Optimizing On-Site Electric Vehicle Charging: Routing for Efficient Last-Mile Operations

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Abstract

The global shift towards sustainable transportation is centered around the growth of electric vehicles (EVs) primarily due to their zero tailpipe emissions. To facilitate the seamless transition from non-EVs to EVs and to alleviate the range anxiety experienced by EV users, substantial improvements in charging infrastructure is required. This involves the development of new fast charging stations and battery-swapping facilities. This research focuses on a step ahead and proposes an innovative solution by providing recharging and battery swapping services to EV users at their preferred time and location with mobile EV recharging and mobile battery swapping vans. The problem is formulated as a Multi-Depot Capacitated Vehicle Routing Problem (VRP) considering Hard Time Windows and Simultaneous Pickup and Delivery, using integer linear programming. The objective is to minimize the total cost of routing the recharging and battery swapping vans from charging stations to customer locations by satisfying the customer's requirements effectively. The proposed mathematical formulation was tested on a small set of 8 customers and solved using Gurobi solver. Furthermore, this NP-hard problem is tackled by developing heuristics known as large neighborhood search aimed at scalability for larger instances of the problem. The heuristics was successfully implemented and tested for the same small set of 8 customers and a larger instance with two sets (100,200) customers and different depots generated randomly. Therefore, this study introduces an innovative approach to tackle challenges related to EV adoption thereby contributing to a more sustainable and accessible future for electric mobility.

Keywords
Battery swapping, EV recharging, Integer linear programming and Neighborhood search

1. Introduction
The future of mobility is shifting towards electric vehicles (Oh and Yun 2022) as they play a crucial role in addressing the concerns related to environmental sustainability and reducing the dependence on conventional fossil fuels. However, for the users to adopt an EV, developing a reliable and accessible charging infrastructure is essential (Paniyil et. al 2021). The current EV charging infrastructure faces several challenges, such as limited charging stations and longer charging duration at stations, resulting in range anxiety for potential EV users. Range anxiety is the concern experienced by EV users that the EV may not have enough battery capacity to reach its destination or the next charging station. Hence, a well-developed EV charging network is essential which will bring users the confidence to switch from non-EVs to EVs, contributing to a cleaner and greener future.

This study introduces a more flexible and customer-centric approach by bringing battery swapping and recharging services directly to the customer's doorstep through the use of mobile battery swapping and recharging vans. This approach overcomes the challenges associated with traditional charging stations, where customers are required to travel to the station and wait for the vehicle to charge. In the method proposed by this paper, customers can request

services at their convenience, allowing for vehicle charging anywhere according to the customer's preference. This provides users with the convenience of seamlessly integrating EV charging into their daily routines.
The primary issue addressed by this paper involves optimizing the routes of mobile battery swapping and recharging vans to facilitate on-demand battery swapping and recharging services. The goal is to minimize costs while ensuring efficient service fulfillment for the customers.

1.1 Objectives
The paper focuses on tackling the challenge of improving the current electric vehicle charging infrastructure. This is possible by leveraging mobile battery swapping/recharging vans to recharge an EV at the customer location thereby inspiring confidence for prospective EV buyers.

- Introducing a novel approach by providing recharging and battery swapping services directly to the customer's chosen location through the use of mobile battery swapping/recharging vans.
- Creating mathematical model for the vehicle routing problem, addressing the routing problem associated with mobile battery swapping/recharging vans.
- Development of a neighborhood search heuristic to solve the problem for larger instances, given the inherent time complexity of this NP-hard problem.

2. Literature Review
In our comprehensive literature review, we address two critical aspects of research: firstly, an examination of existing EV charging infrastructure models, and secondly, an exploration of vehicle routing problems in the context of EV services. The surge in electric vehicle adoption requires a robust charging infrastructure, and our review explains diverse models proposed to optimize the placement and operation of charging stations.

2.1 Existing EV Charging Infrastructure Models
The surge in the sales of EVs has attracted many researchers to introduce innovative solutions to effectively tackle the challenges associated with range anxiety and charging infrastructure. Based on the commuting behaviors of electric vehicle users, (Zhu et al. 2016) suggested an optimization model using genetic algorithm to estimate the position and capacity of the charging station with the aim of lowering the total cost. Bian et al. (2019) developed a Mixed Integer Linear Programming (MILP) model based on geographic information systems to determine the best site for charging stations in urban areas by optimizing investment returns. A cell-based MILP model that uses GPS trajectory data of vehicles that optimizes both cost and service quality was proposed by (Bai et al. 2019) to determine the location, capacity and type of charging station. Hybrid non-dominated sorting genetic algorithm was utilized to solve the bi-objective model. Li et al. (2021) proposed a model that uses an improved genetic algorithm that focuses on the determination of public charging stations with the aim of minimizing the investment costs and travel costs for EV users. Erdogan et al. (2022) proposed a strategy to prioritize the placement of electric vehicle charging stations on EV designated corridors rather than other sites. The model is based on the flow refueling location model and with the objective of maximizing the corridor miles traveled. Using an innovative integer linear programming approach, (Ullah et al. 2023) proposed a strategic solution by constructing fast-charging stations into already-existing gas stations, giving stakeholders the knowledge for charging infrastructure decisions. In order to minimize the annual investment cost as well as the annual operation and maintenance cost of charging stations, (Wang et al. 2023) suggested a neighborhood mutation immune clone selection algorithm for the location and sizing of electric vehicle charging stations.

2.2 Vehicle Routing Problems
Vehicle Routing Problem is a classical optimization problem in the field of operations research and logistics. The goal of the vehicle routing problem is to determine the most efficient way to deliver goods or services from a central depot to a set of customers using a fleet of vehicles. Zhen et al. (2020) introduced a Mixed-Integer Linear Programming (MILP) model for addressing the Vehicle Routing Problem (VRP) with practical constraints, including time windows and the release date of customer orders. Their objective was to minimize travel time, and they employed a hybrid approach integrating both particle swarm optimization and genetic algorithm techniques to solve the problem efficiently. Gil et al. (2021) proposed a metaheuristic approach to solve the vehicle routing problem with pickup and delivery for logistics service companies that aims at minimizing the emission from fuel consumption by efficiently combining resources from multiple depots. Phuc and Thao (2021) addressed the multiple pickup and multiple delivery VRP with time windows and heterogenous fleet with the aim of minimizing the total travelling costs for e-logistics service providers. Ant colony optimization was employed to solve the problem on a large scale. Parayoga and Asih

(2022) addressed the multi-objective multi-compartment split delivery location routing problem with time windows that considers multi-compartment vehicles used store goods separately. They employed non-dominated sorting genetic algorithm to solve the model with the aim of minimizing overall cost and maximizing service level. Dubey and Tanksale (2023) introduced a multi-depot vehicle routing problem with time windows, split pickup, and split delivery for surplus food recovery and redistribution. They proposed a MILP model and solved it using genetic algorithm hybridized with local search. Agrali and Lee (2023) addressed the pickup and delivery problem with electric vehicles considering challenges such as multi-depots, time-windows, and EVs' battery and vehicle capacity. They proposed a MILP model and solved it using a hybrid heuristic combining simulated annealing and Large Neighborhood Search (LNS). Xu et al. (2023) proposed a MILP model that optimizes routes for the distribution of emergency relief materials to all the demand points using EVs considering time windows. Further a hybrid genetic algorithm and LNS is used to determines delivery routes that minimizes the overall cost.

While previous studies have primarily focused on optimizing charging station location and logistics, this research introduces a novel approach by directly addressing charging needs through on-site battery swapping and recharging. This approach offers a more flexible and efficient EV charging service, catering to the convenience of EV users. It not only meets the immediate requirements of users but also contributes to a greener future by promoting sustainable and user-friendly charging solutions.

3. Methods

In this paper, the on-site battery swapping and recharging problem is formulated as a Multi-Trip Multi-Depot Capacitated Vehicle Routing Problem with Hard Time Windows and Simultaneous Pickup and Delivery (MTMD-CVRP-HTW-SPD). The primary objective is to minimize the overall cost associated with routing vehicles that cater to customer requests for battery swapping and recharging of their electric vehicles. The proposed model addresses the problem for a single period, where customer orders are accumulated and solved in a single iteration, ensuring efficient planning and optimization within a specific timeframe.

3.1 Assumptions

These assumptions collectively contribute to simplifying the on-site electric vehicle charging problem and establishing a structured foundation for our approach:

- The demand and time windows of each customer is deterministic and known
- Co-ordinates of each customer is known before planning the routing of fleets
- Each customer can be visited exactly once and entire demand is fulfilled in single service
- Each depot or charging station has its own fleet of trucks and trucks can make multiple trips if required
- The trucks start and end its route only at the charging station to which it belongs
- The inventory capacity of the recharging/battery swapping stations is sufficient to meet the demand
- The travel times and distances between customers and charging stations are deterministic and known
- Service time at customer locations, including both pickup and delivery operations, are deterministic and known
- Real-time information on road conditions, traffic, and any disruptions is not considered
- Customer deliveries cannot occur before or after their specified time windows, ensuring adherence to agreed-upon schedules

3.2 Notation

In order to facilitate a clear and concise representation of our model, the following notations are adopted:

Sets

C	the set of customers
D	the set of depots
N	the set of customers and depots
K	the set of vehicles
W	the set of trips

Parameters

t_{ij}	the travel time from *customer*$_i$ / *depot*$_i$ to *customer*$_j$ / *depot*$_j$
ear_i	the earliest service time of *customer*$_i$
lat_i	the latest service time of *customer*$_i$
q_i	the goods to be delivered at *customer*$_i$
p_i	the goods to be picked up at *customer*$_i$
H	the time horizon
Q	the vehicle capacity
S	the total number of customers

Decision variables

X_{ijkw}	the binary variable indicating customer$_i$ / *depot*$_i$ to *customer*$_j$ / *depot*$_j$ served using *vehicle*$_k$ in *trip*$_w$
Y_{kw}	the binary variable indicating *vehicle*$_k$ operating in *trip*$_w$
T_{ikw}	the time of arrival at *customer*$_i$ / *depot*$_i$ using *vehicle*$_k$ in *trip*$_w$
TS_{kw}	the time of start from depot using *vehicle*$_k$ in *trip*$_w$
TE_{kw}	the time of return to depot using *vehicle*$_k$ in *trip*$_w$
LD_{kw}	the load of *vehicle*$_k$ in *trip*$_w$ at depot
L_{ikw}	the load of *vehicle*$_k$ in *trip*$_w$ at *customer*$_i$ / *depot*$_i$

3.3 On-Site Electric Vehicle Charging: Mathematical Formulation

The Objective Function - Minimization

$$\sum_{i}^{N}\sum_{j}^{N}\sum_{k}^{K}\sum_{w}^{W} X_{ijkw} * D_{ij} \tag{1}$$

The Constraints

$$\sum_{j}^{N}\sum_{k}^{K}\sum_{w}^{W} X_{ijkw} = 1 \qquad \forall\, i \in C \tag{2}$$

$$\sum_{i}^{C}\sum_{i}^{C} X_{iikw} = 0 \qquad \forall\, k \in K, w \in W \tag{3}$$

$$\sum_{d}^{D}\sum_{i}^{C} X_{dikw} = Y_{kw} \qquad \forall\, k \in K, w \in W \tag{4}$$

$$\sum_{i}^{C}\sum_{d}^{D} X_{idkw} = Y_{kw} \qquad \forall\, k \in K, w \in W \tag{5}$$

$$\sum_{i}^{D}\sum_{j}^{D} X_{ijkw} = 0 \qquad \forall\, k \in K, w \in W \tag{6}$$

$$\sum_{i}^{N}\sum_{j}^{N} X_{ijkw} \le S * Y_{kw} \qquad \forall\, k \in K, w \in W \tag{7}$$

$$Y_{kw+1} \le Y_{kw} \qquad \forall\, k \in K, w \in W \tag{8}$$

$$\sum_{i}^{N} X_{ijkw} = \sum_{i}^{N} X_{jikw} \qquad \forall\, j \in C, k \in K, w \in W \tag{9}$$

$$\sum_{i}^{N}\sum_{j}^{N} X_{ijkw} * q_j = LD_{kw} \qquad \forall\, k \in K, w \in W \tag{10}$$

$$LD_{kw} \leq \; Q * Y_{kw} \qquad \forall\, k \in K, w \in W \qquad (11)$$

$$L_{ikw} \leq Q \qquad \forall\, i \in N, k \in K, w \in W \qquad (12)$$

$$L_{ikw} \geq LD_{kw} - M * \left(1 - \sum_{j}^{C} X_{ijkw}\right) \qquad \forall\, i \in D, k \in K, w \in W \qquad (13)$$

$$L_{jkw} \geq L_{ikw} + \; p_j - q_j - M * (1 - \; X_{ijkw}) \qquad \forall\, i \in N, k \in K, w \in W \qquad (14)$$

$$TS_{kw} \geq \; s - M * (\, 1 - \; Y_{kw}) \qquad \forall\, i \in D, k \in K, w \in W \qquad (15)$$

$$TS_{kw+1} \geq \; TE_{kw} + \; s - M * (\, 1 - \; Y_{kw+1}) \qquad \forall\, i \in D, k \in K, w \in W \qquad (16)$$

$$T_{jkw} \leq \sum_{i}^{N} X_{ijkw} * lat_j \qquad \forall\, j \in C, k \in K, w \in W \qquad (17)$$

$$T_{jkw} \geq \sum_{i}^{N} ear_j * X_{ijkw} \qquad \forall\, j \in C, k \in K, w \in W \qquad (18)$$

$$T_{jkw} \geq \; T_{ikw} + s + t_{ij} - M * (\, 1 - \; X_{ijkw}) \qquad \forall\, i \in C, j \in C, k \in K, w \in W \qquad (19)$$

$$T_{jkw} \geq \; ear_i + s + t_{ij} - M * (\, 1 - \; X_{ijkw}) \qquad \forall\, i \in C, j \in C, k \in K, w \in W \qquad (20)$$

$$T_{jkw} \geq \; TS_{kw} + t_{ij} - M * (\, 1 - \; X_{ijkw}) \qquad \forall\, i \in D, j \in C, k \in K, w \in W \qquad (21)$$

$$TE_{kw} \geq \; T_{ikw} + s + t_{ij} - M * (\, 1 - \; X_{ijkw}) \qquad \forall\, i \in C, j \in D, k \in K, w \in W \qquad (22)$$

$$TE_{kw} \geq \; ear_i + s + t_{ij} - M * (\, 1 - \; X_{ijkw}) \qquad \forall\, i \in C, j \in D, k \in K, w \in W \qquad (23)$$

$$TE_{kw} \leq H \qquad \forall\, k \in K, w \in W \qquad (24)$$

Constraint (2) and (3) ensures that each customer is visited only once. Constraint (4) and (5) ensures that each vehicle starts and ends its trip from its corresponding depot. Constraint (6) ensures that depot to depot travel is not permitted. Constraint (7) ensures that the cumulative number of customers served for each trip in each vehicle does not exceed the total number of customers available for the day. Constraint (8) ensures that subsequent trips can be operated only if the current trip is operated. Constraint (9) satisfies the flow conservation. Constraint (10) and (11) ensures that the load of the vehicle at the start of the trip is same as the total demand of customers to be served by that vehicle in that respective trip and less than the vehicle capacity. Constraint (12) ensures that at any point during the trip, the load of the truck is less than or equal to its capacity. Constraint (13) introduces a new variable which plays a crucial role in supporting the subsequent truck load constraints. Constraint (14) takes into account the pickups and deliveries at each customer location in the sequence. Constraint (15) and (16) captures the start time of the vehicle for its trips by considering service time and end time of pervious trip. Constraint (17) and (18) ensures that the truck arrives within the time windows specified by each customer. Constraint (19), (20) and (21) captures the arrival time of truck at a customer taking into account the start time at depot, service time, sequence in which service is done and travel time between customers. Constraint (22) and (23) captures the entire of a trip. Constraint (24) ensures that the end time of the vehicle for each trip does not exceed the time horizon for which the routing is planned.

3.4 On-Site Electric Vehicle Charging: Neighborhood Search Heuristics

The exact models are limited to solving small instances of the VRP with a few customers. To extend the scalability of our solution to a larger set of customers, we introduce a neighborhood search heuristics algorithm that employs a combination of swap and insert schemes. The insert scheme involves selectively adding or removing elements to reduce the complexity of a solution, often applied in route optimization problems. On the other hand, the swap scheme focuses on iteratively exchanging elements to enhance a solution, refining the overall quality by rearranging components for better efficiency or performance. Both schemes play crucial roles in fine-tuning solutions within heuristic algorithms.

<u>Neighborhood search algorithm:</u>

1. *Initialization:*
   1.1 Load customer, depot, vehicle, maximum trips, time windows and distance matrix data

2. *Assign customers to nearest depot using linear programming:*
   2.1 For each customer identify the nearest depot using Manhattan distance and assign that customer to the nearest depot

3. *Sort the assigned customer in each depot:*
   3.1 For each depot sort customer based on their earliest time windows

4. *Allocate customers to vehicles:*
   4.1 For each depot and each vehicle in the depot, allocate customers to the vehicle while satisfying the capacity, time window, flow conservation constraints

   4.2 If any constraint is violated, exclude the customer from consideration

5. *Repeat the process for the maximum number of trips the vehicle can make*

6. *Apply Insert and Swap scheme:*
   6.1 For each depot and each vehicle in the depot apply the insert scheme to optimize the route

   6.2 Repeat until no further improvement

   6.3 For each depot and each vehicle in the depot apply the swap scheme to further improve the quality of solution

   6.4 Repeat until no further improvement

4. Design of Experiments

In this section, for the VRP model, a systematic approach was employed to generate meaningful and realistic data for simulation. The spatial configuration involved an area of 25 x 25 square kilometers, within which coordinates for eight customers were randomly generated. In addition, two depot coordinates were randomly assigned, each associated with two vehicles capable of completing a maximum of three trips. Following the generation of customer and depot coordinates, a distance matrix was computed using Manhattan distance, capturing the distance between each customer and each depot. Time windows for each customer were randomly generated, featuring both earliest and latest time. To ensure temporal feasibility, the condition was imposed that the latest time must surpass the earliest time. For the depot, service hours were assumed for operational time considerations. Further both delivery and pickup quantities for each customer were randomly generated, reflecting the dynamic nature of real-world scenarios. Table 1 provides a snapshot of the sample customer data for all the parameters mentioned above. Table 2 depicts the assumptions for all the parameters used in the models. Table 3 shows a sample distance matrix between customers.

Table 1: Sample customer data

Customer ID	Co-ordinates	Earliest time	Latest time	Pickup qty.	Delivery qty.
C01	(19,20)	170	208	4	3
C02	(25,0)	85	236	5	3
C03	(8,1)	114	127	4	4

Table 2: Assumption of the parameters for the model

Notation	Description	Value
C	No. of customers	8
D	No. of depots	2
N	No. of nodes	10 (C + D)
K	No. of vehicles	4
W	No. of trips for each vehicle	3
Q	Vehicle capacity	25
H	Planning period	300
s	Service time	5

Table 3. Sample distance matrix between customers and depots

	C01	C02	C03
C01	0	26	30
C02	26	0	18
C03	30	18	0

5. Results and Discussion

The multi-trip multi-depot capacitated vehicle routing problem with hard time windows and simultaneous pickup and delivery is solved using Gurobi solver version 10.0.1. Simulation experiment was conducted on a computer equipped with a Ryzen 7 5800U processor, 16GB of DDR4 RAM, Radeon graphics card, and 1 TB solid-state driver. The problem is solved using both exact and neighborhood search heuristics for a single period with the parameters as mention in Table 2.

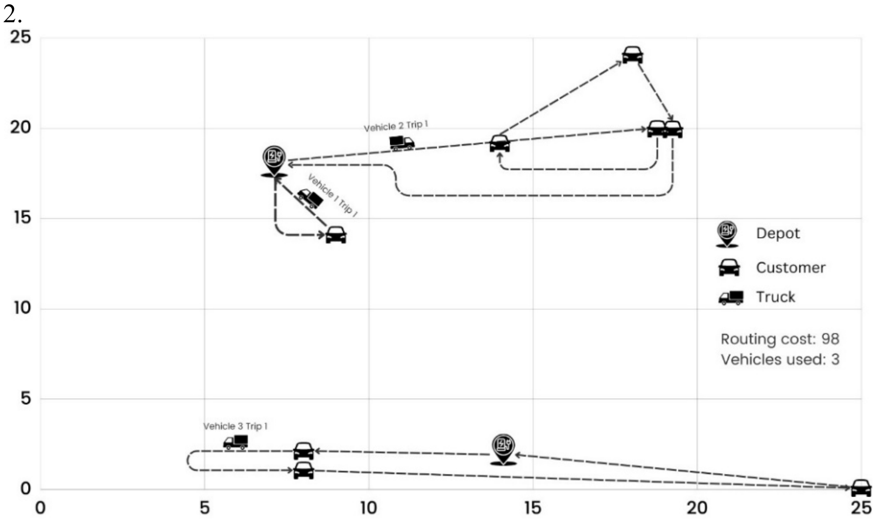

Figure 1. Graphical representation of the routes obtained using exact model

Both the models are solved with the objective of minimizing the total cost of routing the vehicles to satisfy the customer's requirements and the results are presented in Figure 1 and Figure 2. The results show that optimizing the exact VRP model incurs a total cost of 98 units, with 3 vehicles utilized for routing. Specifically, two vehicles originate from the first depot wherein first vehicle serves just one customer and second vehicle serves three customers. The remaining vehicle commences its route from the second depot and serves three customers. All vehicles complete only a single trip. From Figure 1, it is intuitive that customers who are close to depot 1 are being served by the respective depot, and customers close to depot 2 are being served by the respective depot in order to minimize the routing cost. The results obtained by solving the neighborhood search heuristics for the same parameters as described in Table 1 and Table 2, incurs a total cost of 108 units, with 2 vehicles utilized for routing. Specifically, one vehicle originate from the first depot and second vehicle originates from second depot. All vehicles complete only a single trip.

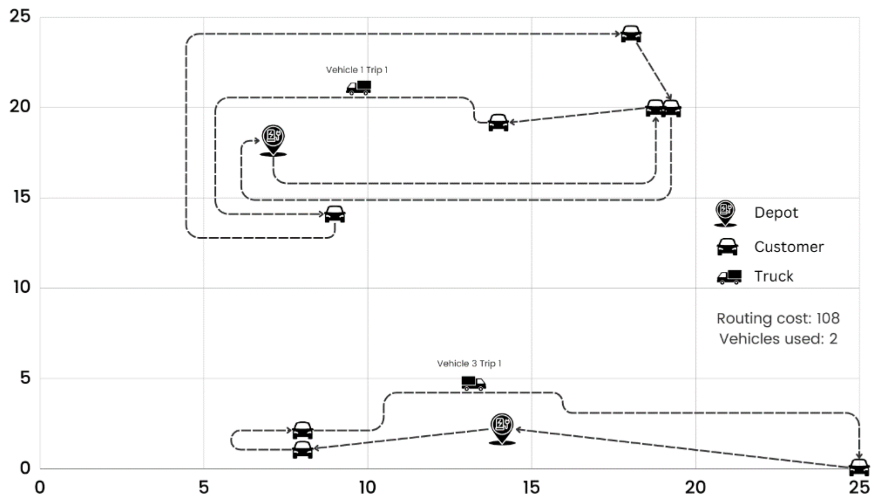

Figure 2. Graphical representation of the routes obtained using neighborhood search heuristics

Table 4. Depicts the comparison of results obtained from solving exact model and neighborhood search heuristics from 8 customers and 2 depots

No. of depots	Customers	Model used	No. of vehicles required	No. of routes operated	Total distance	Computation time (secs)
2	8	Exact formulation	3	3	98	11.37
2	8	Neighborhood search heuristics	2	2	108	1

From Table 4 it is shown that the exact model resulted in a total distance of 98 which is 9.25% less than the total distance of 108 obtained from the neighborhood search heuristics for the same set of customers and parameters. It is also seen that the number of vehicles required by exact model is more than that of heuristics.

5.1 Proposed Improvements

The heuristic aims to increase the scalability of exact method and efficiently optimize routing for a larger number of customers by inherently reducing the number of routes, with the objective of minimizing the total cost. In the process of optimization using neighborhood search heuristics algorithm, it is also made sure that the intermediate as well as final solution satisfies the pickup, delivery and time window constraints. Table 5 depicts the assumptions for all the parameters used for the heuristics model.

Table 5. Assumption of the parameters for the model

Notation	Description	Value
C	No. of customers	100, 200
D	No. of depots	1, 3, 5
N	No. of nodes	C + D
W	No. of trips for each vehicle	3
Q	Vehicle capacity	50

H	Planning period	660
s	Service time	5

5.2 Results and Discussion

The multi-trip multi-depot capacitated vehicle routing problem with hard time windows and simultaneous pickup and delivery is solved using neighborhood search heuristics algorithm. The computations were done on the same laptop with the specifications mentioned previously.

Six distinct instances were implemented, altering the number of depots (1, 3, 5) and varying the number of customers (100 and 200). The results revealed notable trends. As the number of depots increased while maintaining a constant number of customers, both the number of vehicles and routes exhibited an increase. Conversely, the total distance covered decreased with an augmented number of depots for a constant customer count. This outcome aligns with intuition, as a greater number of depots enables customers to be served from the nearest location, subsequently reducing the overall travel distance. Additionally, the average number of customers served per depot decreased as the number of depots increased, holding the total number of customers constant (Figure 3m Table 6).

Table 6: Results of neighborhood search heuristics algorithm for six different instances

No. of depots	Customers	No. of vehicles required	No. of routes operated	Avg. no. of customers per route	Total distance	Computation time (secs)
1	100	5	8	15	412	11.05
3	100	6	7	16	332	10.98
5	100	9	10	12	266	13.07
1	200	8	14	16	774	46.26
3	200	8	16	15	552	46.60
5	200	13	18	13	466	49.50

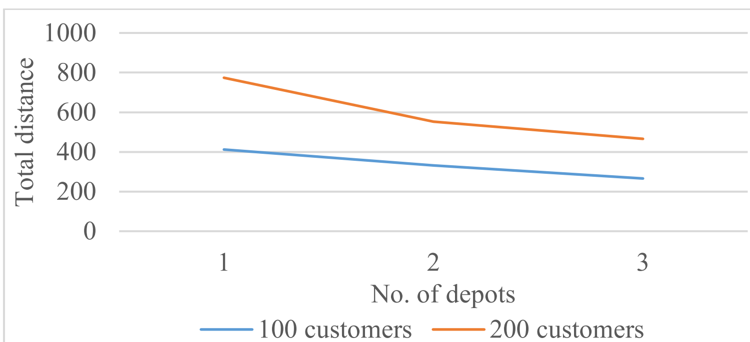

Figure 3: Graph represents the reduction in the total distance with increase in the number of depots for 100 and 200 customers implemented using neighborhood search heuristics

6. Conclusion

This research has provided insights and an effective solution to the challenges associated with multi trip muti depot capacitated vehicle routing problem with hard time windows and simultaneous pickup and delivery with the help of both exact model and neighborhood search heuristics algorithm. The exact model is limited to smaller instances due to the inherent NP-hard time complexity. On the other hand, the neighborhood search heuristics algorithm, designed to handle larger datasets, has showcased its efficiency in optimizing the routes and costs for a large number of customers. Apart from optimizing the costs, the heuristics algorithm is also made sure that is satisfied the constraints of the VRP. The iterative implementation of insert and swap scheme within the heuristics model has significantly improved the overall routing efficiency. Furthermore, the unique research contribution lies in the introduction of an on-site battery swapping and recharging solution through mobile units. This customer-centric approach addresses the limitations of traditional charging stations and enhances the overall appeal of electric vehicles to potential adopters. By effectively addressing the challenges in day-to-day mobility, we contribute to the advancement of eco-friendly practices in logistics and transportation. Potential future research areas include Integration of real time data such as traffic conditions and weather into routing algorithms to enhance the responsiveness and adaptability of the system, dynamic vehicle routing problem where customer requests arrive dynamically during the routing process.

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Biographies

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Viswanath Kumar Ganesan earned his PhD from the Indian Institute of Technology Madras, India. Currently he serves as a Principal Scientist at Tata Consultancy Services (TCS) since April 2005, specializes in applied research, design, and development of large-scale data and decision science engagements across diverse business verticals. Prior to TCS, he served as a Research Fellow at the Singapore MIT Alliance, NTU Singapore.

Haripriya K is currently an M.S. research scholar specializing in Operations Management in the Department of Management Studies at Indian Institute of Technology Madras, India. Concurrently, she holds the position of IT Analyst at Tata Consultancy Services. Her research focuses on Operations Management, with specific expertise in vehicle routing problems and data science.