)
B_{max}	Maximum number of batteries carried by battery swapping van	Van_e	Energy consumption rate per unit of time of battery swapping van (kWh/ min)
Decision Variables			
x_{ijk}	= 1 if vehicle k travels from node i to node j; 0 otherwise		
Y_{jk}	= 1 if the battery of vehicle k is replaced at node j; 0 otherwise		
Output Parameters			
$Power_B^{out}$	The power out at the battery terminals	$swap\_cost_k$	The swap cost for vehicle k
$Power_B^{in}$	The regenerative braking at the battery terminals	QB_{jk}	Battery power level of vehicle k at node j (kWh)
Energy_Consumption	The energy consumption from batteries (kWh)	VW_{jk}	The loading weight of vehicle k departing from node j (kg)
$Energy\_Consumption_{ij}^k$	The energy consumption of vehicle k from nodes i to j (kWh)	DT_{jk}	The departure time of vehicle k at node j
$fixed\_cost_k$	The fixed vehicle cost for vehicle k	NB_j	Number of remaining fully-charge batteries on the battery swap van upon arrival at node j
$travel_{cost_s}$	The travel cost for vehicle k	Van_j^b	A battery charge level of the battery swap van when arrival at node j

3.2.1. Objective Function

This research is intended to develop an integrated model for the electric vehicle routing problem while considering the energy consumption under time windows battery swapping van. The objective of this model is to minimize the overall costs of EVRP (including fixed vehicle cost, travel cost, and swap cost), as shown in Equation 1.

$$Minimize\ Z = \sum_{k=1}^{K} fixed\_cost_k + travel\_cost_k + swap\_cost_k \text{ .... (1)}$$

Where,

$$fixed\_cost_{\,k} = UC_f \left(1 - \sum_{i\in S} \sum_{j\in D} x_{ijk}\right);\ \forall\, k = 1 \ldots K \text{ .... (2)}$$

$$travel\_cost_{\,k} = UC_{tr} \left(\sum_{i \in D} DT_{jk} - SW_t \sum_{j \in F} Y_{jk}\right);\ \forall\, k = 1 \ldots K \text{ .... (3)}$$

$$swap\_cost_{\,k} = UC_s \sum_{j \in F} Y_{jk}\ ;\ \forall\, k = 1 \ldots K \text{ .... (4)}$$

3.2.2. Constraints

Equation 5 expresses the battery power out, equal to the resistance power and any power losses in the transmission and motor drive. (The first term is for the rolling resistance of tires on a hard surface, the second term describes the grading resistance, the third term defines the aerodynamic drag, and the last term is for acceleration force) [4]

$$Power_B^{out} = \frac{\beta v^t}{\eta} \left(VM * Gc * R_r * \cos\alpha + VM * Gc * \sin\alpha + \frac{1}{2}\, \rho_a * AC_D * Area_{\,f} * {v^t}^2 + VM * \delta * \frac{dv^t}{dt}\right) \ldots \text{ ....(5)}$$

The regenerative braking power at the battery terminals can be expressed in Equation 6, which equals the battery power out multiplied by the percentage of the total braking energy. [4]

$$Power_B^{in} = \frac{v^t}{\eta} \left(VM * Gc * R_r * \cos\alpha + VM * Gc * \sin\alpha + \frac{1}{2}\, \rho_a * AC_D * Area_{\,f} * {v^t}^2 + VM * \delta * \frac{dv^t}{dt}\right) \text{ ....(6)}$$

Motivated by equations 5 and 6, the energy consumption from batteries can be calculated by equation 7. [4]

$$Energy_{Consumption} = \int_{Tractiontime} Power_B^{out}\, dt + \int_{Brakingtime} Power_B^{in}\, dt \text{ .... (7)}$$

Where the traction time is the time period when the acceleration is positive, whereas the braking time is the time period when the acceleration is negative.

Equations 8 and 9 ensure that each customer is visited by only one electric vehicle.

$$\sum_{i \in C \cup F \cup S} x_{ijk} = 1\ ;\ \forall\, k = 1 \ldots K, \forall\, kj = 1 \ldots C \text{ .... (8)}$$

$$\sum_{j \in C \cup F \cup D} x_{ijk} = 1\ ;\ \forall\, k = 1 \ldots K, \forall\, ki = 1 \ldots C \text{ .... (9)}$$

To satisfy the flow conservation, in which the number of arrivals at a node must equal the number of departures for all types of nodes, Equation 10 is performed.

$$\sum_{\forall\, i \in C \cup F \cup S} x_{ijk} = \sum_{\forall\, m \in C \cup F \cup D} x_{jmk}\ ;\ \forall\, k = 1 \ldots K,, \forall\, j \in C \cup F \text{ .... (10)}$$

Where m is an index for the remaining nodes that the electric vehicle had not yet visited.

Equations 11 and 12 ensure that all vehicles leave from the start depot and return to the end depot (the start depot and end depot have the exact location).

$$\sum_{j \in C \cup F \cup D} x_{Sjk} = 1\ ;\ \forall\, k = 1 \ldots K \text{ .... (11)}$$

$$\sum_{j \in C \cup F \cup S} x_{jDk} = 1\ ;\ \forall\, k = 1 \ldots K \text{ ....(12)}$$

Moreover, two vehicles consume different amounts of energy from the same path because of variations in the load weights of the two vehicles, which indicates the residual battery power as expressed in Equation 13. In contrast, Equation 14 states that the residual battery power at any node must be more significant than zero. In addition, Equation 15 indicates that each vehicle at the starting point has an entire batter.

$$QB_{jk} = x_{ijk} \left[QB_{jk} \left(1 - Y_{jk}\right) + Y_{jk} * QB_{max} - Energy_{Consumption}{}_{ij}^{k} \right];$$

$$\forall\, k = 1 \ldots K, \forall\, i \in C \cup F \cup S, \forall\, j \in C \cup F \cup S \text{ .... (13)}$$

$$QB_{jk} < QB_{max} ; \forall k = 1 \dots K, \forall j \in C \cup F \cup D \dots\dots\dots (14)$$

$$QB_{Sk} = QB_{max} ; \forall k = 1 \dots K \dots\dots\dots\dots\dots (15)$$

On the other hand, the load weight of the vehicle departing from a node is calculated by Equation 16. Furthermore, Equation 17 specifies that the vehicle must pick up the loads from the customers, while Equation 18 ensures that the collected load of each vehicle does not exceed its load capacity.

$$VW_{jk} = \left(fw_j + VW_{ik}\right) x_{ijk}; \forall k = 1 \dots K, \forall i \in C \cup F \cup S, \forall j \in C \cup F \cup D \dots\dots\dots (16)$$

$$VW_{jk} = 0 ; \forall k = 1 \dots K, \forall j \in S \dots\dots (17)$$

$$VW_{jk} \leq Vehicle_{capacity} ; \forall k = 1 \dots K, \forall j \in S \cup C \cup F \cup D \dots\dots\dots (18)$$

The time when the vehicle departs from one node equals the sum of the departure time at the last node, travel time between the last node, service time of the current customer and the current node, swapping time and queue time as shown in Equation 19 (It is important to highlight that the Electric Vehicle (E.V.) has issued a request to the Battery Service Vehicle (BSV) for an early battery replacement and has specifically requested the swapping to take place at the subsequent node immediately after customer service. This implies that the waiting time for the swapping process is equivalent to the time taken for the service itself). Meanwhile, the initial operation time is assumed to be zero, as indicated in Equation 20. On the other hand, Equation 21 ensures that every customer is visited within the time windows.

$$DT_{jk} = \left(DT_{ik} + t_{ijk} + \text{service\_time}_{\text{j}} + SW_t * Y_{jk}\right) x_{ijk} ;$$

$$\forall k = 1 \dots K, \forall i \in C \cup F \cup S, \forall j \in C \cup F \cup D \dots\dots\dots (19)$$

$$DT_{ik} = 0 ; \forall k = 1 \dots K, \forall i \in S \dots\dots\dots\dots (20)$$

$$E_j \leq service_{time\,j} \leq L_j ; \forall j \in C \cup F \cup D \dots\dots\dots\dots (21)$$

Equation 22 involves only vehicles with the battery swapping van visited to replace its battery when needed.

$$0 \leq Y_{jk} \leq z_j ; \forall k = 1 \dots K, \forall j \in S \cup C \cup F \cup D \dots\dots\dots\dots (22)$$

Moreover, Equations 23 and 24 ensure meeting the demand while not exceeding the capacity of the battery swap van.

$$0 \leq NB_j \leq NB_i - Y_{jk} + B_{max}(1 - Y_{jk}) ; \forall k = 1 \dots K, \forall i \in S \cup C \cup F, \forall j\, C \cup F \cup D \dots\dots\dots (23)$$

$$0 \leq NB_i \leq B_{max} ; \forall i \in S \dots\dots\dots (24)$$

Equations 25 and 26 to make sure that the battery charge level of the battery swap van never falls below zero.

$$0 \leq Van_j^b \leq Van_i^b - Van_e * t_{ij}^{Van} * Y_{jk} + Van_b\left(1 - Y_{jk}\right) ;$$

$$\forall k = 1 \dots K, \forall i \in S \cup C \cup F, \forall j\, C \cup F \cup D \dots\dots\dots (25)$$

$$0 \leq Van_i^b \leq Van_b ; \forall i \in S \cup C \cup F \dots\dots\dots\dots (26)$$

Equations 27 and 28 ensure that the decision variables representing the swapping plans and vehicle routes are binary.

$$x_{ijk} = \{0, 1\} ; \forall k = 1 \dots K, \forall i \in C \cup F \cup S, \forall j \in C \cup F \cup D \dots\dots\dots\dots (27)$$

$$Y_{jk} = \{0, 1\} ; \forall k = 1 \dots K, \forall j \in S \cup C \cup F \cup D \dots\dots\dots\dots (28)$$

4. Solution Methodology

We constructed a heuristic to solvethe new problem. The hybrid G.A. (HGA) is a combination method of G.A. and local search strategy to strengthen the ability of a local search based on the advantages of G.A. In the case of Hybrid Genetic Algorithms (HGA), a local search strategy is executed for each individual following both crossover and mutation phases. The objective of the local search strategy is to uncover additional opportunities. For the solution technique, the proposed program in Section 4.1 is viewed to determine the routing costs of the routing plan for the required number of vehicles while preserving the vehicle load capacity and battery charge level of Evs restrictions. We will permit deviations from the time window restrictions for each customer. G.A. is followed by local search improvement heuristics that search the neighborhood for better solutions.

Our solution method is outlined in Algorithm 1. The order of the different heuristics is set after computation experiments to achieve the best solution quality in a limited runtime. As seen in Algorithm 1, we will iterate for different generation values until a predetermined number of iterations is completed within a specified time limit until we find the routing plan with the lowest costs. We employ local search to transition between solutions within the search space of potential solutions. This involves making local changes until a set number of iterations is reached. We used (i) 2-interchange, (ii) 2-opt, and (iii) Cross-exchange as improvement heuristics in the local search method. Overall, our algorithm will determine the best sequence of visits to the customers (delivery plan) and the schedule of the required number of electric vehicles, along with the type of service (BSV) used at each arc between nodes while minimizing the overall delivery costs.

Next, we will describe the routing algorithm in the second step. Details about the local search in the first step can be found in Section 4.2.

4.1. Routing algorithm

The genetic algorithm is a well-known heuristic applied to complex VRPs with realistic constraints. The algorithm's fitness function is determined by the total cost of EVRPTW-BSV-EC presented in Equation1 of **the mathematical model formulations section**. The detailed steps of the algorithm for solving the underlying routing problemare presented in Algorithm 1. In the EVRPTW-BSV-EC, the following three attributes can lead to infeasibility: overload, time windows, and battery charge level. The proposed GAallows infeasible solutions regarding time windows during the search process. To ensure solution validity, each individual must be tested against all constraints before steps 12-14; this step is rerun if invalid. The total cost of any solution is evaluated using the total costfunction described in Equation 1. This is facilitated by efficiently encoding decision variables into chromosomes describing an individual in the current population. The chromosome representing an individual in the population should be defined such that we are easily able to decode both the delivery plan (schedule of the customers in the route visited by different vehicles) and the swapping plan (sequence of BSV visits to the customer nodes to replace the E.V.s' battery). The individual chromosome should represent all visited nodes comprising$n$ customers. The n customers are represented by index numbers $1, ..., n$.

Started with a random permutation of n customers to build a chromosome. This starting configuration represents the sequence of customers visited by vehicles. Hence, we guarantee that each customer is visited exactly once and that the number of electric vehicles is established. This process yields the final sequence of the required vehicles to the customers from the start depot. To determine the vehicle assignments to the customers, we start with the first node in the sequence and assign it to the first available vehicle.We move to the next node in the sequence and determine whether the combined load of the first two nodes exceeds the vehicle load capacity. Ifnot, we assign the second node to the first vehicle; otherwise, we assign the second node to a new vehicle. The new vehicle becomes the current available vehicle, andthe process is repeated until all nodes have been assigned to a vehicle. In this way, we split the sequence of nodes into multiple routes.

4.1.1. ***Algorithm 1*** *Pseudocode Genetic Algorithm for EVR Problem*

- **procedure**
- Parameter Initialization
  - Total number of chromosomes in the population, N.
  - The maximum number of generations, T.
  - The maximum number of elite individuals, N_e.
  - Crossover rate, p_c.
  - Mutation rate, p_m.
- **Initial Population**

- Randomly generate a chromosome.
- Check if the load capacity is satisfied; go to step 12; If not, go back to step 9.
- If the number of chromosomes is N, go to Step 10; otherwise, go back to Step 9.

- **Fitness Evaluation**
  - For each chromosome in the population, solve its corresponding routing problem and obtain its fitness value (objective cost as described in Equation 1 in Section 4.2).
- Identify Elite Individuals
  - Select Ne individuals from the population with the lowest fitness values. The elite individuals are not processed for crossover and mutation. These elite individuals will be part of the next generation.
  - Find the lowest fitness value, F ∗ , of all chromosomes in the current generation.
  - Find all generations' lowest fitness value, F ∗∗ , so far.
- Stopping Criteria
  - If the total number of generations equals T, stop and return F; otherwise, go to Step
  - Generate the Next Generation of Chromosome
- Reproduction of children.
- *Crossover:*
  - Randomly pick chromosomes from the current population with a probability pc.
  - Apply the two-point crossover on the picked chromosomes.

  Mutation:
  - Randomly pick chromosomes from the current population with a probability pm.
  - Apply the mutation on the picked chromosomes
- Check that the load capacity and battery charge level constraints are satisfied for each chromosomein the new generation. If not, then discard it.
- Improvement heuristics:
  - 2-interchange
  - 2-opt
  - Cross exchange
  - close
  - Return F

The individual can quickly obtain the values of the decision variables related to the delivery plan (x_{ijk}) and the swapping plan (z_j *and* y_{jk}). In addition, the variables related to the departure time of the vehicle at each node can be deduced from the sequence of BSVs, assuming that we start from the depot at the earliest departure time. Also, we can update the battery level (QB_{jk}) at each visited node using the residual driving range at the preceding node (QB_{ik}) and whether we use the battery swapping (y_{ik})or not at the preceding node, as explained in Equation 22. Similarly, we can obtain the departure time DT_{jk} using Equation 19.

Three neighborhood operators were next used in the following order:

- 2-interchange,
- 2-opt, and
- cross-exchange to improve the final routing solution obtained by G.A.

These three neighborhoods are nested within each other and allow for solid diversification. These neighborhoods and their order were carefully chosen after a series of computation experiments in order to achieve maximum improvement with the limited runtime [24]. The improvements are rejected if the vehicle load capacity level is violated.

First, a 2-interchange routine is run that improves the total cost of the existingroutes. Customers and BSVs are potentially swapped to different locations onthe same route or other routes. All possible moves are considered for each candidate, and the move that created the best improvement is selected. This process isiterated until no more improving moves are found. Second, the standard 2-opt improvement heuristic is run to improve individual routes. The best-improving move is chosen among all the candidates on each route, and the process is repeated until no more improvements are found. Third, the standard cross-exchange routine exchanges two arbitrary segments in different routes. The process is repeated until no improvement is found.

The output routes from the improvement subroutine can be infeasible concerning time windows. The infeasibility concerning battery charge is repaired by calling the insert BSVs routine. First, BSVs are inserted greedily to improve the battery infeasibility for each route. Identify the initial customer in the route where the vehicle arrives witha depleted battery level. The best node for insertion of BSV on all arcs among the customer's odes and the depot was determined. The lowest cost option among BSVs is preferred. The best insertion position on the infeasible route is the one that offers the least insertion cost. This insertion can also yield infeasible routes but reduces the overall battery charge infeasibility.

The fitness value of the individual is calculated by the total cost function presented in Equation 1. As discussed earlier, the service by a vehicle at a customer location should start during the time windows specified by the customer. Therefore, tracking time windowviolations at each customer is necessary precisely because battery swapping can satisfy tight time windows compared to traditional recharging methods and might affect these costs. Compared to recharging, the battery swapping alternative by a BSV is expensive.

4.2. Local search

In Algorithm 1, local search techniques such as 2-interchange, 2-opt, and Cross-exchange are employed to iteratively improve routing solutions by making local changes until a set number of iterations is reached. Solutions that enhance total cost, as per Equation 1, are accepted. The algorithm evaluates routing solutions for various total vehicle requirements, with the local search selecting the best solution. Genetic Algorithm (G.A.) constraints ensure battery-swapping whenever a battery-swapping van (BSV) visits an electric vehicle (E.V.), allowing multiple uses of BSVs. The EVRPTW-BSV-EC problem is solved using Algorithm 1, followed by improvement routines in the order of 2-interchange, 2-opt, and Cross-exchange, aiming to minimize total travel time while ensuring each customer is visited exactly once. The resulting routes have at most n + K + 1 arcs, where K is the number of vehicles used and n is the number of customers.

4.3. Computational Study

In this section, computational experiments are performed to test the proposed GA-LS algorithm. All the programs were coded in Python and were implemented on an Intel Core i7 processor with 3GHz speed and 8GB RAM.

For deriving the different cost values specified in mathematical model , the authors investigated practical logistics companies and determined the costs related to E.V. operations. the authors assume that there are two available E. Vs to collect the different cargo loads from 5 different customers. Each E.V has a mass of 2000 kg at the start depot and its mass will be changed in each node depends on the cargo loads of that node while ensure the total freight weight must not exceed the vehicle load capacity which considered to equal 1200 kg. E. Vs can replace their batteries by calling the BSV to visit them in the next customer node and the swapping process takes a time of 3 min. The fixed cost for employing an E.V., UC_f , is SR 35000 which includes purchasing cost of the E.V and any other fixed cost. The per unit travel cost of the E.V., UC_{tr}, is set as 2 SR /min. Since the battery swapping employs more infrastructure the per unit swapping cost, UC_s, is 3 SR/min. The above values and other features of E.V are summarized in Table 2.

Table 2 Illustrates different features of E.V.s

Vehicle	**1**	**2**
Unit Fixed Cost (SR)	35000	35000
Unit Travel Cost (SR/min)	2	2
Unit Swap Cost (SR/min)	3	3
Vehicle Travel Speed (m/min)x10^3	2	2
Vehicle Mass (kg)	2000	2000
Vehicle Frontal Area (m^2)	3	3
Acceleration (m/s^2)	1.2	1.2
Vehicle Load Capacity (kg)	1000	1000
Battery Capacity (kWh)	70	70

On the other hand, BSV has a battery capacity of 100 kWh and it consumes one kWh per minute while it travels to the E.V and the other limitations of BSV are shown in Table 3. In addition, the selected customers are located in different sites and each one has a unique time window to be visited during it be the assigned E.V and will be serviced by a certain service time. The different parameter values are presented in Table 4. Furthermore, for the energy consumption calculations; different constants and parameters will be considered which be listed in Table 4. Finally, this dataset can be generalized and improved to work with a large size instance.

Table 3 Demonstrates different limitations of BSV

	Travel Time of Battery Swap Van (min)					**NO. of Carried Batteries**	**Battery Capacity (kWh)**	**Energy Consumption Rate (kWh/ min)**
Van	1	2	3	4	5			
1	53	35	47	43	38	10	100	1

Table 4 Customer's specifications and limitations

	Travelling Time (min)					**Service Time (min)**	**Time Windows (min)**		**Freight Weight (Kg)**
Customer	**1**	**2**	**3**	**4**	**5**		**Earliest**	**Latest**	
1	0	52	49	46	52	13	32	48	23
2	52	0	41	45	48	11	72	86	30
3	49	41	0	59	39	13	119	135	27
4	46	45	59	0	39	15	154	172	24
5	52	48	39	39	0	13	190	206	15

Table 5 List of several constants and parameters

Parameters / Constant Name	**Parameters / Constant**
Mass factor (δ)	1.1
Power Losses (η) %	80
Gravitational constant (m/s2)	9.8
Rolling Resistance Coefficient	0.01
Angle of the road (α)	0
The percentage of braking energy (β)%	90
Air Density (kg/m3)	1.205
Aerodynamic drag coefficient	0.6

After applying the designed GA-LS we come up with an acceptable result during a reasonable running time. For example, the first iteration generated a minimum total cost of SR 70.126 as presented in Table 6, and the resulted route was to visit customers 1 and 3 respectively by first E.V without any requirement of BSV, while customers 2,5 and 4 are serviced respectively by the second E.V with swapping demand at customer 4 to return the E.V to the end depot as displayed in Table 7. Moreover, the resulted routes were checked to make sure that they satisfied the load capacity constraint, battery level constraint, time window constraint and all other designed constraints, while considering the energy consumption calculations that are demonstrated in Table 8.

Table 6 Total cost of different routes

Iteration's Summary		
Route NO.	**Fitness (Total cost)**	**Rank**
1	70.182	3
2	70.186	4
3	70.160	2
4	70.126	1
5	70.208	5

Table 7 The resulted paths of E. Vs for the min-cost route

	Vehicle 1							**Vehicle 2**					
Customer	1	2	3	4	5	Depot	Customer	1	2	3	4	5	Depot
Depot	1	0	0	0	0	0	Depot	0	1	0	0	0	0
1	0	0	1	0	0	0	1	0	0	0	0	0	0
2	0	0	0	0	0	0	2	0	0	0	0	1	0
3	0	0	0	0	0	1	3	0	0	0	0	0	0
4	0	0	0	0	0	0	4	0	0	0	BSV	0	1
5	0	0	0	0	0	0	5	0	0	0	1	0	0

Table 8 Total energy consumption for the min-cost route

The power out at the battery terminals (kWh)	**57,12**
The regenerative braking at the battery terminals (kWh)	12.5
The energy consumption from batteries (kWh)	44.6

5. Conclusions

This manuscript presents a variant of the Electric Vehicle Routing Problem withTime Windows that includes battery swaps in conjunction with traditional recharging methods. Systematically, the research combines mathematical modeling techniques with optimization algorithms to formulate and solve the Electric Vehicle Routing Problem with Time Windows, Battery Swapping Van, and Energy Consumption (EVRPTW-BSV-EC). A local search routine combined with a Genetic Algorithm and improvement heuristics is developed to produce high-quality solutions in a limited time.

The results show that the additional choice of battery swaps at a swapping van led to better delivery routes, thereby reducing the overall costsparticularly for cases where battery swapping time and battery swapping cost are relatively lower. The impact ofproblem characteristics such as battery swapping time and battery swapping coston the routing solution is also discussed. The likelihood of battery swaps reduces as the battery swapping time and cost increase.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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