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Electric Vehicle Routing Problem: A Comprehensive Review

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ABSTRACT: Transportation plays an important role in today's era. To manage the on-time delivery in logistics, it is crucial to manage the fleet for the delivery. Because of environmental concerns and new regulations, green vehicles and electric vehicles are becoming more famous in logistics. Due to their limited driving range, the authors need to be recharge again and again. The vehicle routing problem (VRP) is extended to electric vehicle routing problem (EVRP) having different characteristics. The problem is NP hard and computationally challenging to solve large scale instances. To solve such problems, algorithms were introduced such as exact algorithms, metaheuristics, and machine learning to solve real-life problems, energy consumption and environmental considerations. EVRP is applicable in urban logistics, fleet management, and goods distribution. Research in EVRP combined with sustainable development goals give solutions to optimization problems that aim to manage the social, economic, and environmental objectives. EVRPs increase the operational efficiency as well as contribute as a greener and more sustainable future by promoting eco-friendly logistics practices. From all this, we can conclude that EVRPs are a strong tool to support the SDGs, particularly for the clean environment, sustainable infrastructure, and logistics. In this paper, a literature review on electric vehicle routing problem is given and research gaps along with future directions are also discussed. To deal with the new and complex routing challenges in EVRP, heuristics and metaheuristics approaches are developed and adapted by different researchers. Research publications from the past 13 years has been taken into consideration including 95 research articles, that deal with EVRP. An overview on these procedures has been introduced in this review article.

Key Words: Electric vehicle routing problem, sustainability, metaheuristics, logistics, solution approaches, algorithms.

Contents

1. Introduction

Transportation problems are one of the leading issues nowadays. Logistics are the base of every business to import multiple goods and products from one place to another. The main objective is to minimize the travelling cost which is mostly defined in terms of distance, time, or fuel consumption. Transportation problems include travelling salesman problem which includes a delivery man, sources, and destinations. Sources are the distribution centres from where the product has to be distributed to the destinations i.e. customers or vendors. These problems are applicable on logistics, supply chain management and

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distribution networks. Travelling salesman problem is further specified as vehicle routing problems which are somehow complex with more than one constraint. The problem becomes more complex as Vehicle Routing Problems are one of the most considerable issues noticed by the researchers as it is related to the daily life. Logistics companies have to focus on so many things to keep their company in a good and reputed position. Their main motive is to make more and more profit by spending less. Therefore, the authors try to make their travel cost and the distance travelled lesser to make more profit. This can only be possible if the authors apply the optimality rules in their industries to find the best solutions. These best solutions can be found only by using metaheuristic algorithms as the data available in the companies is large as well as complex having huge number of constraints and conditions. VRPs initially taken into notice by [19] where the authors have focused on a truck dispatching problem which was based on delivery of oil from one place to another. Vehicle routing problems have so many variants based on different conditions and situations. The main variants of vehicle routing problem are Capacitated vehicle routing problems(CVRP), where vehicle cannot exceed the loading capacity, vehicle routing problem with time window (VRPTW), where a time window constraint is given for timely delivery of the products and goods, multi depot vehicle routing problem (MDVRP), where more than one vehicle can be used for delivery of products, split delivery vehicle routing problem (SDVRP) , where multiple trips can be done by vehicle to visit a single customer and transportation of goods, stochastic vehicle routing problem is that some factors like time and demand are uncertain. **Figure 1** represents the variants of VRP. To solve these VRPs, many exact, heuristics and metaheuristics approaches were developed starting from 1959 and the work is still going on. Vehicle Routing Problems were then extended to Green VRPs because of the environmental sustainability goals as with the increment in the number of vehicles on the roads, the consumption of non-renewable fuels and carbon emission also increased. In Green Vehicle Routing Problems, green vehicles are used such as the electric vehicles and vehicles running on Compressed Natural Gas (CNG). Along with the introduction of Green VRP, the complexity of the problem is also increased as now the researchers have to focus on reduction of consumption of fuels are carbon emissions. Therefore, more mathematical models were developed and were optimized using hybrid metaheuristics algorithms. EVRP is a branch of green VRP which deals with electric vehicles where charging stations are involved in the mathematical model to charge the vehicles according to their needs. Green vehicle routing was first introduced in 2012 by [25]; however, electric vehicle routing was introduced in 2014 by [69] just after a gap of two years. EVRP is better than green VRP as there is no use of any kind of fuel, only electricity is used to recharge the vehicles which can be generated by using renewable sources of energy such as water and wind.

Along with pros there are some cons also. Electric vehicles use electricity as their fuel but there is problem of recharging again and again and because of this the electric vehicles are unable to cover long routes. Electric vehicles are required to be recharged regularly on their routes. Therefore, routing decisions must account for battery consumption which is basically dependent on several components such as load, traffic congestion and energy efficiency of automobile. From this, it is concluded that energy management is the key element in the functioning of EVs and it should be calculated in a proper manner that when and where the vehicle must stop to get charged again. Another challenge is the distribution of charging stations on the routes. Unlike the traditional vehicles, electric vehicles are not that much popular in use in the remote areas like rural and less developed areas. This means that while planning the route of the electric vehicle towards a remote area, it should be focused that the area must have enough charging stations for the EVs to get recharged. The problem- solving model must include the availability of the charging stations and their capacity of recharging the EVs, this condition also adds to the complexity of the model in the optimization procedure. Moreover, since the usage of electric vehicles costs lesser than the traditional vehicles, still these vehicles are costlier during the purchasing. This decreases the purchasing of electric vehicles in comparison with the gasoline and diesel-based vehicles. One more thing is that there is not much variety in electric vehicles and have limited carrying capacities based on their engine counterparts. This limits the variety of vehicles in case of fleet and there is always same kind of vehicles are to be used for short and long routes. For long routes, the vehicles need to recharge at several intervals of time. Several methods and mathematical models were developed by many researchers to cover these issues. Metaheuristics approaches were applied to the models by using different software to increase the optimality of the routes under certain conditions.

The main aim of this paper is to provide a review of the work done till now and the future directions that can be applied to find optimal solutions for these kinds of complex optimal problems. In this article, classification of solution methods based on different years is also presented. Part 2 discusses about the Electric vehicle routing problems in depth. A proper pathing of electric automobiles is given in Figure 4. In Part 3, literature related to EVRP is given from last 11 years. Solution approaches are reviewed in Part 4, while in Part 5, a mathematical model is introduced with some constraints and conditions. Part 6 compares different constraints. Part 7 includes the applications of EVRP. Part 8 and Part 9 gives the future directions and conclusion of the whole article respectively.

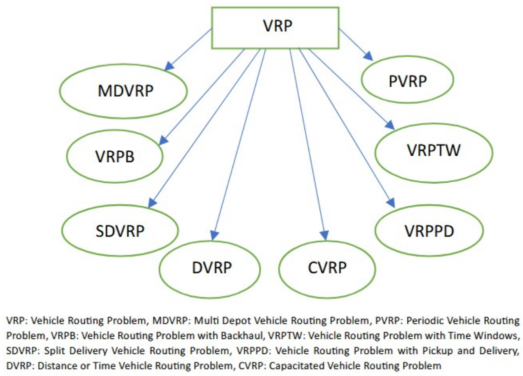

Figure 1: An illustration of VRP

2. Electric Vehicle Routing Problem

EVRP is an extension of VRP as in vehicle routing problem, the problem is related to the logistics with fleet of vehicles having multiple constraints however, GVRPs and EVRPs are the extensions with some extra conditions of decreasing fuel consumption and pollution in the environment. **Figure 2** shows the working of a vehicle routing problem covering the route from depot to different consumers.

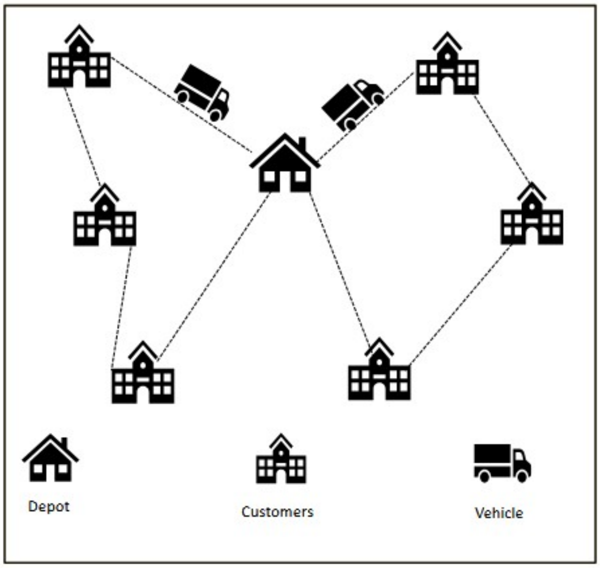

Figure 2: An illustration of VRP

Due to environmental concerns, green and electric vehicles were introduced in logistics to reduce the fuel consumption. In case of GVRP, there is a condition of reducing fuel consumption along with fulfilling other constraints of minimizing travel cost, time windows, meeting customer demands, minimizing distance or maximizing profit. **Figure 3** depicts the path covered by a green vehicle. On the other hand, electric vehicles satisfy the charging conditions along with the conditions of VRPs. Sometimes, it is mandatory for an electric vehicle to visit a charging station again and again to continue its route. In addition to this, condition of partial charge or full charging of the battery can also be considered. Charging speed can be fast or standard depending on the time a e-vehicle is taking to be fully charged.

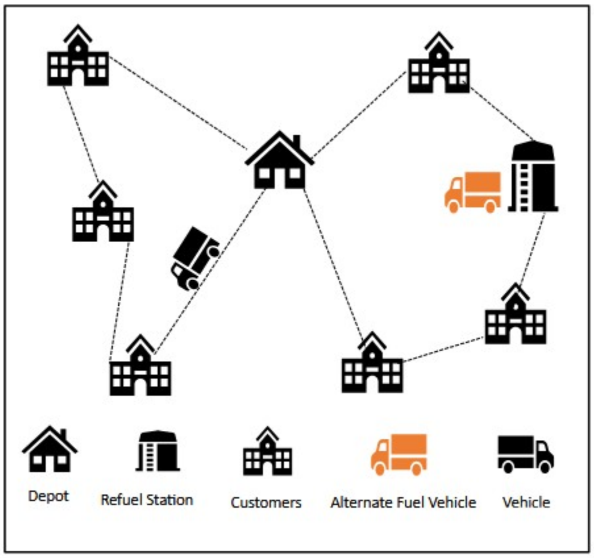

Figure 3: An illustration of GVRP

In simple definition, EVRP means meeting the customer demands by using least vehicles, consuming less fuel and minimizing the total travelling cost. **Figure 4** represents the route of electric vehicles visiting the charging stations.

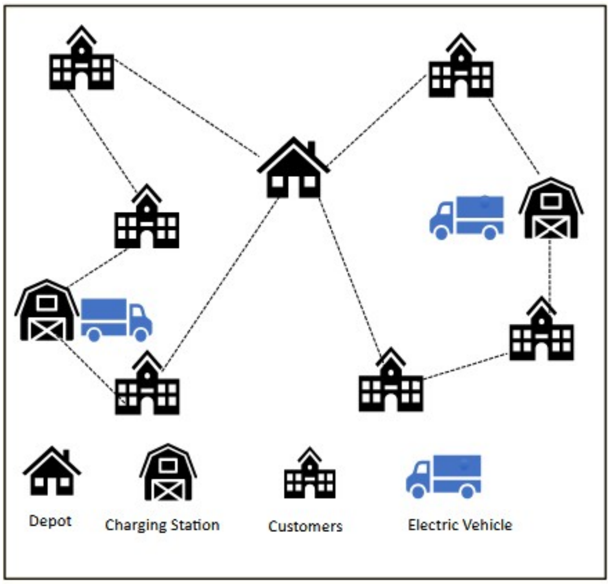

Figure 4: An illustration of EVRP

3. Literature Review

VRP was initially studied by [19]. Their aim was to minimize the travel cost and the authors considered a truck dispatching problem. Moreover, the problem was also based on the capacity i.e. the vehicles could carry a limit load. After their research, other researchers also divert their focus on VRP models and the authors focused on complex constraints relating to the real-world issues. Time windows constraint was also taken into consideration as sometimes the delivery was not on time. [69] were the first to work with the time window constraint where the authors used the Tabu search for their work and considered a data stet provided by Solomon having 56 instances. Furthermore, [25] were first who dealt with green VRP. The authors considered alternate fuel vehicles. Electric vehicle routing problem was first introduced by [69] where the authors used the constraint of time windows. [20] considered EVRP with partial charging where the authors used condition of limited charging load of an e-vehicle. The authors used Tabu search and variable neighbourhood search to solve large scale instances. [42] proposed adaptive large neighbourhood search algorithm for partial recharging to full recharging of electric vehicles with minimizing the total distance. Focusing on vehicle count and composition, [37] proposed the electric vehicle routing problem with mixed fleet of vehicles using ALNS combining with embedded local search and labelling procedure. Furthermore, [43] introduced electric vehicle routing problems having scheduling constraints with quick charge and single charging and worked on two different models for these two situations. The authors find their conclusions based on the small instances that fast charging can minimize the fleet volume. [59] worked with mixture of electric and traditional automobiles using partial charging for EVs. [45] extended the electric vehicle routing problems using non charging linear functions by taking into consideration the shared charging stations and minimized the total cost. A new investigation was also conducted by [58] and the authors considered non- linear charging stations as like Koc et al. but the authors developed a hybrid metaheuristic approach to find the solutions. [13] investigated EVRPTW concerned with half recharging and satellite customers aiming to decrease the power charging duration at the recharging stations. [1] proposed genetic algorithm for two echelon electric vehicle routing problem with a mixed fleet of vehicles. The objective was to minimize the operational costs and the authors found that their algorithm gives superior results. [2] gave modified Clarke and wright algorithm for two echelon electric vehicle routing problem with time windows where the authors considered small sized instances and found the solutions on CPLEX. [3] used a hedging based heuristic algorithm to solve Location- based routing issues based on EVRPs with fast charging. [4] performed their experiments on electric vehicle routing problems with hard and soft time windows including partial recharging. The authors applied nature inspired algorithms along with epsilon constraint algorithm to find suitable results. [5] worked on a research paper regarding the mathematical model and results based on two- echelon EVRP considering scheduling constraint, dual pickup and delivery, and partial deliveries. [76] applied an exact approach known to be branch and cut approach for EVRP. Piecewise linear charging function underestimated the real state of charge at some points; therefore, Arne introduced this new method to overcome this drawback. [10] also worked with electric vehicles considered a problem with time windows constraint where the authors preferred two stage problem with best path calculating and route planning. In the same year, [11] used two echelon problem having a combination of battery driven automobiles and traditional petrol and diesel-based automobiles and found results using large neighbourhood approach along with exact mathematical algorithm. This algorithm gave optimal or near to optimal results. [8] targeted non-linear charging of electric vehicles along with the condition of time restriction in delivery of the products. The authors used differential algorithm to find the optimal solutions. The authors also focused on a case study of airport shuffle service to exemplify the proposed methodology. [7] came up with a new study of electric vehicles where the main aim was to decrease the total traveling cost, waiting and recharging time with the number of employed vehicles. A variable neighbourhood search algorithm was used by them to find the optimality of the given instances. [9] also worked together and modified the work of 2015 by proposing a variable neighbourhood search algorithm along with an exact algorithm. [93] preferred genetic algorithm to find the solutions and battery swapping stations were also used in the research work.[14] implemented variable large neighbourhood search algorithm with exact method to solve a problem on EVRP having scheduling condition and battery service stations. [21] used an exact approach known as branch and cut algorithm. The authors found that allowing multiple and partial recharges helps in reducing traveling costs along with the reduction in number of vehicles employed. [22] used a branch-price-cut method that is based on column generation method to work with scheduling constraint and charging stations. [23] considered EVRPs with adjustable deliveries. The authors generated novel column generation method associated with branch and price method to find the results. [68] worked with capacitated vehicle routing problems having limited number of charging stations. The authors proposed a hyper-heuristic approach formed by combination of simulated annealing and reinforcement learning. The implementation of this Hyper heuristic approaches improved multiple minimum best-known results. [26] proposed simulated annealing for the electric vehicles. The authors found the computational results for various instances and analysed the different elements of the problem such as geographic configuration, recharging stations, size, and anatomy. [27] provided the research results for electric vehicle routing problem with non-linear charging and partial recharges of the e-vehicles. The authors used exact labelling algorithm and heuristic algorithm to find the optimality and found that these two algorithms together give better results from the results till available in the literature. [64] worked with EVs and investigated EVRPs with charging stations using the deep reinforcement learning algorithm. The authors developed an intelligent charging model that indirectly reflects the charging through charging expenses, energy consumption charges and time cost. [30] preferred to work with mixed fleet of electric commercial vehicles and conventional internal combustion commercial vehicles. The authors introduced adaptive large neighbourhood search enhanced by local search method to find the optimal values. [31] worked with the issue of pick-up and delivery. The objective was to minimize the total traveling cost, total distance, total cost for the e-vehicles and penalty costs for unsatisfied time. The authors preferred the weighted sum method to obtain the results. [32] used four different methods for charging stations' spots and a heuristic solution approach for routing of automobiles. The superior results were generated by implementing location strategy at site of the customer. [33] alone worked for EVRP with partial recharge, pick-up delivery, time windows and charging stations. The authors used tabu search for pick-up and delivery of the goods along with time windows constraint. The authors examined that the research was suitable for small as well as large scale instances. [34] worked to obtain results for a fuzzy time window constraint for a problem of pick-up and delivery having multi depots. As this was a very complex problem, three metaheuristics algorithms such as, simulated annealing, variable neighbourhood search and a hybridized algorithm involving simulated annealing and variable neighbourhood search method. In the same year [35] did their research on non-linear charging for electric vehicles with the location routing problem. The authors used three staged algorithms for their research including Clarke and Wright, adaptive large neighbourhood search and integrated greedy algorithm. Moreover, sensitivity analysis was also done to check the results.[[36] used a well-developed moth flame algorithm which was applied on two-echelon EVRP. [57] used an exact method branch-cut-and-price approach to perform experiments related to time dependent EVRPTW. The experiments were conducted on 100 customers having different time dependent configurations. The experiments showed that ignoring the traveling speed of the vehicles can affect the quality of the solutions found. [38] proposed algorithm for routing and location problems with battery exchange hubs and preferred adaptive variable search neighbourhood algorithm to find results. [40] worked for the electric vehicle routing problems using the column generation and ALNS (adaptive large neighbourhood search algorithm) with two echelon CVRP and battery swapping stations. Sensitivity analysis was also performed to check the electric vehicle range and effectiveness of vehicle emission reduction. [75] used adaptive large neighbourhood search algorithm for driverless EVRPs and the authors also studied some new benchmarks. [41] worked for the EVRP with uncertainty in driving range of EV delivery fleet. The authors proposed a column-and-constraint generation based heuristic algorithm and robustness of the proposed algorithm was tested by calculating some computational results. [42] worked for the electric vehicle routing problem having time window constraint. The authors also applied adaptive large neighbourhood search algorithm to find optimality. The authors preferred benchmark instances from recent literature of that time and found that their algorithm gives better solutions. After two years, [43] again worked with the same issue but this time the authors used ALNS with exact method to calculate the solutions for time windows constraint and for fast chargers. [46] proposed ALNS for load dependent discharging and non-linear charging of e-vehicles. Their algorithm matches the optimal results of instances by 31 %. [47] introduced multi depot electric vehicle routing problem with time windows and used two-layer genetic algorithm for optimality. [44] worked with electric vehicle routing problems having time-dependent waiting times for recharging stations. [48] again worked together and this the authors used simulation based heuristic approach and undetermined waiting durations at the recharging stations. [45] used ALNS and found 38 new best results for the instances the authors have used in their research. [49] proposed the study of multi charging stations location routing problem with time windows. An adaptive variable neighbourhood search algorithm related to tabu search to address the problem. This hybrid algorithm gave near to optimal solutions for small scale instances and was also effective for large scale instances. [50] did a case study of Austin, Texas and compared the Diesel trucks with electric vehicles and compared the travel time and distance. [52] used an exact algorithm called as branch and cut algorithm to find better results for e-vehicle routing problem with non-linear charging time. [51] worked for EVRPTW and proposed iterated variable neighbourhood search algorithm to minimize cost function. The authors did their computational findings on CPLEX and found 39 best results as compared to the used instances. [53] proposed lagrangian relaxation algorithm with hybrid variable neighbourhood search/Tabu search algorithm to obtain lower bounds and feasible solutions. [59] proposed mixed fleet of vehicles with scheduling constraints and half recharging stations. A hybrid adaptive large neighbourhood search algorithm along with ant colony algorithm by [28] is applied on an open EVRPTW having replenishment techniques. Their research showed that the results are very useful for urban logistics transportation. [55] applied hybrid algorithm which was a combination of crow search algorithm combined with tabu search algorithm. [58] used non- linear charging function. The authors proposed a hybrid algorithm to compare 120 instances and found that their algorithm works well on these instances. [60] proposed e-vehicle routing problem with time windows and multi charging stations. The authors used ant colony algorithm and local strategies to enhance the efficiency of solving the problem. [61] worked on soft time windows constraint to reduce the traveling charges, automobile charges, power supply charges, and punishment charges. Moreover, the authors tested ant colony algorithm through an example. [6] worked with electric vehicle routing problem having heterogenous fleet, all the data was based on real life and the approach was divided in three categories. First approach was the portion where customers were assigned to the vehicles. Second part included the use of genetic algorithm to obtain a set of optimal paths and third part was based on charging stations assigned on selected routes. Solomon's instances were used to test the effectiveness of given approach. [54] used genetic algorithm to find optimal value for the travelled distance. The authors used a live example from Poland for the total distance travelled, considering the exact locations of slow and fast charging stations. [63] used MDEVRP including time windows. Battery swapping stations were used and the solutions were found using C++ and CPLEX. [65] used integer programming and dynamic programming to solve an e-vehicle routing problem with time windows and synchronised mobile swapping stations. [66] used electric vehicle routing problem with for commercial vehicles. The authors used two interdependent fleets such as electric commercial vehicles and battery swapping vans. Certain numerical experiments were performed to find the optimal results. [71] preferred study of electric commercial vehicles with time windows constraint and recharging stations. [72] did a case study of Beijing with 100 customers, and 30 charging stations to analyse the performance of the proposed model. The classical Dijkstra algorithm with some improvements was replaced with dynamic Dijkstra algorithm to find optimal routes. [70] used electric and hybrid vehicles to find shortest routes. [73] went for stochastic battery depletion for the electric vehicles used for pickup and delivery. The authors preferred MINLP (mixed integer non-linear programming) to find the solution of several numerical experiments. [74] used clustering approach for optimal positioning of EV charging facilities along with time window constraint. The authors found a huge decrement in the time used to solve the problem. [15] considered dynamic electric vehicle routing problem where the authors applied genetic algorithm and ant colony algorithm to find results. [94] preferred adaptive large neighbourhood search approach for the electric vehicle routing problem with multiple time windows having time dependent hybrid recharging. The authors conducted various experiments to check the efficiency of the proposed algorithm. A Mixed integer linear programming method and heuristic approach for time-dependent EVRP and scheduling problem with time windows was proposed by [95]. The authors developed a MILP and Variable neighbourhood Search approach with partial model method.

Capacitated vehicle routing problem was considered by [77] where the authors approached exact algorithm called as branch and cut algorithm on a set of 125 instances. [78] worked with flexible time windows for electric vehicles and applied generation column approach to find the solution of suggested model. [62] preferred hybrid iterated local search algorithm for electric fleet size and mixed VRP with scheduling constraint and power stations. The authors showed the ability of their proposed approach to find the results for different instances. [79] considered the route planning for fully electric vehicles. Their main contribution was the vehicle-to-vehicle communication for context awareness and used a Constrained A^* algorithm to obtain the solutions. [80] preferred to work with multi compartment vehicles for perishable products as there is need of temperature and humidity conditions. The authors have applied adaptive large neighbourhood search algorithm with a combination of tabu search, the authors conducted several experiments and derived better results. [67] used drones and synchronized battery swapping for EVRP having TW constraint. In this paper, the researchers have also designed Lagrangian Relaxation algorithm to compare with large neighbourhood search- Q algorithm. [84] proposed a problem with battery swapping stations for capacitated vehicle routing problems. This study explores the results based on the usage of four phase heuristic approach called as SIGALNS and two-phase heuristic approach called as Tabu search and modified Clarke and wright approach. [85] concentrated on fast charging and regular charging of the electric vehicles and tested their model on 36 nodes and 112 nodes system and found that their algorithm works efficiently on them. Clarke and Wright algorithm was used by [86], some alternatives of variable neighbourhood search algorithm were examined and reduced-variable neighbourhood search approach was applied to obtain best solutions. [16] used a multi layered search approach for CVRP. This algorithm was efficient to find new and best results for 11 out of 17 instances. A Double-assistant nature inspired multitasking approach for enhanced EVRP with backup batteries and battery swapping stations was used by [17]. This algorithm involves a two-stage system for collaboration and adaptive methods for managing knowledge transfer. [87] preferred ant colony algorithm for minimizing energy consumption at the recharging stations by electric vehicles. It was also observed that it is beneficial to use energy consumption minimizing objective function rather than distance minimizing objective function. [88] used adaptive large neighbourhood search algorithm along with integer programming for their research. 20 instances from real- world data are used to illustrate the proposed algorithm. The results showed that this approach reduce the operational cost by 7.52 %. [89] used mixed integer linear programming model for Solomon's instances to verify the proposed mathematical model and comparison was also done with traditional models. [90] developed fuzzy optimization model based on credibility theory for the given issue. [91] optimized the route for urban cold chain transportation for fresh goods under traffic conditions. Simulation test results showed that the proposed methodology allows EVs to bypass traffic during the delivery process. [92] researched on time-dependent EVRP with congested tolls and used adaptive large neighbourhood search algorithm along with mixed integer linear programming model. [81] used multi depot VRP having shared power stations with time windows constraint. The authors implemented Gaussian mixture clustered algorithm on a real-life case study of Chongqing City of China and found the results. [82] used an exact algorithm known as branch and price algorithm to solve 2-echelon EVRP, where in the first echelon, goods are transferred from depots to satellites and in the second echelon, the goods are transferred from satellites to customers. [56] worked on delivery of perishable products in electric vehicles with multiple compartments considering hard time windows, temperature conditions and charging more than once during delivery. Moreover, this study explores the EVRP research articles deeply while noticing the conditions, assumptions, the developed models, and solution methods. **Table 1** and **Table 2** represent the data compiling different constraints considered by many researchers during the years from 2013 to 2024. Moreover **Figure 5** depicts the network based on these papers using the keywords involved in these research papers.

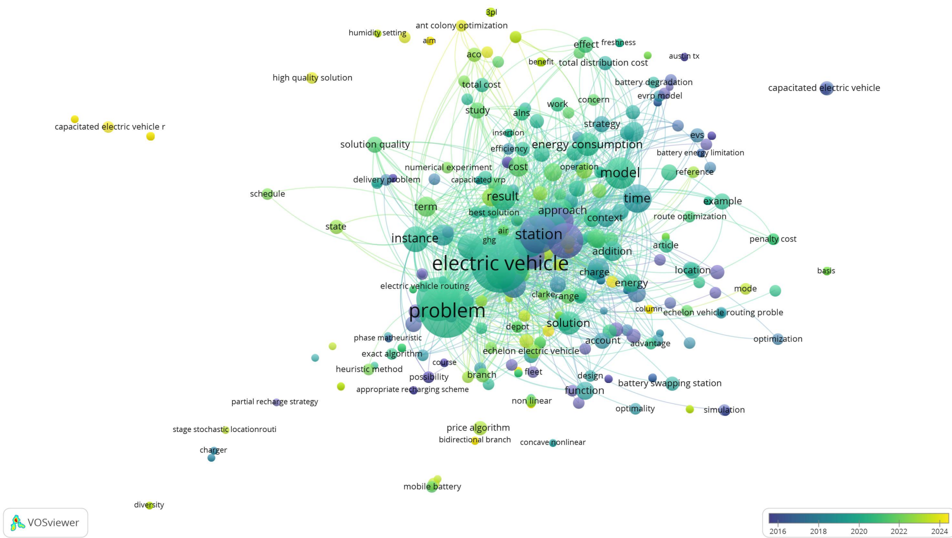

Figure 5: A network based on Bibliographic Coupling

Table 1: EVRP Literature

Study	Year	PR	PD	NL	SPD	2E	SC	MD	HF	BSS	CS	FSM	LRP
Agardi et al. [1]	2019	-	-	-	-	*	-	-	*	-	*	-	-
Akbay et al. [2]	2022	-	-	-	-	*	*	-	*	-	-	-	-
Amin Aglahari et al. [3]	2023	-	-	-	-	*	-	-	-	-	-	-	*
Amir Hossein et al. [4]	2024	*	-	-	-	-	*	-	-	-	*	-	-
Akbay et al. [5]	2024	-	*	-	-	*	*	-	-	-	-	-	-
Arne Schulz [76]	2024	-	-	*	-	-	*	-	-	-	-	-	-
Basso et al. [10]	2019	-	-	-	-	-	*	-	-	-	*	-	-
Breunig et al. [11]	2019	-	-	-	-	*	-	-	*	-	*	-	-
Barco et al. [8]	2017	-	-	*	-	-	-	*	-	-	*	-	-
Bruglieri et al. [7]	2015	*	-	-	-	-	*	-	-	-	*	-	-
Bruglieri et al. [9]	2017	*	-	*	-	-	*	-	-	-	*	-	-
Bida Zhang et al. [93]	2023	-	-	-	-	-	-	-	-	*	-	-	*
Cortés-Murcia et al. [13]	2019	*	-	-	-	-	*	-	-	-	*	-	-
Catay et al. [14]	2023	-	-	-	-	-	*	-	-	*	-	-	-
Desaulniers et al. [21]	2016	*	-	-	-	-	*	*	-	*	-	-	-
Duman et al. [22]	2022	-	-	-	-	-	*	-	-	-	*	-	-
Erick et al. [68]	2024	-	-	-	-	-	-	-	-	-	*	-	-
Felipe et al. [26]	2014	*	-	-	-	-	-	-	-	-	*	-	-
Froger et al. [27]	2019	*	-	*	-	-	-	-	-	-	*	-	-
Gang Pan et al. [64]	2024	-	-	-	-	-	-	-	-	-	*	-	-
Goeke and Schneider [30]	2015	-	-	-	-	-	*	-	*	-	*	*	-
Grandinetti et al. [31]	2016	-	*	-	-	-	*	-	-	-	*	-	-
Gatica et al. [32]	2018	-	-	-	-	-	-	-	-	-	*	-	*
Goeke [33]	2019	*	*	-	-	-	*	-	-	-	*	-	-
Ghobadi et al. [34]	2021	-	*	-	-	-	*	*	-	-	*	-	-
Guo et al. [35]	2022	*	-	*	-	-	-	-	-	-	*	-	*
Goli et al. [36]	2024	-	-	-	-	*	-	-	-	-	-	-	-
Gonzalo et al. [57]	2024	-	-	-	-	-	*	-	-	-	-	-	-
Hiermann et al. [37]	2016	-	-	-	-	-	*	-	*	-	*	*	-
Hof et al. [38]	2017	-	-	-	-	-	-	-	-	*	-	-	*
Jie et al. [40]	2019	-	-	-	-	*	-	*	-	*	-	-	-
Jianhua et al. [83]	2023	-	-	-	-	-	*	-	-	-	-	-	-
Jianmai Shi et al. [75]	2023	-	-	*	-	-	-	-	-	-	*	-	-
Keskin and Catay [42]	2016	*	-	-	-	-	*	-	-	-	*	-	-
Keskin and Catay [43]	2018	*	-	-	-	-	*	-	*	-	*	-	-
Kancharla and Ramadurai [46]	2020	-	-	*	-	-	-	-	-	-	*	-	-
Karakatič [47]	2021	*	-	*	-	-	*	*	-	-	*	-	-
Keskin et al. [44]	2019	*	-	-	-	-	*	-	-	-	*	-	-
Keskin et al. [48]	2021	*	-	*	-	-	*	-	-	-	*	-	-
Koç et al. [45]	2019	*	-	*	-	-	*	*	-	-	*	-	*
Li-Ying and Yuan-Bin [82]	2015	-	-	-	-	-	*	-	-	-	*	-	*
Lin et al. [50]	2016	-	*	-	-	-	-	-	-	-	*	-	-
Lee [52]	2021	-	-	*	-	-	-	-	-	-	*	-	-
Lu et al. [51]	2020	-	-	-	-	-	-	-	-	-	*	-	-
Lin et al. [53]	2020	*	-	-	-	-	*	-	-	-	*	-	-
Lijun Fan [28]	2023	-	-	-	-	-	*	-	-	-	-	-	-
Li Y et al. [55]	2024	-	-	-	-	-	-	-	-	-	*	-	-
Macrina et al. [59]	2019	*	-	-	-	-	*	-	*	-	*	-	-
Montoya et al. [58]	2017	*	-	*	-	-	-	-	-	-	*	-	-
Mao et al. [60]	2020	*	-	-	-	-	*	-	-	*	*	-	-
Meng and Ma [61]	2020	-	-	-	-	-	*	-	-	-	*	-	-
Meryem et al. [6]	2024	-	-	-	-	-	-	-	*	-	*	-	-
Norbert et al. [54]	2022	-	-	-	-	-	-	-	-	-	*	-	*
Paz et al. [63]	2018	*	-	-	-	-	*	*	-	*	*	-	*
Raeesi and Zografos [65]	2020	-	-	-	-	-	*	-	-	*	-	-	-
Raeesi and Zografos [66]	2022	-	-	-	-	-	*	-	-	*	*	-	-
Schneider et al. [69]	2014	-	-	-	-	-	*	-	-	-	*	-	-
Schiffer and Walther [71]	2017	*	-	-	-	-	*	-	-	-	*	-	*
Shao et al. [72]	2018	-	-	-	-	-	-	-	-	-	*	-	-
Strehler et al. [70]	2017	*	-	-	-	-	-	-	-	-	*	-	-
Soysal et al. [73]	2020	-	*	-	-	-	-	-	-	*	*	-	-
Sánchez et al. [74]	2022	*	-	-	-	-	*	-	-	-	*	-	*
Simon et al. [15]	2024	-	-	-	-	-	*	-	-	-	-	-	-
Shuai et al. [94]	2024	-	-	-	-	-	*	-	-	*	-	-	-
Saiqi et al. [95]	2024	-	-	-	-	-	*	-	-	-	-	-	-
Tahami et al. [77]	2020	-	-	-	-	-	-	-	-	-	*	-	-
Taş [[78]	2021	-	-	-	-	-	*	-	-	-	*	-	-
Vaz Penna et al. [62]	2016	-	-	-	-	-	*	-	*	-	*	*	-
Wang et al. [79]	2013	-	-	-	-	-	*	-	-	-	*	-	-
Wang et al. [80]	2023	-	-	-	-	-	*	-	-	-	-	-	-
Xiao R et al. [67]	2023	-	-	-	-	-	*	-	-	*	-	-	-

Table 2: EVRP Literature Continued

Study	Year	PR	PD	NL	SPD	2E	SC	MD	HF	BSS	CS	FSM	LRP
Yang and Sun [84]	2015	-	-	-	-	-	-	-	-	*	-	-	-
Yang et al. [85]	2015	*	*	-	-	-	*	-	-	-	*	-	*
Yilmaz and Kalayci [86]	2022	-	-	-	*	-	-	-	-	-	*	-	-
Yanguang et al. [17]	2024	-	-	-	-	-	-	-	-	*	-	-	-
Zhang et al. [87]	2018	-	-	-	-	-	-	-	-	-	*	-	-
Zhao and Lu [[88]	2019	-	*	-	-	-	*	-	*	-	*	-	-
Zuo et al. [89]	2019	-	-	*	-	-	*	-	-	-	*	-	-
Zhang et al. [90]	2020	*	-	-	-	-	-	-	-	-	*	-	-
Zhao et al. [91]	2020	-	-	-	-	-	*	-	-	-	*	-	*
Zhang et al. [92]	2020	-	-	-	-	-	*	-	-	-	*	-	-
Zhou J et al. [81]	2023	-	-	-	-	-	-	*	-	-	*	-	-
Zhiguo Wu et al. [[82]	2023	-	-	-	-	*	-	-	-	-	-	-	-
Zhishuo Liu et al. [56]	2024	-	-	-	-	-	*	-	-	-	*	-	-

PR: Partial Recharging, PD: Pickup and Delivery, NL: Non-Linear, SPD: Simultaneous Pickup and Delivery, 2E: 2 Echelon, SC: Scheduling Constraint, MD: Multi Depot, HF: Heterogenous Fleet, BSS: Battery Swapping Stations, CS: Charging Stations, FSM: Fleet Size and Mix, LRP: Location Routing Problem

There are numerous publications and research work is done related to electric vehicle routing problem. The progress in this field during the past ten years is represented in the form of a graph in **Figure 6**. A graphical representation of papers published related to the concerned area is given as below:

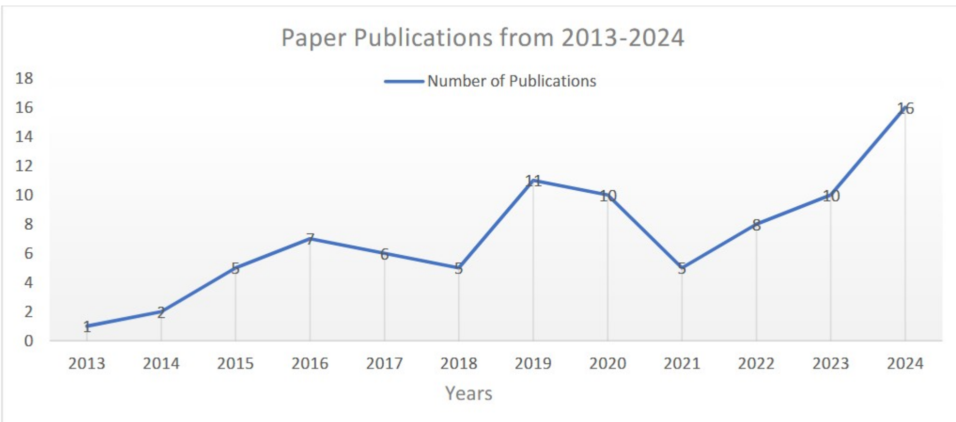

Figure 6: Publications by years

4. Solution Approaches

EVRPs cannot be solved manually because of their complexity as there are many constraints and conditions that make them NP Hard problems which are hard to solve. Now, there is a need to understand the meaning of NP hard problems that comes under the section of complexity classes. Therefore, a proper discussion related to these complexity classes is given here under this section.

Complexity Classes: A complexity class [12] is described to be set of some decision issues that can only be solved by using an algorithm having certain about of resources. Two commonly preferred resources in complexity classes are time and space. Time is the number of steps that are required by an algorithm to find the solution of a problem and space refers to the memory of the algorithm. Each complexity class is defined by as a set of decision problems that can be solved in a certain amount of time or space. For instance, class P has all the decision issues that can be solved by using deterministic algorithm in polynomial time, whereas NP class has all the decision problems that can be verified in polynomial time by using a non-deterministic algorithm. Moreover, to understand the complexity classes more precisely, there is a need to understand some more basic terms of complexity such as polynomial time, time complexity, exponential time, deterministic and non-deterministic algorithms.

Time Complexity: Time complexity [39] is related to computer sciences theory as the time complexity

is computational complexity that the total computational time taken by an algorithm to give the solution to a problem. Time complexity is estimated by counting the number of elementary operations performed by an algorithm. To exemplify, suppose that each elementary operation takes a fixed amount of time for the performance. Therefore, the amount of time taken and number of elementary operations performed by an algorithm are interrelated. As, it is known that the running time of an algorithm can vary depending on different inputs of the same size, is the worst-case time complexity, which is the maximum time taken by an algorithm for inputs of given size. Next, the average case complexity, which is average of the time taken on inputs of a given size. In both the cases, time complexity is generally expressed as a function of size of the input. The time complexity is generally expressed by using *Big O Notation*, $O(n)$, $O(nlogn)$, $O(n\alpha)$, $O(2^n)$, where n is size in units of bits representing the inputs. In simple words, n is the complexity of input.
Polynomial Time: An algorithm Hartmanis J et al. (1971) is said to be in polynomial time if its running time is upper bounded by the polynomial expression in size of input for the algorithm. Polynomial time is usually represented as $T(n) = O(n^k)$ where k is positive constant and n is the complexity of input. In other words, it can be said that if time complexity of an algorithm to solve a specific problem can be represented using a polynomial function, then the problem is called to be polynomial time problem. Polynomial is a word which simply represents: "feasible", "fast" and "efficient".
Exponential Time: Now, after polynomial time, next comes the exponential time [39]. An algorithm is said to be exponential time algorithm if the running time is upper bounded by $2^{poly(n)}$, where $poly(n)$ is some polynomial in n. An algorithm is exponential time if $T(n)$ is bounded by $O(2^{n^k}))$ for some positive constant k. Problems that admit exponential time algorithms on a deterministic Turing Machine form the complexity class known as EXP.

Deterministic Algorithm: Deterministic algorithm [24] is the algorithm that for a given input, it always produces a same output every time, as the underlying machine always go through the same sequences of states. Deterministic algorithms are most studied and familiar kind of algorithms, as these can be run on real machines efficiently. More precisely, a deterministic algorithm is the algorithm that computes a mathematical function, a function has a unique value for any input in its domain and algorithm is a procedure that produces this value as output.
Non- Deterministic Algorithm: In Computer programming, a non-deterministic algorithm is that algorithm where even for the same input, different outputs can be received in every different run. It is just a counter part of deterministic algorithm. An algorithm that solves a problem in non-deterministic polynomial time can run in polynomial time or exponential time depending on the choices it makes during execution. The non-deterministic algorithm usually gives approximate solution to the given problem. A comparison between deterministic and non-deterministic algorithm is shown in the **Table 3**.

Table 3: Comparison of Deterministic and Non- deterministic Algorithm

S. No	Deterministic Algorithm	Non- Deterministic Algorithm
1.	Behaviour is completely determined by the inputs and sequence of instructions.	Outcomes cannot be predicted with certainty, even if the inputs are known.
2.	For a particular input, there is always same output.	For a particular input, there will be different outputs on different executions.
3.	Problem can be solved in polynomial time.	Cannot solve the problem in polynomial time.
4.	Next step of the execution can be determined.	Next step of the execution cannot be determined as more than one path can be taken by algorithm.
5.	Operations are uniquely defined.	Operations are not uniquely defined.
6.	Linear Search and Binary Search.	0/1 Knapsack problem.
7.	Provides precise solutions to the problems.	Provide approximate solutions to the problems.
8.	Examples of deterministic algorithms are: bubble sort, insertion sort, selection sort and many numerical algorithms.	Examples of non-deterministic algorithms are: Monte Carlo methods, genetic algorithms, traveling salesman problem and simulated annealing.

Now, the discussion about different Complexity classes is as follows:

P Class Problem: In computational complexity, P is also known as PTIME, which is a fundamental complexity class. P- class problems can be solved in polynomial time or it can also be said that all the decision problems can be solved by a deterministic Turing machine using a polynomial amount of computational time or polynomial time. [18] holds that P is the class of computational problems that are efficiently solvable or tractable.

NP Class Problem: NP (Non- Deterministic Polynomial Time) is a complexity class used to classify decision problems. NP is a set of decision problems have proofs that these problems can be verified in polynomial time by a deterministic Turing Machine or alternatively this kind of set of problems can be solved in polynomial time by a non- deterministic Turing Machine. Simply, it can be said that the problems that cannot be solved in polynomial time but can be verified in polynomial time. For instance, Traveling Salesman Problem.

It can be easily seen in **Figure 7** that complexity class P lies in complexity class NP, as if a problem is solvable in polynomial time, then its solution is also verifiable in polynomial time by simply solving the problem.

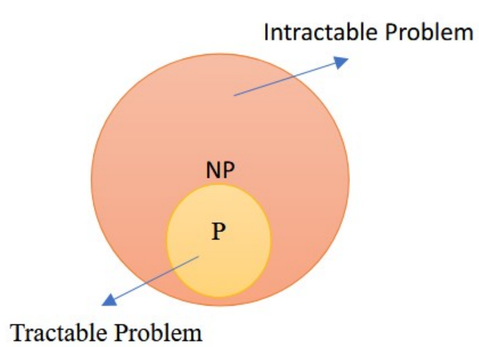

Figure 7: P and NP Problems

Reduction: In computability theory and computational complexity theory, a reduction is an algorithm for converting one problem to another problem. Suppose, problem H is reducible to problem L, if an algorithm for solving problem L efficiently could also be used as a subroutine to solve problem H efficiently. If it is true, solving H cannot be harder than solving L. Harder means having a higher estimate of the required computational resources.

NP-Hard Complexity Class: In computational complexity theory, a computation problem H is called NP-hard, if for every problem L which can be solved in non-deterministic polynomial time, there is a polynomial time reduction from L to H. Let us assume that a solution for H takes 1 unit time, H's solution can be used to solve L in polynomial time. As a result, finding a polynomial time algorithm to solve single NP-Hard problem Fu B et al. (1994) would give polynomial time algorithm for all the problems in the complexity class NP.

NP-Complete Complexity Class: NP- complete complexity classes where the decision problems are considered where for any input to the problem, the output can be either yes or no. Such kind of problems can be solved in polynomial time and give solutions by using all the possible ways. Knapsack problem is one of the best examples of NP-complete complexity class. **Figure 8** represents the Venn diagram considering P, NP, NP-Complete and NP- Hard Problems.

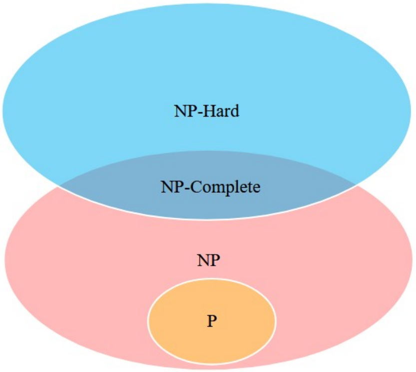

Figure 8: P, NP, NP-Hard, NP-Complete Problems

NP- Hard problems are the hardest kind of complexity classes. Therefore, many heuristics and metaheuristics algorithms described in **Table 4** and **Table 5** were developed by many researchers to reduce the complexity of such problems. A tabulated data of methods used till now is given below:

Table 4: Solution Approaches

Study	Year	GA	Exact Methods	TS	CPLEX	ACO	SA	VNS	LNS	ALNS	Others
Wang et al. [79]	2013	-	-	-	-	-	-	-	-	-	*
Schneider et al. [60]	2014	-	-	*	-	-	-	-	-	-	-
Felipe et al. [26]	2014	-	-	-	-	-	*	-	-	-	-
Bruglieri et al. [7]	2015	-	-	-	*	-	-	*	-	-	-
Goeke et al. [30]	2015	-	-	-	-	-	-	-	-	*	-
Li Ying et al. [49]	2015	-	-	*	-	-	-	-	-	*	-
Yang J et al. [84]	2015	-	-	-	*	-	-	-	-	-	-
Yang H et al. [85]	2015	*	-	-	-	-	-	-	-	-	-
Desaulniers et al. [21]	2016	-	*	-	-	-	-	-	-	-	-
Grandinetti et al. [31]	2016	-	-	-	-	-	-	-	-	-	*
Hiermann et al. [37]	2016	-	-	-	-	-	-	-	-	*	*
Keskin et al. [42]	2016	-	-	-	-	-	-	-	-	*	*
Lin J et al. [50]	2016	-	-	-	-	-	-	-	-	-	*
Penna PH et al. [62]	2016	-	-	-	-	-	-	-	-	-	*
Barco J et al. [8]	2017	-	-	-	-	-	-	-	-	-	*
Bruglieri et al. [9]	2017	-	*	-	*	-	-	*	-	-	-
Hof J et al. [38]	2017	-	-	-	-	-	-	-	-	-	*
Montoya et al. [58]	2017	-	-	-	-	-	-	-	-	-	*
Schiffer et al. [71]	2017	-	-	-	-	-	-	-	-	-	*
Strehler et al. [70]	2017	-	-	-	-	-	-	-	-	-	*
Gatica et al. [32]	2018	-	-	-	-	-	-	-	-	-	*
Keskin et al. [43]	2018	-	*	-	-	-	-	-	-	*	-
Paz et al. [63]	2018	-	-	-	*	-	-	-	-	*	-
Shao et al. [72]	2018	-	-	-	-	-	-	-	-	-	*
Zhang S et al. [87]	2018	-	-	-	-	*	-	-	-	-	-
Agardi et al. [1]	2019	*	-	-	-	-	-	-	-	-	-
Basso et al. [10]	2019	-	-	-	-	-	-	-	-	-	*
Breunig et al. [11]	2019	-	-	-	-	-	-	-	*	-	-
Cortes Murcia et al. [13]	2019	-	-	-	-	-	-	*	-	-	*
Froger et al. [27]	2019	-	-	-	-	-	-	-	-	-	*
Goeke D [33]	2019	-	-	*	-	-	-	-	-	-	-
Jie et al. [40]	2019	-	-	-	-	-	-	-	-	*	*
Keskin et al. [44]	2019	-	-	-	-	-	-	-	-	*	-
Koc et al. [45]	2019	-	-	-	-	-	-	-	-	*	-
Macrina et al. [59]	2019	-	-	-	-	-	-	-	-	-	*
Zhao M et al. [88]	2019	-	-	-	-	-	-	-	-	-	*
Kancharla et al. [46]	2020	-	-	-	-	-	-	-	-	*	-
Lu J et al. [51]	2020	-	-	-	*	-	-	*	-	-	-
Mao et al. [60]	2020	-	-	-	-	*	-	-	-	-	-
Meng et al. [61]	2020	-	-	-	-	-	-	-	-	-	*
Raeesi et al. [65]	2020	-	-	-	-	-	-	-	-	-	*
Soysal et al. [73]	2020	-	-	-	-	-	-	-	-	-	*
Tahami et al. [77]	2020	-	*	-	-	-	-	-	-	-	-
Zhang S et al. [90]	2020	-	-	-	-	-	-	-	-	*	-
Zhao Z et al. [91]	2020	-	-	-	-	*	-	-	-	-	-
Zhang R et al. [92]	2020	-	-	-	-	-	-	-	-	*	*
Ghobadi et al. [34]	2022	-	-	-	-	-	*	*	-	-	-
Karakatič et al. [47]	2021	*	-	-	-	-	-	-	-	-	-

Table 5: Solution Approaches Continued

Study	Year	GA	Exact Methods	TS	CPLEX	ACO	SA	VNS	LNS	ALNS	Others
Keskin et al. [48]	2021	-	-	-	-	-	-	-	-	*	-
Lee [52]	2021	-	*	-	-	-	*	-	-	-	-
Lin B et al. [53]	2021	-	-	*	-	-	-	*	-	-	-
Tas et al. [78]	2021	-	-	-	-	-	-	-	-	-	*
Akbay et al. [2]	2022	-	-	-	*	-	-	-	-	-	*
Duman [22]	2022	-	*	-	-	-	-	-	-	-	-
Guo et al. [35]	2022	-	-	-	-	-	-	-	-	*	*
Norbert et al. [54]	2022	*	-	-	-	-	-	-	-	-	-
Raeesi et al. [66]	2022	-	-	-	-	-	-	-	-	-	*
Sanchez et al. [74]	2022	-	-	-	*	-	-	-	-	-	-
Yilmaz et al. [86]	2022	-	-	-	-	-	-	-	-	-	*
Bida et al. [93]	2023	*	-	-	-	-	-	-	-	-	-
Wang et al. [80]	2023	-	-	*	-	-	-	-	-	*	-
Zhou J et al. [81]	2023	-	-	-	-	-	-	-	-	-	*
Xiao et al. [67]	2023	-	-	-	-	-	-	-	*	-	*
Jianhua et al. [83]	2023	-	-	-	-	-	-	-	-	-	*
Çatay et al. [14]	2023	-	*	-	-	-	-	*	-	-	-
Lijun Fan et al. [28]	2023	-	-	-	-	*	-	-	-	*	-
Zhiguo Wu et al. [82]	2023	-	*	-	-	-	-	-	-	-	-
Jianmai Shi et al. [75]	2023	-	-	-	-	-	-	-	-	-	-
Amin Aglahari et al. [3]	2023	-	-	-	-	-	-	-	-	-	*
Amir Hossein et al. [4]	2024	-	-	-	-	-	-	-	-	-	*
Li Y et al. [55]	2024	-	-	*	-	-	-	-	-	-	*
Gang Pan et al. [64]	2024	-	-	-	-	-	-	-	-	-	*
Zhishuo Liu et al. [56]	2024	-	-	-	-	*	-	-	-	-	-
Akbay et al. [5]	2024	-	-	-	-	-	-	-	-	-	*
Simon et al. [15]	2024	*	-	-	-	*	-	-	-	-	-
Goli et al. [36]	2024	-	-	-	-	-	-	-	-	-	*
Shuai et al. [94]	2024	-	-	-	-	-	-	-	-	*	-
Yuning et al. [16]	2024	-	-	-	-	-	-	-	-	-	*
Gonzalo et al. 57]	2024	-	*	-	-	-	-	-	-	-	-
Meryem et al. [6]	2024	*	-	-	-	-	-	-	-	-	*
Erick et al. [68]	2024	-	-	-	-	-	*	-	-	-	*
Arne Schulz [76]	2024	-	*	-	-	-	-	-	-	-	-
Yanguang et al. [17]	2024	-	-	-	-	-	-	-	-	-	*
Saiqi et al. [95]	2024	-	-	-	*	-	-	*	-	-	-
Jaehee et al. [42]	2024	-	-	-	-	-	-	-	-	-	*

GA: Genetic Algorithm, TS: Tabu Search, ACO: Ant Colony Algorithm, SA: Simulated Annealing, VNS: Variable Neighbourhood Search, LNS: Large Neighbourhood Search, ALNS: Adaptive Large Neighbourhood Search

5. Mathematical Model

An electric vehicle routing problem works on a mathematical model that was developed by [86] having many assumptions and several constraints. The mathematical model is summarized as follows:

- All customer demands must be satisfied.
- Only one customer can be attended by one automobile.
- Partial charging is prohibited. Vehicle needs to be fully charged.
- Fleet should be homogeneous.
- Objective is to reduce the total distance covered by vehicle.
- Vehicle must start its route from distribution centre and return to the same after the completion of journey.
- Loading capacity must not be exceeded.
- Depot has unlimited storage capacity.
- E-vehicle can visit the charging station more than once.
- Vehicle is recharged at a fixed speed at charging station.

Notations, Parameters, objective function, constraints, sets, and decision variables are presented below:

D= Distribution Centre

CS= Charging Stations

C=Customers

EV= Electric Vehicles

n_D = Set of Distribution Centres $\{1, 2, 3, \ldots, D\}$
n_{CS} = Set of Charging Stations $\{1, 2, 3, \ldots, D + CS\}$
n_C = Set of Consumers $\{D + CS + 1, \ldots, D + CS + C\}$
n_{CSC} = Set of Charging Stations and Consumers $\{D + 1, \ldots, D + CS + C\}$
n_{DCSC} = Set of Distribution Centres, Charging Stations, and Consumers $\{1, \ldots, D + CS + C\}$
S = Set of nodes $\{1, 2, 3, \ldots, D + CS + C\}$
S_k = Set of Electric Vehicles at the Distribution Centres $\{1, 2, 3, \ldots, EV\}$
d_{xy} = Distance from node x to node y
L_k = Highest load limit of electric vehicle k
B_k = Maximum energy reserve of electric vehicle k
G_k = Charge flow of electric vehicle k
H_k = Battery consumption rate of electric vehicle k
DG_y = Delivery requirement of consumer y for all $y \in n_C$

$$i_{kxy} = \begin{cases} 1, & \text{if electric vehicle } k \text{ visits node } y \text{ after node } x \\ 0, & \text{otherwise} \end{cases} \quad \forall(k \in n_{CS}),\ \forall(x, y \in n_D \cup n_C)$$

$$A_{kxy} = \text{Amount of goods delivered by electric vehicle } k \text{ on arc } (x, y) \quad \forall(k \in n_{CS})$$

$$CLR_{xk} = \text{Charging level of electric vehicle } k \text{ upon arrival at node } x \quad \forall(x \in S,\ \forall k \in S_k)$$

$$CLD_{xk} = \text{Charging level of electric vehicle } k \text{ upon departure from node } x \quad \forall(x \in S,\ \forall k \in S_k)$$

Objective Function:

$$\sum_{k \in S_k} \sum_{x \in S} \sum_{y \in S} d_{xy} \cdot i_{kxy} \tag{5.1}$$

$$\sum_{k \in S_k} \sum_{x \in S} i_{kxy} = 1, \forall y \in n_C \tag{5.2}$$

$$\sum_{x \in S} i_{kyx} - \sum_{x \in S} i_{kxy} = 0, \forall k \in S_k \tag{5.3}$$

$$\sum_{y \in n_{CSC}} i_{kxy} \leq 1, \forall k \in S_k, \forall x \in n_D \tag{5.4}$$

$$\sum_{y \in n_{CSC}} i_{kyx} \leq 1, \forall k \in S_k, \forall x \in n_D \tag{5.5}$$

$$A_{kxy} = 0, \forall x \in n_{CSC}, \forall y \in n_D, \forall k \in S_k \tag{5.6}$$

$$A_{kxy} = L_k \cdot i_{kxy}, \forall x, y \in S, \forall k \in S_k \tag{5.7}$$

$$i_{kxx} = 0, \forall x \in S, \forall k \in S_k \tag{5.8}$$

$$CLR_{xk} \geq 0, \forall x \in S, \forall k \in S_k \tag{5.9}$$

$$CLD_{xk} = B_k, \forall x \in n_D, \forall k \in S_k \tag{5.10}$$

$$CLR_{yk} \leq CLD_{xk} - (H_k \cdot d_x y) i_{kxy} + B_k(1 - i_{kxy}), \forall x \in n_C, \forall y \in S, x \neq y, \forall k \in S_k \tag{5.11}$$

$$CLR_{yk} \leq CLD_{xk} - (H_k \cdot d_x y) i_{kxy} + B_k(1 - i_{kxy}), \forall x, y \in S, x \neq y, \forall k \in S_k \tag{5.12}$$

$$CLR_{xk} \leq CLD_{xk}, \forall x \in K, \forall k \in S_k \tag{5.13}$$

$$CLD_{xk} \leq B_k, \forall x \in K, \forall k \in S_k \tag{5.14}$$

$$CLR_{xk} = CLD_{xk}, \forall x \in n_C, \forall k \in S_k \tag{5.15}$$

$$CLR_{xk} = B_k, \forall x \in n_{CS}, \forall k \in S_k \tag{5.16}$$

$$\sum_{x \in S} A_{kxy} = \sum_{x \in S} A_{kyx}, \forall y \in n_{CS}, \forall k \in S_k \tag{5.17}$$

$$\sum_{k \in S_k} \sum_{x \in S} A_{kxy} \sum_{k \in S_k} \sum_{x \in S} A_{kyx} = DG_y, \forall y \in n_{CSC} \tag{5.18}$$

$$d_{xy} \geq i_{kxy}, \forall x, y \in S, \forall k \in S_k \tag{5.19}$$

$$i_{kxy} \in 0, 1, \forall k \in S_k, \forall x, y \in n_D \cup n_R \cup n_C \tag{5.20}$$

$$A_{kxy}, CLR_{xk}, CLD_{xk} \geq 0, \forall x, y \in S, \forall k \in S_k \tag{5.21}$$

The primary aim of this model is to reduce the distance travelled by electric automobile from distribution centres to the consumers. (2) constraint ensures that only one customer can be visited only once. In constraint (3) it is shown that if vehicle leaves the distribution centre, after visiting all the customers it must return to the depot. Condition (4), (5) and (19) restricts the usage of e-vehicle that it should be used only when required. Constraint (6) guarantees that no vehicle will distribute the products while returning to the depot. (7) states that total load cannot outstrip total capacity of automobile. Condition (8) restricts setup of sub-tours. Restraint (9) says that vehicle battery percentage is not harmful when one route is completed. (10) ensures that vehicle leaves the distribution centre with full battery, no partial charging is allowed. Battery constraints exist from (11)-(16). Condition (17) says that vehicles must have the same load while visiting the charging stations. In condition (19), it is shown that requirements of customers must be fulfilled by the related vehicle. Lastly, limitations (20) and (21) talk about nature of decision parameters.

6. Use of Different Constraints

As the above model is concerned with electric vehicle routing problems and there are some constraints as well but still more constraints can be added to make the conditions different as those constraints may increase the difficulty of the problem and there may be need to develop new metaheuristics or hybrid approach to solve such kind of problem. The constraints that can increase the difficulty of the problem are as follows:

1. **Time Windows:** Time windows constraint is usually used to restrict the time duration from the starting point of the vehicle till the completion of delivery. The constraint that is related to time windows consider the arriving and departing time of the vehicle at the customers' location and the depots respectively. A condition of penalty cost can also be taken into consideration i.e. if the delivery man does not reach to the destination in the given time a punishment cost can be charged to him. The constraint

of time windows shown in **Figure 9** will be as

$$qv_m(em^*) = rqv \times max(r_m - em^*, 0) + tqv \times max(em^* - tm, 0) \tag{6.1}$$

where
rqv, tqv = Unit penalty charges every hour for reaching before and late than the given time window respectively.
rm, tm= A time window of the customer node.
em^*, em^{**}= The arrival and departing phase of EV at node m.
qvm =depicts punishment cost for breaking the time window.

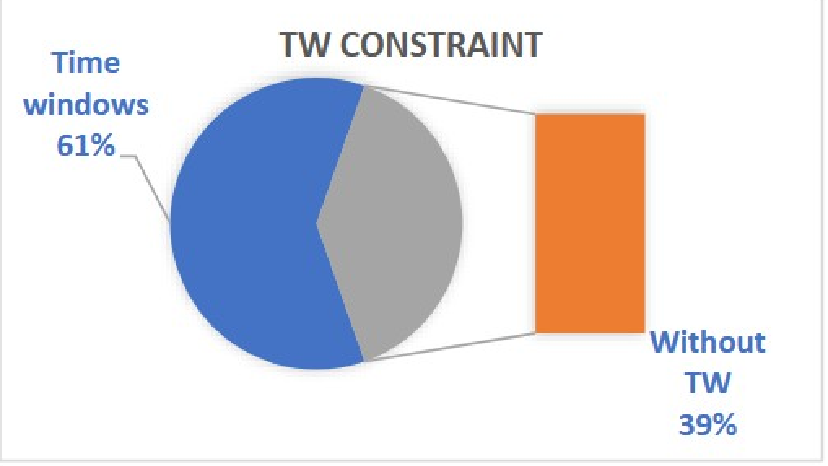

Figure 9: Publications by years based on Time Windows Constraint

2. **Capacity Constraint:** Capacity Constraint is already existing in the given model. It is that condition in which the loading capacity of the vehicle is restricted. Vehicle can carry a load to a limited capacity. The capacity constraint shown in **Figure 10** is written in the form as

$$A_{kxy} = L_k \cdot i_{kxy}, \forall x, y \in S, \forall k \in S_k \tag{6.2}$$

$$A_{kxy} = \text{Amount of goods delivered by electric vehicle } k \text{ on arc } (x, y) \quad \forall (k \in n_{CS})$$

L_k = Highest load limit of electric vehicle k

$$i_{kxy} = \begin{cases} 1, & \text{if electric vehicle } k \text{ visits node } y \text{ after node } x \\ 0, & \text{otherwise} \end{cases} \quad \forall (k \in n_{CS}),\ \forall (x, y \in n_D \cup n_C)$$

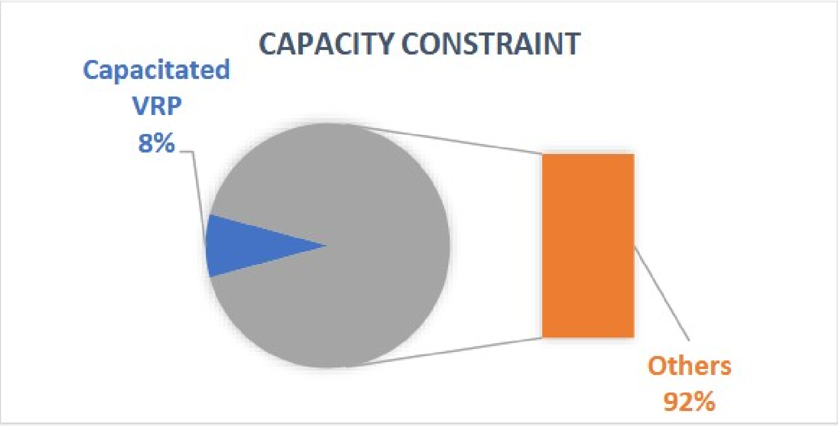

Figure 10: Capacity Constraint

3. **Depots Distributions:** There are some EVRPs based on the number of depots that whether there is single depot or multiple depots. The pie chart in **Figure 11** is based on single and multiple depots is given as below:

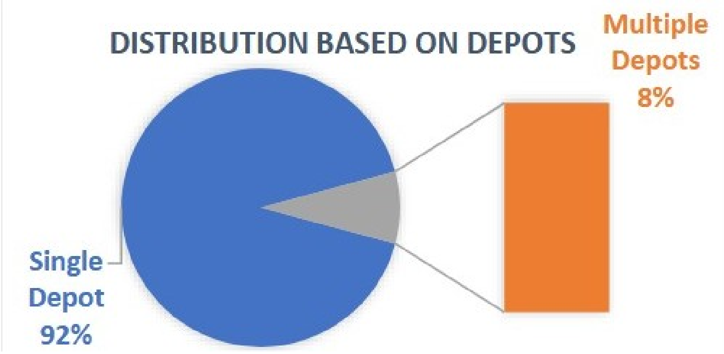

Figure 11: Research based on count of Depots

4. **Charging Conditions:** This includes the charging of vehicles partially or fully. The given model has the charging condition of being fully charged, partial charging is not allowed according to the given mathematical model. Pie chart in **Figure 12** repesents the distribution of fully and partially charged conditions. If the condition of partial charging is permitted then an extra constraint will be added which are

$$0 \leq y_j \leq y_i - (hd_{ij})x_{ij} + Q(1 - x_{ij}), \forall i \in V, \forall j \in V'_{n+1}, i \neq j \tag{6.3}$$

$$0 \leq y_j \leq Y_i - (hd_{ij})x_{ij} + Q(1 - x_{ij}), \forall i \in F'_0, \forall j \in V'_{n+1}, i \neq j \tag{6.4}$$

where
h= rate of charging of battery
hd_{ij} = consumption of battery used at every traveled arc
Q = battery capacity of the vehicle
Y_i= battery state of charge on departure from station i.

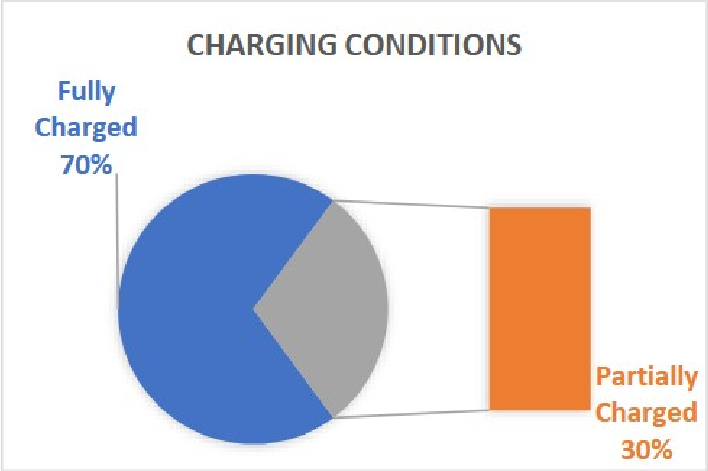

Figure 12: Charging Conditions

7. Applications of EVRP

EVRP can be applicable to a wide range in real life, out of which logistics, transportation, and delivery systems are essentials. Applications of EVRP in some key areas are as follows:

1. Supply Chain Management: Electric vehicles are very useful in logistics management. When companies consider charging constraints and routing problems, the supply chains can be made more sustainable and the deliveries can be on time while reducing the operating charges. EVRP gives a better solution by reviewing different constraints of EVs such as the need of charging infrastructures and battery storage capacity of the e-vehicle. One of the main motives of EVRP is optimizing the traveling path, ensuring that the electric vehicle completes its path in less time while minimizing the battery consumption and downtime for charging. EVRPs maintain sustainability goals by minimizing the greenhouse gas emissions and help industries to fulfil the environmental rules and regulations. EVRPs are also beneficial for last-mile delivery solutions as most of the urban areas are concerned with the environment and prefer more environmentally friendly transportation options. In summary, EVRP in supply chain management provides a wide range of benefits, including improved efficiency, environmental sustainability, and cost minimization, that makes the use of electric vehicles to face the new challenges in modern logistics.

2. Bus Routing in Public Transport: Cities are opting electric buses to maintain the environmental sustainability in the cities. EVRP will help the buses to complete their route timely and visiting charging stations when needed. While applying EVRP to public transport system, the main consideration is that electric buses are less as compared to the traditional diesel buses. As electric buses are dependent on the battery power, this means that the range is totally based on their capacity of the battery. EVRPs must consider these battery limitations into account that electric buses must complete their routes on time without running out of charging. This means that routing strategy must be formed based on location of charging stations. Another alternative is that the charging stations must be located strategically so that there should be no delay in the completion of routes and the e-vehicles reach their destinations on time. Another factor is cost minimization in electric buses. Electric vehicle can reduce the fuel emission and fuel costs, still there are other expenditures that need to be managed such as maintenance of the vehicles and infrastructure needed to manage the charging network. The application of EVRP in public transport system provides many benefits as cities are transforming to green and pollution free areas.

3. Travel and Tourism: In the field of tourism, electric vehicles can be useful for the guides for sightseeing, reducing the environmental impact of the vehicles. The EVRP can be applied here to consider the vehicle range, recharge time, and tourist destinations, providing sustainable traveling options for tourists. Similarly, as in case of public transport system, charging infrastructure is an essential element for EVRP. The availability of EV chargers increases the utilization of EVs in this sector. In tours, long distances, multiple stops, different areas of land are some additional constraints included in EVRPs that can impose an extra strain on electric vehicles. EVRP takes these factors in consideration and works for the optimization of long routes ensuring that the electric vehicle do not run out of its battery power. To exemplify, it is required to locate charging stations at key point during the sight-seeing so that the low battery power of e- vehicle does not interrupt the enjoyment of the visitors by delaying the traveling. Different demands of visitors and scheduling are other factors that can affect the tourism. In tourism, the demand of tourists regarding the path can vary according to the timings of the day, season, or any other special event. EVRP allows for the dynamic scheduling of the electric vehicles accordingly, ensuring that the most popular sites are visited during the high times, managing the optimal routes and the battery of the e-vehicles. EVRP in travel and tourism provides a range of benefits including green and clean environment, less fuel consumption, travelling cost savings, sustainability without sacrificing the best tourist experience.

4. Medical Services: In health services, EVRP is primarily related to the ambulance fleets. Ambulances are a crucial part of health services as these are important for emergency medical services. It is important to gain the optimality to provide the medical care to the patients timely. If the electric vehicles are being adopted by the hospitals to use as ambulances, e-vehicles can reduce the fuel consumption while maintaining the speed and reliability needed for emergencies. Another significant use of electric vehicles is in delivering the pharmaceuticals and medical supplies. Electric vehicles can be used for these deliveries but thinking about the condition of chargers and their range for covering routes. The optimization is specifically important for the urban areas as there is problem of traffic congestion and limited charging infrastructures can pose challenges.

8. Future Directions

In future, electric vehicle routing problems can be more focused on sustainable development goals as electric vehicle routing is also related to the sustainability of the environment. Moreover, real-life data from cities, from sources to destinations makes the problems more complex because in real data, many types of conditions come in knowledge that cannot be ignored. The increase in smart infrastructure and autonomous vehicle create opportunity to filter EVRPs, particularly through vehicle autonomy and cooperative routing. Multi-depots with multi-vehicles with uncertainty in demand of customers and time in delivering the products can increase the complexity of the EVRPs and to obtain optimality, the mathematical models will need some extensions of new constraints. Machine learning and AI can play a crucial role in maintaining the precise results for optimality as the models are becoming complex day by day. New mathematical models and algorithms can be developed for new generated constraints. Real-time decision making will be important to handle large fleets, and future solutions will need to integrate multiple objectives into a user centric approach, which will make the decisions according to the given conditions, preferences, and needs of the customers.

9. Conclusion

From all the research articles viewed from the past 13 years, it is concluded that electric vehicle routing problems are a crucial area of research as it is related to the sustainability and transportation. In this review article, an in-depth examination of electric vehicle routing problems has been given. The literature shows a significant progress in this field focusing on various challenges and handling those challenges by using exact methods, heuristics, and metaheuristics approaches. This review has also marked the key complexities in EVRPs, such as battery management, long routes, and charging infrastructures. However, many issues are still unresolved related to the larger and complex instances and real-time situations related to traffic conditions, weather, variation in demand and supply, and availability of charging stations. Moreover, there is also a need for standardised benchmarks to compare different solution approaches effectively. By considering these challenges, EVRP can contribute to a more sustainable environment in the urban areas and a great improvement in the urban transportation systems. In the previous years, most of the EVRPs are concerned with the time windows and there is less work done related to the uncertainty in the constraints. These uncertainties can be related to the demand of customers, uncertainty in delivery time of the goods and many more. To solve such kind of problems, stochastic approaches can be applied that gives better results for such problems. EVRPs are the intersection of transportation, environmental sustainability, and energy that make them an essential area of research in both industry and academics area. As in the upcoming days, transportation sector is moving more towards the electrification, therefore, optimization of routes is becoming more important to reduce the fuel emission, minimizing the total operational charges, and increasing the total efficiency of electric vehicles.

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