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Optimizing the Number of Electric Vehicle Charging Stations at Forecourts to Meet Demand

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Abstract

Due to an unexpected increase in the number of people using electric vehicles (EVs), there is an urgent need for more charging infrastructure. In order to reduce wait times and improve user happiness, it is essential to strike the ideal balance between the number of electric vehicles (EVs) and the number of charging stations that are available. For the purpose of the investigation, a data-driven methodology was utilized , which involved conducting hypothetical surveys with a hundred electric vehicle (EV) users. This approach is occurred due to the university's quality control department requires a lengthy approval process for survey questions. Based on this fact, assumptions were made about the experiences of electric vehicle users. To overcome the challenge of optimizing EV charging stations to number of EV users and reducing waiting charging time. MATLAB-based artificial neural network (ANN) simulations were employed.

Keywords—EV, Forecourt , charging station , ultra-fast charger , ANN

I. Introduction:

Traditional transport is the main contributor to greenhouse gas emissions due to its significant use of fossil fuels. Light duty vehicles contribute 44% of global CO2 emissions [1].

Private transport relies on fossil fuels for 95% of its fuel supply, accounting for nearly 50% of global oil consumption [2]. Non-renewable energy will eventually run out as the global population grows. Actions are needed to reduce CO2 emissions and non-renewable energy use. [2].

Electric vehicles (EVs) are one of the most significant technological advances in transportation. Although electric vehicles (EVs) were invented in the early 19th century, their popularity declined as oil prices fell in the second half of the 20th century. Laws and environmental concerns revived interest in electric vehicles (EVs) in the 1990s, and the Toyota Prius—the first hybrid car—debuted in 1997.[3]

Because of pollution from gasoline-powered vehicles and environmental concerns, electric vehicles (EVs) have become more and more popular in the twenty-first century. Around the world, governments have also started helping the electric vehicle (EV) sector with a number of efforts, including tax exemptions and credits. [1]

With their excellent batteries and charging systems, today's EVs are an attractive option to cars powered by gas. They are becoming more and more cheap, and they have good performance and extended range. [4]

The automotive industry is currently undergoing a transformation, with the emergence of vehicles (EVs). These vehicles represent a shift from internal combustion engines towards eco-friendly forms of transportation. Of relying on petrol or diesel engines EVs are primarily powered by motors that draw energy from rechargeable batteries. [4]

There are two types of EVs; plug in electric vehicles (PHEVs) and battery electric vehicles (BEVs). BEVs operate on electricity. Require external charging while PHEVs have both an electric motor running on batteries and a petrol engine. This dual setup allows PHEVs to utilize petrol for journeys and electricity for trips. [3]

The increasing popularity of EVs can be attributed to factors. Firstly they have the potential to significantly reduce carbon emissions especially when charged using energy sources. This aligns with initiatives aimed at combating climate change. Secondly advancements in battery technology have improved driving ranges and alleviated concerns about running out of power during trips ("range anxiety"). Lastly when considering factors such, as fuel efficiency and maintenance costs the overall ownership expenses associated with EVs have become increasingly competitive compared to gasoline powered cars. [2]

The promising future of vehicles (EVs) is being driven by advancements, supportive government policies and increasing consumer demand, in the global transportation industry. [2]

II. Literature review

A. *Infrastructure for Charging EVs Is Critical to Their Implementation*

Having a established network of charging stations is crucial, for cars (EVs) to gain widespread acceptance in the market. The convenience and practicality of vehicles (EVs) greatly rely on the availability of charging infrastructure. Without a network of charging stations potential customers might hesitate to embrace EVs due to concerns about being stranded without access, to charging facilities. [5]
Having a charging station network not increases customer confidence but also enhances the appeal of electric vehicles (EVs), as primary modes of transportation. Moreover it

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enables long distance travel and road trips in EVs bringing us closer, to adoption. Furthermore the successful elimination of petrol and diesel powered vehicles heavily relies on a established charging network.

To ensure the acceptance and success of mobility it is crucial to develop efficient vehicles while simultaneously expanding the accessibility of charging infrastructure. [6]

B. Factors Complicating Optimization

Optimizing the number of EV charging stations is a complex endeavour influenced by numerous variables. Wait times for EV users become a significant concern, particularly during peak hours and at locations with limited chargers. Additionally, user preferences for charging speed (fast vs. standard chargers), diverse EV characteristics (battery capacity, range), and fluctuations in utilization patterns further complicate this optimization process.

C. Focus on Forecourts

This research focuses on optimizing the number of charging stations specifically within forecourts. Forecourts serve as vital refuelling and rest stops for travellers, making them strategic hubs within the EV charging network. Efficient forecourt design is integral to ensuring positive user experiences, especially for long-distance journeys.

D. Research Question and Objectives

The central research question guiding this study is: What is the optimal ratio of EVs to charging stations in forecourts to minimize user wait times and maximize satisfaction? The primary objectives are:

- To identify the key factors influencing EV charging demand and behaviour at forecourts.
- To develop a predictive model, employing artificial neural networks, to optimize the number of charging stations under varying scenarios.
- To provide actionable recommendations for forecourt planners and operators informed by both data analysis and simulation results.

III. Methodology

The methodology of this study involved conducting hypothetical surveys with 100 EV users. These surveys were hypothetical due to the lengthy approval process required by the university's quality control department for survey questions. The aim was to gather data on their usage patterns and preferences regarding the number of charging stations available. A total of 100 users who utilized the forecourt for recharging their electric vehicles but the table of 10 users were provided in this paper .

The data used were based on responses to 7 questions from a hypothetical survey. These questions were crafted to collect details about what people thought and experienced. The assumed participants were EV users based on whether they were using the charging station area when the survey was conducted. This method was chosen to make sure that the information was assumed directly applicable and accurately represented the views of those who use these facilities.

Once the assumed questionnaires were completed by the participants, the data analysis began. The responses to each question were compiled and assumed. The analysis focused on identifying patterns, trends, and common themes among the participants' hypothetical responses. Simple statistical techniques, such as calculation of percentages, were used to summarize and interpret the data.

The analysis techniques employed helped to capture the essence of the assumed participants' perspectives on the number of charging stations available in the EV forecourt.

Overall, These assumed data used as a foundation for further analysis and the exploration of optimal solutions for the number of EVs to the number of charging stations in the forecourt.

For the users, the assumed data includes their EV type, frequency of use and charging per week , duration of charging , experience of queuing , daily distance travelled in kilometres, average duration of each charging session in hours, charger type used, peak charging time, battery capacity in kilowatt-hours (kWh), and average energy consumption in kilowatt-hours per 100 kilometres (kWh/100km). This information provides insight into the users' EV models, their driving habits, charging behaviour, and overall energy consumption.

With this comprehensive data set, analysis can be conducted to identify patterns, trends, and relationships among the variables. Statistical techniques, such as calculating averages, frequencies, and correlations, can be applied to summarize and interpret the data. This analysis can help uncover insights about the demand for charging stations, the peak usage times, the preferred charger types, and other factors that can inform decisions regarding the optimal number and configuration of charging stations in the forecourt.

The hypothetical survey consisted of the questions that are designed to capture the core variables influencing optimization and below are the details of each question and its effect on the optimization process :

- Type of Electric Vehicle Owned: The type of electric vehicle (EV) owned (Small Car, Sedan, SUV) is a critical variable as it directly influences the vehicle's battery capacity, energy consumption, and charging needs. Different vehicle types have varying efficiencies and battery sizes, which affect how users interact with charging infrastructure. This question aims to understand the diversity of EVs in use and tailor charging solutions to meet varied requirements.

- Average Daily Driving Distance: Knowing the average daily driving distance in kilometres helps estimate the

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frequency and urgency of charging sessions required by EV owners. This variable is essential for assessing whether current charging infrastructure meets the needs of EV users and for planning future expansions that accommodate longer-distance travellers.

- Frequency of Charging per Week: This question sheds light on user behaviour and charging patterns, which are crucial for understanding the demand on charging stations. It allows operators to evaluate whether the current number of charging stations is sufficient and to plan for peak usage times.
- Average Duration of Charging Sessions: The average length of charging sessions (in hours) indicates the types of charging stations (e.g., ultra-fast, fast) that are most in demand. This information is vital for charging station operators to ensure that the right mix of charging options is available to meet user needs.
- Preferred Type of Charging Station: Understanding users' preferences for charging station types (Ultra-fast, fast, Tesla Supercharger, Low Power) informs operators about the most popular and potentially profitable charging solutions. It also highlights areas for potential upgrades or expansions.
- Typical Peak Times for Charging: Identifying typical peak times for charging (e.g., Weekday Evening, Weekday Night, Weekend Noon) helps in managing the load on the power grid and ensures that charging stations are adequately prepared to handle high demand periods. This planning is crucial for maintaining a reliable service for EV users.
- Battery Capacity and Average Energy Consumption: Questions regarding the EV's battery capacity in kWh and the average energy consumption in kWh per 100 km provide insights into the efficiency of different EV models and their impact on the charging infrastructure. These variables help in designing services that can support a wide range of vehicles and usage patterns.
- Types and Utilization of Charging Stations: Understanding the variety and average utilization rate of charging stations operated addresses the supply side of the EV charging infrastructure. It's essential for assessing whether the current types and numbers of stations meet the demand and for identifying opportunities for strategic expansions.
- Frequency of Use and Peak Hours: Knowing how frequently each type of charging station is used per day and the peak hours for usage helps operators optimize their operations, ensuring that stations are available when most needed and can sustain the wear and tear from consistent use.
- Tracking Types of EVs and Operational Status: Questions about tracking the types of EVs that use the stations and the operational status of these stations (Working, Under Maintenance, Out of Service) are crucial for maintaining high service quality and reliability. This information enables operators to make informed decisions about maintenance schedules and upgrades.
- Future Expansions or Upgrades: Inquiry into planned expansions or upgrades to charging stations provides insights into the growth and evolution of the charging infrastructure. It reflects the operator's commitment to supporting increasing EV adoption and improving the user experience**.**
- Experience of Queuing: at EV charging stations is crucial for assessing user satisfaction and infrastructure efficacy. Analysing such data helps identify demand mismatches, guiding necessary enhancements in the number and distribution of charging stations to optimize wait times and improve user experiences.

IV. Results of the questioner

For the purpose of determining which of the many survey questions would be most useful for application with Artificial Neural Networks (ANNs), a careful study of the questions was carried out. Because of this evaluation, crucial parameters necessary for ANNs to produce rational predictions were identified. As a consequence, the focus was directed towards four crucial aspects: the frequency of use, the length of time spent charging, the experience of waiting in queue, and the need for additional stations. These factors establish a foundation for compiling data that accurately forecasts the ideal adjustments necessary in the number of charging stations. Also the table reflects diverse user experiences with electric vehicle charging stations this data underscores the need for expanded infrastructure to accommodate growing demand.

TABLE I . user questionnaire data

User	Frequency Of Use	Duration Of Charging	Experience Of Queuing	Additional Stations Needed
1	4	30	2	2
2	3	40	3	3
3	7	25	1	1
4	5	35	4	4
5	2	45	2	1
6	6	20	1	1
7	4	50	3	3
8	3	30	0	0
9	5	40	4	4
10	2	60	2	2

Frequency of use , duration of charging , experience of queuing are the inputs and additional stations needed is the output.This MATLAB script is designed for assessing the need for additional electric vehicle (EV) charging stations at a forecourt. It employs a feedforward neural network to analyze survey data, including frequency of use, charging duration,

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and queuing experiences, to predict the precise number of additional charging stations required. This approach allows for a data-driven decision-making process, enabling infrastructure planners to effectively enhance service levels by accurately addressing the capacity needs of EV charging facilities. The nueral network is shown below in fig. 3 , consists of 3 inputs and one output .

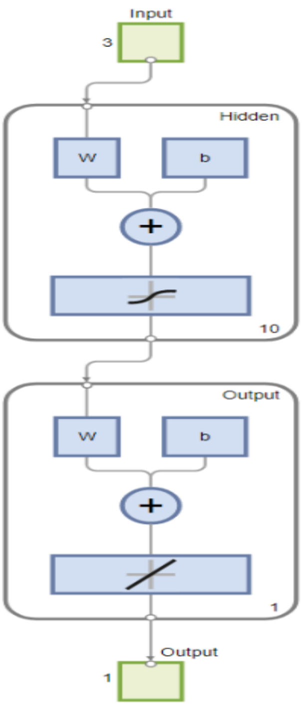


Fig.3 Nueral network with 3 inputs and 1 output.

```
% Survey Data
X = [4 30 2; 3 40 3; 7 25 1; 5 35 4; 2 45 2; 6 20 1; 4 50 3; 3 30 0; 5 40 4; 1 60 0];
```

Min-Max Normalization Equation

The Min-Max normalization equation to scale data to the range [0, 1] is:

Xnorm= X−Xmin / Xmax−Xmin

Where:

Xnorm is the normalized value.

X is the original value.

minXmin and maxXmax are the minimum and maximum values in the data, respectively.

```
% Survey Data (FrequencyOfUse, DurationOfCharging, ExperienceOfQueuing)
X = [4 30 2; 3 40 3; 7 25 1; 5 35 4; 2 45 2; 6 20 1; 4 50 3; 3 30 0; 5 40 4; 2 60 2];
Y = [2; 3; 1; 4; 1; 1; 3; 0; 4; 2]; % AdditionalStationsNeeded

% Normalize the Input Data
X_min = min(X);
X_max = max(X);
X_norm = (X - X_min) ./ (X_max - X_min);

% Define the ANN for regression
net = fitnet(10); % Using fitnet for numeric prediction
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
```

the part of the code above creates an Artificial Neural Network (ANN) using fitnet with 10 neurons for regression analysis. It splits data into 70% training, 15% validation, and 15% testing, optimizing the model's performance on numerical prediction tasks through training and evaluation phases.

```
% Train the network with normalized data
[net, tr] = train(net, X_norm', Y');
```

This command trains the previously defined Artificial Neural Network (ANN) with normalized input (X_norm) and target data (Y), optimizing its parameters for regression tasks. It returns the trained network (net) and training performance details (tr).

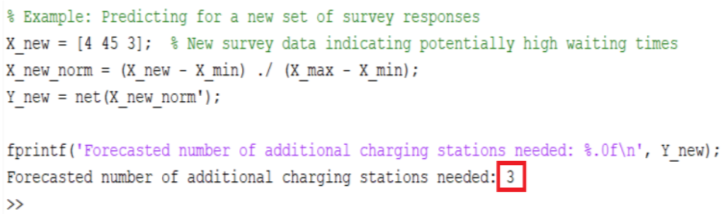
```
% Example: Predicting for a new set of survey responses
X_new = [4 45 3];  % New survey data indicating potentially high waiting times
X_new_norm = (X_new - X_min) ./ (X_max - X_min);
Y_new = net(X_new_norm');
```

The code above snippet predicts waiting times using a trained ANN for new survey responses, normalizing the input data (X_new) based on previously obtained minimum (X_min) and maximum (X_max) values, and then computing the prediction (Y_new).

```
fprintf('Forecasted number of additional charging stations needed: %.0f\n', Y_new);
```

the last command is an output , it outputs the predicted number of additional charging stations needed, rounding the forecast (Y_new) to the nearest whole number, and displaying it as part of a formatted message to the user or log.

the code is predicted the exact number of additional charging stations that are required as shown on the figure below , for a new set of servey response , the output gives 3 additional charging stations required based on the users inputs and the factors that have been assumed .


```
% Example: Predicting for a new set of survey responses
X_new = [4 45 3];  % New survey data indicating potentially high waiting times
X_new_norm = (X_new - X_min) ./ (X_max - X_min);
Y_new = net(X_new_norm');

fprintf('Forecasted number of additional charging stations needed: %.0f\n', Y_new);
Forecasted number of additional charging stations needed: 3
>>
```

Fig. 1 results of the code

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Again, for any new user response, it can be inserted into the matrix X_new to predict the number of additional charging stations needed based on the user's response and input, as it shown in Fig.1 the result of the users data was having or expanding the infrustructure to 3 additonal charigng stations to solve the waiting time isse .

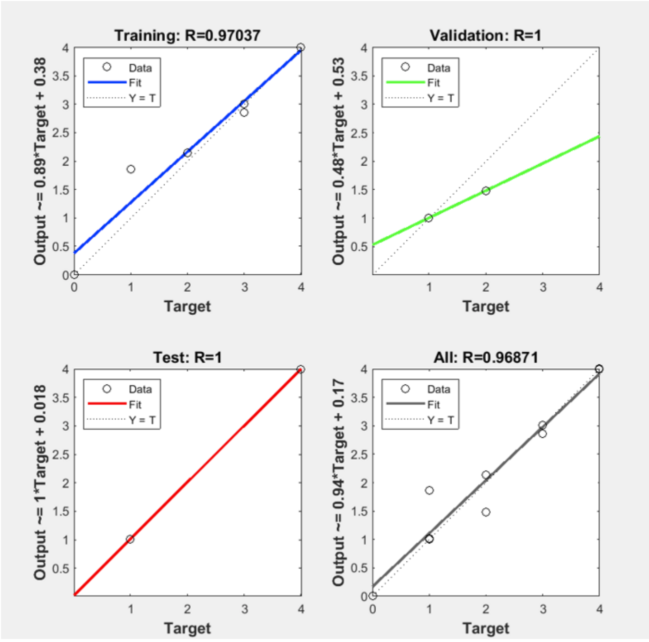

Fig. 2 Rregression of training , validating and testing the data

The above regression analysis graph helps evaluate the performance of the model by comparing the predicted outputs against the actual target values. The presence of data points (dots) extremely close to the diagonal line indicates accurate model predictions. The slope and position of the line that provides the best match, compared to the line representing the ideal forecast, offer insights into the overall bias and accuracy of the model.

And again the main aim of this scenario was to use a data-focused, machine learning method to precisely predict the need for more EV charging stations at certain locations. By using detailed data on how users behave, the plan is to spot where the charging infrastructure is lacking and figure out the best places and times to add new stations. This forward-thinking approach helps keep up with the increasing number of EVs by making sure there are enough charging points, making EV charging networks more efficient and supporting the move towards greener transportation. In the end, we want to make charging EVs easy and convenient, boosting the use of EVs by making sure there are always enough places to charge them.

FUTURE WORK:

Future work for this project will involve securing the necessary approvals to conduct comprehensive surveys across multiple electric vehicle (EV) charging forecourts. Expanding the scope of the survey to include a larger number of users will significantly increase the dataset size, enhancing the robustness of the data-driven models. Additionally, with a more extensive dataset, the training of the neural network can be refined to yield more accurate predictions. This expansion will facilitate a deeper understanding of user needs and behaviors, allowing for more precise infrastructure planning and potentially uncovering new trends in EV charging station usage. Further exploration might also include integrating real-time data feeds to enable dynamic prediction capabilities, adapting to changes in usage patterns as they occur.

Reference :

[1] Rachid, A., El Fadil, H., Gaouzi, K., Rachid, K., Lassioui, A., El Idrissi, Z. and Koundi, M., 2022. Electric vehicle charging systems: comprehensive review. Energies, 16(1), p.255.

[2] Alrubaie, A.J., Salem, M., Yahya, K., Mohamed, M. and Kamarol, M., 2023. A comprehensive review of electric vehicle charging stations with solar photovoltaic system considering market, technical requirements, network implications, and future challenges. Sustainability, 15(10), p.8122.

[3] Rajashekara, K., 1994. History of electric vehicles in General Motors. IEEE transactions on industry applications, 30(4), pp.897-904. Environment

[4] Sanguesa, J.A., Torres-Sanz, V., Garrido, P., Martinez, F.J. and Marquez-Barja, J.M., 2021. A review on electric vehicles: Technologies and challenges. Smart Cities, 4(1), pp.372-404.

[5] Veneri, O., Ferraro, L., Capasso, C. and Iannuzzi, D., 2012. Charging infrastructures for EV: Overview of technologies and issues. 2012 Electrical Systems for Aircraft, Railway and Ship Propulsion, pp.1-6.

[6] Mastoi, M.S., Zhuang, S., Munir, H.M., Haris, M., Hassan, M., Usman, M., Bukhari, S.S.H. and Ro, J.S., 2022. An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. Energy Reports, 8, pp.11504-11529.

[7] Monikandan, A.S., Chellaswamy, C., Geetha, T.S. and Sivaraju, S.S., 2022. Optimized convolutional neural network-based capacity expansion Framework for Electric Vehicle Charging Station. International Transactions on Electrical Energy Systems, 2022.