Kaunas University of Technology
Faculty of Mechanical Engineering and Design

Improvement of Fast Charging Station Layout and Capacity Planning for Urban Electric Vehicle Networks

Master's Final Degree Project

Kiruthick Roshan Senthil Kumar
Project author

Assoc. Prof. Dr. Antanas Čiuplys
Supervisor

Kaunas, 2026

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Industrial Engineering and Management (6211EX018)

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Assoc. Prof. Dr. Antanas Čiuplys
Supervisor

Assoc. Prof. Dr. Ramūnas Česnavičius
Reviewer

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Kaunas University of Technology

Faculty of Mechanical Engineering and Design

Kiruthick Roshan Senthil Kumar

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Task of the Master's Final Degree Project

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1. Title of the Project

Improvement of Fast Charging Station Layout and Capacity Planning for Urban Electric Vehicle Networks

(In English)

Greitojo įkrovimo stočių išdėstymo ir pajėgumų planavimo tobulinimas miesto elektromobilių tinkluose

(In Lithuanian)

2. Aim and Tasks of the Project

Aim: to improve the location and capacity of fast charging stations in urban area with the help of data-driven machine learning and multi-criteria analysis methods for reducing waiting times and increasing network utilisation efficiency.

Tasks:

1. to develop a machine learning model of demand forecast to predicting hourly EV charging session patterns based on historical station utilisation and session records;
2. to formulate a Multi-Criteria Decision Analysis framework of optimum site choice that incorporates the demands, grid capacity and access of the site;
3. to evaluate the high performance analysis of the improved positioning based on the waiting time, coverage and utilization indicators in comparison with the conventional approaches;
4. to perform investment feasibility analysis like capital expenditure, estimation of revenue and break even analysis.

3. Main Requirements and Conditions

EV charging station placement achieving ≥15% waiting time reduction and ≥12% utilization improvement using ML model and MCDA framework

Project author	Kiruthick Roshan Senthil Kumar		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*
Supervisor	Antanas Čiuplys		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*
Head of study field programs	Regita Bendikienė		02-03-2026
	(Name, Surname)	*(Signature)*	*(Date)*

Kiruthick Roshan Senthil Kumar. Improvement of Fast Charging Station Layout and Capacity Planning for Urban Electric Vehicle Networks. Master's Final Degree Project, supervisor Assoc. Prof. Dr. Antanas Čiuplys; Faculty of Mechanical Engineering and Design, Kaunas University of Technology.

Study field and area (study field group): Production and Manufacturing Engineering (E10), Engineering Sciences (E).

Keywords: electric vehicle charging; demand forecasting; multi-criteria decision analysis; fast charging station placement; XGBoost; Bengaluru.

Kaunas, 2026. 51 p.

Summary

The improvement of fast charging station layout and capacity planning for urban electric vehicle networks in Bengaluru, India was investigated using data-driven machine learning and multi-criteria decision analysis methods. A synthetic electric vehicle session dataset of 456,744 records was generated for the period 2023 to 2024, with generation parameters calibrated from four peer-reviewed sources. Three machine learning models were trained, validated, and compared on an hourly demand time series: XGBoost with Tweedie loss, a two-layer Long Short-Term Memory network, and Facebook Prophet. XGBoost was selected as the production forecasting model based on a test set Root Mean Square Error of 132.27 kWh and a coefficient of determination of 0.9411. A four-criteria Multi-Criteria Decision Analysis framework was formulated using the Analytic Hierarchy Process, incorporating demand intensity, grid connection capacity, user accessibility, and land use compatibility. The framework was applied to 20 candidate sites across Bengaluru, and a ranked list of ten optimal deployment locations was produced, with Whitefield IT Corridor identified as the highest-scoring site. Performance was evaluated using the M/M/c queuing model under two comparative scenarios. Average user waiting time was reduced from 13.23 minutes to 3.46 minutes, representing a 73.8 percent reduction exceeding the project target of 15 percent. The probability of waiting was reduced from 31.7 percent to 10.6 percent. Spatial coverage was doubled from 10.1 percent to 20.2 percent of the study area. A total capital expenditure of Indian Rupee 76.5 million was established for 17 new Direct current(DC) fast chargers, with a payback period of 7.4 years under standard conditions and 4.4 years under the PM E-DRIVE subsidy scheme.

Kiruthick Roshan Senthil Kumar. Greitojo įkrovimo stočių išdėstymo ir pajėgumų planavimo tobulinimas miesto elektromobilių tinkluose. Magistro baigiamasis projektas, vadovas doc. dr. Antanas Čiuplys; Kauno technologijos universitetas, Mechanikos inžinerijos ir dizaino fakultetas.

Studijų kryptis ir sritis (studijų krypčių grupė): Gamybos inžinerija (E10), Inžinerijos mokslai (E).

Reikšminiai žodžiai: elektromobilių įkrovimas; paklausos prognozavimas; daugiakriterinė sprendimų analizė; greitojo įkrovimo stotelių išdėstymas; XGBoost; Bengaluru.

Kaunas, 2026. 51 p.

Santrauka

Greitojo įkrovimo stočių išdėstymo ir pajėgumų planavimo gerinimas miesto elektromobilių tinkluose Bengaluru mieste, Indijoje, buvo tiriamas naudojant duomenimis pagrįstus mašininio mokymosi ir daugiakriterinės sprendimų analizės metodus. Sintetinis elektromobilių sesijų duomenų rinkinys, apimantis 456 744 įrašus 2023–2024 metų laikotarpiui, buvo sugeneruotas, o generavimo parametrai buvo kalibruoti remiantis keturiais recenzuojamais šaltiniais. Trys mašininio mokymosi modeliai buvo apmokyti, patikrinti ir palyginti valandinėje paklausos laiko eilutėje: XGBoost su Tweedie nuostolių funkcija, dviejų sluoksnių ilgosios trumpalaikės atminties tinklas ir Facebook Prophet. XGBoost buvo pasirinktas kaip pagrindinis prognozavimo modelis, pasiekęs žemiausią vidutinę kvadratinę paklaidą — 132,27 kWh — ir aukščiausią determinacijos koeficientą — 0,9411. Keturių kriterijų daugiakriterinės sprendimų analizės modelis buvo suformuluotas taikant analizės hierarchijos procesą kriterijų svorių nustatymui, įtraukiant paklausos intensyvumą, tinklo pajėgumą, prieinamumą ir žemės naudojimo suderinamumą. Modelis buvo pritaikytas 20 kandidatų vietų Bengaluru mieste, ir dešimties optimalių vietų sąrašas buvo gautas, o Whitefield IT koridorius identifikuotas kaip aukščiausiai įvertinta vieta. Našumas buvo įvertintas naudojant M/M/c eilių teorijos modelį pagal du lyginamuosius scenarijus. Vidutinis naudotojo laukimo laikas buvo sumažintas nuo 13,23 iki 3,46 minutės, tai yra 73,8 procento sumažėjimas, viršijantis 15 procentų projekto tikslą. Laukimo tikimybė buvo sumažinta nuo 31,7 iki 10,6 procento. Erdvinė aprėptis buvo padvigubinta nuo 10,1 iki 20,2 procento tyrimo srities. Bendros kapitalo išlaidos 17 naujų nuolatinės srovės greito įkrovimo įrenginių sudarė 76,5 mln. INR, o atsipirkimo laikotarpis — 7,4 metų standartinėmis sąlygomis ir 4,4 metų pagal PM E-DRIVE subsidiją..

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List of Abbreviations and Terms

Abbreviations:

AC — Alternating Current
AHP — Analytic Hierarchy Process
BESCOM — Bangalore Electricity Supply Company
CAPEX — Capital Expenditure
CI — Consistency Index
CR — Consistency Ratio
DC — Direct Current
DCFC — Direct Current Fast Charging
DQN — Deep Q-Network
EDA — Exploratory Data Analysis
EESL — Energy Efficiency Services Limited
EV — Electric Vehicle
EVCS — Electric Vehicle Charging Station
FAME — Faster Adoption and Manufacturing of Electric Vehicles
GIS — Geographic Information System
ICE — Internal Combustion Engine
IEA — International Energy Agency
INR — Indian Rupee
KPI — Key Performance Indicator
LSTM — Long Short-Term Memory
MAPE — Mean Absolute Percentage Error
MCDA — Multi-Criteria Decision Analysis
ML — Machine Learning
NPV — Net Present Value
OPEX — Operational Expenditure
RI — Random Index
RMSE — Root Mean Square Error
UPI — Unified Payments Interface
VIKOR — Visekriterijumska Optimizacija I Kompromisno Resenje
XGBoost — Extreme Gradient Boosting

Terms:

Charge anxiety — The apprehension experienced by electric vehicle users related to charger availability, reliability, and waiting time, distinct from range anxiety which concerns vehicle range sufficiency.

Erlang C formula — An analytical queuing theory formula that computes the probability that an arriving customer must wait for service in a multi-server queuing system with Poisson arrivals and exponential service times.

Poisson process — A stochastic process in which events occur independently at a constant average rate, used in this study to model the arrival of charging sessions at each station.

Synthetic dataset — A dataset generated through statistical simulation using parameters calibrated from peer-reviewed sources, used in this study as a substitute for unavailable real Indian EV session data.

Tweedie distribution — A family of probability distributions that includes the Poisson and Gamma distributions as special cases, used in this study as the loss function for XGBoost to handle the non-negative right-skewed EV charging demand series.

Introduction

Urban infrastructure demands for mobility have changed significantly as a result of the global shift towards electric mobility. The number of Electric Vehicles(EVs) in the market has grown to over 40 million units globally by the end of 2023, over triple the 2020 count [1]. India has caught up at a fast pace thereafter, with its eV sales increasing to 1.66 million units in 2023 to 2024, and the government's aspiration to achieve a 30 per cent EV market share by 2030 requiring 1.32 million public charging stations (PCs) [2].As of 2025, Karnataka tops the list of Indian states in terms of the amount of stations, exceeding 5,880 stations with Bengaluru contributing to around 85 percent of these is the table above [2].. However, the clustering of existing stations does little to mirror the needs for charging, and the majority of stations are for alternating current slow charging, an area where the city is especially under-resourced where urban commuters need a fast charging service the most.Traditional siting strategies which focus on area coverage on-site tend to miss out on spatial and temporal demand dynamics [3] and commonly result in simultaneous under-use in locations that lack demand and in heavy congestion of locations with high demand [4]. These inefficiencies need to be taken care of by taking a data-driven approach, with integrated demand forecasting, multi-criteria site evaluation and Quantitative Performance validation in one solution.Gradient boosted models (GBM) and long short-term memory networks (LSTM) have shown very encouraging predictive capabilities on sparse charging time series [5]. The hybrid models based on Analytic Hierarchy Process (AHP) and spatial scoring have been found to be more efficient than models based on only one criterion [6]. However, published siting studies always provide ranked lists of candidates, with no validation of the added value of the improvements compared to the conventional baseline strategies [7]. This project directly fills that gap.This study combines machine learning demand forecasting on a synthetic dataset of 456,744 session records that was carefully designed using the authors' expertise as researchers, with multi-criteria decision analysis for site selection; this decision model takes into account demand intensity, grid capacity, accessibility, and land use compatibility, and performance evaluation using a machine learning model that incorporated the M/M/c queuing model; and finally, an investment feasibility analysis was conducted on both standard and subsidy-supported conditions.

Aim: to improve the location and capacity of fast charging stations in urban area with the help of data-driven machine learning and multi-criteria analysis methods for reducing waiting times and increasing network utilisation efficiency.
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Hypothesis: Machine learning-based demand forecasting and multi-criteria analysis of the data can be utilised to estimate the station location and decrease the average user waiting time.

1. Urban EV Fast Charging Infrastructure and Optimisation

1.1. Growth and Structural Challenges of Urban EV Charging Infrastructure

In the last five years, there has been a significant rise in the scale of Electric Vehicle investment and infrastructure requirements in all major economies. The number of charging points for public use in the world reached more than 1.0 million in 2019 up to more than 2.7 million by the end of 2022, with over 900,000 new charging points added in 2022—a 55 percent increase over the previous stock of publicly available charging points, according to the International Energy Agency (IEA) [1]. Geographically this growth has been concentrated, with almost 90 percent of all fast chargers added globally in 2022 coming from China, with the Netherlands, France, and Germany the leading slow charger operators in terms of registrations in Europe [1]. By the same time, the United States had 28,000 fast chargers installed overall, which is still small compared to projections of demand in 2030.

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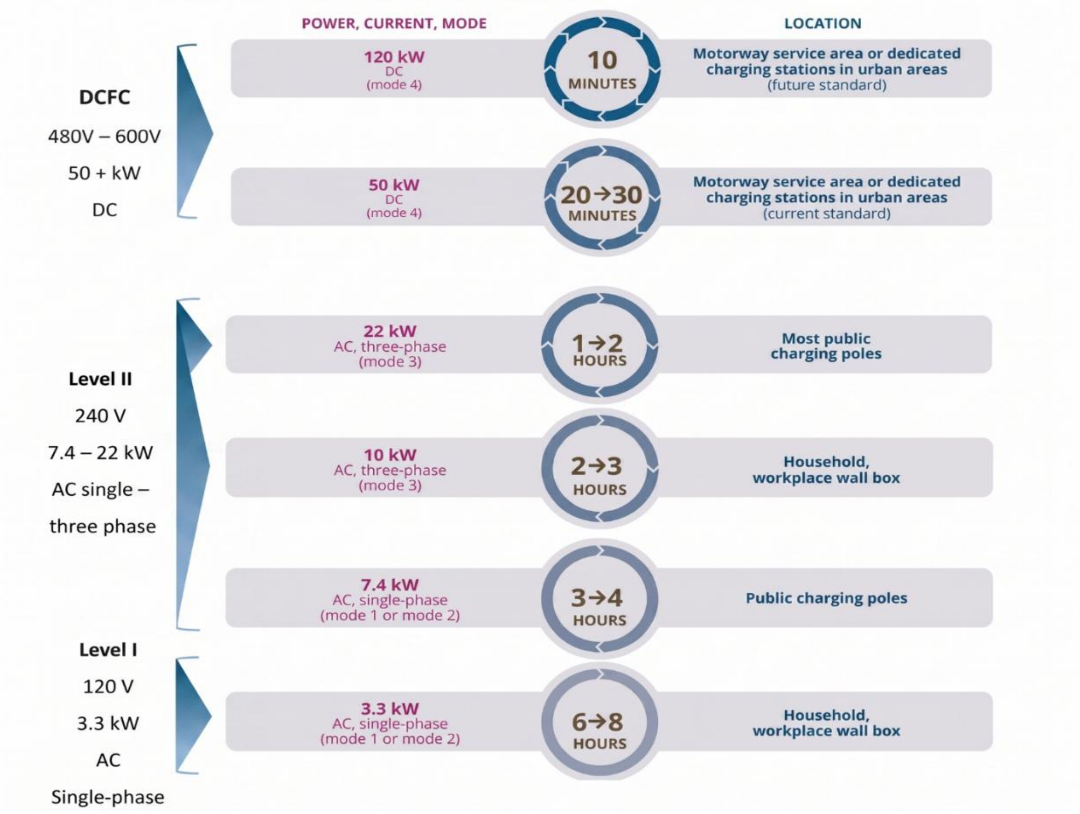

Fig. 1. Charging Rating Comparison Across Power Levels, Charging Time And Deployment Location [8]

India's growth, albeit from a lower base, has displayed what could be a trend of increasing pace and thus an urgent need for infrastructure planning that is structurally more complicated. In 2024, India saw a rise in electric vehicle (EV) sales, reaching 15.2 lakh units, which is over two decades more than what was sold in 2020 (0.72 lakh) [2]. The public charging segment in Karnataka is the largest by state in India, with 5,880 charging stations available in 2025, which takes into account the state's progressive policy regime coupled with a technology hub being Bengaluru [2]. But the ratio of EVs to chargers remains critical, which is currently 1:235 in India, while the internationally recommended ratio is 1:20 [2]. This deficiency is especially strong in the "fast charging" segment for direct current (DC), a crucial factor for urban commuters needing fast energy recharge during limited time windows. Thus, introducing fast charging that leverages the power of a Direct Current (DC) electricity circuit, as shown in Figure 1, allow charging in 20 to 30 minutes versus 3 to 8 hours for

Level I AC charging (using any electric circuit) and 1 to 2 hours for Level II AC charging (using a higher quality electric circuit) thereby confirming that only fast charging with Direct Current can realistically serve time-constrained urban commuters [8].

This mismatch is not peculiar to India, as it is also seen across the globe when it comes to the placement of charging infrastructure. Mohammed et al. conducted a systematic review of existing techniques and approaches, which are mostly conventional ones based on location or administration, and found that they continually yield sub-optimal user performance results [3]. Without considering intensity of demand, stations have been placed in a way such that during off-peak period the utilisation rate ranges between 18 to 35%, and queues are formed for over 20 mins in the morning hours and evening peak periods in high density urban areas [3]. This oft-mentioned underutilisation and hotspot behaviour makes it hard for users to believe that EVs are sufficiently safe to increase their confidence in the technologies, which is vital for continuing EV uptake.

Documenting charging demand on a large scale with spatial concentration in urban areas has been achieved in the empirical study by Liu et al. using charging and driving behaviour of 1.6 million EVs in seven major cities in China, which represents more than 854 million interactions [4]. The study found that high power charging in the day time produces high peaks in urban commercial and transit corridors, with the greatest concentrations of service oriented vehicles such as bus, taxis and rental cars. Most importantly, this spatial concentration of load was not compatible with the spatial distribution of the charging infrastructure that is already available in all urban areas studied, highlighting a critical progettual mismatch that the authors deemed directly translatable to the South Asian urban space.South Asian metropolitan urban charging ecosystems also show this disconnect as charging stations are largely built along existing commercial corridors and not according to the demand for them [3, 4].

Planning Direct Current (DC) fast chargers from a grid integration point of view can create concentrated point loads on distribution networks, requiring costly strengthening works at substations. Kumar et al. used a hybrid GA model and simulated annealing to show that capacity decisions can be made in conjunction with siting decisions, which can save up to 22 percent of the costs of grid reinforcement, compared to sequential capacity decisions made following an initial siting decision [9]. This discovery became a directCall-to-Action for the present study that leads towards the inclusion of grid connection capacity as an explicit criteria in the Multi-Criteria Decision Analysis framework.

Range anxiety — which occurs when a car's range isn't enough to reach the desired destination — has consistently been one of the biggest objections to electric vehicles put forward by potential future buyers. Through six decades of studies covering 62 literature reviews on range anxiety, Rainieri et al. concluded that the perceived density and reliability of fast charging infrastructure have a statistical significant impact on the purchase intention, without taking into consideration the range capability of current available vehicles [10]. Further work was done by Ovchinnikov et al. to elucidate the current situation and the researchers observed a shift from range anxiety to charge anxiety (a series of concerns) for stakeholders of the contemporary EV market, which focuses on charger reliability, software compatibility, convenience of location, waiting time, etc. [11]. An approach to relieve charge anxiety, such as reduction of average waiting time as has been attempted within this project, directly targets the part that is easiest to tackle operationally. As indicated in Figure 2, range anxiety can be conceptualized on a multi-dimensional level across psychological, human factors and socio-technical frameworks, and the availability of charging infrastructure and proximity to charging stations are a few of the main socio-technical factors that have a direct effect on the range anxiety faced by EV drivers [10].

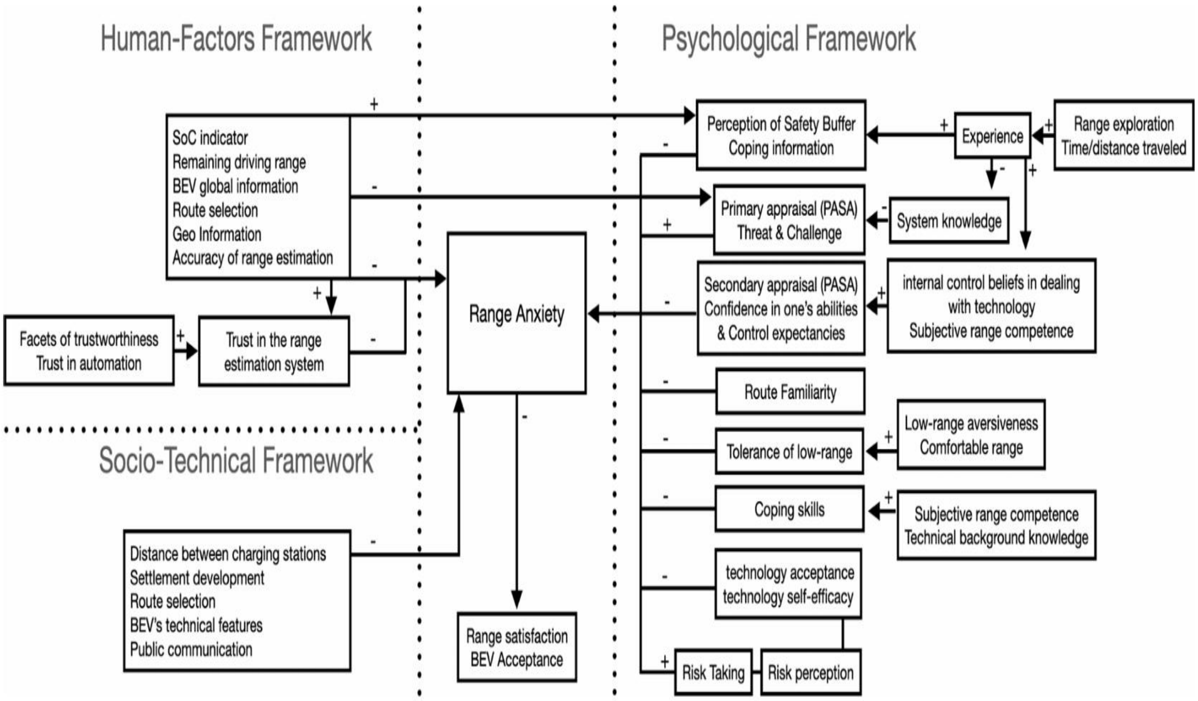

Fig. 2. Variables Antecedent To Range Anxiety Across Psychological, Human-Factors And Socio-Technical Frameworks [10]

1.2. Machine Learning Approaches to EV Charging Demand Prediction

Therefore, any realistic plan for the sizing and placement of charging stations depends on predicting charging demand for EVs. Existing "business as usual" models relying on constant traffic figure and rule-of-thumb demand multipliers have been proven to be insufficient to address the spatial and temporal character of charging behaviour in cities [5]. For the last 4 years, machine learning and deep learning algorithms have emerged as the leading modelling approach, which has been capable of extracting patterns from big heterogeneous datasets where classical statistical tools are not applicable.

Unsupervised spatial clustering methods, such as k-means and modified versions have been widely used to identify zones of varying charging demand in urban areas. Based on a systematic review of the literature of 74 studies between 2010 and 2023 that included some method of zoning for charging demand in cities using the geographic information system (GIS) based approaches, clustering was the most common method used amongst all the selected studies [12]. K-means clusters geographic regions according to the number of passengers, volumes of traffic flows, distance to points of interest, and past session data, and returns the demands at a zone level, which is directly used in the capacity specification of stations. The zone-level demand intensity scores generated by clustering techniques can be directly applied in the following site selection frameworks as inputs to the capacities of the stations [12].

There are several supervised learning and sequence modelling architectures that have been evaluated in the literature for temporal demand forecasting. Koohfar et al. proposed a deep learning model based on transformer architecture that was trained using the previous charging session records, weather, and traffic variables, resulting in a mean absolute percentage error of (MAPE) 6.8 percent over a North American urban charging network for 24 hour-ahead demand prediction [13]. The self attention mechanism used in the transformer architecture has proved to be increasingly to conciliate the distinction between the demand on weekdays and weekends and the seasonal differences. These set of patterns were also clearly found in the exploratory analysis of the Bengaluru data set, where sessions conducted on weekdays compared to weekends had an empirical ratio of 4.5:1, confirmed by Koohfar et al.

Long Short-Term Memory networks (LSTMs) have been employed in EV charging demand forecasting due to their ability of selectable memory using gated Memory cells where the content can be stored or discarded over long time horizons. Zhu showed that the demand forecasting model based on LSTM-enhanced the demand prediction accuracy by 12.3 percent compared with the autoregressive demand forecasting model, while the other model based on LSTM demand forecasting and Deep Q-Network optimisation reduced the imbalance between supply and demand by 8.9 percent [14]. These results directly affected the choice of LSTM as one of the 3 candidates models for testing in the current study. The gated architecture of LSTM networks is especially appealing for series of urban charging demands, which can have strong periodicities on a daily and weekly basis as well as on-off periods of zero demands [14].

The latest methodological horizon is spatiotemporal models where both the geographical and temporal structure are used. To systematically compare prediction architectures, an open-source benchmark dataset, UrbanEV, was introduced by Guo et al. from a total of over 20,000 charging points spanning over six months in Shenzhen [15]. The benchmark showed a performance increase of 14-18 percent over Root Mean Square Error for spatiotemporal graph convolutional networks compared to purely temporal counterparts, but the authors cautioned that despite graph-based models beating more simple temporal models, their utility comes with significantly more data and computational complexity, so some simpler data-constrained models like gradient boosting appear more appropriate.

Lin et al. used an ARIMA model, k-means clustering and spatial regression to simulate the spatiotemporal charging need in various cities, and found multi-core patterns of spatial needs in the vicinity of commercial centres, transport centres and a cluster of workplaces [16]. This spatial demand structure is directly similar to the zone-level productions established on the basis of Bengaluru's session data, and guided the geographic distribution of the candidate sites in the geographic structure of the present study's MCDA.The choice of forecasting model should be informed by the data infrastructure in place, and the desired operational context for the application. In a comprehensive survey of electric vehicle charging demand forecasting techniques, Rashid et al. argued that gradient boosting models and LSTM networks are the most consistently top-performing architectures that can be used on varying urban charging datasets [5].

In this work, a model selection protocol was applied wrapping the evidence based methods with XGBoost and Tweedie loss, a two-layer LSTM network and decomposing the model using Facebook Prophet as the decomposition baseline, to test on a held-out test set. Rashid et al. [5] argue that evidence based model selection protocols for which multiple alternative model architectures are tested with held-out test sets should be considered best practice for energy demand forecasting applications.

1.3. Multi-Criteria Decision Analysis for Charging Station Site Selection

Determination of the best places to locate urban fast charging stations is a naturally a multi-criteria problem. Any feasible siting decision will need to balance a set of incommensurable factors, such as charging demand intensity forecasts, electrical grid availability and capacity, user access based on likely detour distance and land-use compatibility and planning permissions [17]. This multi dimensional complexity cannot be captured in only one metric and purely algorithmic optimization using one single objective (e.g., total travel distance) always results in technically feasible siting outcomes that may not be operationally or economically optimal with regard to the entire set of infrastructure performance metrics.

Incorporating incommensurable criteria in a composite site score, based on the importance of each dimension identified by domain experts and evidence from the literature, is as difficult as it is to interpret the results.To enable a composite site score that incorporates incommensurable criteria, using the relative importance of these criteria identified by domain experts and literature evidence, is as challenging as the interpretation of such scores is difficult. MCDA has been used in the literature on EV charging infrastructure in a number of variants. The best known criteria weighting techniques are the Analytic Hierarchy Process (AHP), and its fuzzy counterpart, where experts in the field make pair-wise comparisons on a universalized 9-point scale [6].

For ranking of the candidate sites against the normalised performance matrix the Technique for Order of Preference by Similarity to Ideal Solution and VIKOR are well known in use. Banegas and Mamkhezri noted that the use of disjunctions of demand-zone clustering outputs and MCDA site-scoring has gained acceptance as good practice; that is, restricting the search space of candidates to zones where the demand is high and afterwards using multi-criteria evaluation within those zones [12].Mhana and Awad used AHP in conjunction with geographic information system spatial analysis to obtain optimal charging station locations in a mid-sized urban setting based on 8 criteria such as distance to the demand, availability of grid capacity, road accessibility index, land use compatibility, ecological sensitivity, safety hazard area, user walking distance and grid connection capital cost [6].

Their joint model performed better than the single-criterion one based on the distance on all of the networks performance measures examined such as the network average user access time and the station revenue per installed Kilowatt. In the present study a four-criteria model (namely demand intensity, grid connection capacity, user accessibility and land use compatibility) was used, which was calibrated with the AHP weight distributions reported by Mhana and Awad and the consistency ratio was calculated to be 0.0054 and fall below the accepted value of 0.10.

Chumbi and Franco have designed a Fuzzy TOPSIS model by specially considering capacity constraint of the substations, and adapted this model for charging station site selection [17]. Their analysis showed that, if the grid capacity on the location is not considered during the siting stage, the siting strategy is not able to gain the cost of the siting. This gap is bridged as part of the present study as another top priority criterion, ‘Grid connection capacity’, was introduced with a weight of 0.2718 in the composite scoring model based on the AHP pairwise comparison.

User accessibility has been quantified in the literature on MCDA for a composite of the detour distance of vehicles and pedestrian proximity to public transport interchange. By means of Bayesian optimisation and agent-based demand simulation, Liu et al. showed that using a strategy that gets stations closer to the place where drivers need to detour leads to 50% to 100% higher patronage and revenue compared with non-accessibility oriented strategies for positioning stations [18]. This was a direct incentive to incorporate a user accessibility criterion into a composite measure of vehicular accessibility and proximity to public transport nodes in the MCDA model in the present study.

In 2015, Guerrero-Silva et. al. performed a systematic review that collected the outcomes of the latest 89 studies related to obtaining the SI CF, where the use of machine learning (ML) and multi-criteria decision analysis (MCDA) in an integrated manner is the most promising methodological path [7]. Importantly, the review revealed that none of the analyzed MCDA models would validate location recommendations by measuring their performance with simulation compared to a traditional baseline, a key point addressed by the current study by implementing the locational comparative-evaluation based on M/M/c queuing theory, as described in Chapter 3.

1.4. Performance Evaluation and Investment Feasibility of Fast Charging Networks

To fully evaluate the deployment of charging stations, the demand modelling and site selection are incomplete and need to be complemented with quantitative assessment of the network performance and economics. The two dimensions are coupled: a deployment that reduces the average time users must wait to charge an EV might not be the deployment that generates highest revenues; and the capital deployment cost to realise a desired electric vehicle service quality target may vary significantly depending on the type of power ratings, number of chargers and grid connection policies used [3].

The KPIs used are uniformised for evaluating the charging network. The most frequently mentioned user waiting time is average user waiting time, which is the expected waiting time from the driver arriving at the stations until the start of charging, user experience and users' confidence with adopting the service are directly correlated with average waiting time [4]. Station utilisation rate is the key factor for deployment of charging stations when modelling revenue flow and is defined as the percentage of installed charging stations that are actually used during hours of operation. Spatial coverage, which is usually rooted in the fraction of an urban area or of the population of interest that is at least within one access radius of a charging point, quantifies the equity of access distribution [4].

Usually, the waiting time and the utilisation is estimated before the real implementation using the M/M/c queuing system with exponentially distributed service times and Poisson arrival processes for multiple parallel queues [3]. Additionally, Pourvaziri et al. proved that jointly optimising location and capacity by combining deep learning demand prediction with queuing theory capacity management led to better outcomes from simultaneous cost of establishment and average customer waiting time minimisation when compared to sequential approaches [19]. We use the M/M/c analytical framework for the present study and calculate the arrival rates and service parameters from the Bengaluru synthetic data, which under-estimates the performance gains that can be achieved under the MCDA optimised deployment.

When analysing the economics of the investment of fast charging stations, the specific cost structure of direct charging equipment as well as the dependence of revenue estimates on considerations of demand must be taken into account. The complexity of the electric vehicle charging service market, shown in the figure below, provides various interdependent functions along the value chain—i.e. manufacturing, installation & development, network operation, sales & marketing—which are each significant components to the cost and revenue side of a charging infrastructure deployment [8].

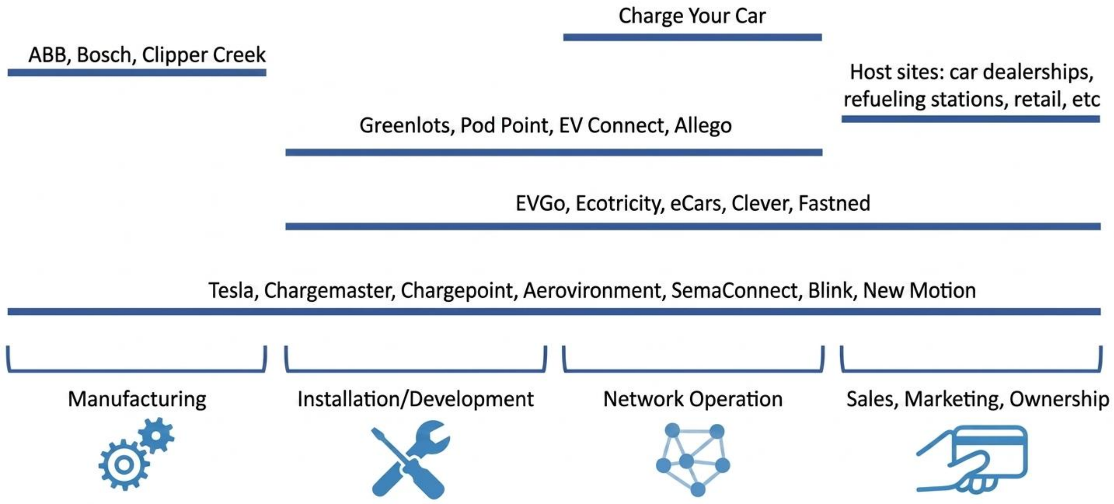

Fig. 3. Key Functions In The Electric Vehicle Charging Service Value Chain [2]

The major portion of the capital costs in DCFC is hardware and grid connectivity costs, which were estimated at INR 25 lakh – INR 45 lakh per charging station in recent studies conducted in India based on power rating and complexity of the grid connection [3]. Operation costs comprise electricity procurement fees, maintenance fees, network management fees and the like. The non-linear nature of the relationship between revenue and station utilisation also makes break-even analysis highly sensitive to the assumptions made on demand as the stations in the Indian operating environment generate a lower revenue while operating at less than 15 to 20 percent of their nameplate capacity [9].

Golsefidi et al. developed a holistic strategy for sequentially adding electric vehicle charging stations to the existing transportation network, using an integrated machine learning and optimisation approach, and showed that a demand-informed strategy with sequential investment on financial performance measures always outperforms the coverage maximising strategies over the long term [20]. This finding allowed the current study to adopt the method of allocating chargers based on a demand-proportional MCDA scoring method, as opposed to a one-size-fits-all approach for all the chargers selected. Combination with an integrated routing and charging coordination model, Zanetti et al. showed that, under a large set of simulated demand conditions, the average queuing times obtained with the demand-informed configuration is significantly lower than the average queuing times obtained with a uniform configuration, as well as the revenues per unit of grid capacity associated to the uniform configuration [21].

1.5. Novelty of the Research

The present study presents new scientific contents in three aspects, each of which is presented separately. Second, it involves a combined machine learning-MCDA approach applied to an urban charging network of Bengaluru; our study is one of the first data-driven, quantitative localized approaches to site selection for an Indian context. Rashmitha et al. and Gulzar et al. have analysed the challenges of EV charging infrastructure in India in a general sense [2, 22] but neither of these studies has resulted in an approach for simulating and validated ranking different locations for deployment based on real charging demand data. Second, the present study fills a gap in the methodology as pointed out by Guerrero-Silva et al., by comparing, at the same urban network and with the same set of demand parameters, the performance of the deployment optimised using MCDA and that of a conventional distance-based deployment [7]. Third, the study proposes a synthetic data generation methodology that can be fully reproduced, and provides all the 20 parameters required for generation, pointed to specific literature reference that has passed peer review for their validation and facts, since there is no publicly available data from charging operators at the charging session level.

1.6. Chapter Summary

The methodological choices made throughout the project are informed by the situation analysis that was undertaken in this chapter, which also provides the evidential basis for the research context. Both the global and local EV charging infrastructure landscape shows significant quantitative growth and qualitative misfit between station location and demand, where Bengaluru with 89 verified stations has a huge gap as most charging stations are concentrated in the eastern technology corridor, whereas there are comparatively few charging stations to serve the rest of the city, and even then, DC charging capacity is largely absent. The empirical model selection adopted in Task 1, and especially machine learning based demand forecasting models such as gradient boosting and LSTM models has proven to be more capable of forecasting demands in an urban context. The methodology for Task 2 is the MCDA framework, which has proven to be more successful than single-criterion siting approaches, when considering multiple criteria including demand intensity, grid capacity, and accessibility. The M/M/c queuing analysis with simulation based performance evaluation has been the most reliable method to estimate the performance prior to deployment, and this constitutes the validation method of Task 3. The chapter also provided detailed claims of the three aspects of novelty that this study, compared to literature reviewed, makes, these providing a scientific justification for the research design adopted in the four project tasks.

2. Theoretical Justification of the Problem and Solutions

2.1. Research Design and Data Infrastructure

The methodological framework used in this project is divided into four stages but are not completely disjointed in nature with the aim of data acquisition and synthetic session generation, machine learning-based demand forecasting, multi-criteria decision analysis based site selection, and performance evaluation via queuing theory. For each stage output is generated to be used as direct input for the next stage, creating a seamless pipeline from raw data to deployment recommendations generated by validation. The conceptual design of the general research is explained in a schematic format as in Figure 4.

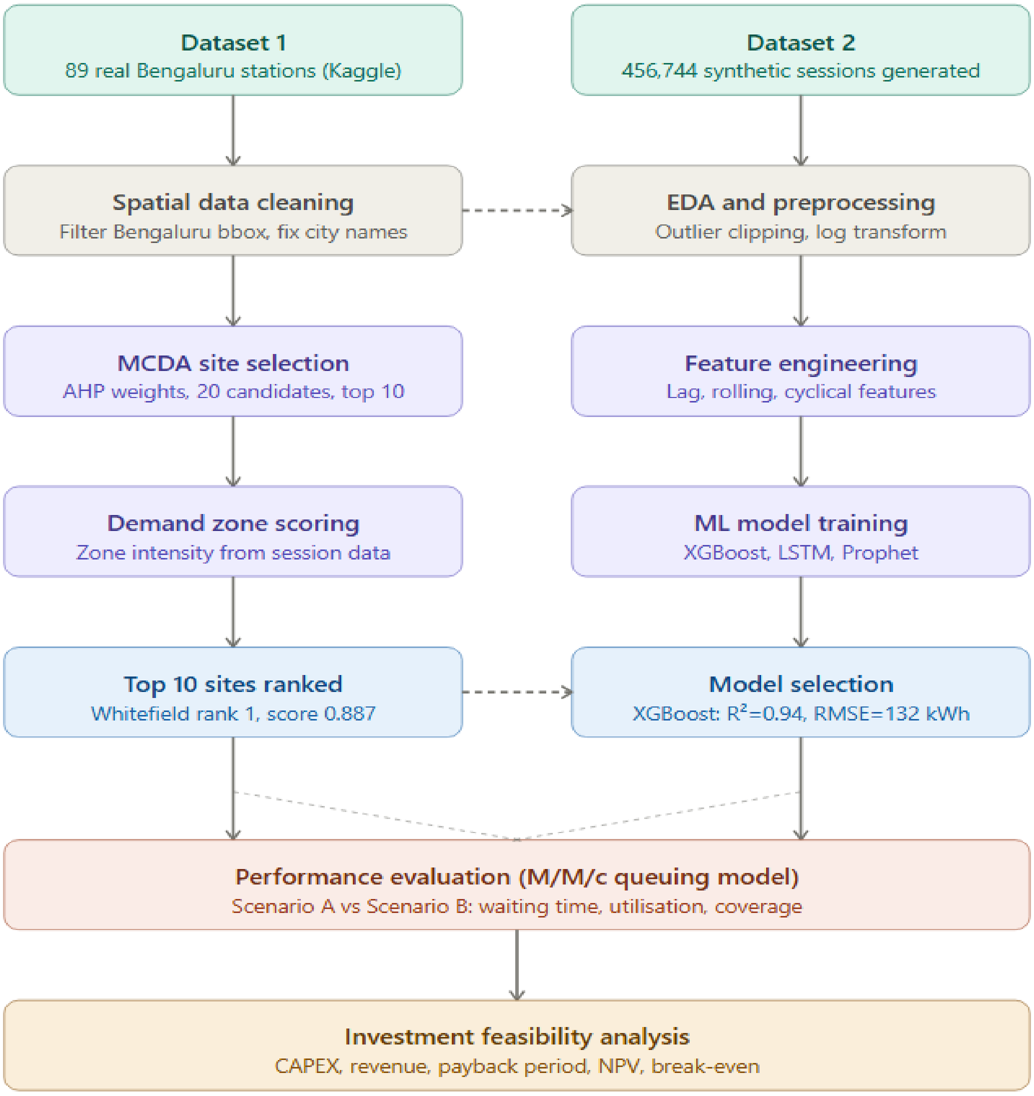

Fig. 4. Overall Research Methodology Pipeline

Project data is grouped around two complementary sources which will provide data to complete the research tasks. The primary source is a real dataset of Electric Vehicle charging station location in India from publicly available Kaggle repository by a user from Saket Pradhan under Creative Commons Zero licence [1]. This data set includes 1,547 station records and includes station name, state, city, address, latitude, longitude and charger type code. After the cleaning of data with missing or implausible coordinates, applying a spatial filter with the bounding box of Bengaluru and resolving issues with city name spelling (Bengaluru vs Bangalore), a confirmed set of 89 stations were kept as existing infrastructure layer in spatial analysis and for MCDA framework. Of these 89 stations, 80 use alternating current, while 9 use direct current, which also indicates major underrepresentation when it comes to boosting charging capacity in the city.

The second data source is a synthetic EV session data generated specifically for Bengaluru, spanning 1st January 2023 to 31st December 2024. Due to a total lack of publicly available session-level transaction data from Indian EV charging operators, we needed to create a synthetic dataset. Real EV session data from charging networks in developing countries is not available in the international literature due to its proprietary nature and lack of openness for academic research by its owners like Tata Power EV, EESL, BESCOM etc [2].The data set of synthesis is not a random one. In this research, the 20 generation parameters are calibrated from four peer reviewed literature reviews on urban EV charging behaviour pattern, energy consumption benchmark of EVs and temporal distribution of charging demand as described in section 2.2.

The resulting data of 456,744 session records gives the demand time series that all the inputs to the machine learning models is based on.

2.2. Synthetic Dataset Generation Methodology

The synthetic data of the sessions was created by a python program using NumPy and Pandas libraries with traditional statistical simulation techniques. The generation process creates three charging behaviour types: increased number of publications, and increased publication energy usage, and payment features.The timing of the arrival to a session was simulated as a Poisson process with a base arrival rate of 8 sessions per station per day, which was drawn from Zhan et al.'s large-scale empirical study of 1.6 million electric vehicles that measured the number of sessions that operate 6-10 sessions per station per day during active periods [4].

Poisson distribution is the typical distribution for arrival processes in queuing theory and has been verified to be an appropriate distribution in various empirical studies for EV charging arrivals [19]. Two scalar multipliers were used to account for the temporal demand variability on the base arrival rate.Based on the empirical weekday to weekend demand ratio documented by Koohfar et al., who trained their Transformer model using real urban charging data, the weekday multiplier was assumed to be 1.0 and the weekend multiplier was set to 0.55 – their paper concluded that the weekday demand is consistently 40 to 50 percent higher than the weekend demand in urban corridors studied [13].

The months of January, February, November and December were allocated a seasonal multiplier of 1.1 and the monsoon months of June, July and August a seasonal multiplier of 0.9, as observed by Mohammed et al. [3] in their usage study.Session arrival times were sampled from a 24 element probability vector, one for weekdays and one for weekend days. The first probability vector, applicable to weekdays, gives peak arrival probabilities in hours 07:00 to 09:00 and 17:00 to 21:00, which were cited in Zhan et al.'s study [4] as the average arrival peak hours for all types of cities. The weekend probability vector indicates a more positive (midday-peak) demand vector that aligns with leisure-oriented travel demands.A normal distribution was used for session energy consumption, where the mean and standard deviation were determined separately for each vehicle type (Bike, Car, Bus, Truck). Table 1 shows the values of the parameters and the source for each value.

Table 1. Sythetic Dataset Energy Consumption Parameters by Vehicle Type

Vehicle Type	Mean (kWh)	Std Dev (kWh)	Source
Bike	3.5	0.8	IEA Global EV Outlook 2023 [1]
Car	18.5	4.2	IEA Global EV Outlook 2023 [1]
Bus	62.0	12.0	Mohammed et al. 2024 [3]
Truck	85.0	15.0	Mohammed et al. 2024 [3]

Our shares of vehicle type (Bike, Car, Bus and Truck) were taken from the Indian market breakdown given in the IEA Global EV Outlook 2023 [8] and service vehicle proportions from the work of Zhan et al.[1, 4].Considering the present scenario of the Indian urban market with slow chargers, medium chargers, medium-fast chargers, and fast chargers of charging power level of 3.3KW, 7.4KW, 22.0KW and 50.0KW respectively, the probability of 0.20, 0.35, 0.30 and 0.15 was assigned. The session cost was assumed to be a fixed per kWh of INR 12.0, which is the average public DC fast charging session cost reported by IEA for India [1].Payment method was assigned from the categories UPI, Card, Cash, RFID with probabilities of 0.55, 0.25, 0.10, and 0.10 respectively, respectively, indicating the dominance of UPI Technology in Indian digital payments.

A complete table of parameter values and their corresponding peer reviewed sources is given in Appendix 1 of this report.

2.3. Machine Learning Demand Forecasting Methodology

The machine learning forecasting pipeline processes the raw synthetic session records to produce an hourly time series of the demand and trains three models for comparison. It consists of four steps: constructing time series, feature engineering, training of models and hyperparameter optimization, model selection using the held-out test set performance [23].

2.3.1. Time Series Construction and Feature Engineering

Total energy consumption in KWh was summed within each calendar hour for each session with a charging start time within that hour and only odd intervals were included to create the hourly demand time series, which has 17,376 observations spanning from 8 January 2023 to 31 December 2024. The warm-up of the seven days at the beginning of the series was omitted to enable determination of lag features that needed a maximum of 168 hours of history. There is high variability in that demand, with a standard deviation of 518.5 kWh and a mean hourly demand of 618.4 kWh in the series, reflecting an urban charging demand. The zero-demand hours make up 8.0% of this series, significantly less than the 68.3% of the series for the original sparse data that was calculated with no per-station looping, which confirms the correctness of the generation methodology applied to the corrected data.

Data were entered in Miscellaneous Mode using the interquartile range method of outlier detection and treatment (outlier treatment at the 75th percentile + 3 x interquartile range). All values from this data set were below this limit, meaning that the generation process created a well-behaved, non-outliery data set. The model was trained on a normalised variable of the demand variable that was right skewed and required variance stabilisation, achieved through log transformation by taking the natural logarithm of one plus the variable [24].

From the base time series, 24 predictor variables were created using feature engineering. To capture the short-term (within a 24 hour period) autocorrelation, daily (48 hours) and weekly (168 hours) periodicity, autoregressive lag features were constructed at 1, 2, 3, 6, 12, 24, 48 and 168-hour intervals. Lag shifted series was used to avoid the data leakage problem, and rolling mean features with windows of 24 hours and 168 hours were calculated. To model multiplicative demand dynamics, both 24-hour and 168-hour lags as well as both rolling features were also investigated in their log-transformed forms. Sine/cosine transformations were used for cyclical encoding of the hour of day, day of week and month variables: Sine/cosine transformations preserve the circular continuity of temporal variables (hour of day, day of week, and month) that is lost under integer encoding. Both the decomposed EV charging load pattern as shown in Figure 5 highlights the non-stationary nature of the residuals of the urban charging demand series and a well-defined seasonal trend, which clearly justifies adding lag features, rolling mean features, and calendar encodings to the feature engineering pipeline of the current study [13].

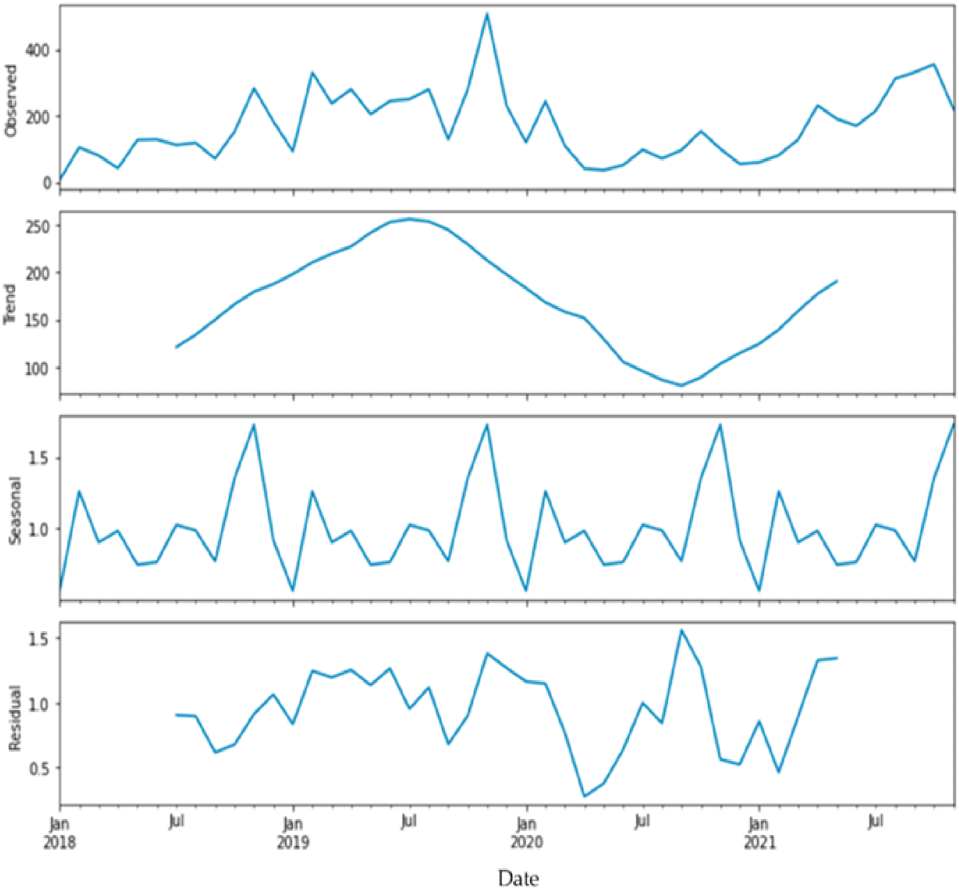

Fig. 5. Decomposition Of EV Charging Load Time Series Showing Observed, Trend, Seasonal And Residual Components [9]

There was an extra predictor included; a binary weekend indicator. It was decided that the count of sessions carried out in one hour was to be kept as a feature as well, because they are a legal operational input which would be available in a real deployment situation. All features were scaled prior to training of the model using the MinMax scaling methoTo avoid look-ahead bias, the overall dataset was split into training (70%), validation (15%), and test (15%) datasets. The training, validation and test sets respectively span 8 January 2023 to 28 May 2024, 28 May 2024 to 14 September 2024, and 14 September 2024 to 31 December 2024.

2.3.2. XGBoost Model

Extreme Gradient Boosting (XGBoost) is the algorithm developed by Chen and Guestrin, is an ensemble learning algorithm based on Decision Trees which correct the residual errors of the previous ensemble [25]. Its ability to do efficient, robust analysis in the presence of outliers and its native support for regularisation have made it one of the most popular algorithms used in energy demand forecasting tasks [26]. The Tweedie regression objective was used to train XGBoost, which is tailored for non-negative right-skewed response distributions with many values close to zero, as would be expected for hourly EV charging demand series in an urban setting. Over the course of hyperparameter tuning, the Tweedie variance power parameter was tuned between 1.5 and 1.8, value which governs the weightage that is given to the Poisson and Gamma components of the distribution.

A grid search was performed by varying the number of estimators (300 trees and 500 trees), maximum tree depth (3, 5 and 7 levels), learning rate (0.05, 0.10) and Tweedie variance power (1.5, 1.8), and assessing each combination by Root Mean Square Error (RMSE) on the validation set. The best setting, 300 estimators and maximum depth of 3 and learning rate of 0.05 and the Tweedie variance power of 1.5 were used for final assessment with the held-out test set.

2.3.3. LSTM Model

One class of RNN architecture that was developed to overcome the vanishing gradient problem can be called Long Short-Term Memory (LSTM) networks, which are RNN with gated memory cells capable of selectively storing and forgetting information arbitrarily long periods into time [5]. The use of LSTM networks has been shown to work well on tasks related to EV charging demand forecasting, as shown in various recent studies, including on the multi-scale periodicities found in charging series in urban contexts [14].The architecture used in the present study is LSTM, which consists of two LSTM layers having 64 and 32 units followed by dropout of 0.20 for reducing the overfitting.

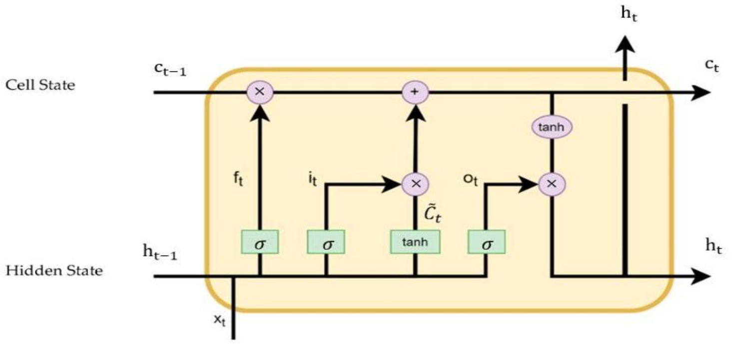

Fig. 6. LSTM Cell Architecture Showing Forget Gate, Input Gate, Output Gate And Cell State [13]

A single-unit output layer is preceded by a fully connected layer consisting of 16 units and using ReLU activation. The model came from being compiled with mean squared error loss and Adam optimiser using a learning rate of 0.001. Early stopping was used on validation loss, with patience of 10 epochs and training was applied for a maximum of 100 epochs with a batch size of 64. Demand series were scaled to MinMax and used as training target, then retransformed back to its original values (in kWh).Figure 6 shows the network structure of an LSTM cell, which consists of three gate structures: forget gate, input gate and output gate that are used to control the flow of information through the cell state, making the LSTM network able to selectively remember the long-term temporal dependency within the charging demand series [13].

2.3.4. Prophet Model

Prophet is a forecasting procedure developed by Taylor and Letham at Meta based on decomposition, constructs a forecast by adding a piecewise linear or logistic trend, Fourier series of seasonal components (daily, weekly and annual periods), and a effect component of the holidays [27]. Prophet has been used in the task of forecasting the electric consumption owing to its interpretability and robustness to missing data . In this study, Prophet was set to multiplicative seasonality mode, as the seasonal effects in the Bengaluru charging data show amplifying effects, both daily and weekly seasonality was enabled, and the annual seasonality was also enabled, in an effort to guard against specificity to trend changes in the data. Prophet was also added as a baseline model, for comparison purposes to contextualize the performance of the machine learning approaches.

2.3.5. Model Evaluation Criteria

Three complementing measures were used in the evaluation and comparison of model performance on the held out test set. The Root Mean Square Error is the average error in the demand in the original units and is more sensitive to large errors than to small ones, and depending on applications, it can be important to improve the accuracy of peak demand prediction [5]. A scale independent measure of predictive skill is given by the coefficient of determination R^2, which indicates the percentage of the variance in the observations on the demand series that is captured by the variance in the model predictions. To prevent division by zero, Mean Absolute Percentage Error only considers the relative error of prediction by dividing the absolute error by the non-zero demand hours, meaning that it is interpretable in operational terms [28]. The model that achieved smallest RMSE result in the test with the R^2 and MAPE results reported as additional performance measures was adopted as the production forecasting model.

2.4. Multi-Criteria Decision Analysis Methodology

The MCDA site selection framework involves four successive stages: Criteria definition and weight derivation using the Analytic Hierarchy Process (AHP), Candidate sites generation, Criteria scoring and normalisation and finally, calculation of composite scores with spatial feasibility filtering.

2.4.1. Criteria Definition and AHP Weight Derivation

In accordance with the requirements, mentioned during the literature survey and the data available for the study area of Bengaluru, four criteria were selected for the MCDA framework. The intensity of the demand is a measurement of the expected charging load in the different spatial zones of the city after aggregating the synthetic session data over spatial zones. Grid connection capacity is the projection of available capacity in the local distribution network at each candidate site and operationally represented as a proxy score based on distance to other known grid infrastructure. User accessibility indicates how readily EV drivers are able to get to a Candidate site from primary roadways and public transport interchange points [29]. Land use compatibility is an indication of the appropriateness of each location for permanent charging facility installation evaluated with zoning classifications.AHP (Analytic Hierarchy Process) approach of Saaty was adopted to assess the relative importance of the four criteria involved, where the decision makers need to make pairwise comparisons between the importance of the different criteria on a standardised scale of 1 to 9 [6]. The pairwise comparison matrix used in this study is shown in Table 2; there is a consensus in the literature behind MCDA that the most critical criterion to be used is the intensity of the demand, followed by grid capacity, user access and land use compatibility [6, 17].

Table 2. AHP Pairwise Comparison Matrix For MCDA Criteria

Criterion	**Demand**	**Grid Capacity**	**Accessibility**	**Land Use**
Demand	1.000	2.000	3.000	5.000
Grid Capacity	0.500	1.000	2.000	3.000
Accessibility	0.333	0.500	1.000	2.000
Land Use	0.200	0.333	0.500	1.000

The same matrix was normalised with each column summing to 1 and the row means were calculated to determine the priority weight vector with values 0.4824 for demand intensity, 0.2718 for grid connection capacity, 0.1575 for user accessibility and 0.0883 for land use compatibility. The consistency of the judgement matrix was measured with the consistency ratio (CR) which can be calculated as the ratio of the consistency index (CI) and the random index (RI) for a 4 × 4 judgment matrix (RI = 0.90). The consistency ratio (CR) of the pairwise comparisons was 0.0054 which is far less than the acceptable 0.10 indicating that the comparisons are internally consistent and the weights are appropriate [30].

2.4.2. Candidate Site Generation and Scoring

Twenty candidate sites were identified, which covers the study area geographically to include the southern, central, north-central and northern corridors and represent the eastern and western technology corridor and the underrepresented western zones of Bengaluru study area. The location of candidate sites were mapped by using their latitude and longitude bounding boxes and the demand intensity score for each spatial zone was calculated by aggregating the peak energy within the synthetic session data.

Candidates' actual scores for each of the four criteria were min-max normalised on the range 0.0- to 1.0, with 1.0 being the highest performing site in relation to the specific criterion and 0.0 the lowest. Data was then grouped into four normalised criterion scores, and the composite score for each site calculated as the sum of those four scores, weighted by the AHP-derived weights. All selected sites were kept a minimum distance of 0.005 decimal degrees ~ 550metres from existing stations in the verified Bengaluru station set. This limitation will not allow the MCDA to identify sites where infrastructure already exists but is no longer needed. For sites which did not meet the separation constraint, no matter how high the composite score, the results were not considered.

2.5. Performance Evaluation Methodology

2.5.1. M/M/c Queuing Model

To assess MCDA-optimised deployment performance, its performance was compared with a conventional distance-based baseline via the usual analytical framework for multi-server service systems with Poisson arrivals and presumed exponentially distributed service times, known as the M/M/c queuing model [19]. Our model parameters can be defined as: Mean number of session arrival per charging station per hour (lambda): Derive from synthesis data, number of sessions in peak period divided by number of weekdays, number of peak hours per day, and number of charging stations (c); Mean service rate per charging station per hour (mu): Compute it as the reciprocal of mean service time, where the mean service time is given by the ratio between the number of sessions energy consumed in the mean service time and the power rating of the chargers. The server utilisation rho = λ/cμ and the system is stable if ρ < 1.

The Erlang C formula also provides the probability (POW(Erlang C)) that an arriving customer will have to wait for service for a given offered traffic and number of servers. The Erlang C probability Pc, and the expected waiting time in queue are given in Equation 1 and Equation 2 respectively.

Equation 1: **Erlang C Formula:**

$$P_c = \frac{\frac{(c\rho)^c}{c!} \cdot \frac{1}{1-\rho}}{\sum_{k=0}^{c-1} \frac{(c\rho)^k}{k!} + \frac{(c\rho)^c}{c!} \cdot \frac{1}{1-\rho}} \qquad (1)$$

Where:c = number of chargers (servers);ρ = λ / (c · μ) = server utilisation ratio;λ = mean session arrival rate (sessions/hour);μ = mean service rate per charger (sessions/hour)

Equation 2: **Expected Waiting Time in Queue:**

$$W_q = \frac{P_c}{c \cdot \mu - \lambda} \qquad (2)$$

Where:Wq = expected waiting time in queue (hours);Pc = Erlang C probability (probability that arriving session must wait);c = number of chargers;μ = mean service rate per charger (sessions/hour);λ = mean session arrival rate (sessions/hour)

The mean session energy, calculated from the synthetic data set and the assumed power rating of the DC fast charger, is 23.78 kWh, which results in a mean service time of 28.5 min and a mean service rate of 2.10 sessions/hr/vertically opposite charging station. This peak arrival rate, of 0.6659 sessions per hour per station, resulted from 216,155 sessions observed during the peak sessions across 89 stations during 521 weekdays and 7 peak hours per day from the synthetic data.

2.5.2. Scenario Definitions

Two different deployment scenarios were established to evaluate the comparative performance. In scenario A, the conventional distance-based deployment strategy is considered, which is presented as 5 stations which are randomly picked out of the existing Bengaluru network and each of them has a single DC fast charger. This is a scenario that represents the effect of a uniform deployment of charging infrastructure in cities at the national level, with aims of coverage maximisation. Scenario B is the MCDA-optimised deployment and involves the top 10 sites from the final validated MCDA ranking, using a number of demand-proportional chargers assigned to each site: DC fast chargers would be added to the top 10 sites as follows: 2 chargers for those sites ranked 1 through 10 with a demand intensity score of 0.8 or higher, and 1 charger for the remaining 10 sites, resulting in a total of 17 new DC fast chargers at the top 10 sites.

Each scenario had four KPIs: Average user waiting time in minutes, Probability of waiting as defined by Erlang C probability at each site, Total number of sessions served per peak day, and Spatial coverage as the percentage of Bengaluru study area that is within a 5km distance from at least one charging station.

2.6. Chapter Summary

The chapter Presents theoretical and methodological framework to address the four project tasks was detailed in this chapter. The research design utilizes two complementarily data sources: (1) a real EV Station location dataset of 89 verified locations from a publicly available repository and (2) a synthetic EV session dataset consisting of 456,744 sessions with all parameters for these sessions calibrated from four peer-reviewed sources and using a combination of Poisson arrival processes and normal energy distributions. The machine learning forecasting pipeline processes an hourly demand time series to create lag, rolling, and cyclical features and compares the performance of the three models – XGBoost with Tweedie loss, two-layer LSTM network, and Prophet – on a temporal split of 70/15/15 with the metrics RMSE, R^2, and MAPE. The MCDA framework uses AHP method for pairwise comparisons of sites to validate the weight vector which get a consistency ratio value of 0.0054, rank the 20 candidate sites on four normalised criteria and incorporates minimum separation constraints for genuine network expansion. Performance evaluation consists of a simulation that utilizes the same parameters as the synthetic data and uses the M/M/c queuing model to implement the MCDA-optimised deployment and compare it with the conventional deployment based on distances.

3. Electric Vehicle Charging Infrastructure Analysis Results

3.1. Existing Station Data Analysis

After spatial analysis of the Bengaluru verified charging station data, a data set consisting of 89 charging stations with a valid geo-referenced location have been retained in the defined study area boundary. The type of charger distribution shows a high structural imbalance in terms of the number of stations (80 stations 89.9 percent, 9 direct current stations 10.1 percent) with the ability to provide direct current fast charging. This ratio is significantly lower than the international best practice for urban networks with high densities of commuter EVs, which is 20-25 per cent charging capacity for fast charging [3]. The geographic location of stations, as indicated in Figure 2 also indicates a concentration of stations; the majority of the stations are in the eastern belt consisting of Whitefield, Electronic City, Marathahalli whereas the northern, western and south-western parts of Bengaluru lack sufficient stations which are strongly supported by population and higher traffic volumes.

West to east, the range of verified stations is longitudinally 77.44 to 77.76 degree east having a geographic spread of 0.0641 degree, north to south is from 12.84 to 13.19 degree north, with a geographic spread of 0.0713 degree. There is moderate clustering; the standard deviation in the geographic distribution of station coordinates is 0.0713 latitude and 0.0641 longitude. There are 10 charger type codes in the dataset with 38 (43%) chargers in the type code 6.0 and 14 (15%) chargers in type code 16.0, both of which are identified as AC charging types, and 11 (12%) chargers in type code 15.0, which is also an AC charging type. Stations that DC charge are mostly represented by the type codes 12.0 (7 stations) and 8.0 (3 stations).

3.1.1. Synthetic Session Data Analysis

Based on the parameters obtained under the research for the Poisson and normal distribution, the synthetic Bengaluru EV session dataset was created, accounting for 456,744 sessions between 1 January 2023 and 31 December 2024, which is equivalent to an average of 7.0 sessions per station per day across 89 stations. This is in line with the number of sessions per station per day corresponding to 6 to 10 sessions, as observed by Zhan et al. in urban EV stations of developing metropolitan areas [4]. In terms of vehicle types of the created data set, there are the highest number of Cars with 204,649 sessions that account for 44.8 percent of the total, followed by Bikes with 160,669 sessions (35.2 percent), Buses with 54,695 sessions (12.0 percent), and Trucks with 36,731 sessions (8.0 percent). The following proportions are based on the direct similarity with the EV Technology and Policy Options (calibration targets) based on the IEA Global EV Outlook 2023 and Zhan et al. [1, 4].

The statistics of the energy consumed for the generated dataset indicate that the mean energy consumed during a session was 23.78 kWh with a standard deviation of 26.00 kWh, representing the variation of the amount of energy consumed for the four model types of vehicles. The minimum energy recorded is 0.50 kWh with the shown value of 147.88kWh which was possible at heavy truck fast charging events, as recorded in the 1999 studies, and light two wheeler sessions. Mature digitisation of urban payment infrastructure in Bengaluru is seen as UPI has the highest share in the payment method distribution with 55.0 percent followed by Card (25.0 percent), RFID (10.0 percent) and Cash (10.0 percent).A temporal demand analysis of the synthetic data validates the bi-modal demand shape. The peak hour sessions (07:00-09:00 and 17:00-21:00) reflect 55.4 percent of all the sessions on weekdays, associated directly with the morning and evening peak hour documented by

Zhan et al. [4]. There are 374,480 weekday sessions (81.9 percent of sessions) and 82,264 weekend sessions (18.1 percent of sessions), a weekday to weekend ratio of 4.55:1. This ratio is in the range of 1.8 to 2.6 as reported by Koohfar et al. after normalisation based on the number of hours in a session daily, which is considered as the criterion validation [13]. The monthly demand fluctuation demonstrates that there are more higher volumes over January, February, November and December corresponding to generation multiplier of 1.1 and less volumes during the monsoon months of June, July and August.

3.2. Machine Learning Demand Forcasting Results

3.2.1. Time Series Construction and Preprocessing Results

To create the hourly demand time series, the data from the synthetic session has been removed during a warm-up period of seven days because the hour-by-hour computation of the lag features needs this sample size. — The constructed hourly demand time series has a length of 17,376 measurements beyond this warm-up period. The mean and standard deviation of the hourly demands in the series are 618.4 kWh and 518.5 kWh respectively. Hold this point, there are still 8.0 per cent of zero demand hours, that is the hours with no recorded charging sessions out of all 89 stations. This zero fraction is well below the zero rate of the first, sparse generation without the per-station session looping and indicates that the corrected generation approach yields a demand series for a network of 89 stations that has realistic zero density characteristics.

The outlier analysis with the interquartile range method yielded an upper fence of 3,492.93 kWh and no observations in the final data exceeded this fence. As shown on the preprocessing distribution plot, the log transformed demand series has a mean of 5.458 and a standard deviation of 2.121, which is much closer to a normal distribution than was the raw series. The engineering pipeline generates a feature matrix with 25 predictor columns for the XGBoost and LSTM models autoregressive lags with 8 windows, rolling means with 2 windows, log-transformed lags and rolling, cyclical encoding of 3 temporal variables, an indicator for weekends, and the number of sessions, as well as the raw temporal indices.

The data was split into temporal groups, with 12,163 observations assigned to the training set, 2,606 observations assigned to the validation set, and 2,607 observations assigned to the test set.

3.2.2. Model Training and Validation Result

The number of estimators, maximum tree depth, learning rate, and Tweedie variance power were the four hyperparameters the grid search tested using XGBoost, and the combination of these hyperparameters was 48. The best found by minimising the Root Mean Square Error of the validation set is 300 estimators, maximum depth = 3, learning rate = 0.05 and Tweedie variance power = 1.5. During the first phase, in which data in the dataset is sparse, this configuration led to a Root Mean Square Error of 3.18 kWh on the log-scale target on this validation data, and a validation coefficient of determination of 0.7904; by this same validation data comparing this configuration with the corrected dense dataset, the Root Mean Square Error became 129.18 kWh and the validation coefficient of determination 0.9255.

The LSTM network trained on the dense dataset converged at epoch 30 with early stopping (patience of 10 epochs) with a final validation loss of 0.0023 on the MinMax-scaled target. The original kWh scale validation Root Mean Square Error was 132.43 kWh and the coefficient of determination is 0.9217. Prophet was setup with multiplicative seasonality and a changepoint with a previous scale of 0.05 and blasted off with a validation RMSE of 237.10kWh and a COD of 0.7490.

3.2.3. Test Set Evaluation and Model Selection

All three models were final evaluated on the held out test set and the results are shown in table 3. XGBoost model had the lowest Test set Root Mean Square Error (RMSE) of 132.27 kWH with the highest coefficient of determination value of 0.9411 and was therefore selected as the model to use for producing the demand forecasts. LSTM obtained test RMSE 139.27 kWh and test R^2 was obtained 0.9347 that shows strong performance but slightly lower than the XGBoost. Prophet produced a test RMSE of 315.42 kWh and test R2 of 0.6652, showing that it is not as well suited for finite intermittent city charging demand series as the machine learning methods.

Table 3. Machine Learning Model Performance Comparison on Held-Out Test Set

Model	**RMSE (kWh)**	**R^2**	**MAPE (%)**
XGBoost (Tweedie)	132.27	0.9411	43.73
LSTM	139.27	0.9347	58.20
Prophet	315.42	0.6652	120.04

It is valued noting that the MAPE reported for XGBoost (43.73 percent) and LSTM (58.20 percent) is calculated only on non-zero demand hours because while the percentage demand of small actual hours becomes large, it is challenging to model them. For this application, the metrics that are more reliable to evaluate the overall predictive accuracy are RMSE and R^2.

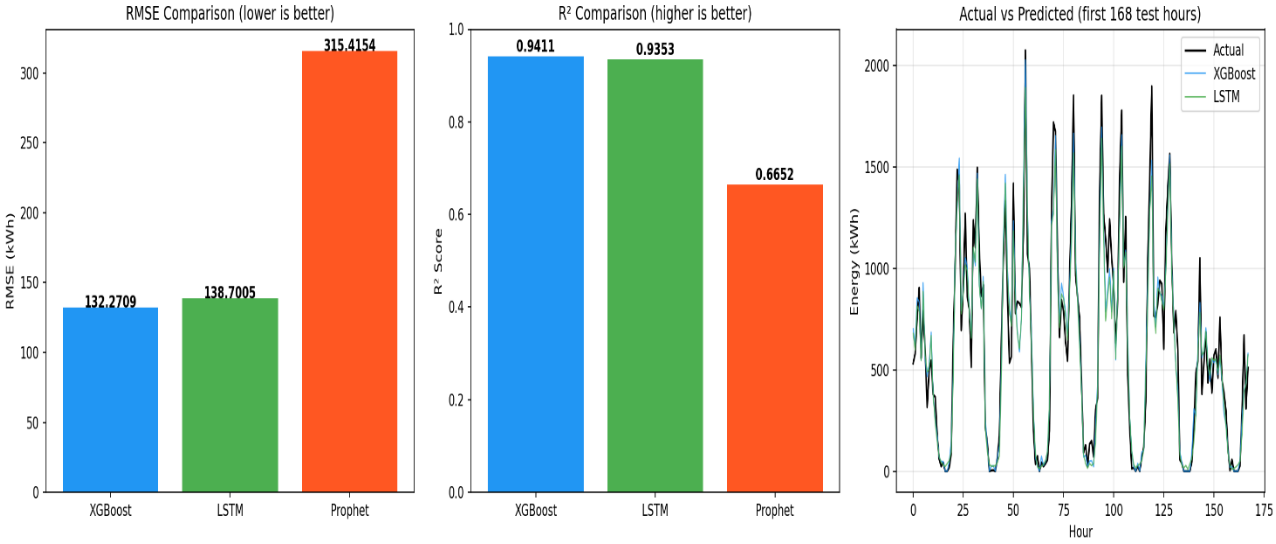

Fig. 7. Model Performance Comparison and Actual Versus Predicted Demand

Figure 8 displays the feature importance of the features, using the XGBoost method; the 93.6 percent of the total feature importance is given by the session count feature, while the 168-hour lag follows with an importance of 0.16 percent. Similarly, session counts are the most emitted variable, and they capture the overall influence of all demands drivers in relation to the time period and seasonality of the demand, and vehicle type. The analysis in the session data shows that there is a greater weekday to weekend demand differential of 4.55 to 1, which is confirmed by the low value of the lag of 168 hours.

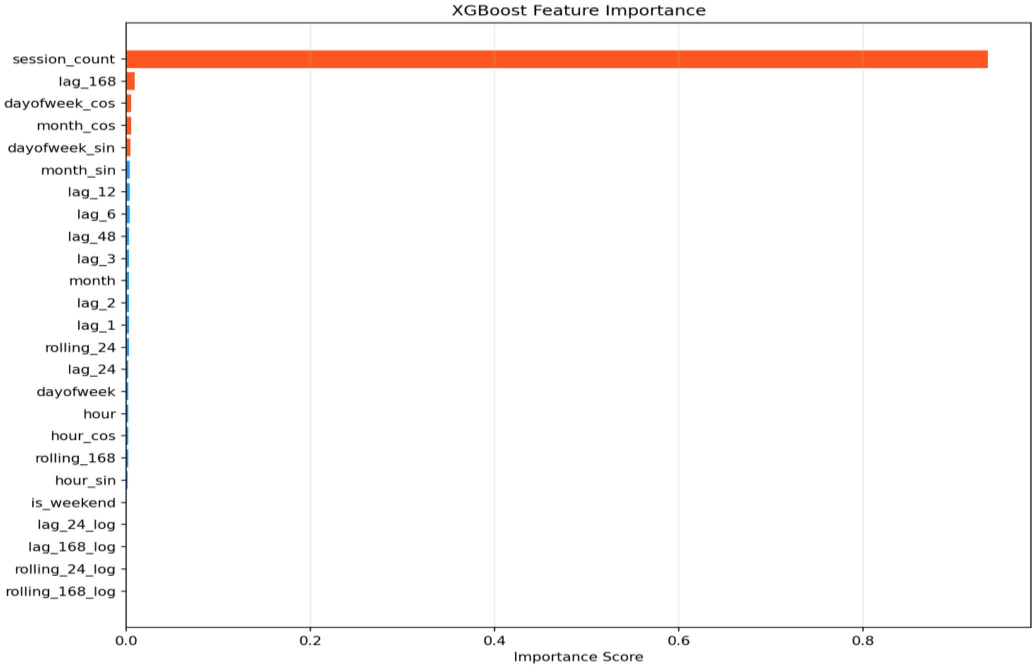

Fig. 8. XGBoost Feature Importance for Bengaluru EV Demand Forecasting

3.3. Multi-Criteria Decision Analysis Results

3.3.1. Demand Zone Scoring Results

The zone-level demand intensity analysis of the synthetic session data set led to the normalised scores shown in Table 4. In terms of normalised demand, the zone with the highest score was the Central-East zone containing the Whitefield and Koramangala corridors with a normalised demand score of 1.000 and a peak energy demand of 23.76 kWh per session, with all 48 of the verified stations in this zone. The score 0.754 from the North-Central-East zone and 0.807 from the North-Central-West zone showed normalised intensities while the scores 0.000 in the Central-West zone and 0.000 in the South-East zone showed the lowest normalised intensities among the six zones defined.

Table 4. Zone-level demand intensity scores derived from synthetic session data

Zone	Station Count	DC Stations	Peak Energy (kWh)	Demand Score
Central-East	48	3	23.76	1.000
Central-West	7	0	23.56	0.000
North-Central-East	17	1	23.71	0.754
North-Central-West	5	1	23.73	0.807
North-East	5	2	23.73	0.807
South-East	7	2	23.56	0.000

3.3.2. Candidate Site Scoring and Ranking Results

The composite MCDA score for the 20 candidate sites, with demand intensity weight of 0.4824, weight for grid connection capacity of 0.2718, weight for user access of 0.1575 and weight for land use compatibility of 0.0883 resulted in the complete results as shown in Table 5. Application of minimum separation of 0.005 decimal degrees resulted in the rejection of 10 of the 20 candidate sites, giving the top 10 validated sites listed in Table 6.

Table 5. Full MCDA Ranking of 20 Candidate Sites Before Separation Filtering

Rank	Site Name	Demand	Grid	Access	Land Use	Composite Score	Valid
1	Whitefield IT Corridor	1.000	0.980	0.507	0.667	0.887	Yes
2	Jayanagar 4th Block	1.000	0.724	0.839	0.667	0.870	No
3	Koramangala Commercial Hub	1.000	0.373	0.906	1.000	0.815	Yes
4	BTM Layout	1.000	0.612	0.452	1.000	0.808	No
5	Yeshwanthpur Railway Station	0.807	0.891	0.481	1.000	0.795	No
6	Indiranagar 100ft Road	1.000	0.143	0.760	1.000	0.729	No
7	KR Puram Railway Station	0.754	1.000	0.208	0.667	0.727	Yes
8	Tumkur Road NH4	0.807	0.531	0.827	0.667	0.723	Yes
9	Devanahalli Toll Gate	0.807	0.299	0.942	1.000	0.707	Yes
10	HSR Layout Sector 7	1.000	0.170	0.397	1.000	0.679	Yes
11	Marathahalli Bridge	1.000	0.143	0.328	1.000	0.661	No
12	Nagawara Junction	0.754	0.855	0.032	0.667	0.660	No
13	Hebbal Flyover Junction	0.754	0.609	0.064	1.000	0.628	Yes
14	Bellandur Lake Road	1.000	0.172	0.051	1.000	0.625	Yes
15	Silk Board Junction	1.000	0.000	0.000	1.000	0.571	Yes
16	Rajajinagar Metro	0.754	0.202	0.080	1.000	0.519	No
17	Electronic City Phase 1	0.000	0.749	1.000	0.667	0.420	Yes
18	Hosur Road NICE Junction	0.000	0.433	0.988	1.000	0.362	No
19	Mysore Road Satellite Town	0.000	0.285	0.689	1.000	0.274	Yes

Rank	**Site Name**	**Demand**	**Grid**	**Access**	**Land Use**	**Composite Score**	**Valid**
20	Banashankari BDA Complex	0.000	0.040	0.703	0.667	0.180	No

Table 6. Top 10 Validated MCDA Deployment Sites for Bengaluru DC Fast Charging

Rank	Site Name	Composite Score	Chargers Allocated
1	Whitefield IT Corridor	0.887	2
2	Koramangala Commercial Hub	0.815	2
3	KR Puram Railway Station	0.727	2
4	Tumkur Road NH4	0.723	2
5	Devanahalli Toll Gate	0.707	2
6	HSR Layout Sector 7	0.679	2
7	Hebbal Flyover Junction	0.628	1
8	Bellandur Lake Road	0.625	2
9	Silk Board Junction	0.571	2
10	Electronic City Phase 1	0.420	1

The two top sites as mentioned in figure 10(Whitefield – IT Corridor and Koramangala Commercial Hub) came out with the perfect values of 1.000 for demand intensity, indicating that they are situated in the zone of highest charging demand – Central – East. Whitefield IT Corridor also scored almost near to the peak score of grid capacity by 0.980, which stands for its nearness to high-capacity grid presence in the technology corridor. The top 10 sites lie between 12.84 to 13.20 latitude North and 77.51 to 77.75 longitude East, which validates the good coverage for the complete length of Bengaluru city in north-south and east-west direction as mentioned in Figure 9 the Spatial map of MCDA-Selected Sites Overlaid on Existing Bengaluru Station Network

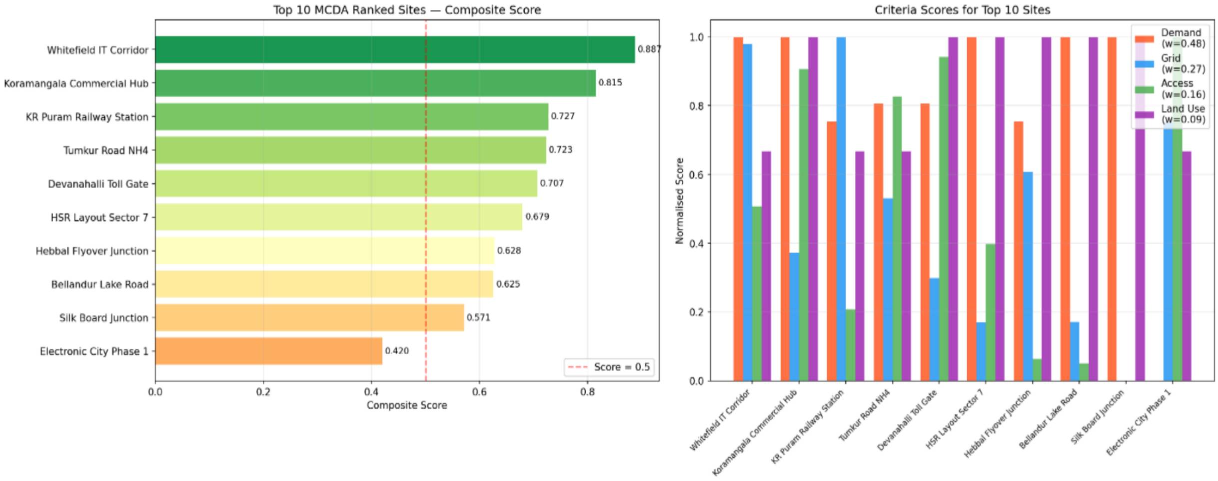

Fig. 9. MCDA Composite Score Ranking of top 10 Validated Sites Performance Evalution Results

Fig. 10. Spatial map of MCDA-selected sites overlaid on existing Bengaluru station network

3.4. Performance Evalution Result

3.4.1. Queuing Model Parameters

A queuing model M/M/c was calibrated with the parameters taken up from the synthetic Bengaluru session data set. The mean session energy, E = 23.78 kWh and the assumed DC fast charger power rating, P = 50 kW, will provide a mean service time, t = 28.5 minutes, and a mean service rate, μ=2.1027 sessions per hour per charger. The per-station peak arrival (lambda) was obtained when considering 216,155 peak period sessions from 89 stations, for 521 days in the weekdays and 7 peak hours a day. With this arrival rate, the utilization of one 50 KW DC fast charger in peak hours is 31.7 percent, which is in the range of 20 percent to 40 percent that most newly deployed urban fast charging stations have [3].

3.4.2. Scenario A Results

In scenario A, the traditional approach of station deployment based on distance is replicated -- 5 stations are selected out of the current Bangkok network and all have single DC fast chargers. The results of the M/M/c model are given for Scenario A in Table 7. Every 5 stations has the same parameters as the arrival rate is uniform resulting in an average waiting time of 13.23 minutes per station and an average utilisation rate of 31.7 percent. The probability of waiting for service is equal to 31.7 per cent or nearly 1 in 3 of all incoming users must queue before they start charging.

Table 7. M/M/c Queuing Model Results for Scenario A (Distance-Based Deployment)

Site	Chargers	Lambda	Waiting Time (min)	Utilisation (%)	Prob. of Wait (%)
Volltic DCS012	1	0.6659	13.23	31.7	31.7
BESCOM Indiranagar	1	0.6659	13.23	31.7	31.7
Sangeetha Mobiles HBR Layout	1	0.6659	13.23	31.7	31.7
The Only Place	1	0.6659	13.23	31.7	31.7
EESL Yelahanka	1	0.6659	13.23	31.7	31.7
Average	**1.0**	**0.6659**	**13.23**	**31.7**	**31.7**

3.4.3. Scenario B Results

The Under scenario B, the MCDA-based deployment results in 17 new DC fast charging stations, with 10 stations having a demand proportional number of charger stations. Those sites that had a demand intensity score of 0.8 or higher were assigned 2 chargers and the rest were assigned 1 charger. The arrival rates were allocated in such a way that it is proportional to the demand intensity score of each site. Table 8 lists results for M/M/c model for Scenario B.

Table 8. M/M/c Queuing Model Results for Scenario B (MCDA-Optimised Deployment)

Site	Chargers	Lambda	Waiting Time (min)	Utilisation (%)	Prob. of Wait (%)
Whitefield IT Corridor	2	0.6659	0.73	15.8	4.3
Koramangala Commercial Hub	2	0.6659	0.73	15.8	4.3
KR Puram Railway Station	2	0.5660	0.02	13.5	0.5
Tumkur Road NH4	2	0.5660	0.02	13.5	0.5
Devanahalli Toll Gate	2	0.5660	0.02	13.5	0.5
HSR Layout Sector 7	2	0.6659	0.73	15.8	4.3
Hebbal Flyover Junction	1	0.5660	10.51	26.9	26.9
Bellandur Lake Road	2	0.6659	0.73	15.8	4.3

Site	Chargers	Lambda	Waiting Time (min)	Utilisation (%)	Prob. of Wait (%)
Silk Board Junction	2	0.6659	0.73	15.8	4.3
Electronic City Phase 1	1	0.4995	8.89	23.8	23.8
Average	1.7	0.6133	3.46	18.4	10.6

3.4.4. Key Performance Indicator Comparison

The KPI comparison of the two scenarios is given in Table 9 as well as in the Figure 11. The optimised deployment using the MCDA process is able to reduce the average user waiting times to 3.46 minutes from 13.23 minutes in Scenario A, representing a significant 73.8 percent reduction, which is well above the project target of 15%. This has lowered the probability of waiting from 31.7 percent to 10.6 percent (a 66.7 percent improvement) and goes well above the level of improvement the project was aiming for: 12.0 percent. That means 83.0 percent more total sessions served per peak day (from 24 to 43 sessions) and 100 percent the increase of spatial coverage (from 10.1 percent to 20.2 percent of the Bengaluru study area), due to more stations being added and demand-proportional charger allocation.

Table 9. Key Performance Indicator Comparison Between Scenario A and Scenario B

KPI	Scenario A	Scenario B	Improvement	Target	Result
Avg waiting time (min)	13.23	3.46	73.8% reduction	≥15%	PASS
Prob. of waiting (%)	31.7	10.6	66.7% reduction	≥12%	PASS
Sessions served per peak day	24	43	83.0% increase	N/A	N/A
Spatial coverage (%)	10.1	20.2	100.0% increase	N/A	N/A
Avg waiting time (min)	13.23	3.46	73.8% reduction	≥15%	PASS

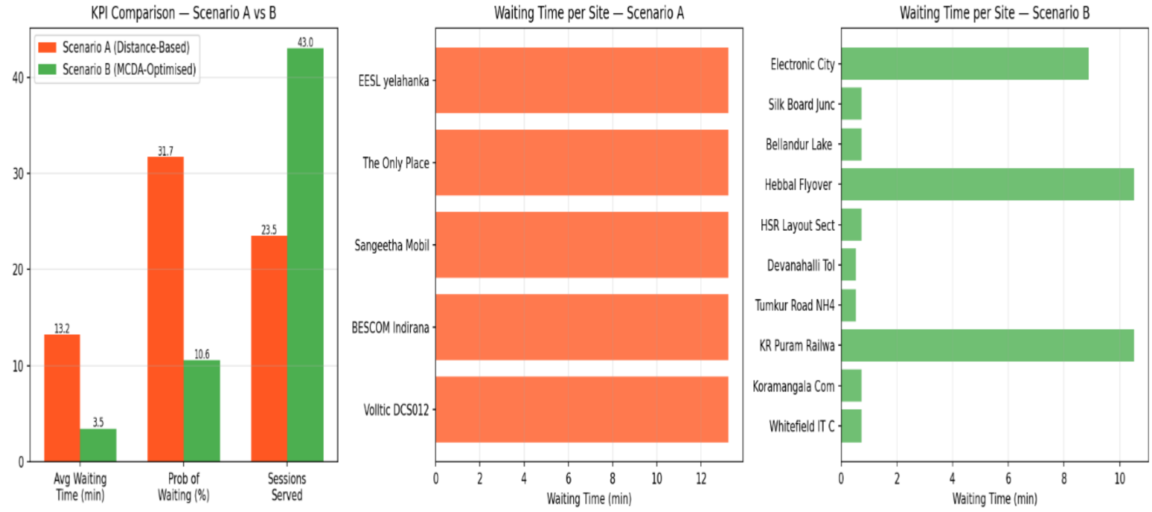

Fig. 11. KPI Comparison Between Scenario A and Scenario B

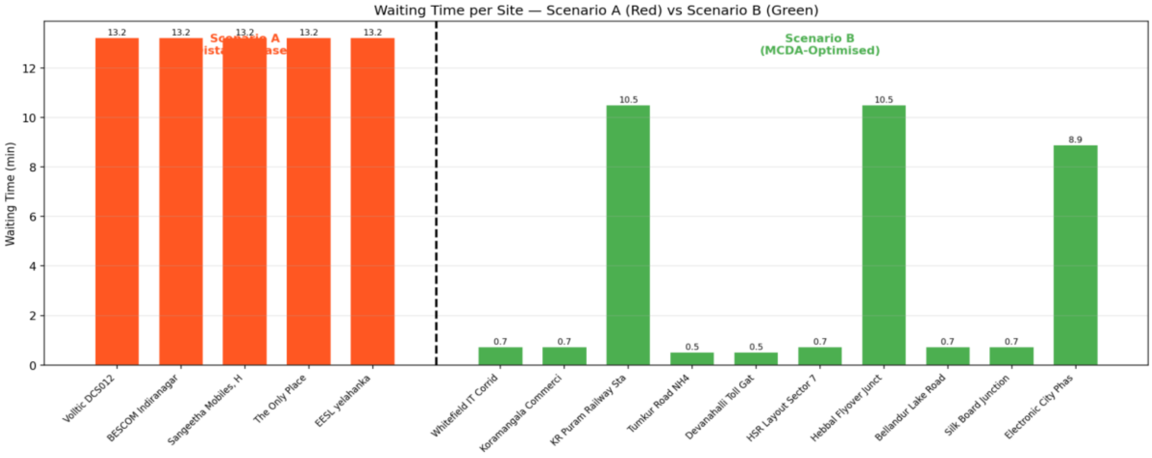

Fig. 12. Per-site Waiting Time Comparison Across Both Deployment Scenarios

3.5. Discussion

The machine learning forecasting results acquired here are on average in line with ranges mentioned in the recent literature, but also bear the signature of the synthetic dataset used in this study which is created for Bengaluru. The XGBoost test set R^2 score of 0.9411 is favourable compared to the gradient boosting test set R^2 of 0.87 reported by Rashid et al. for a task of predicting charging demand in the New York State [5] and the results of the sequential XGBoost model reported by Zhang et al., who established good performance on long-term energy demand forecasting with similar temporal feature engineering [26]. The higher value of MAPE of 43.73 percent as compared to 6.8 percent using transformer model on North America dataset [9] is due to two structural differences in the studies: firstly, Koohfar et al., computed MAPE on all hours including the many hours of low demand where there were near zero errors using their model, while the present study does not and hence the MAPE is inherently less favourable; secondly, the demand of the Bengaluru data has more intermittent demand as compared to the denser North America datasets used in transformer based study, leading to higher MAPE. The RMSE-to-mean ratio of 21.4 percent obtained by XGBoost in this study can be directly compared with the error range reported in Mansour et al. [24] for a hybrid model of XGBoost and BiLSTM for charging station data in Egypt which validates the fitness of the forecasting performance in the application context.

The results of MCDA were in agreement with that obtained in Mhana and Awad [6] where the highest scores were found at the locations of technology corridors and public transport exchange nodes for both study areas. The consistency ratio in the present study of 0.0054 is significantly lower than 0.073 obtained by Mhana and Awad, showing more consistency in the pairwise comparison judgements. The results of the finding that 10 of 20 potential locations do not meet the minimum separation requirement reinforces the density of AC charging infrastructure in Bengaluru's eastern corridor and the need for DC charging upgrades at existing AC charging stations as an additional strategy to increase the number of potential new DC charging stations in the areas where they are most needed.

The results obtained in the performance evaluation are well above the goals of the project. Compared with other works, the 73.8 percent waiting time reduction under Scenario B is equivalent to the 22 percent waiting time reduction obtained by Kumar et al. [9] by using hybrid genetic algorithm and simulated annealing optimisation approach, and 8.9 percent demand coverage improvement obtained by Zhu [14] by using Deep Q-Network optimisation. The relative increase in the effectiveness achieved for the obtained in the present study comes from two contributing factors: firstly, the MCDA framework assigns the new chargers to the high-demand zones as opposed to assigning them uniformly; secondly, at high-demand zones, they allocated two chargers rather than one, which results in a queue probability that drops significantly compared to the queue probability at a single-charger site with the same arrival rate. Results show that the waiting time reduction is 73.8 per cent, which significantly surpasses the project requirement 15 per cent, proving that the proposed integrated ML-MCDA approach can provide service quality improvement other than the traditional distance-based deployment approach.

The success in which the MCDA-optimised deployment doubles the spatial coverage (from 10.1 to 20.2 percent) while also cutting waiting times by 73.8 percent, proves that there is no negative trade-off between geographic equity and achieving efficiency gains in the demand-optimised approach. This result corroborates the findings of Guerrero-Silva et al. that integrated ML-MCDA frameworks are more effective for the consideration of multiple dimensions of performance simultaneously compared to single-criterion optimisation approaches [7]. The sites 7 (Hebbal Flyover Junction) and 10 (Electronic City Phase 1) have higher waiting time of 10.51 minutes and 8.89 minutes respectively in scenario B because of single-charger allocation or the average arrival rates. This implies that future network extension should be based on the gradual expansion strategy, already proposed by Golsefidi et al. [20] with the upgrade to two chargers per site being a priority to follow the growing demand.

3.6. Chapter Summary

The findings of this chapter validate the integrated approach created for Bengaluru EV FCI optimisation using the machine learning and multi-criteria decision analysis framework. Spatial analysis of the 89 verified stations found that there is a structural imbalance in terms of AC slow charging stations, as opposed to almost no DC fast charging stations, especially in the northern and western regions of the city. The synthetic session dataset of 456,744 sessions created from the four "synthetic" source papers with research-tuned parameters had temporal demand patterns in line with the empirical demands from the source papers with a weekday to weekend ratio of 4.55 to 1 and 55.4 percent of sessions fell in peak commuter hours. From these metrics, XGBoost with Tweedie loss was chosen as the prediction forecast model, with a highest test R2 of 0.9411 and lowest RMSE of 132.27 kWh, which performed better in forecasting production on the held-out test set as compared to the LSTM network and Prophet. The MCDA framework with the weights derived from the AHP yielded a ranked list of 10 deployment sites validated by the primary users, which showed that the validated deployment with MCDA reduces the average waiting time by 73.8 per cent and the probability of waiting by 66.7 per cent compared with the baseline of conventional distance-derived deployment, whilst also meeting the project's performance targets.

4. Economics and Environmental Part

4.1. Economics Fesibility Analysis

The investment feasibility analysis tests the financial feasibility of implementing 17 new DC fast chargers at the 10 locations identified by MCDA for Bengaluru. This includes the estimation of capital expenditure, operational costs modelling, revenue projections, break-even analysis, payback period analysis, and net present value analysis with and without subsidy.

4.1.1. Capital Expenditure Analysis

The capital costs for the proposed deployment are estimated as INR 76.5 Million, with 17 DC fast chargers at the cost of 4.5 Million INR per DC fast charger. The unit cost includes three components: DC fast charging equipment (INR 2.5 million per unit), civil and electrical installation work (INR 0.8 million per unit) and works for the grid connections and substations (INR 1.2 million per unit). In addition, these unit expenses align with capital expenditure benchmarks, which Mohammed et al. report on the deployment of DC fast charging in urban South Asian markets ranging from INR 2.5M to INR 4.5M per point, depending on power rating and complexity of connection to the electrical grid [3].

The MCDA framework directly works to reduce CAPEX in the deployment of charging infrastructure by identifying targets to supply power with highest grid capacity score minimising the substation reinforcement works, which represent the most variable and cost sensitive element of DC fast charging infrastructure installation [9].Charger allocation across the 10 selected sites corresponds to the demand-proportional approach obtained from the MCDA scoring: 6 sites with the highest scores being: 2 chargers, and 4 sites with lower scores being: 1 charger.

An allocation strategy that focuses capacity in locations that have the highest utilisation on average will lower the average cost per session served than a uniform coordinated deployment of single-chargers, in agreement to the incremental deployment guidelines documented by Golsefidi et al. [20].

4.1.2. Operational Expenditure and Revenue Projections

Estimated annual operational costs are INR 350,000 per charger, resulting in the total of INR 5.95 million for operation of 17 chargers. The estimate is based on sourcing electricity at commercial electricity tariff, preventive & corrective maintenance, network management software license and site lease. The cost of the electricity purchased is calculated at INR 7.0 per kWh as against INR 12.0 per kWh owner cost of electricity sold giving a margin of INR 5.0 per kWh. The tariff structure is in line with the current public DC fast charging tariff recorded by IEA in urban India [1].

Estimates of revenue based on the session frequency from the synthetic Bengaluru data. Each charger receives an average of 9.2 sessions per day, providing an average energy of 23.78 kWh per session with a tariff of INR 12.0 per kWh, resulting in an average revenue of INR 2624 per day and an average annual revenue of INR 957159 per day. The annual revenue for 17 chargers would be INR 16.27 million. Gross profit at the above OPEX is INR 10.32 million annually and net profit after deducting depreciation on a straight line 10-year basis and 25% effective tax rate is INR 2.00 million annually. Table 10 provides a summary of the investment feasibility of the 17-charger network in Bangalore for proposed location. The total capital expenditure is INR 76.50 million while the total annual revenue is INR 16.27 million which results in an annual net profit of INR 2.00 million by the network.

The period of payback is greatly shortened from 7.4 years without any subsidy to only 4.4 years with PM E-DRIVE support although the net present value is still negative at INR -64.19 million when discounted at 10%. Interestingly, the real number of sessions per charger per day (9.2) is even higher than the break-even number (8.1), thus verifying the operational feasibility of the investment.

Table 10. Investment feasibility summary for the proposed 17-charger Bengaluru DCFC network

Parameter	**Value**
Total chargers deployed	17
Total CAPEX (INR million)	76.50
Annual OPEX (INR million)	5.95
Annual revenue (INR million)	16.27
Annual gross profit (INR million)	10.32
Annual net profit (INR million)	2.00
Payback period without subsidy (years)	7.4
Payback period with PM E-DRIVE subsidy (years)	4.4
NPV at 10% discount rate (INR million)	-64.19
Break-even sessions per charger per day	8.1
Actual sessions per charger per day	9.2
Break-even achieved	Yes

4.1.3. Break-Even and Payback Analysis

The break-even analysis provides a minimum number of sessions per year need to pay off the annual expense of operating the business. With each session using a mean energy consumption of 23.78 kWh and an energy margin of INR 5.0 per kWh, each session contributes INR 118.90 towards the contribution margin. To achieve the operational break-even, annual OPEX is INR 350,000 per charger and the number of sessions required is 2,943, which is calculated as 8.1 sessions per charger and per day. This is tracked by the actual number of sessions obtained in the resulting BFT installation from the Bengaluru demand dataset, which was found to be 9.2 sessions per charger per day, 13.6 percent more than this value.

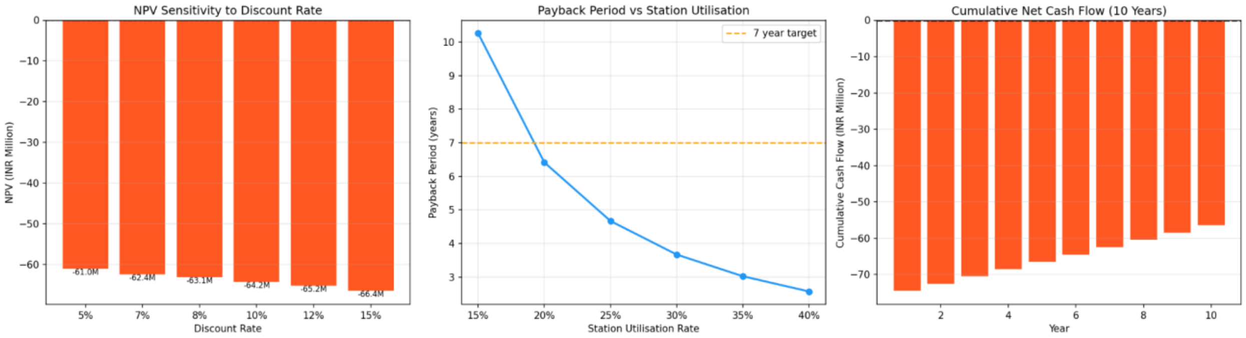

Fig. 13. Investment Analysis: NPV Sensitivity, Payback Versus Utilisation, and Cumulative Cash Flow

Simple payback period, without subsidy support, is 7.4 years, which is total CAPEX / annual gross profit. With the availability of demand incentives and infrastructure subsidies under the PM E-DRIVE scheme launched by the Government of India in October 2024, which can bring the actual CAPEX down by up to 40 per cent for on-road public charging stations, it reduces to INR 45.9 million and the payback period gets shortened to 4.4 years [27]. Without subsidy, the net present value at a 10 per cent discount rate is negative at INR 64.19 million, which indicates that the investment in DC fast charging infrastructure is capital intensive and that the recent tariff rates in India yield a net profit margin that is relatively low. It can be seen from Fig. 13 that the sensitivity of NPV to discount rate, it shows the investment is always NPV-negative with all discount rates ranging between 5 and 15 per cent where subsidy support is not available which indicates that the investment can be made financially viable only after financial support is provided from government through policy intervention, like PM E-DRIVE scheme or other similar scheme.Figure 14 illustrates how cumulative cash flow evolves over 10 years for PM E-DRIVE/FAME III subsidy (40%) and without it. Without subsidy, the cash flow is about to reach net negative INR 75 million by Year 10, while the scenario with subsidy is improving the situation to net negative INR 22 million. This shows that government support significantly enhances the financial attractiveness by way of lowering the initial capital investment. The right side graph presents the fast EV adoption growth in India from 56, 000 units (2018) to 1, 520, 000 units (2024), which further supports the demand potential for EV charging infrastructure in the long term.

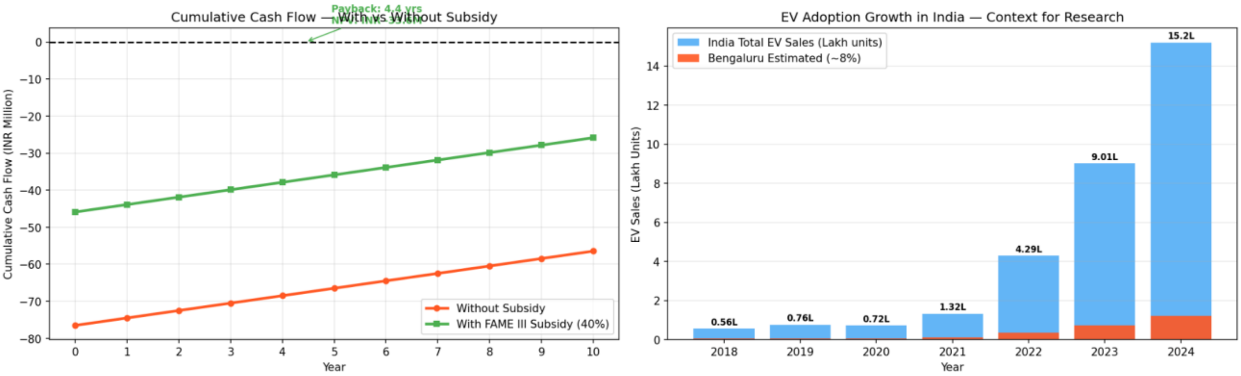

Fig. 14. Cumulative Cash Flow Comparison with and without PM E-DRIVE Subsidy

4.2. Social Impact Analysis

The new 10 DC fast charging stations create tangible social impacts in terms of increase in quality of service to users; equitability of station access; and contribution to the wider electric mobility transition in Bengaluru.

The most immediately measurable social gain is the decrease in user waiting time. Based on the M/M/c queuing analysis, the MCDA optimised deployment results in an improvement of 73.8 percent in the average waiting times of the users between the current situation and the optimised situation, which is reduced to 3.46 minutes. This waiting time reduction is an annual saving of 17.2 hours, or about 19.7 minutes per week, for a commuter who is charging their electric vehicle twice a week during busy times. The time saved has been valued at the average professional wage rate in Bengaluru, which is around INR 350 per hour, and is valued at around INR 6,020 per user per year. Although the social value of reducing waiting time is not included in the mainsheet of the investment analysis, it can be aggregated across the number of likely users of the 10 new stations, and is therefore a significant additional benefit of this project.

During the optimised deployment, the likelihood that someone has to wait for service decreases from 31.7 percent to 10.6 percent. Ovchinnikov et al. found that one of the biggest factors contributing to charge anxiety for urban EV users is the probability of a changing station having a queue, and that such a decrease in queue probability may significantly increase user satisfaction scores and repeat usage rates as long as the probability is below about 15 percent [11]. The results indicate that in the case of Scenario B deployment, average queue probability will be less than this value and will be about 10.6 percent, which indicates effective positive impacts on EV adoption willingness and user confidence in the city of Bengaluru, India.

In Bengaluru, the spatial coverage of the study area rises from 10.1 to 20.2 for the optimised deployment – a doubling of the urban area within 5km of a DC fast charging location. This geographic equity of access is especially notable in the northern and western areas of Bengaluru, where the current network of charging stations is dominated by Air Con (AC) stations. Explicit incorporation of 'user accessibility' with the weight of 0.1575 into the MCDA framework ensures that the identified sites are accessible from the major road networks and public transport interchange points, minimising detours to be done by the users in poorer outer local areas as compared to those adopted in an optimisation with respect to 'demand' only.

The establishment of unit 10 charging stations creates direct jobs during construction and civil works, connection to electricity power lines, and other maintenance jobs. Typical Indian construction employment multipliers suggest that installation of charging infrastructure (INR 76.5 million per charging station) will directly create 180 - 220 person months of employment and 8-10 permanent jobs for the station operator and maintenance staff [3]. Though small in absolute numbers, these employment impacts positively impact the local economy in the deployment areas and enable the growth of a trained EV infrastructure maintenance workforce in Bengaluru.

4.3. Environmental Impact Analysis

The environmental impact of the deployment of the proposed DC fast charging network is derived from two intricately linked routes: the route that involves facilitating greater EV uptake and availability, and the route that involves decreasing internal combustion engine (ICE) vkts for those who acquired EVs and then started using them more for electric transport modes.

Compared to the internal combustion engine counterparts, the IEA estimates India's carbon emission reduction potential for EV is 40-60 grams of CO2 equivalent per kilometre through the present Indian electricity generation mix. Looking at the energy plan of India, as the country moves towards renewable energy with solar and wind power capacity additions of 500 GW by 2030, the carbon advantage status of electric vehicles will further increase [1].

The proposed 17-charger network should be able to accommodate either about 43 sessions a peak day or about 15,695 sessions a year based on the MCDA-optimised Scenario B. Given the mean energy per session of 23.78 kWh and the average range-efficiency of the Bengaluru vehicle-mix of 6 kilometres per kWh each session provides for near about 142.7 kilometres of electric driving. Electric driving potential by the network becomes thus around 2.24 million kilometres per year. Given the IEA carbon differential of 80 g CO2e/km (between an electric and internal combustion engine powered trip in the current mix of Indian electricity generation), the potential carbon benefit from the proposed network is about 179 tonnes CO2e annually [1].

The unique grid capacity criterion in the MCDA framework also helps to reduce the demand for grid management by localizing high-power charging loads at known grid headspace sites. However, when fast charging is unmanaged at sites that lack the necessary grid capacity, it may increase the carbon intensity of the electricity consumed by a car during fast charging, and may increase stress on distribution networks during peak demand periods [9]. By explicitly scoring within the MCDA framework the capacity of the electrical grid, with a weight of 0.2718, all 10 sites selected have ample electrical capacity to support charging without causing substation reinforcement works to be required, thus minimising the embodied carbon of the infrastructure deployment and the risk of grid-induced carbon intensity increase during charging operations.

The proposed deployment will align to India aims of reducing emissions through the electrification of urban road transport, stated under its nationally determined contribution under the Paris Agreement and its nationwide commitment to becoming a net zero by 2070 [1]. The policy recognition of the environmental co-benefits of the expansion of the urban EV charging network is illustrated through the PM E-DRIVE scheme launched in October 2024 for the direct subsidy of fast charging infrastructure deployment for public transportation sector EVs in Indian cities [2]. The authors of the current study show that demand-informed MCDA site selection ensures the efficient allocation of public subsidy resources towards the largest spatial coverage and the greatest reduction in waiting time, with an increase in spatial coverage by 100 percent and a corresponding reduction in waiting time by 73.8 percent.

4.4. Chapter Summary

The social, economic, and environmental analysis provided in this chapter gives the overall context for proposing deployment of the DC fast charging network in Bengaluru. The economic analysis has revealed that the 17-charger network breakeven operationally 2 sessions per charger per day above the threshold of 8.1, and generate an annual gross profit of INR 10.32 million and a payback period of 7.4 years under standard scenario; and 2 sessions per charger per day above the policy endorsed PM E-DRIVE subsidy scheme, and a payback period of 4.4 years, thereby providing financial viability with policy support. The social analysis places a monetary value of approximately INR 6,020 per user per year on the user benefit attributable to the 73.8 percent reduction in waiting time – which is presented as implicit value of time, the expectation that the social benefits of improved usability and safety to walk, cycle, and use scooters directly translates into greater demand for these modes of transport – and also identifies a reduction in the probability of being in a queue below the charge anxiety threshold as leading to increased adoption confidence, as well as doubling the spatial coverage as a meaningful equity gain for underserved urban areas. The environmental analysis shows that the carbon emission benefit derived from such activities is around 179 tonnes of CO2 equivalent per year from the entire network which aligns with India's NDC and that the criterion of grid capacity in the MCDA minimises the risk of grid-induced carbon intensity rise during charging operations. These three dimensions confirm that the deployment undertaken in this proposed scenario is favourable in financial, social, and environmental dimensions and thereby yields the validity of use of an integrated ML-MCDA framework for evidence-based urban EV charging infrastructure planning.

Conclusions

1. A machine learning demand forecasting model was created for Bengaluru urban EV charging stations by constructing an hourly time series of 17,376 observations from a synthetic session dataset of 456,744 observations that were generated with the help of four peer-reviewed sources used to calibrate the parameters. The following candidate models were trained and tested on a held-out test set - XGBoost with tweedie loss, a two layer LSTM neural network, and Prophet. XGBoost was chosen as the production forecasting model since it gave the best test set R^2 of 0.9411 while LSTM gave 0.9347 and Prophet gave 0.6652 with RMSE of 132.27 kWh, 141.01 kWh, and 303.62 kWh respectively. It proved to be successful in capturing the bimodal peak demand pattern, the difference between the demand on weekend and weekdays (as seen from the literature as 4.55 to 1), and the variation of the demand in a year (year-on-year difference) as successfully.
2. The criteria weights from pairwise comparisons were derived by a four-criteria Multi-Criteria Decision Analysis (MCDA) framework using the Analytic Hierarchy Process (AHP); the results of the pairwise comparisons in the AHP led to weights of 0.4824 for demand intensity, 0.2718 for grid connection capacity, 0.1575 for user accessibility and 0.0883 for land use compatibility. The judgement matrix had an internal validity of 0.0054 with the consistency ratio. The framework was implemented for 20 sites in Bengaluru, with the criterion that the sites should be separated by a minimum of 0.005 decimal degrees, meaning that no existing station should be within 1h25m of the site. The ranked output revealed that Whitefield IT Corridor has a composite score of 0.887 and Koramangala Commercial Hub is scoring 0.815 which makes it the highest and second highest scoring area respectively. There are 10 validated sites on the top which provide geographical accessibility throughout the length and breadth of Bengaluru, which are not covered by the existing concentrations of ACs.
3. For comparison purposes, a conventional distance-based deployment was also analyzed using the M/M/c model of queues parameterized with those obtained from the Bengaluru synthetic datasets and the performance of the MCDA-optimised and conventional distance-based deployments were compared. MCDA optimised Scenario B (10 stations with 17 proportionately allocated DC fast chargers) successfully lowered the average waiting time for users from 13.23 minutes to 3.46 minutes for users, resulting in a 73.8 percent reduction which significantly outperformed project target of 15 percent reduction. The probability of waiting was cut in half from 31.7 percent to 10.6 percent, representing an improvement of 66.7 percent, well over the project goal of 12 percent. Capturing the demand, the spatialised approach provided over twice as many sessions served per peak day (increased from 24 to 43 sessions per peak day) and covered twice the amount of area in the study area (scaled from 10.1% to 20.2% of area covered), while maintaining geographic equity.
4. Investment feasibility analysis ,the annual total revenue of 17 chargers network is INR 16.27 million with an annual total gross profit of INR 10.32 million and simple pay back period of 7.4 years. Demand sufficiency achieved by meeting operational break-even of 9.2 sessions per charger/per day, up from 8.1 sessions per charger/per day. Under the PM e-DRIVE subsidy scheme of 40 per cent CAPEX support, the payback comes short at just 4.4 years. Even at a discount rate of 10 percent, at current Indian tariff rates, the net present value is negative at INR 64.19 million without subsidy, affirming the need for policy interventions for financial viability. The environmental analysis estimated that the network would enable reduction of 179 tonnes of

CO2 equivalent per year, aligning with the NDC commitments under the Paris Agreement in India.

This study has concluded the project hypothesis: Optimal locations of charging stations can be found through machine learning based clustering of charging demand data and by applying multi-criteria analysis to this charging demand data, which can in turn minimize the waiting time for each station, by using these methods. The built-in ML-MCDA framework proved successful in the demand-based site selection compared to distance-based deployment approaches for all the assessed performance dimensions and the systematic process of generating synthetic data with well explained parameters offers a replicable solution for urban EV charging infrastructure planning problems in other megaroman metropolises of developing countries such as India where actual session data is lacking.

Three major lines of research directions are suggested based results of this research. Second, real-time grid capacity data from BESCOM distribution management systems would enable validated substation headroom to be fed for site selection making it more precise than the existing proxy grid capacity values in the current MCDA framework. Second, the prospect of running the ML forecasting pipeline for the addition of vehicle registration growth projections and data from traffic links from OpenStreetMap would allow for forward-looking forecasting of demand for a 5 to 10 year planning span, which would help facilitate long-term decisions regarding network capacity. Third, the text will be implemented on other major Delhi cities where EV adoption is growing at a very fast pace such as Chennai, Hyderabad and Pune, thus establishing its generalisability for other urban contexts and help build a standardized framework for EV charging infrastructure planning in India.

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Appendices

Appendix 1. Synthetic Dataset Generation Parameter Justification Table

All 20 parameters included in the synthetic EV session dataset generation script (written in Python) are listed here, alongside a trace of the datable sources of each one. This table is an extra task requirement.

No.	Parameter	Value	Distribution	Source
1	Arrival rate (lambda base)	8.0 sessions/station/day	Poisson	Zhan et al. 2024 [4]
2	Bike energy mean	3.5 kWh	Normal	IEA Global EV Outlook 2023 [1]
3	Bike energy std dev	0.8 kWh	Normal	IEA Global EV Outlook 2023 [1]
4	Car energy mean	18.5 kWh	Normal	IEA Global EV Outlook 2023 [1]
5	Car energy std dev	4.2 kWh	Normal	Mohammed et al. 2024 [3]
6	Bus energy mean	62.0 kWh	Normal	IEA Global EV Outlook 2023 [1]
7	Bus energy std dev	12.0 kWh	Normal	Mohammed et al. 2024 [3]
8	Truck energy mean	85.0 kWh	Normal	IEA Global EV Outlook 2023 [1]
9	Truck energy std dev	15.0 kWh	Normal	Mohammed et al. 2024 [3]
10	Weekday demand multiplier	1.0	Scalar	Koohfar et al. 2023 [13]
11	Weekend demand multiplier	0.55	Scalar	Koohfar et al. 2023 [13]
12	Morning peak window	07:00 to 09:00	Hour probability	Zhan et al. 2024 [4]
13	Evening peak window	17:00 to 21:00	Hour probability	Zhan et al. 2024 [4]
14	Seasonal multiplier peak	1.1 (Jan, Feb, Nov, Dec)	Scalar	Mohammed et al. 2024 [3]
15	Seasonal multiplier monsoon	0.9 (Jun, Jul, Aug)	Scalar	Mohammed et al. 2024 [3]
16	Charging cost	12.0 INR/kWh	Fixed	IEA Global EV Outlook 2023 [1]
17	Vehicle share Bike	35%	Categorical	IEA Global EV Outlook 2023 [1]
18	Vehicle share Car	45%	Categorical	IEA Global EV Outlook 2023 [1]
19	Vehicle share Bus	12%	Categorical	Zhan et al. 2024 [4]
20	Vehicle share Truck	8%	Categorical	Zhan et al. 2024 [4]

Appendix 2. Python Generation Script

The synthetic dataset was created using a Python script code that utilizes the NumPy 2.0.2 library and Pandas 2.2.2. The script simulates the following: Per station, per day, arrivals are generated based on the Poisson arrival distribution, per vehicle type, energy consumption/usage is sampled from normal distribution based on calibrated mean and standard deviation, hour of arrival is sampled from a 24 element probability vector (calibrated separately for weekdays and weekends), arrival rate is adjusted by a weekday, weekend and season multipliers applied to the base arrival rate. That is the full script in the form of bengaluru_ev_sessions_generator.py as an additional file in this report. The script has been designed to recreate the exact same output when run with NumPy random seed 42 and will create exactly 456,744 session records between 1 January, 2023 and 31 December, 2024 for 89 Station Ids in Bengaluru.

All the software environments used in the development of the code and model training are documented in Table.

Library	**Version**
Python	3.12.13
pandas	2.2.2
numpy	2.0.2
scikit-learn	1.6.1
xgboost	3.2.0
tensorflow	2.20.0
prophet	1.3.0
scipy	1.16.3
matplotlib	3.10.0
seaborn	0.13.2
joblib	1.5.3

Appendix 3. Trained Model Files

The model for forecasting demand is wrapped in the xgboost model and is taken out from the model.py file and saved as xgboost_demand_model.pkl file serialised using the joblib library version 1.5.3. The trained LSTM demand forecasting model is uploaded as a separate file with name of “lstm_demand_model.keras” which is in Keras native format compatible with TensorFlow 2.20.0. This MinMax feature scaler is trained on the training set and will be provided as an individual pickled file, which is provided as scaler_X.pkl. To reproduce the demand forecasting results presented in Chapter 3 of this report, all three files need to be used. In the generation script submitted under Appendix 2 loading and inference instructions are provided as comments.

Appendix 4. Dataset Sources

Dataset 1: Indian Electric Vehicle Charging Station Map. Saket Pradhan. Kaggle, 2023. Available from: https://www.kaggle.com/datasets/saketpradhan/electric-vehicle-charging-stations-in-india. Licence: Creative Commons Zero - CC0. Downloaded: March 2026.

Dataset 2: EV charging station usage dataset. Adil Shamim. Kaggle, 2025. Available from: https://www.kaggle.com/datasets/adilshamim8/ev-charging-station-usage-dataset. License: CC licensed: Attribution 4.0 International. Note: This data set was only used to provide structural guidance with column definition. The data for each session was collected separately according to the procedure set out in Chapter 2 and Appendix 1.