

Meta-Heuristic Approach for Identification of Logistic Hotspots Using Demographic Information

Arnav Mukamia¹

Department of Computing
Technologies,
SRM Institute of Science and
Technology
Kattankulathur, Tamilnadu, India
am2265@srmist.edu.in

Adhvit Singh¹

Department of Computing
Technologies,
SRM Institute of Science and
Technology
Kattankulathur, Tamilnadu, India
as2355@srmist.edu.in

B Amutha¹

Department of Computing
Technologies,
SRM Institute of Science and
Technology
Kattankulathur, Tamilnadu, India
amuthab@srmist.edu.in

Abstract— *With the increasing adoption of electric vehicles (EVs) in India, the necessity to establish an efficient and well-distributed public charging infrastructure is getting increasingly more important. The major issue in this regard is identifying high-demand charging hotspots where the deployment of infrastructure is needed most. This paper will recommend an integrated model which will be a Custom K-Means clustering algorithm used together with a Metaheuristic optimization algorithm to identify the Logistic Hotspots locations where EV charging stations should be installed in Kerala. The reason Kerala is selected as the study area is that an increasing number of people are purchasing electric vehicles (EVs), the region has a great diversity of geographic characteristics, and there is an increasing demand to have high-quality charging options in both cities and semi-urban environment.*

Keywords— *Electric Vehicle Charging, Custom K-Means, Metaheuristic Optimization, Charging Station Placement, Kerala, Clustering, Smart Mobility*

I. INTRODUCTION

The urban transport systems in the world remain under a great pressure to reduce the level of vehicular emission and provide sustainable mobility[1]. Electric mobility shift has become a possible measure to reduce pollution in the environment, diversify energy sources, and decrease the reliance on fossil fuels[6]. The worldwide development of battery technology and policy support to encourage clean transportation [2] have seen electric vehicles (EVs) achieve significant growth within the last decade[8,9].

Although the EV adoption process moves rapidly all over the world, the growth of the supporting charging infrastructure is still unequal in most areas and is not enough[7]. Though in some areas, there has been a consistent increase in the penetration of EVs, adoption levels are still geographically skewed[3]. EVs will also make up a large portion of all vehicle sales within a few years[8,10], according to forecast studies, and there is an urgent need to have scalable charging infrastructure systems. The growing adoption of EVs in cities presents novel problems in terms of energy demand control and urban planning[10,11]. The price requirements depend considerably on travel behavior, land use features, and user habits. The growing number of EVs results in the growing load on the electrical grids[10], which requires further infrastructure improvements and smart approaches to energy management. The demand and supply of EV charging, in combination with the integration of renewable energy, also makes the planning process more complex by necessitating a tradeoff between mobility requirements and energy efficiency[4].

There are various contextual factors such as transportation culture, power grid capacity, spatial distribution of population and urban planning characteristics which affect infrastructure requirements[13]. These variables should be known in order to create effective charging networks. It is also possible to involve EV systems in the work of the public transportation systems to make the mobility solutions more sustainable in energy consumption and congestion[5].

The proposed study will offer a hybrid EV charging infrastructure planning framework in the state of Kerala, India. The framework brings together deterministic range-based modeling, clustering and metaheuristic optimization to determine optimal charging station locations. Demand patterns among districts are then analyzed using A Custom Weighted K-Means to cluster and a metaheuristic optimization module optimizes the placement strategy taking into account accessibility and range constraints. The distributed and scalable structure allows an efficient regional analysis and promotes the long-term planning of the infrastructure[12].

The experimental analysis proves the enhancement of the accessibility of the charging device, the decrease in the number of travel interruptions, and the even distribution of the charging device demand in the major areas. The suggested solution offers a statistical basis to the sustainable EV adoption and smart infrastructure planning.

II. RELATED WORK

The problem of EV charging infrastructure development has been actively studied with the application of different areas of research, such as simulation modeling, sustainable mobility planning, demand analysis, and integration of urban energy systems[13]. The current literature may be divided into four major fields, which include (1) frameworks of electric vehicle simulations, (2) policies of sustainable EV implementation in cities, (3) demand modeling and user behavior, and (4) the approach to infrastructure planning of e-mobility systems.

Simulation tools of electric vehicles are critical in the knowledge of the demand of charging and mobility behavior[11]. The elements that are often added to these tools include trip generation, charging station location, energy consumption model, and decision-making by users. The simulation environments may be built on top of the existing traffic simulators, including SUMO and MATSim, or be created as separate systems[11] power distribution networks. In this field of research, the analysis of charging behavior, vehicle-to-grid (V2G), and the effects of EV penetration on power distribution networks are studied[10].

Vehicle-to-grid approach was widely researched as one of the means to control charging loads and stabilization of electrical networks[14]. These technologies help EVs to serve as distributed storage units of energy and eliminate variations in peak demand, which enhances grid efficiency. Moreover, transportation-based policies like travel path optimization and congestion minimization have also been suggested in order to decrease charging requirements and energy usage.

The other significant research area is the study of the travel behavior and its impact on charging demand. Research has indicated that travel distributions of space and time are closely connected with charging patterns. Real-world mobility patterns are often represented using the activity-based models and agent-based approaches to simulation. Such models are used to estimate the energy demand in a wide range of conditions of the traveling process and to make the decision regarding the planning of infrastructure.

The modal shift strategies that help to promote EVs-public transportation integration have also been examined in recent studies. Tools like Park-and-ride, multimodal transportation planning and others have been suggested to decrease traffic jams and maximize energy consumption. Logit-based models, Bayesian networks, decision trees, and support vector machines are some of the modeling methods that have been used in analyzing user behavior and transportation decisions. There has also been a lot of attention as regards to the relationship between EV adoption and urban development. The patterns of land use, the density of the city, and the distribution of infrastructures are significant in define the charging demand.

A number of studies have been aimed at determining the best location of charging stations depending on the functional blocks of the cities like residential, commercial and industrial areas. Moreover, it has been pointed out in a study that EVs may cause urban sprawl and changes in transportation demand. Regardless of these achievements, the literature commonly focuses on EV infrastructure planning and route feasibility as two distinct issues. There are no unified frameworks that would take into account both the viability of travel and charging demand and infrastructure optimization. Besides, no extensive research has been conducted on combining the spatial clustering methods with optimization algorithms with real-world multi-factor datasets.

In order to fill such gaps, the current study suggests a combined framework, which incorporates deterministic modeling, graphical reachability analysis, clustering, and metaheuristic optimization. The suggested solution allows the thorough assessment of EV mobility and allows to make a well-informed decision by basing it on the data regarding the planning of the charging infrastructure.

Enhanced planning of EV charging infrastructure has been concentrating on data-driven solutions more recently. Similar methods of analysis (spatial and temporal patterns of demand) based on real-world data are commonplace, utilizing machine learning and clustering algorithms. These methods aid in determining the high demand areas and enhancing the precision of placement of charging stations determinations depending on the population of the regions, traffic rates and trends of movement.

There has also been the increased importance of graph-based modeling in modeling transportation and charging networks. In these modeling, the nodes are considered as locations and

charging stations, whereas the edges are considered to be road connections that allow to conduct a route feasibility analysis effectively. These methods are efficient in determining accessible routes and infrastructure shortages but the vast majority of the current techniques pay more attention to routing as opposed to incorporating demand-informed infrastructure planning.

Moreover, other metaheuristic optimization methods like Genetic Algorithms and Particle Swarm Optimization have been extensively used to find the best location of charging stations under a variety of constraints[15]. These techniques are useful in the investigation of large solution spaces, however, they are typically applied on their own. So, it is still necessary to have a unified system that will encompass the demand analysis, route feasibility, and optimization. The proposed work fills this gap by integrating deterministic modeling, the graph-based analysis, clustering and metaheuristic optimization into a single scalable system.

III. METHODOLOGY

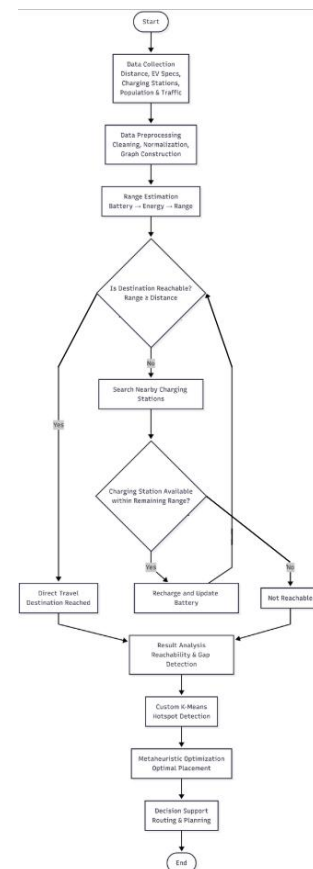


Fig. 1. Proposed hybrid framework for EV route feasibility and charging infrastructure optimization.

A. The range-based deterministic decision algorithm

The main working logic of the proposed system relies on a deterministic range estimation and decision making model. The algorithm identifies the ability of an electric vehicle (EV) to get to a certain destination with the existing battery charge.

It adds a safety buffer to avoid the possibility of exhausted batteries. The battery percentage that can be used is obtained using the following formula:

$$Usable\ battery(\%) = battery\% - buffer \quad \dots(1)$$

The kilowatt-hours (kWh) of available energy is determined by the battery capacity of the vehicle:

$$Available\ Energy = Battery\ Capacity \times Usable\ Battery / 100 \quad \dots(2)$$

Vehicle efficiency is used to estimate the maximum distance that can be traveled (range):

$$Range = Available\ Energy \times Efficiency \quad \dots(3)$$

The estimated range is compared with the route distance in the system.

If

$$Range \geq Distance \Rightarrow Direct\ Reach \quad \dots(4)$$

Otherwise:

$$Range < Distance = Search\ for\ Intermediate\ Stations \quad \dots(5)$$

This is a deterministic decision algorithm rule that is rule based since there is no probability variation in giving the same output with the same input parameters of the battery and the route distance.

The system then calculates the range which the electric vehicle is expected to cover and then it tries to determine whether the vehicle will be able to achieve the intended destination using the battery energy available. This assessment is the initial decision making phase of the proposed framework. The algorithm will match the computed distance of the travel and the real route path based on the transportation network dataset. In case the estimated range exceeds or matches the distance required to go to the destination, the system concludes that the vehicle will make the trip without the necessity of any intermediate charging stations. In these scenarios, the path is defined as reachable directly and the EV will be able to move to the destination with the help of the existing amount of batteries.

But in the case the estimated travel range is less than the route distance, then the system decides that direct travel cannot be done. In the case, the algorithm will start a search of intermediate charging stations on the path. The algorithm of the search is based on the existing charging station dataset and road network graph to find the nearest charging stations that can be reached within the remaining range of vehicle movement. These stations are completely recharge points where the vehicle can refuel and resume the trip to the destination.

This strategy is a deterministic decision algorithm rule based because it has no probabilistic variation over yielding the same output with the same input battery parameters and route distance.

B. Graph Based Reachability Algorithm

The EV charging infrastructure network is a directed weighted graph where charging stations are the nodes and travel pathways between the charging stations are the edges. The cost weight of each edge is proportional to the physical distance of the charging stations in kilometers. In order to support the efficient storage and access of the information about the connectivity, the graph is stored in a relational database in the form of adjacency-list representation comprising of attributes of the form: fromStationId,

toStationId, and distance. The availability of direct and indirect routes between source and destination stations is conducted on this graph structure to determine route feasibility decisions.

The system first tries a direct edge look up between the source and destination node. When there is a direct route and meets the vehicle range restriction, then the route is said to be feasible without charging in between. In situations where direct reachability cannot succeed because the vehicle range is too small, however, the system conducts a limited adjacency search of the immediate nodes.

This neighbor search algorithm retrieves all the neighboring charging stations within the range of the remaining battery of the vehicle by the distance of the connecting edge. Officially, an adjacent station Fig. j is regarded as accessible at station i if:

$$d_{ij} \leq R_{remaining} \quad \dots(6)$$

where d_{ij} is the edge distance of stations and remaining indicates the distance that the EV can cover. This traversal is repeated via feasible neighbors and ultimately an intermediate charging stop is identified until the destination or no continuation is feasible. This procedure is a useful way to represent a range-constrained graph visiting process, so the practical EV routing is made possible, as well as the essential charging corridors and infrastructural gaps are found.

C. Custom K Means Algorithm

The Every location in the state of Kerala is modeled as a feature vector:

$$X = (x_i, y_i, P_i, T_i, R_i) \quad \dots(7)$$

Where:

- x_i, y_i – Geographic coordinates
- P_i – Population density
- T_i – Traffic density
- R_i – Residential cluster score

A weighted distance functional is defined instead of simple Euclidean distance:

$$d_{spatial} = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \quad \dots(8)$$

Once the spatial distance between each location and centroid of the cluster is calculated, the clustering algorithm takes all the locations with similar demand characteristics in one cluster. The component of spatial distance is such that similar localities which are geographically closer are combined with each other, which is significant in the planning of the regional infrastructure. Nevertheless, the proximity of EV charging is not solely what dictated demand. The characteristics of the population density, traffic density and residential concentration are also the demographic and mobility factors that are very critical in defining the potential charging demand. Thus, the specified strategy includes some extra demand-related features and geographic coordinates in the process of clustering. Population density and traffic activity of the location can be generally associated with more possible use of EVs, whereas residential clustering demonstrates long-term demands for charging by the local EV users. When these factors are factored in, the algorithm can

determine the areas where EV charging infrastructure can best be installed.

Thus, the specified strategy includes some extra demand-related features and geographic coordinates in the process of clustering. Population density and traffic activity of the location can be generally associated with more possible use of EVs, whereas residential clustering demonstrates long-term demands for charging by the local EV users. When these factors are factored in, the algorithm can determine the areas where EV charging infrastructure can best be installed.

Custom K-Means clustering algorithm divides the set of data into K clusters where the places in one cluster have similar spatial and demand features. First, Kcluster centroid is randomly chosen on the data. All the locations are then allocated to the closest centroid, according to the obtained measure of distance. Once all the locations are assigned, the centroid of each group is recomputed by averaging the features vectors of a cluster. This assignment and centroid update is done over and over again until the cluster centers converge and no further significant changes are realized.

IV. EXPERIMENTAL RESULTS AND EVALUATION

The framework of the proposed EV route feasibility and charging infrastructure planning was tested on the data of several districts in the state of Kerala, India. The data will be in the form of geographical location of districts, inter-district transportation distances, EV battery characteristics, and demand-related variables in the form of population density, traffic density, residential clustering, and road connection indexes. These parameters were chosen since they directly affect the mobility patterns of electric vehicles and the demand of charging as a component of the transportation network in cities and semi-urban areas.

The test assessment is dedicated to two large aims. The deterministic range-based decision algorithm is applied, in the first, to determine the feasibility of the EV routes at various battery charge conditions.

Second, the clustering and infrastructure analysis modules will be used to determine possible gaps in the current EV charging infrastructure and identify the most appropriate sites to add other charging stations. The experiments were done by modeling various EV travel activities in the districts of Kerala. In every case, the algorithm estimates the range of travel with the help of the battery percentage, battery capacity, and vehicle efficiency variables. Comparison is then made between the computed range and the actual route distance between districts. In case the estimated range exceeds the route distance, the destination is said to be reachable at once. Otherwise, the intermediate charging stations are searched with the help of the graph-based reachability model within the system.

★ TABLE-2 – Starting: Kollam

INITIAL CHARGE (%)	EST. RANGE (KM)	DESTINATION	DISTANCE (KM)	CHARGING STATION	REMARK
25%	70 km	Thiruvananthapuram	70 km	✓ Yes (Attappal)	➔ Reachable with charging stop
30%	90 km	Pathanamthitta	65 km	✗ No	➔ Easily reachable
35%	100 km	Alappuzha	85 km	✓ Yes (Kannuram)	➔ Charging mandatory
35%	100 km	Kottayam	95 km	✗ No	➔ Reachable with charging stop
40%	130 km	Idukki	180 km	✓ Yes (Kottayam)	➔ Charging mandatory
50%	150 km	Ernakulam	140 km	✓ Yes (Alappuzha)	➔ Reachable with charging stop
50%	150 km	Thiruv	150 km	✓ Yes (Ernakulam)	➔ Charging mandatory
60%	180 km	Palakkad	250 km	✓ Yes (Thiruv)	➔ Charging mandatory
60%	180 km	Malappuram	270 km	✗ No	✗ Not reachable
65%	195 km	Kozhikode	310 km	✓ Yes (Malappuram)	➔ Charging mandatory
70%	210 km	Wayanad	360 km	✗ No	✗ Not reachable

Fig. 2. EV reachability analysis starting from Kollam

Reachability outputs of a sample scenario are illustrated in Fig. 2 upon the selection of Kollam as the starting district. The table shows different traveling conditions and initial battery charge levels that were 25 per cent to 70 per cent. The estimated EV range is determined and compared with that of the distance to various destination districts based on each battery level.

It can be shown that some destinations like Thiruvananthapuram and Pathanamthitta are accessible directly even with moderate battery levels as they have relatively shorter travel distances. But in the case of longer distances like the Kozhikode and Wayanad, even the estimated range of the EV will be limited when the battery is depleted. Under these circumstances, the system determines the necessity to have intermediate charging stations along the route. This discussion shows that battery capacity and availability of infrastructure are two factors that affect the viability of EV travel together.

The reachability analysis also allows defining significant travel routes on the basis of which EV mobility is impossible without adequate charging infrastructure. These observations form the basis of the analysis of charging infrastructure gap given in the following step.

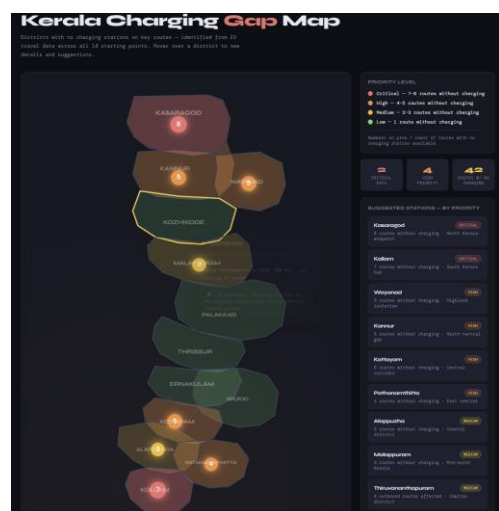


Fig. 3. EV charging infrastructure gap analysis across Kerala

Based on the obtained outcomes of the reachability analysis, a gap assessment of the regional charging infrastructure was

carried out. The map of Charging Gap in Kerala produced by the suggested framework is illustrated in Figure 3. The visualization groups districts by the amount of charging infrastructure gaps which occurred through the test simulations.

The map has separated the areas into several levels of priority. Critical regions are the regions in which EV travel is often not practicable because the charging coverage along the travel routes is lacking. These areas need immediate installation of new charging facilities to facilitate EV long-haul travel. Moderate priority areas are areas that have charging stations but the number of charging stations are not high enough to accommodate more EV adoption. Low-priority regions refer to the areas with the current infrastructure of the charging system that is adequate to accommodate the current mobility demand.

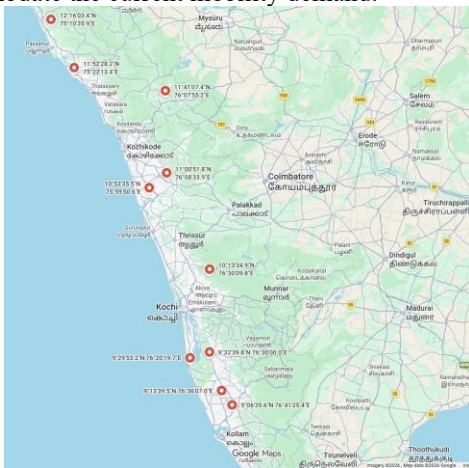


Fig. 4. Recommended EV charging station locations generated using Custom K-Means clustering

This analysis of the gaps indicates that some of the northern and central districts have majority of the charging demands because they have long travel distances and the movement of vehicles in the major transportation corridors is on the rise. It is very important to identify these areas in the planning of future EV charging networks that will ensure smooth inter-district movements. In a bid to fill in the infrastructure gaps that were realized in the preceding step, the Custom Weighted K-Means clustering algorithm was used on the dataset. Clustering process uses various characteristics such as the geographic coordinates, population density, traffic density, residential clusters as well as the economic activities indicators. All these factors are the potential demand and EV charging in the respective districts.

The clustering algorithm manages to cluster locations that are characterized by similarities and calculates cluster central points serving as the point of demand representative of each cluster. The interpretation of these centroids is that they are the preference areas to install EV charging stations. The suggested coordinates of the charging stations as shown in figure 4 are plotted on the geographic map of Kerala. The station locations suggested are spread out in large transportation highways to make them as accessible to the EV users as possible.

The clustering outcomes suggest that the presence of charging stations located close to high population centers and other key intersections along highways have a great impact

on the feasibility of routes in a variety of districts. Also, the efficient placement of charging stations in the areas of high demand decreases the number of interruptions in traveling and enhances the efficiency of the network of charging stations. Lastly, the experimental findings indicate that the suggested hybrid mechanism is effective in combining deterministic range estimation with graph-based reachability analysis and clustering-based infrastructure planning into one unified decision-support system of the electric vehicle mobility. The deterministic decision algorithm is significantly effective to assess the viability of the route; it compares the estimated EV travel range, with real route distances, allowing the system to know situations in which direct travel can be done, and when intermediate support of charging is needed. This system implies a consistent basis of assessing EV mobility limitations with the dissimilar change in battery charge conditions.

The graph-based reachability model also increases the framework by investigating viable pathways of travel via the intermediate charging stations where they are not accessible. Having the charging network as a weighted graph of nodes and edges, the system can recreate realistic conditions of EV travel and find alternative paths that will still provide the continuation of travel. The strategy has a major advantage about route feasibility analysis, as well as, it provides the EV users with practical charging strategies when traveling long distances.

Besides, the further implementation of the Custom Weighted K-Means clustering algorithm allows designating the charging areas with high demand based on the spatial, demographic, and infrastructure-related characteristics. With the introduction of parameters (geographic coordinates, population density, traffic density, residential clustering, and economic activity indicators) the clustering process is effective and effective in terms of identifying demand hotspots where the implementation of charging infrastructure would make the most difference. Centroids of the clusters produced by the algorithm are strategic points used to install the EV charging stations.

The experimental evaluation also shows that by integrating route feasibility study and infrastructure demand analysis, there will be better informed infrastructure planning decisions. The suggested framework does not only determine the routes where the lack of charging coverage is observed but also suggests the optimal location of charging stations, which would enhance the accessibility in various districts. Consequently, the system helps to decrease the range anxiety, enhance the reliability of the routes, and promote the popularization of electric vehicles.

In terms of infrastructure planning, the suggested framework provides a data-driven and scalable system of designing EV charging infrastructure in urban and inter-city traffic systems that are rapidly expanding. The methodology can help policy makers, transportation authorities and infrastructure planners understand priority areas of the deployment of charging stations and also optimize the allocation of scarce resources. Additionally, the system has a modular architecture that enables the incorporation of more data sources in the future like real-time traffic data, EV usage data, and renewable energy availability data to plan Smart charging infrastructures.

In general, the findings indicate that a combination of deterministic modeling, graph-based analysis, clustering algorithms with optimization approaches presents an all-encompassing solution to the planning of EV charging infrastructure. The presented system is one of the significant steps to the evolution of the intelligent transportation infrastructure that facilitates the sustainable electric mobility and allows to build the EV charging network efficiently.

V. CONCLUSION

The present study tried to analyze the feasibility of the concept of electric vehicle (EV) mobility within the 14 districts of Kerala through a range-based deterministic decision model. The analysis took into consideration battery charge level, vehicle distance estimation, and inter-district distance, and charging station availability in order to create a complete EV reachability dataset. The findings indicated that the viability of EV traveling is extremely dependent on the battery capacity and the spatial location of the charging equipment, wherein the medium- and long-range routes would need intermediate charging equipment.

A Custom Weighted K-Means Clustering algorithm was used to tackle the problem of infrastructure planning by determining a possible site of the new charging stations after considering the population density, traffic intensity, and residential clustering. The findings of the clustering allowed determining high-demand areas, which offered a data-driven ground of the first placement of charging stations. Moreover, a metaheuristic optimization model was added to streamline the establishment plan of charging stations[16]. The metaheuristic model was more efficient than the traditional deterministic techniques because it examined numerous candidate solutions and reduced the possibility of travel delays and the range anxiety.

By the joint application of the clustering and optimization methods, the spatial relevance and efficiency of the infrastructure planning were guaranteed. It was found that infrastructural deficiencies existed in various travel paths, especially long journey paths, which stressed the necessity to focus on the development of charging infrastructures and become less dependent on fossil fuels. On the whole, this research proves that the combination of range-based feasibility modeling, clustering, and optimization offers a scalable and smart system of EV route planning and the design of charging infrastructure

VI. FUTURE WORK

The proposed framework can be expanded into future work to include real-time sources of data concerning traffic congestion patterns, dynamic EV demand, and real-time availability of charging stations to be more precise in drawing the feasibility of routes analysis. Also, the introduction of renewable energy sources into the system like solar-powered chargers can help to make EV infrastructure more sustainable. Another aspect of adaptive and intelligent optimization models can also be further investigated to create dynamically changing the location of charging stations depending on the changing mobility patterns and EV adoption rates. Demand forecasting can be enhanced with the introduction of the latest machine learning methods and predictive analytics, and it may also allow planning infrastructure more intelligently. In addition, a larger scope of the framework to a national or

global one can give more extensive information on EV mobility planning and facilitate the introduction of charging networks on a large scale.

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