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Enhancing electric vehicle charging infrastructure: A framework for efficient charging point management

Prajeesh C B [a], Krishna Priya R [b], Anju S Pillai [a,*], Ahmed S Khwaja [c], Alagan Anpalagan [c]

[a] Department of Electrical and Electronics Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India
[b] Department of Research and Consultancy, University of Technology and Applied Sciences, Musandam, Khasab, Sultanate of Oman
[c] Department of Electrical and Computer Engineering, Toronto Metropolitan University, Canada

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ABSTRACT

The rise of electric vehicles (EVs) in the transportation sector aids in curbing global greenhouse gas emissions yet efficiently integrating them into the existing infrastructure presents challenges in guaranteeing the real-time availability of charging points and the dynamic nature of electric mobility. This paper presents a novel dynamic demand scheduling framework that utilizes predictive analytics to address the issue of emergency charging requests; situations where an EV urgently require to reach a charging point due to critically low battery levels. The framework is integrated with advanced dynamic demand scheduling algorithm (ADDSA), which utilizes real-time charging data collected from Trivandrum, Kerala state, India. Using the comprehensive dataset, the framework identifies delayed EVs and considers the charging point status (active, idle or faulty) and charging point pricing to optimize the charging station allocation. By employing the K-Means clustering algorithm, the ADDSA categorizes charging points based on their performance and availability. To evaluate the effectiveness of these clusters, we utilize internal metrics such as the Silhouette score, Calinski-Harabasz (CH) index, and Davies-Bouldin (DB) index. Our findings demonstrate that K-Means outperforms other clustering algorithms, including DBSCAN, K-Medoids, Agglomerative clustering, and Gaussian mixture models (GMM), with a CH score of 1200, a Silhouette score of 0.45, and a DB score of 0.74. In the final stage of ADDSA, groups of available charging points along with their pricing information is generated, facilitating informed decision-making for EV users. With the rapid growth of the EV population, our unique dynamic demand scheduling framework, featuring real-time constraints, offers a promising solution for efficiently addressing the emergency charging needs of EVs.

1. Introduction

Electric vehicles are becoming increasingly popular due to their capability to reduce air pollution and carbon dioxide emissions compared to conventional internal combustion engine vehicles (ICEVs). Using regulations, incentives, and other strategic points, several countries have already incorporated EVs into their public transport systems to varying degrees [1]. For instance, many American towns are undergoing a transition period in which the ICEVs are gradually being replaced by hybrid and EVs [2]. According to various reports, the fleet of EV taxis has achieved business break-even [3]. By the end of December 2023, China installed 5.411 million charging piles, of which 1.839 million are public charging piles according to data given by the China Charging Alliance [4]. As the EV population increases, the number of charging piles also needs to increase, and most need to be more evenly distributed to improve accessibility.

In practice, drivers of EVs frequently encounter various issues, including non-functional charging stations, protracted wait times for charging and parking, power fluctuations, and high energy costs [5]. Meanwhile, the charging station operators may need help with problems like underutilization of charging points due to uneven road traffic, energy issues due to grid instability, and interoperability issues relating to charging connectors. There is still considerable potential for improvement of operational efficiency in public and private EV transportation. Due to insufficient battery capacity, EVs must recharge their batteries during working hours [6]. No matter how battery efficient the EVs are, it is unlikely that they will only need to recharge once outside of working hours in the foreseeable future, as the EVs can travel vast distances daily, especially the EV fleets. The rapid growth in the EV population may result in a bottleneck due to the smaller number of charging stations and

* Corresponding author.
E-mail address: s_anju@cb.amrita.edu (A.S. Pillai).

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the time taken for charging. Consequently, optimizing and selecting a reliable charging station dynamically at run-time will increase the effectiveness of the EV industry.

The EV drivers are not aware of the occupancy state of the charging stations or the estimated charging cost before they arrive without any live information about the stations. When a driver selects the station, the number of idle charging piles in a station at that time may differ from the actual number of inactive piles when the driver arrives, and even this information may not be reported to the drivers. It is time-dependent because it will become outdated every time a new driver arrives. Lack of global information such as existing reservations, live dynamic demand requests, and station selection by users may cause EVs to wait at charging stations for extended periods at a higher cost. It becomes challenging to recommend specific charging locations for each EV motorist based on what others might choose [7].

This work addresses optimizing the charging points' availability considering the existing reserved pool data when a live request arrives. In this work, a framework to analyse large-scale charging datasets, vehicle GPS data, and grid operating datasets is designed and implemented. The framework helps to recommend real-time charging points for EV users based on their dynamic on-demand charging point requests. Enhancing the users' charging experience depends significantly on intelligent and successful charging service recommendations. Additionally, it promotes the healthy growth of the clean energy sector and the general efficiency of charging stations. To the best of our knowledge, this work proposes one of the first recommendation systems for dynamic scheduling and allocating charging points in the EV market with real-time data.

The rest of the paper is organized as follows. Section two presents the related work carried out in this field, followed by the proposed framework in section three. Details of the real-time charging dataset and the data analysis are presented in section four. Section five illustrates the results and the findings of the work. The paper is concluded in section six.

2. Literature review

Electric vehicle smart charging and scheduling are required to manage the EV charging demand using the current grid infrastructure and generation capacity. It is essential for achieving several goals, including cost and loss minimization, bottleneck management, network support, and grid stability, depending on user preferences and the required computing and physical resources [8]. Designated charging techniques are primarily categorized according to the location of an EV charging station. The main benefit of a smart charging and scheduling approach is that it offers the chance to use optimized charging and scheduling while considering grid factors and the user's preferences [9]. Delaying or reducing the need for mandatory infrastructure upgrades while rapidly recovering related expenses is another advantage of using these strategies. Time-of-use (TOU) or dynamic pricing is often used in EV charging electricity tariffs [10] while the other systems use fixed tariff.

The network and the EV operator, and the aggregator are the three parties involved in scheduling and charging of EVs [11]. An EV user and the system operator communicate through the aggregator. To enable the system operator to maintain the essential operating network parameters within a reasonable range, the aggregator is responsible for scheduling and charging the EVs while minimizing the price charged to EV owners. The best methods for determining the ideal solution while considering all requirements and limitations are smart charging and scheduling [12]. The scheduling and charging approaches are chosen based on the computational and communication infrastructure.

Conversely, the infrastructure for communication consists of the systems or networks that transmit the required data. Local charging favours low-cost computational infrastructure, where the EV user has a direct connection to the charging station operator, while medium-cost options are preferred for hierarchical, distributed, and decentralized techniques. In the hierarchical approach, the EV user communicates to the charging station operator through the aggregator. The advantages of hierarchical and other distributed and decentralized techniques are sharing of the charging points schedule with all participating entities [13]. The different charging and scheduling approaches are given below.

2.1. Artificial intelligence/ machine learning–based charging approach

One of the feasible methods for planning and coordinating EV charging is to use data-driven Artificial Intelligence (AI) and Machine Learning (ML) solutions [14]. In this method, models are created and trained using several scenarios to understand the behaviour and characteristics of various participating entities. Training is conducted using standard training sets or other simulation-generated procedures, depending on the specific requirements.

The AI/ML-based technique is divided into supervised and unsupervised learning categories based on the available training sets. In supervised learning, the training data should be labelled. The training data used to train a model at one location cannot be used to train a supervised model at any other geographically dissimilar region since it is sensitive to the geographic location. Some supervised approaches include support vector machines (SVM), decision trees, random forests, and linear regression models. When the model is fed with input data, it forecasts changes in the smart charging and scheduling profile and delivers the best charging options to the EVs that need it. Unsupervised learning is the most widely used algorithm because only a few training data sources are available. Using unlabelled training data, unsupervised algorithms find the correlation between EV charging behaviours and given input parameters [15]. Some techniques used for unsupervised learning include Kernel density estimator, Gaussian mixture model (GMM), and K-Means clustering [16,17]. Supervised ML models are reliant on the quality of the training data set. Both residential and non-residential EV charging projects are used to provide the standard training data [18]. Advanced ML and deep learning (DL) algorithms can help to learn from failures and mistakes and improve the models.

2.2. Price-based coordination and scheduling methods

Electricity prices are divided into fixed and dynamic prices based on the time of utilization and the energy demand. The fixed price, however, typically only works well for pricing. Consequently, dynamic prices modify EV charge scheduling and pricing based on coordination techniques. Real-time price (RTP), time of use (TOU), critical peak price (CPP), and peak time rebate (PTR) are the different types of pricing methods for dynamic electricity prices [19]. Each of these pricing techniques affects customers' consumption habits indirectly and is elaborated below.

2.2.1. Real-time pricing

The electricity cost must be changed at intervals according to the network's needs. If EV charging is carried out at a fixed rate, there may be an erratic peak at any time depending on the users' charging behaviour. The EV charging system needs updated prices according to numerous characteristics to prevent the unpleasant peak load state. The main factors influencing pricing variance are demand for charging, energy attainability, maximum permissible power limits, and renewable energy accessibility [20].

Real-time pricing techniques are widely used in decentralized and distributed control strategies. To govern the EV charging while maintaining the grid's safety, the aggregator changes the price signal for the upcoming time slot in a decentralized RTP coordination manner [21]. Real-time pricing is also an option for centralized strategies; however, in this scenario, the aggregator does not change the price and only monitors the pricing market's real-time prices.

2.2.2. Time of use tariff

The predetermined price given to time slots is known as the TOU tariff [22]. These rates are provided on the actual day of operation, and a client can shift the flexible loads to a low-price period accordingly. The TOU tariff can only do smart charging if the operator manages the charging rates. It can produce superior outcomes in terms of electricity cost and requires substantially less extra infrastructure. Therefore, this pricing structure is utilized globally in several projects and locales [23]. Compared to uncontrolled charging, TOU pricing considerably lowers the charging cost [24]. It permits smart charging and cost-cutting in an uncontrolled EV environment.

When centralized charging is employed, the aggregator considers the TOU pricing to optimize the charging and achieve the intended result. Since the underlying idea is built on dynamically adjusting costs according to the need, the TOU tariff is not applicable for decentralized and distributed techniques as they adjust costs dynamically based on needs.

2.2.3. Critical peak price

Critical peak pricing is based on the TOU principles, except that the former is used during a time of peak demand. Forecasted data are used to categorize the charging points swiftly rather than historical data, which are not used to make decisions. As the CPP results in a far higher electricity price than the TOU, it is more successful at reducing peak load. Days are divided into critical and non-critical days to implement CPP using various methodologies, including particle swarm optimization (PSO) and ML-based clustering techniques [25].

2.2.4. Peak time rebate

In this tariff system, the utility gives the client a rebate to keep consumption within a set range. The client sees it as a benefit. The predefined critical baseline load determines the scheme's economic viability [26] because it is necessary to develop an accurate baseline load. Utilities need to accurately predict the minimum level of electricity demand at any given time to design effective tariff structures and incentives that encourage load shifting without compromising grid stability or financial sustainability.

The scheduling and charging of EVs can be carried out in multiple ways as discussed above. Also, there are various works which combine different parameters like road traffic data, dynamic price per unit, grid stability, integration of renewable energy sources, etc. as detailed in Table 1.

In conclusion, the scheduling and charging of EVs can be carried out with different methods and considering different factors like road traffic data, current scheduler, unit price of energy, in a static scheduled manner. When there is an emergency on-demand request for a charging slot, according to the static scheduled models, if any free slots are available, the scheduler allocate charging points to the EV users and if no slots are available, the EV user must wait until the slots become free. The problem associated with static scheduler is, it does not consider the traffic and other real-time situations that may incur a delay in the arrival of a scheduled EVs at respective charging points. Any delay in this regard will affect the existing scheduled pool, station's revenue, and growth of EV industry. Focusing on the above facts, a user centric model is needed to overcome the operational constraints in EV charging domain that can accept the on-demand charging requests and optimize the availability and suggest suitable charging points by considering various factors like status of nearby charging points, present location of scheduled vehicles in each reservation pool, real time traffic, dynamic pricing of energy, and stability of charging services at charging points. The final optimized charging point clusters with slot time are the most suited for satisfying the charging requests within the range.

Even though, different approaches are proposed for charging point scheduling considering different factors, still the existing research lack in addressing the following aspects effectively:

Table 1
Charging point scheduling based on different parameters.

Ref.	Objectives of the research	Research outcome	Research gaps and future scope
[27]	To integrate dynamic pricing system in an advanced EV scheduling system.	Developed a framework for charging station interaction with user, and the user-station interaction is transmitted over the network. The network station develops the pricing policy based on their observation from the previous time slot.	The major limitations of this work are computational overhead and network storage. Also, when a new charging point is introduced, the dynamic pricing policy of the network need to be re-trained from the scratch.
[28]	Addressing the need of smart and intelligent electric vehicle into the grid. A novel vehicle to grid integration system with charging and discharging of parked vehicle is proposed.	The simulation network for charging and discharging is developed with MATLAB. Also, the analysis like cost minimization of users, management of energy demand are also carried out.	The work focusses only on parked electric vehicles, and their charging and discharging. The on-demand charging request, dynamic pricing, and other stake holders concern are not considered.
[29]	A battery swapping station model is proposed for electric vehicle users to overcome the charging issues.	The simulated results shows that the battery swapping station can receive the swapping request and based on the availability and matching of battery, the request will be granted.	The major limitation of this work is it only focuses on the swapping of EV battery. Scheduling or charging of requested vehicles are not considered.
[30]	Multi-level dynamic charging and scheduling model.	The traffic flow and power are simulated based on the charging behaviours and travel characteristics.	Only the power and traffic flow are considered for dynamic scheduling. Other factors like the availability of charging stations, energy price etc. are not considered.
[31]	Block model predictive control approach for in cooperating the demand charge is proposed.	Comparative study with other approaches like economic model prediction control, model predictive control, less laxity first with later deadline are presented.	Real time charging request need to be considered.
[32]	A hierarchical network in cooperating EV, DSO and EVA for optimizing EV charging is proposed.	The hierarchical model is simulated in a decentralized computing manner.	The estimation of reactive power is also to be considered.
[33]	A framework proposed for predicting energy consumption and EV session duration.	The machine learning and ensemble learning algorithms are trained with the dataset and the charging behaviours are identified.	The dynamic pricing of energy is an important parameter while predicting the charging behaviour.
[34]	Optimal charging strategy is proposed using the grid and transport system.	The model is simulated for the scheduling strategy by considering smart grid.	The lack of considering the behaviour of charging stations, the EV user may be led to wrong charging points.
[35]	Develop an EV charging scheduling model by considering shortest path algorithm and real time traffic statics.	The prototype results show that by considering the traffic statics and the shortest path, the queue can be optimized based on the vehicle arrival time for charging.	The cost for charging is not considered.

(continued on next page)

Table 1 (*continued*)

Ref.	Objectives of the research	Research outcome	Research gaps and future scope
[36]	Proposed a concept of real time EV charging system.	Simulation results prove the valley filling for generating the charging schedule.	The charging schedule can interact with other components like home energy management. Due the centralized approach, load balancing and computational complexity is found to be high.

- Current scheduling models are primarily stable but do not accommodate on-demand charging requests effectively, highlighting the necessity for user-centric models that can adapt to real-time demands. Also, current approaches usually rely on static scheduling or simple algorithms that are unable to adjust effectively to changing circumstances in real-time, giving users less than ideal charging experiences.
- Long wait times are experienced by the EV users in the current charging infrastructures during times of high demand and frequent underutilization of infrastructure during times of low demand. The absence of predictive analytics and real-time data integration, which can optimize resource allocation, makes this inefficiency worse.
- Delays in the arrival of scheduled EVs at charging points can disrupt the existing scheduling pool, affecting both station revenue and the overall growth of the EV industry, indicating a gap in addressing these delays.
- The existing literature does not adequately explore strategies for managing emergency on-demand charging requests within the framework of static scheduling models.
- There is a lack of models that comprehensively consider dynamic factors such as real-time traffic conditions, the status of nearby charging points, and dynamic pricing of energy in scheduling algorithms.

The novelty of the proposed research is to provide a solution to the above research gaps, by integrating a predictive analytics over the real time EV data (charging data, vehicle GPS data, and road traffic information). By employing real time data, the framework effectively addresses the dynamic on-demand charging requests of the EV users, by clustering the charging points based on their charging data. In the next step, the framework, analyses the GPS and road traffic information to identify the time delay in vehicle arrival time to respective charging points. Finally, different groups of charging points are generated combing the above information. The proposed framework guarantees optimal utilization of charging point infrastructure, and reduced wait times by providing the charging point groups along with their average expected price per unit information, facilitating informed decision-making.

3. Proposed dynamic demand scheduling framework

The complexity of handling EVs' charging requirements is increasing along with the quantity of EVs on road. Utilizing available charging stations effectively is essential for increasing throughput and cutting down on user wait times. This research proposes a framework, which optimizes the distribution of charging resources based on real-time data by utilizing clustering and predictive analytics techniques. By coordinating resources and modifying schedules according to the situation, the sophisticated scheduling algorithms can greatly enhance resource utilization and will have a direct effect on consumer satisfaction. The goal of this work is to shorten wait times and guarantee allocation of nearby charging stations without any delays. Higher customer satisfaction is a direct result of improved response, and this is a key element in encouraging EV adoption.

The proposed dynamic demand scheduling framework for real-time charging point recommendations is divided into three modules: external entity, central management server (CMS), and the dynamic scheduler. The framework is integrated with the proposed Advanced Dynamic Demand Scheduling Algorithm (ADDSA) that performs the predictive analytics over the dataset available on the central management server, as shown in Fig. 1.

3.1. External entity

The external entities are located outside the system, which include the charging points, EVs with GPS, and road traffic analyser. The charging points are responsible for seamless energy delivery to the EVs. They continuously connect with the CMS server over the MQTT protocol with the help of predefined messages. This will help the CMS to identify the present status of charging points (active, idle or faulty). The framework might rely on past charging trends, charging station utilisation statistics and a dynamic database of available resources by establishing community driven feedback system contributed by EV users when GPS data is scarce. The messages are formatted with JavaScript Object Notation (JSON) and thus achieve communication interoperability over the charging network.

3.2. Central management server

The central management system is designed with essential information such as user, vehicle, and charging point registration, searching, daily price per unit and reservation for charging points. There is a backend database to store all this information. The basic details for registering the charging point are connector ID and connector type and its location. Upon completion of registration, operators can register the charging point with its ID, connector type, latitude, and longitude of EV's location. The daily price per unit is stored at backed database, which is a key ingredient tagged along with each charging point after the final clustering. Fig. 2 shows the charging point data in the developed backend database. This database is one of the core parts of the framework. It has different entities like user registration, charging points registration, reservation, EV registration, and charging price tables. This table stores the basic details of the user, charging points and the EV. While charging the vehicle, the energy utilization is recorded as a JSON formatted CSV (comma-separated) file at the backend.

The EVs with GPS will help to update their live location information to the CMS. Each EV must have a GPS module, and this GPS information should be registered at the CMS. The road traffic analyser helps to collect the live traffic information in between two points. The analyser collects the present location of scheduled vehicles. Analysis is carried out on the collected data and is used to predict the expected time the EV takes to reach the designated charging point. This will enable the charging point owners to identify whether the vehicle will reach the charging point on time or be delayed.

The CMS is assigned with different functions like user registration, assigning charging points, registering new charging points, collecting charging point status, saving charging and communication data etc. In addition, the framework runs the proposed ADDS algorithm, the details of which are presented in the next sub-section. Hence, the framework and the associated ADDS algorithm constitute the core of the system. The CMS has different functional units like a static scheduler, stability analyser, and dynamic price manager. The existing scheduler helps store the data related to charging point reservations. The reservation data in the database have attributes like charging point ID, latitude, longitude, scheduled date and time, scheduled duration, and user ID. Fig. 3 shows the representation of these data over the database.

In the framework, the charging point continuously communicates with the CMS using predefined messages as implemented in our earlier

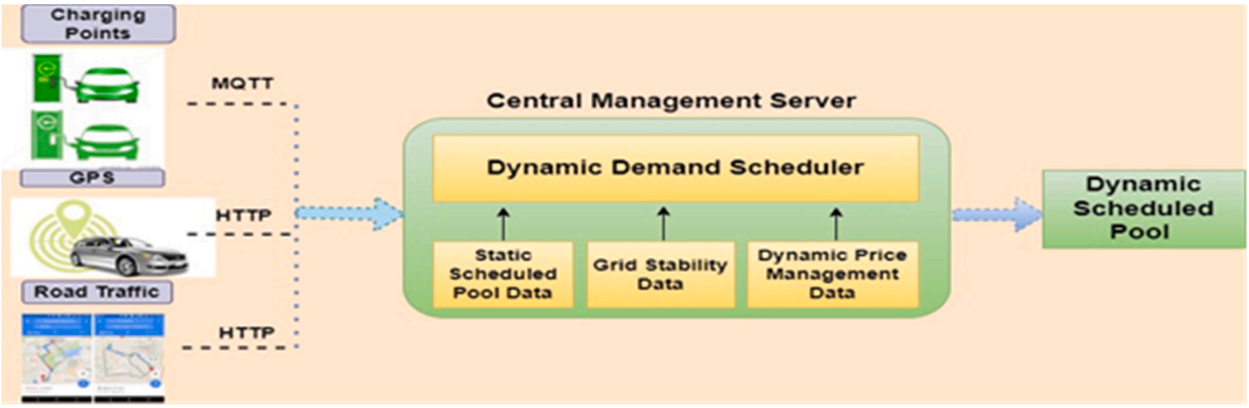

Fig. 1. Dynamic demand scheduling framework.

dbo.tbl_chargingpoints [Data] · reserve1.aspx.cs · reserve1.aspx · dbo.user_reg [Data] · search.aspx.cs · search.aspx · search1.aspx.cs · search1.aspx · dbo.tbl_reserve [Data]

Max Rows: 1000

Id	cp_name	cp_state	cp_district	cp_latitude	cp_longitude	cp_contype	cp_serialno	cp_firmware	cp_meterserial	cp_mobile	cp_email	cp_rem
1439	KSEB01 DCFC P...	Kerala	Trivandrum	8.516602	76.93938	Type-1	TVM_015	CM-S01439-HE...	CM-S01439-HE...	9090909090	test@gmail.com	Electrica
1470	KSEB01 AC001 ...	Kerala	Trivandrum	8.53505109	76.9422314	Type-1	TVM_013	CM-S01469-Z8...	CM-S01469-Z8...	9090909090	test@gmail.com	KSEB Su
1474	KSEB01 DCFC P...	Kerala	Trivandrum	8.53505109	76.9422314	Type-1	TVM_014	CM-S01474-GD...	CM-S01474-GD...	9090909090	test@gmail.com	KSEB, P
1476	KSEB01 DC001 ...	Kerala	Trivandrum	8.516602	76.93938	Type-1	TVM_011	CM-S01452-PZ...	CM-S01452-PZ...	9090909090	test@gmail.com	Electrica
1477	KSEB01 AC001 ...	Kerala	Trivandrum	8.516602	76.93938	Type-1	TVM_012	CM-S01453-SY...	CM-S01453-SY...	9090909090	test@gmail.com	Electrica
1507	KSEB1 AC001 N...	Kerala	Trivandrum	11.1	75.1	Type-1	TVM_010	CM-S01507-EW...	CM-S01507-EW...	9090909090	test@gmail.com	Near KS
1511	KSEB01 DCFC N...	Kerala	Trivandrum	8.4538301	77.004068	Type-1	TVM_009	CM-S01511-TF...	CM-S01511-TF...	9090909090	test@gmail.com	Near KS
1528	KSEB01 DCFC N...	Kerala	Trivandrum	8.40853337	77.0821515	Type-1	TVM_007	CM-S01528-N8...	CM-S01528-N8...	9090909090	test@gmail.com	Neyyatt
1529	KSEB12 DC001 ...	Kerala	Trivandrum	11.5	75.1	Type-1	TVM_008	CM-S01519-X7...	CM-S01519-X7...	9090909090	test@gmail.com	Near KS
1649	EXICOM TEST	Kerala	Trivandrum	8.560553	76.912525	Type-1	TVM_006	CM-S01649-3B...	CM-S01649-3B...	9090909090	test@gmail.com	sreekary
1660	KSEB01 DC001 ...	Kerala	Trivandrum	11.2	55.5	Type-1	TVM_001	CM-S01660-BB...	CM-S01660-BB...	9745057793	test@gmail.com	near Sul
1661	KSEB01 DC001 ...	Kerala	Trivandrum	11.2	85.2	Type-1	TVM_002	CM-S01661-KCI...	CM-S01661-KCI...	9745057793	test@gmail.com	Near su
1662	KSEB01 DC001 ...	Kerala	Trivandrum	11.2	75.2	Type-1	TVM_003	CM-S01662-JQ...	CM-S01662-JQ...	9745057793	test@gmail.com	Near su
1663	GIE MAJESTIC ...	Kerala	Trivandrum	11.2	75.2	Type-1	TVM_004	CM-S01663-UU...	CM-S01663-UU...	9745057793	test@gmail.com	Great In
1664	ALPHA DCFC Y...	Kerala	Trivandrum	8.51093	76.90492	Type-1	TVM_005	CM-S01664-0IJ...	CM-S01664-0IJ...	9090909090	test@gmail.com	Pettah -
587	KSEB1 CB 451 N...	Kerala	Trivandrum	8.4539445	77.0038442	Type-1	TVM_101	CM-S00587-W1...	CM-S00587-W1...	9090909090	test@gmail.com	NH 47 T
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Fig. 2. Charging point information at backend database.

Id	user_id	cp_id	date_time	slot_time_hr	slot_time_min...	present_loc_lati	present_loc_lo...	slot_duration
1	0001	Test1	Jan 6 2022 12:0...	12	11.00	9.44	9.676	10
2	0001	Test2	10-06-2022 0:0...	12	13.00	9.34	9.567	20
3	0002	Test3	11-06-2022 0:0...	12	12	9.55	9.4743	20
4	0002	Test4	24-06-2022 0:00...	12	12:12	9.6	9.6	30
5	0002	001	17-06-2022 0:0...	12	14:10	9.234	9.709	20
6	0002	001	16-06-2022 0:0...	12	17:12	9.453	9.743	15
7	0001	001	14-06-2022 0:0...	12	18:21	9.554	9.456	10
8	0002	001	24-06-2022	12	18:18	9.6	9.6	20
9	0002	Test1	17-06-2022 0:0...	10.00	16:15	9.234	9.563	20

Fig. 3. Reservation data at the CMS.

work [37]. During idle time, the charging point shares its status (idle) information. During charging time, it shares voltage, current, and power information. These data are stored as a CSV file. Based on the collected charging point data, the dynamic demand scheduling framework predicts whether a charging point can provide uninterrupted supply during the charging period. The per unit price of energy [38] may vary from time to time, depending on the demand. The CMS server has a repository to store the daily unit price per energy. Based on the previous data, the dynamic price manager, located in the CMS helps to predict the expected cost per unit. This prediction integrated with other vital data in the next stage of the algorithm makes the final charging point groups.

3.3. Dynamic scheduler

The dynamic scheduler's optimization stage is used to run the proposed ADDS algorithm. The ADDS algorithm helps to optimize the charging slots in the existing reserved pool. The dynamic scheduler optimizes all charging points under the defined radius. It makes the final charging point groups by combining the stability of charging point, dynamic price, charging point status and the expected time of reach of EVs. The proposed approach has two stages: primary algorithm and ADDS algorithm stage. The algorithm steps are given below, and a detailed flow diagram is shown in Fig. 4.

Primary Algorithm:

(*continued on next page*)

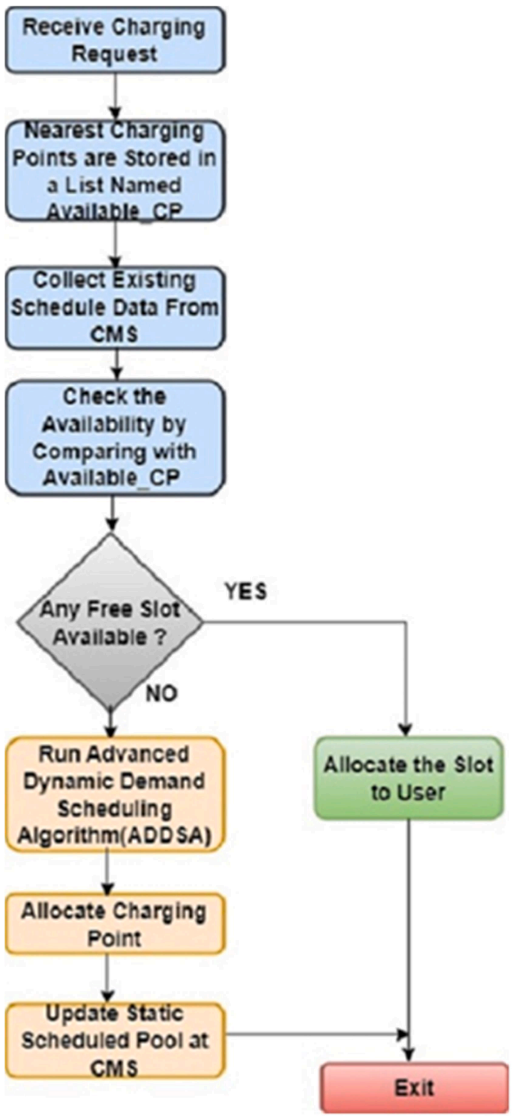

Fig. 4. Primary algorithm flow diagram.

(*continued*)

```
Input: Charging request from user (CR)
Output: Free charging slot (FCS)
CR = receiveChargingRequest() //Receive charging request.
userLocation= collectUserLocation(CR)
// Obtain user's current location from CR
nearestCPList=identifyNearestChargingPoints(userLocation) // Identify the nearest point
staticSchedule=fetchStaticScheduledData() // Check the static schedule data
if(staticSchedule: availableCPList!= Null)
        availableCPList= filterAvailableCPs(staticSchedule, nearestCPList)
else:
        availableCPList = nearestCPList
Cluster available charging points
if(availableCPList:clusterData= clusterAvailableCPs(availableCPList))
        FCS= ClusteredPoint(clusterData)
        //Select charging point from resulting clusters
else:
        Exception("Nocharging points found")
updateReservations (FCS, CR)
```

Advanced Dynamic Demand Scheduling Algorithm

Input: *Available charging points (CP) from primary algorithm*
Output: *Resulting clusters of CPs*

(*continued on next column*)

(*continued*)

```
Initialize:
    CP_ID: ID of the charging point
    Staticdata: Static reservation
    ScheduledTime: Reservation time.
    LocationEV: GPS data of EV
    TimeofReach: Time of reach of EV
    StatusCP: Status of CP
    StabilityCP: Stability values of charging points
    PriceCP: Predicted price
    ADDSA_CP: List to store CP
    Resultcluster: Final prediction
While(static data != Null):
    LocationEV = Get(vehicle GPS)
    TimeofReach = MapboxAPI(GPS)
End
While(Time of Reach != Null):
    if(TimeofReach)≥ (ScheduledTime + 20):
            ADDSA_CP = CP data
            Continue
    Else
            Continue
While(ADDSA_CP != Null):
    StatusCP = Get(CP_ID)
    StabilityCP = Kmeans_Predict(CP_ID)
    PriceCP = Averageprice(CP_ID)
End
ResultCluster=Predict(StatusCP, StabilityCP,
PriceCP, TimeofReach)
Return (ResultCluster)
```

The primary algorithm is the initial step for dynamic demand scheduling. The dynamic demand scheduler first runs the primary algorithm whenever an on-demand charging request arises. On receiving a charging request, the location of the EV is identified using the GPS. From the vehicle location, the nearby charging points are mapped in the framework and the status of the charging point, whether it is free or reserved, is identified. If charging points are available in the vicinity, the framework will suggest this information to the EV users. This update is reflected on the reservation pool. If the primary algorithm fails to find any nearby charging points, the second stage of the ADDS algorithm is initiated.

While running the ADDS algorithm, it receives the input from the list "Available_CP," which has all the charging point information, i.e., CP_ID near the requested vehicle. The ADDS algorithm initially defines various empty lists like "Static_Data," "Location_EV," TimeofReach," "StabilityCP," "PriceCP," and "ResultCluster. ". Each list is designated to store a specific set of information while running the algorithm. The list "Static_Data" collects already reserved details from "Available_CP" including "ScheduledTime". Upon extracting the reserved information, the algorithm finds the present location of all vehicles and optimizes the expected time taken by the vehicle to reach the designated charging point. This optimization is carried out by analyzing the live road traffic data. These results are stored in the list "LocationEV" and "TimeofReach," respectively. The process is continued until the list "Static_Data" becomes null. This concludes the first stage of the ADDS algorithm.

The second stage begins with the list "TimeofReach", which contains the expected arrival time of vehicles to their respective charging points. All the charging points where the scheduled vehicles are delayed are filtered out and the results are stored in the "ADDSA_CP" list. At the end of the second phase of ADDS algorithm, an updated list ADDSA_CP is available.

The third and final phase of the ADDS algorithm is complex due to the predictive analysis. Each charging point from the "ADDSA_CP" list is considered, and its present status is collected. The charging point has different status like "active," "idle," and "faulty," and the status is stored into "StatusCP". By analyzing the historical data with the K-Means predictive algorithm [39], the ADDS algorithm computes whether the charging point can provide a continuous power supply to the user or not based on the charging point current and voltage data. This information is collected in “StabilityCP” list. The K-Means categorizes the charging point data into four clusters and the percentage of majority cluster accounts for the “StabilityCP” value. The detailed analysis of charging point dataset for finding the “StabilityCP” is presented in Section 4. The expected price per unit is computed as the average previous charging price value and is stored in “PriceCP” list. This process is continued for all the charging points available in the “ADDSA_CP” list, and once it becomes null, all the three lists "StatusCP," "StabilityCP," and "PriceCP" are ready for final grouping of charging points.

All the charging points, whose status is either “faulty” or “charging” are removed from the “StabilityCP” list, and this list is considered as “internal threshold factor”. The second list, “TimeofReach” is considered as “external threshold factor” and with the help of internal and external threshold factors; the final charging point groups are created. The charging points are categories into four groups considering stability value and time of reach of the EV as group 1, group 2, group 3 and group 4. With each group of charging points, the respective “PriceCP” values are made available in the framework. Depending on user demands, any of the charging points in the groups can be chosen. Group 1 charging points are highly stable with sufficient time available for EV charging. Similarly, group 2 provides sufficient time for charging the EV, but the stability may be low compared to group 1. Group 3 charging points are stable, but the duration of charging may be less. Group 4 charging points are less stable and provide less time for charging the EV.

This concludes the final phase of the ADDS algorithm, and the details of four groups are stored in "ResultClusters." The resulting set is returned to the primary algorithm. The framework will display the “ResultClusters” to users along with their “PriceCP” information, and a user can choose the charging point from the clustering results. The final selection will be updated in the reservation pool. Detailed predictive analytics, result evaluation, and the comparative study with other clustering algorithms are discussed in the next section.

4. Predictive analytics

The proposed ADDS algorithm predicts the future outcomes based on the current data set. Here, the charging points are clustered based on their future charging behaviour. The previous charging data values such as voltage, current, power, etc. are collected in the framework. From this dataset, voltage and current information are provided as an input to the clustering algorithm. An unsupervised clustering algorithm, K-Means clustering, is used for prediction and clustering [40]. The elbow method is the best way to find the suitable number of clusters in the K-Means algorithm. The measured sum of squares is used to find the optimum cluster number. The following equation is used to calculate the within-cluster sum of squares (WCSS):

$$\mathrm{WCSS} = \sum_{i=1}^{m} (xi - ci)^2 \quad (1)$$

where xi = data point and ci = closest point to the centroid. The WCSS is measured for each value of K, and a plot between WCSS and K is shown in Fig. 5. The optimal point of the K is 4, after which the WCSS changes slowly.

In the K-Means algorithm, the four centroid values c1, c2, c3 and c4 are randomly initialized and each data point is assigned to its nearest centre by calculating the Euclidean distance as follows:

$$\mathrm{D}(\mathrm{p},\mathrm{q}) = \sqrt{\left((q1 - p1)^2 + (q2 - p2)\hat{}2\right)} \quad (2)$$

The actual centroid is identified by calculating the average of all points. The initial centroid points are arbitrarily chosen, and new centroid values are updated. These steps continue until any stopping criteria are met, such as the assigned data points in each cluster remaining the same, the newly calculated centroids remaining the same, or any other fixed criterion is satisfied.

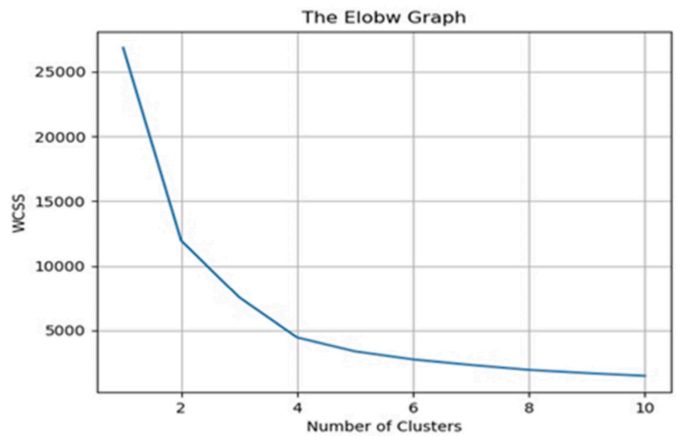

Fig. 5. Elbow plot for K-means clustering.

Based on the elbow plot, the dataset is divided into four cluster groups. Each cluster group is formed depending on each charging point’s previous charging voltage and current values. Using these clusters, the voltage and current nature of each charging point is predicted separately. If most of the charging data set has high voltage and current values, then that charging point is grouped as an excellent cluster. The box plot of the predicted outcome is used for identifying any overlapping between the clusters. The accuracy of the predicted result is evaluated by standard techniques like the Calinski-Harabasz index (CH) [41], Silhouette score (SH) [42], and Davies Bouldin index (DB) [43].

For analysis, we collected the run-time charging data from Trivandrum, Kerala state, India. The collected charging data is in the CSV format on the server. The real-time dataset includes the charging point unique IMEI number, voltage, current, status, and power information. All charging points’ voltage and current values are extracted and stored in separate files.

The dataset values are plotted using a scatter plot for identifying the data distributions and are shown in Fig. 6. The boxplot visualization of the dataset is shown in Fig. 7, which is used for visualizing the distribution of data points. In Fig. 6, voltage values are plotted in X-axis and current values plotted in Y-axis. The voltage and current value are distributed around 225 V to 252 V, and current is between 8A to 16A. From the figures it can be observed that most of the distribution is around 240 to 245 V level in the case-study that is considered of a specific charging station. Similarly, the data distribution of all the charging points are analysed for making the charging point clusters. In

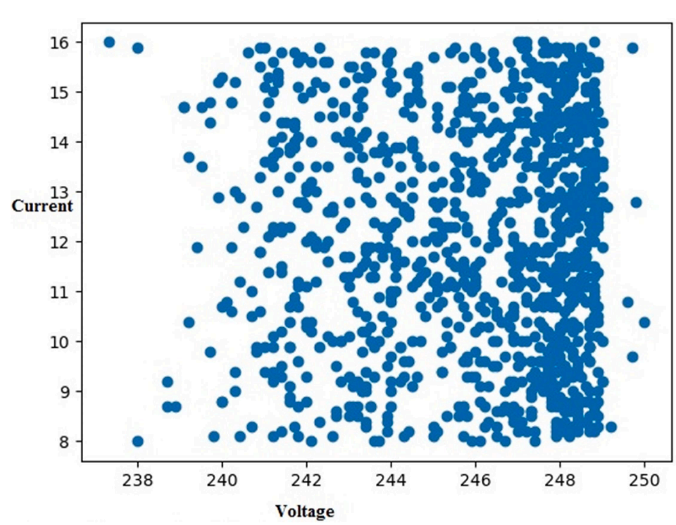

Fig. 6. Dataset values.

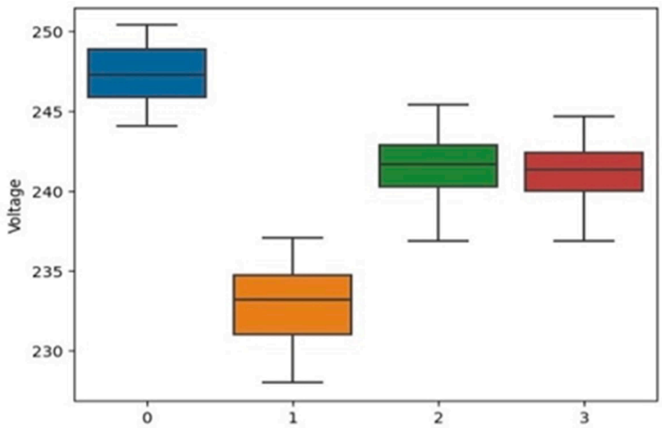

Fig. 7. Boxplot of dataset.

Fig. 7, the box plot visualization is used for analysing the numeric data distribution. For the considered charging dataset, the box plot visualization confirms that the data are symmetrically distributed. The whiskers line is used to represent the variations of the data, and in this case, there are no data distribution available in upper whisker as well as lower whisker of the plot and is the clear indication of no outliers present in the dataset.

The clustering of all the charging points is based on the data distribution in the dataset. The optimal value of clusters is identified using the Elbow plot [44] as $K = 4$. Thus, the charging points are grouped into four categories named excellent, high, medium, and low. By analysing the voltage and current data of charging points in the dataset, the major variations are categorized as four clusters in the format: cluster name (voltage, current). Excellent cluster (245 V and above, 12–16A), high (245 V and above, 8–12A), medium (238–245 V, 12–16A) and low (238–245 V, below 12 A). The predicted results with four clusters are presented in Fig. 8.

Next, we present the evaluation of clustering methods. The CH index measures how similar objects are distributed in the clusters and is shown in Fig. 9. The CH value after plotting shows a cluster number of four for excellent and high clusters, whereas it is not exactly four for the other two clusters. The deviations for low and medium clusters are due to scattering of data points from the centroid [45]. Thus, according to the CH index, the dataset clusters are well and densely separated for a value of four.

The second evaluation is Silhouette score and is used to identify the clustering quality. Fig. 10 shows the Silhouette plot along with its score for the dataset belonging to the excellent category. According to this evaluation index, the Silhouette score will be one if the data clusters are well separated and there is no overlapping between the data in the dataset while clustering. The plot shows that the Silhouette score move towards one and is >0.5. It is a clear indication of dataset clusters being well apart and easily distinguished. Figs. 11A–11C shows the Silhouette score of high, medium and low datasets. In the plot, the different colours indicate the number of clusters. The comparative silhouette plot for all four category datasets, the majority has the highest Silhouette score at cluster number four, and thus it can conclude that each clusters are well apart.

The clustering using the K-Means algorithm applied to one week of charging data of 1100 charging points from Trivandrum, Kerala. From the above real time charging points, more than six hundred thousand data samples are extracted for analysis. The datasets are in the JSON format and each charging point communicates with the server over a period of 30 s. For comparison, we used other clustering methods like density-based [46], distribution-based [47], and other centroid-based models [48]. For density-based models, the DBSCAN algorithm presented in [49] is chosen; for distribution-based, agglomerative [50] and Gaussian mixture models (GMM) [51] are selected; and for centroid-based, K-Medoid is chosen. The charging point clusters within the dataset are created, and the clustering results are evaluated using the CH, SH, and DB score.

The nature of data used in this work is numerical data which are spherically distributed and uniform density in nature with large volume. K-Medoid clustering technique is similar to K-Means but is effective in handling numerical as well as categorical dataset natures. But K-Medoid shows reduced performance while working with large dataset. DBSCAN algorithm operates well on datasets which are irregular in shapes with varying density. GMM does not use a distance measure but applies a probability distribution around the cluster centers to work out the likelihood that whether a data point belongs to a given cluster or not. For agglomerative clustering techniques, the most suitable dataset nature is non-spherical. The nature of the considered dataset is most suited to K-Means clustering algorithm, which gives better accuracies for spherical dataset, with uniform density and large volume. The performance comparison of different algorithms is shown in Table 2 using the evaluation matrices of SH, DB and CH scores. With the help of root mean square error (RMSE) it is verified that K-Means clustering algorithm have better performance when compared to the other algorithms as shown in Fig. 12. Thus, the results confirms that K-Means algorithm outperforms the other algorithms, and the clustering based on K-Means algorithms is appropriate for the chosen dataset.

In many analysis, such as environmental evaluations and predictive modelling; noise in data refers to erratic fluctuations or disruptions that

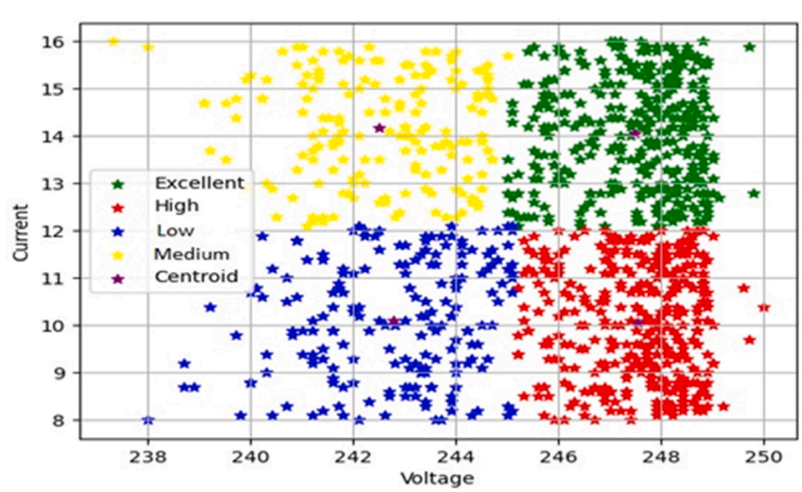

Fig. 8. Clustering of the dataset.

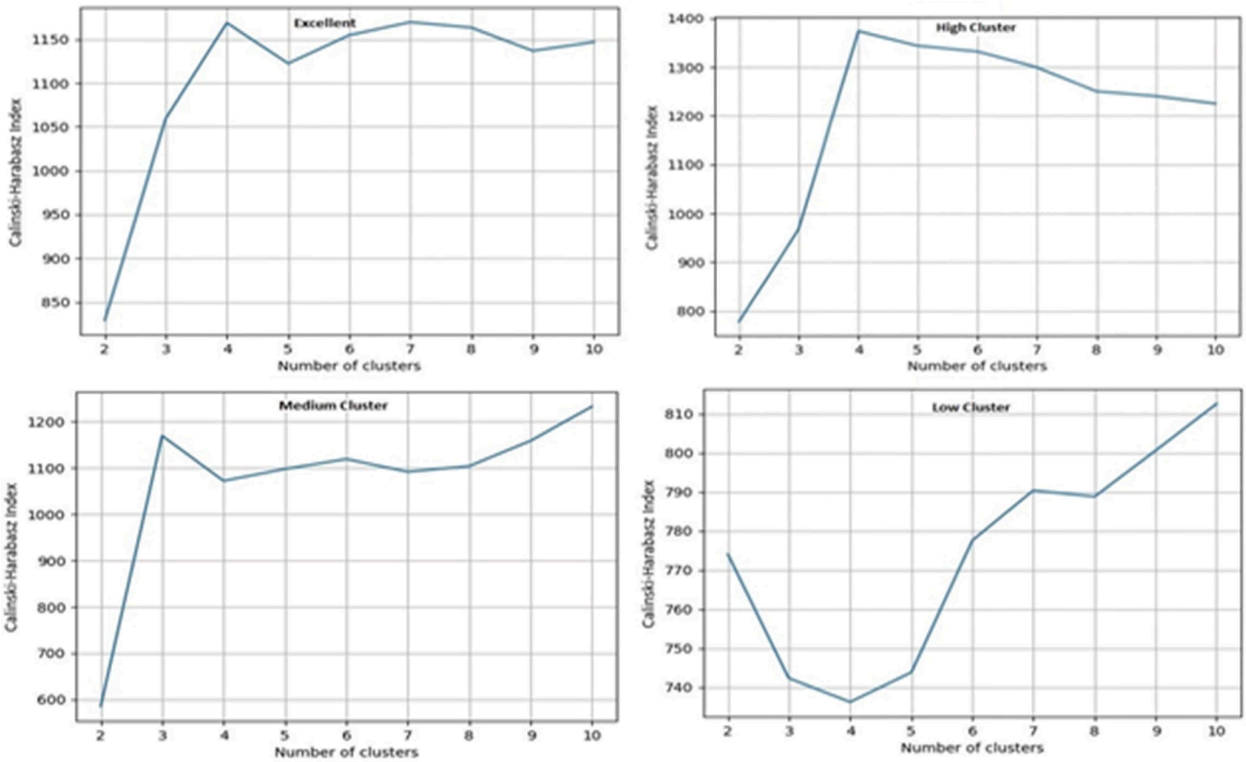

Fig. 9. CH index for all clusters.

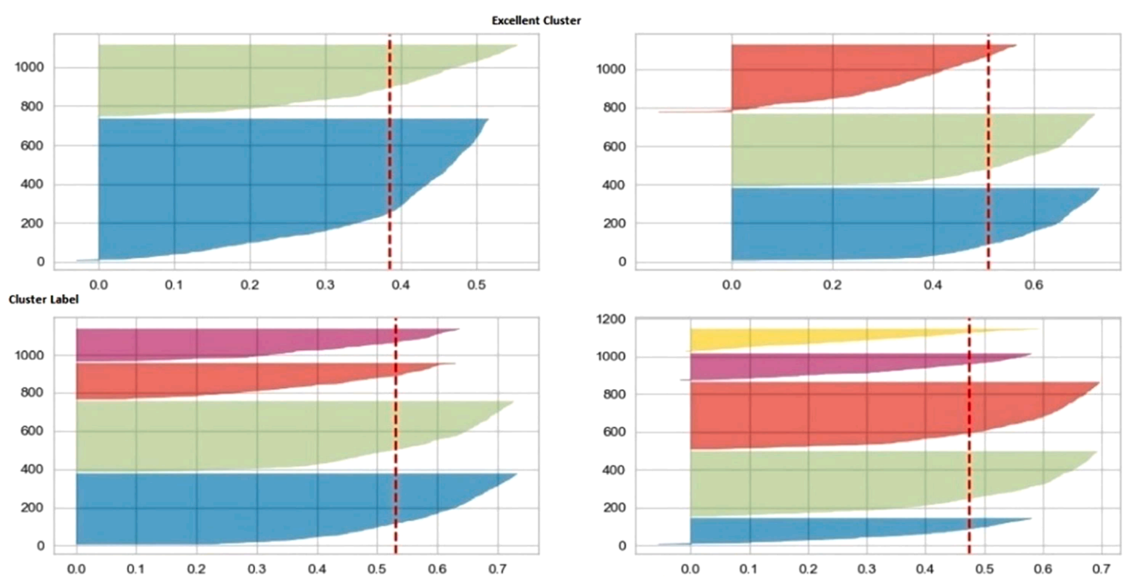

Fig. 10. Silhouette score for excellent dataset.

can mask the real signal and provide incorrect interpretations and conclusions. It is crucial to comprehend and measure noise to enhance data quality and guarantee accurate results. The performance and results of the suggested clustering models in terms of analysing the quality/service of charging points can be greatly impacted by the Z-score, standard deviation and the confidence interval. The statistical metric that shows how far an element deviates from the mean is the Z-score. Incorporating these measurements along with the predictive analytics, the ability of noise quantifying is improved. According to Table 3 the standard deviation and the confidence interval of K-Means algorithm is low compared to the other clustering algorithms. In the charging data-set, the Z-score can be used to find outliers and the value of Z-score for K-Means algorithm is found to be 0.1550. Both measurements exhibit the enhanced performance of K-Means algorithm. By identifying the data fluctuations, through the above indicators, the proposed method makes better suggestion about the recommendation of charging points.

5. Results and discussion

The experimental setup was developed to select 30 charging points

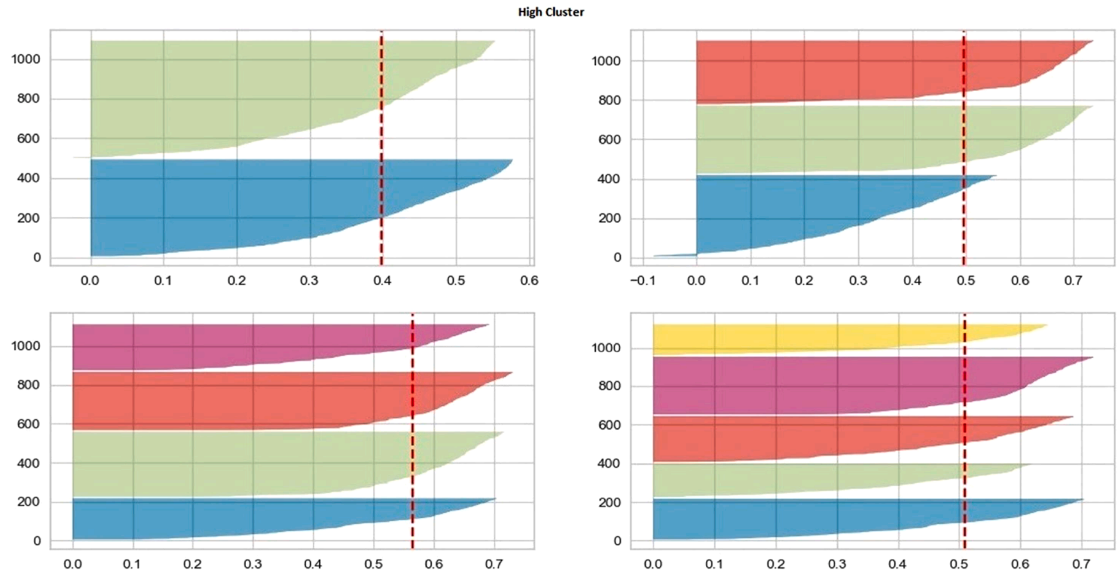

Fig. 11A. Silhouette plot for high cluster datasets.

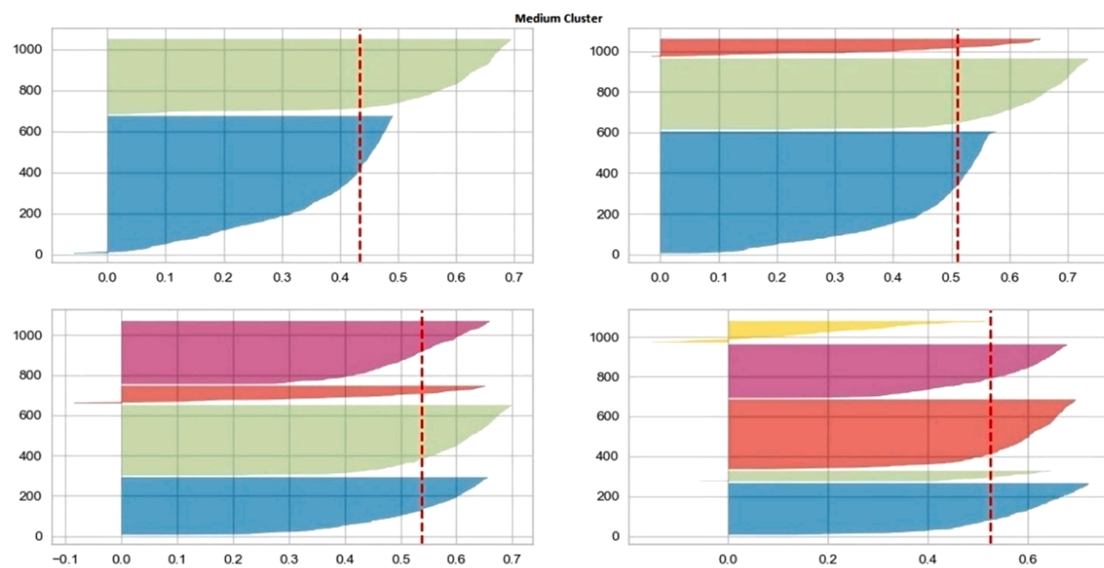

Fig. 11B. Silhouette plot for medium cluster datasets.

from the charging request location within a radius of 25 km. Based on the user requirement, more area can be considered by extending the radius. When an on-demand charging request is received, the framework will satisfy the request using static reservation pool, if any nearby charging points are available. In case of non-availability of a charging point, the framework will run the second stage, i.e. ADDS algorithm. ADDS algorithm considers the charging stability of each charging points ("StabilityCP") data and analyse the road traffic statistics to calculate the time taken by the scheduled vehicle to reach their respective reserved charging points. The "StabilityCP" is calculated based on the voltage and current value of the charging points and groups them as "excellent", "high", "medium" and "low" clusters. The charging points in an excellent cluster are the one with high voltage and current value throughout the service period and exhibit excellent stability. The analysed results are stored in a "TimeofReach" list. The final charging point clusters are formed by considering the internal ("StabilityCP") and external ("TimeofReach") threshold factors. Along with the internal and external threshold factors, energy price per unit is also collected and stored in "PriceCP". The charging points with "faulty" or "active" status are removed from the "StabilityCP" and "TimeofReach" lists before the final clustering.

Once the final data is prepared, with the help of internal and external threshold factors four groups of charging points are prepared by the ADDS algorithm and named it as "group 1″, "group 2″, "group 3″ and "group 4″. The "group 1″ charging point clusters delivers excellent service with sufficient time for charging the vehicle. The second group, "group 2″ offers enough time for charging the vehicle with average charging point stability. The "group 3″ offers better stable service but limited time for charging the vehicle, and the final group "group 4″ offers low service and time for charging the vehicle.

After making the final charging point groups, the "PriceCP" list consisting of the price information of each charging points is tagged with the respective charging points. The attached price per unit tag along with each charging point clearly indicates the current charging price. Using this information, the user can choose the most suitable charging point matching their requirements. This will help the users for selecting

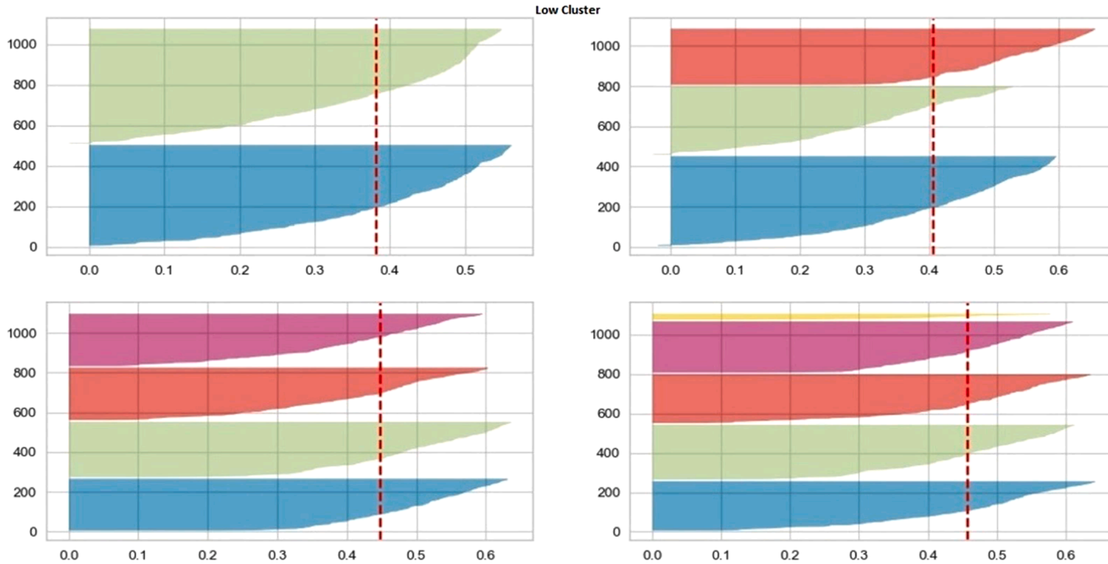

Fig. 11C. Silhouette plot for low cluster datasets.

Table 2
Comparative study with popular algorithms.

Algorithm	CH score	Silhouette score	DB score
DBSCAN	100	0.12	1.78
K-Medoid	850	0.36	0.80
Agglomerative	800	0.36	0.77
GMM	900	0.38	0.81
K-Means	**1200**	**0.45**	**0.74**

low price charging points, with high/moderate stability when there is no emergency demand for charging needs.

The final grouping of charging points based on internal and external threshold factors are shown in Fig. 13. Once the final charging point groups are created, the "PriceCP" is tagged to each charging point and is displayed in the framework. Fig. 14 shows the final charging point groups over the framework. Here, the associated number with each charging point group indicates their group number, and based on user preference, the user can choose the charging points. The final selection of charging point will be updated at the backend pool for further reference and any cancellation of the charging point will be immediately updated at the backend and the charging points are ready for serving the next request.

While evaluating the effectiveness of the proposed work, there are a few potential factors that may impact or biases the results such as:

1. Data quality and integrity – the accuracy of the proposed algorithm is highly correlated with the accuracy of the real-time charging data.
2. In the real context, the EV users may have varying preferences regarding the location of charging points, cost and time. This may lead to increase or decrease the charging demands.
3. The potential factor that affects the effectiveness of the proposed work is the environmental factors. The geographical factors like population density, EV adoption rates, and seasonal variation and climate conditions influence the results of the proposed work.
4. Other external factors like technological advancements like battery efficiency, policy changes by the government and economic factors also may directly or indirectly affect the results.

Table 3
Standard deviation and confidence interval of algorithms.

Algorithm	Standard deviation	Confidence interval
K-Means	0.152	242.55–247.63
GMM	0.170	243.42–248.179
K-Medoid	0.443	242.35–247.62
Agglomerative	0.559	242.25–248.12
DBSCAN	0.277	245.77–246.07

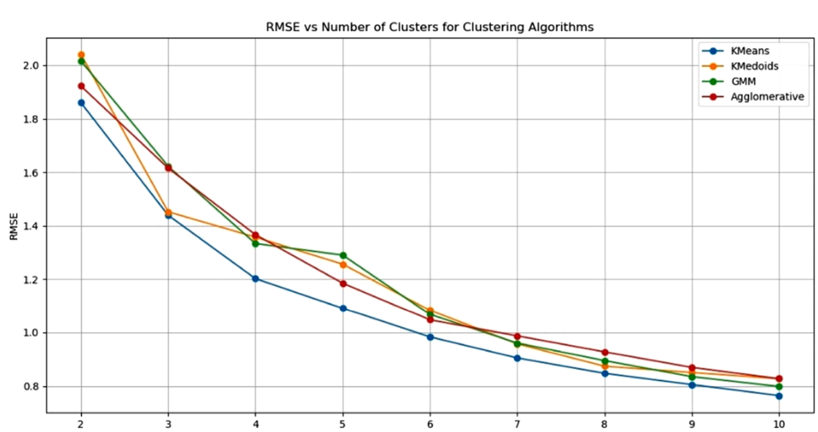

Fig. 12. RMSE plot of different algorithms.

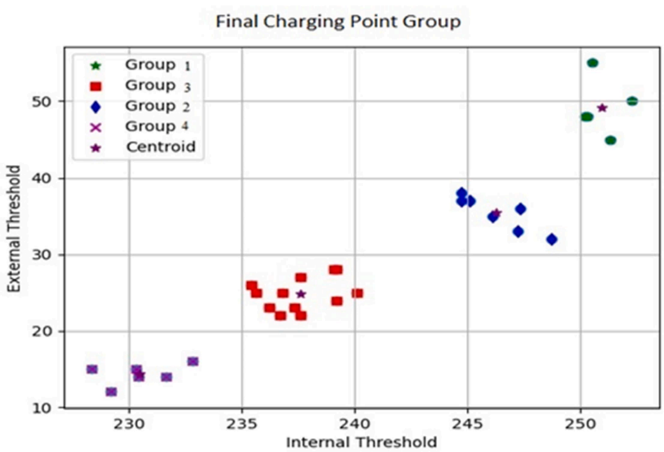

Fig. 13. Final charging point groups.

6. Conclusion

A predictive analytics behaviour finding system was developed to recommend available charging points for dynamic charging requests for electric vehicles. The system incorporated a framework integrated with an optimization, prediction, and clustering algorithm referred to as the advanced dynamic demand scheduling algorithm. The framework efficiently met the charging demands of EV users by optimizing availability of charging points and suggesting suitable options for on-demand requests. The system operated in stages: initially attempting to locate free charging slots using a primary algorithm (static), and if unsuccessful, employing the ADDS algorithm in subsequent stages. The analysis of charging point availability was guaranteed through the K-Means clustering algorithm.

From various perspectives including public, government, charging station operators, and other EV fleet operators, this framework, alongside the ADDS algorithm, facilitates optimal utilization of e-mobility infrastructure. By connecting charging point operators to the framework, we can mitigate the under-utilization issues. Public and fleet operator EV groups can effectively manage their vehicles and businesses by meeting their charging needs. Ultimately, these efforts contribute to building an innovative, eco-friendly, and green society in the future.

The charging point cluster prediction highly depends on the dataset quality. To ensure the quality and data distribution, we used the boxplot for analysing and visualizing the distributions. There are still more factors that can be considered like present climate condition, renewable energy support and the type of scheduled vehicles etc. In future, the proposed framework can be updated by considering all the impactful factors for providing a cutting-edge solution.

The proposed methodology creates opportunities for multidisciplinary study by combining real-time data processing, machine learning, and predictive analytics. To create more thorough models that take user behaviour, infrastructure dynamics, and environmental effects into consideration, future research can investigate the nexus of behavioural economics, data science, and transportation engineering. Policymakers and urban planners can use the knowledge gathered from this work to determine the best locations of EV charging stations based on anticipated demand trends. Cities may improve accessibility, ease port traffic, and encourage broader EV adoption by coordinating infrastructure development with user needs. Operators of charging stations can use the model's insights to create dynamic pricing plans that takes demand into account in real time. By encouraging customers to charge during off-peak hours, this strategy not only maximizes income but also improves customer satisfaction and resource utilization. The results of this study can be used by policymakers to create rules that promote the use of sophisticated scheduling algorithms in EV infrastructure. To improve the prediction accuracy, machine learning strategies like deep learning models or ensemble approaches can be employed. Complex patterns in data that conventional algorithms would overlook can be found using these techniques. With the use of time-series forecasting techniques, charging demand trends can be taken into consideration. By taking historical usage patterns and seasonal variations into account, this can improve projections. Additionally, by collaborating with other EV service providers, the model can gain access to bigger datasets that include a range of customer demographics and geographic locations. This will improve the model's resilience in various situations and that leads to a more sustainable and effective transport environment integrated with cutting-edge technologies.

CRediT authorship contribution statement

Prajeesh C B: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Krishna Priya R:** Writing – review & editing. **Anju S Pillai:** Writing – original draft, Supervision, Methodology. **Ahmed S Khwaja:** Writing – review & editing, Supervision. **Alagan Anpalagan:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial

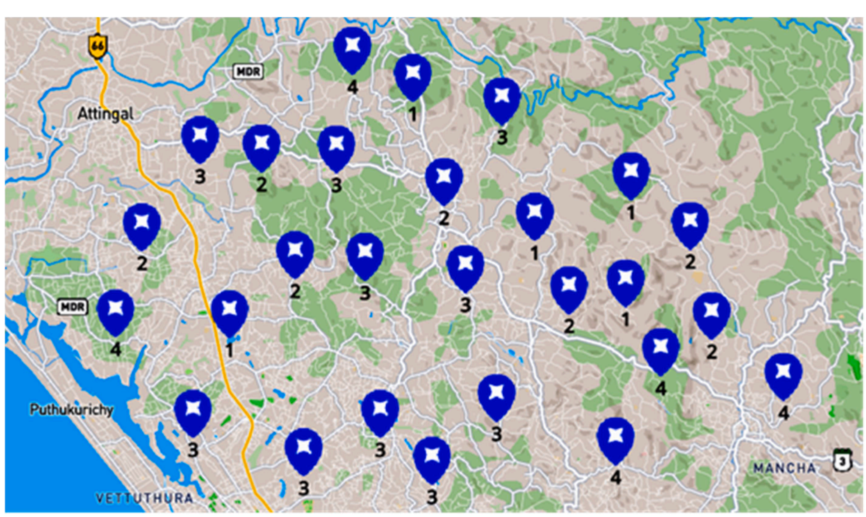

Fig. 14. Charging points with group numbers.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Prajeesh C B is an Assistant Professor in the School of Artificial Intelligence, Amrita Vishwa Vidyapeetham, Coimbatore, India. He has more than ten years of teaching experience. He received his UGC NET in 2018. He worked on a DST-DHI-funded project at Amrita Vishwa Vidyapeetham, India in 2019. Currently, he is doing his Ph.D. at Amrita Vishwa Vidyapeetham, India. His research interests include the development of predictive analytics, embedded solutions to healthcare applications, addressing challenges of electric vehicles, machine learning, and IoT.

Dr Krishna Priya Remamany holds a Ph.D in Electrical Engineering from Kalasalingam Univeristy in 2014. She authored many international journals, published 5 books and received 9 International Patents. Her area of interest lies with medical imaging, control engineering, soft computing, Optimization techniques, sustainability, AI, Data Science, and its applications in multi-disciplinary areas. She received many research grants. She has academic, administrative and research experience for >15 years. She is also a certified in Quality Management Systems, ISO 9001:2015 Quality Lead Auditor. Dr. Priya is currently the Head of Research and Consultancy Department at University of Technology and Applied Sciences, Musandam, Oman.

Dr. Anju S Pillai is an Associate Professor in the Department of Electrical and Electronics Engineering at Amrita Vishwa Vidyapeetham, Coimbatore, India. She received her Ph.D. from Amrita Vishwa Vidyapeetham, India, in 2016. Anju is a recipient of the Chancellor's Collaborative Research Fellowship in 2018 and the EURECA Research Fellowship, funded by the European Commission in 2009. Dr. Anju has published >60 technical articles in scholarly international journals and conferences. Her research interests include developing power-aware embedded systems, data analysis, algorithm development for electric vehicle charging systems and other embedded applications, and broader areas of healthcare and wireless sensor networks.

Dr. Ahmed S. Khwaja (Senior Member, IEEE) received the B.*Sc*. degree in electronic engineering from the Ghulam Ishaq Khan Institute of Engineering Sciences and Technology, Topi, Pakistan, in 2001, and the M.*Sc*. and Ph.D. degrees in signal processing and telecommunications from the University of Rennes 1, Rennes, France, in 2004 and 2008, respectively. He is currently a Senior Research Associate with the WINCORE Laboratory, at Toronto Metropolitan University, Toronto, ON, Canada. His research interests include remote sensing, machine learning, and optimization problems in wireless communication systems and smart grid.

Dr. Alagan Anpalagan Alagan Anpalagan (Senior Member, IEEE) received the B.A.*Sc*. and M.A.*Sc*. degrees in electrical engineering and the Ph.D. degree in electrical engineering in 2001 from the University of Toronto, Toronto, ON, Canada. He joined the ELCE Department, Ryerson University, Toronto, ON, Canada, in 2001, and was promoted to a Full Professor in 2010. He served the department in administrative positions as an Associate Chair, the Program Director of Electrical Engineering, and the Graduate Program Director. Dr. Anpalagan was a recipient of the IEEE Canada J. M. Ham Outstanding Engineering Educator Award in 2018, the YSGS Outstanding Contribution to Graduate Education Award in 2017, the Deans Teaching Award in 2011, and the Faculty Scholastic, Research and Creativity Award thrice from Ryerson University. He served as an Editor for the IEEE Communications Surveys and Tutorials from 2012 to 2014, IEEE Communications Letters from 2010 to 2013, and EURASIP Journal on Wireless Communications and Networking from 2004 to 2009.