Smart Charging Stations: ARIMA Predictions and K-Means Clustering for Efficient ElectricVehicle Charging Networks

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***Abstract*— The quick use of Electric Cars (EVs) is making a big change in the electric vehicle business toward clean and good-natured travel methods. But this change makes it hard to make sure the old charging systems are ready for more and more electric cars. This study uses past numbers on electric vehicle use. Then it employs high-end data examination methods like Auto Regressive Integrated Moving Average (ARIMA) models as well as K-Means Clustering. These techniques are used to accurately pedicts how many people will consider using these vehicles in the future. The study also covers making an eco-friendly system for charging electric cars, and figuring out how many and what kind of chargers are needed. It predicts the daily demand to use a charging station. In simple words, this study is ready for the future electric vehicle change. It predicts how many electric cars will grow and ensures charging stations are designed well so they work well without harming our environment.**

***Keywords*— Smart charging; Autoregressive integrated moving average (ARIMA); Machine learning; K-Means Clustering; Charging demand; Electric vehicles.**

I. Introduction

As world fuel prices go up, electric cars become popular because they're good for the environment instead of regular vehicles. New ways like rule-based and optimization methods make energy management systems better, making sure we use energy in the right way.The carefully deciding where to put these charging stations. These spots are like special gas stations but for electric cars [1]. We aim to place them close to houses, jobs, and roads so people can simply connect their cars easily whenever they need. They use electricity directly, lessening harm to the environment [2]. The problem with EV use is that they are expensive and not many places can charge them. [3] A. Hafeez [4] and others have a plan to make it easier for people to start using electric vehicles, by setting up charging stations that use solar power in small energy grids called microgrids. This helps cut down on pollution and carbon dioxide emissions. Q. Xing and others [5] have explained a way to predict how much EV charging is needed using real traffic data from the world around us. This helps in making plans for infrastructure, managing places where we charge electric vehicles, etc. Y. Liang and some others [6] have worked on the best choice for a group of shared electric cars using deep reinforcement learning with linear programming to help make it better for people running the fleet, save time, and improve efficiency. Many experts are focusing on new methods like machine learning, time-based models, and deep reinforcement learning to overcome these problems. [7] - [11]. M. Majidpour has talked about making a fast cellphone app for guessing how much energy is used at UCLA's electric car charging spots. This uses a time-weighted dot product difference measure to make it faster and more accurate [12]. M. Kovačević has created a way to show electric car numbers. This helps make sure we can forecast and improve charging times with demand answers, solving problems the grid faces [13]. Some studies talk about ARIMA models, used for EV charging. These capture past ways people charged their cars and differences in the data given to predict what happens next with it [14]-[19]. Our study solves the problem of getting ready for a future with more electric cars. The study uses past info about people buying EVs. It then uses advanced skills in working with data and teaching computers, like the ARIMA method, and grouping things into K-Means groups. This helps to predict right when more folks will buy these eco-friendly cars later on. This aids us in deciding where to set up charging spots wisely. making sure they're easy to use and powered by clean, renewable energy.

II. Dataset

Description of the dataset

This data gives us information about the use and development of electric cars (EVs) and their charging stations. It has information about states, people, and electric vehicle numbers from 2020 to 2023 shown in Fig 1. Also included are details regarding different types of charging stations such as quick, normal, and slow chargers [20]. The second dataset of data looks at connections between 230 electric vehicles. It has specific locations for vehicles, where they are found on a map, numbers showing the battery size in kilowatt-hours (Kwh), how many days the vehicle is there or visited times in addition total number of visiting cars shown in Fig 2. These details are important for watching, path checking, and managing resources. They help to make charging things better, watch where car movements happen, or not move around too much.

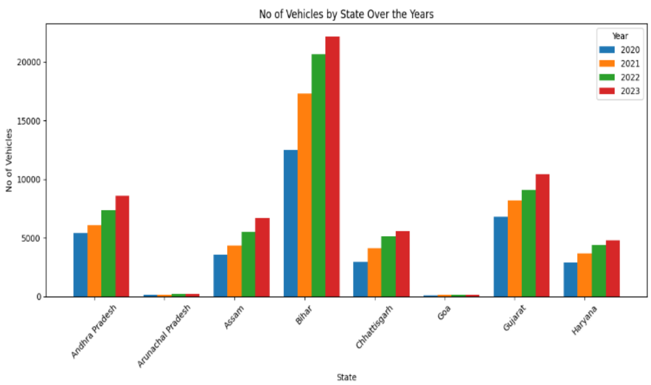

Fig. 1. Visualization of EV's count to States in Different years

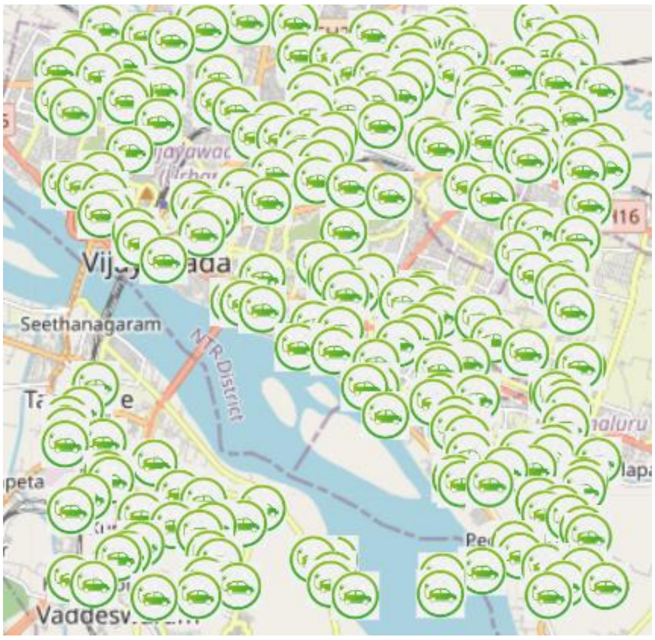

Fig. 2. Geographic visualization of EV locations

III. Block Diagram

A. Data Collection

This way is about counting the number of electric cars (EVs) in a certain place. Even though it gives very exact information, it can be expensive in time energy, and money shown in Fig 3. This works well for smaller places or groups where the work needed is achievable.

- *Collecting Data from Charging Stations*

Collecting information from charge spots can give clues about how people use power and need it. But it might not include electric vehicles that often don't use public charging spots like those mostly charged at home. This way can help make the best of where and how much charging equipment should be.

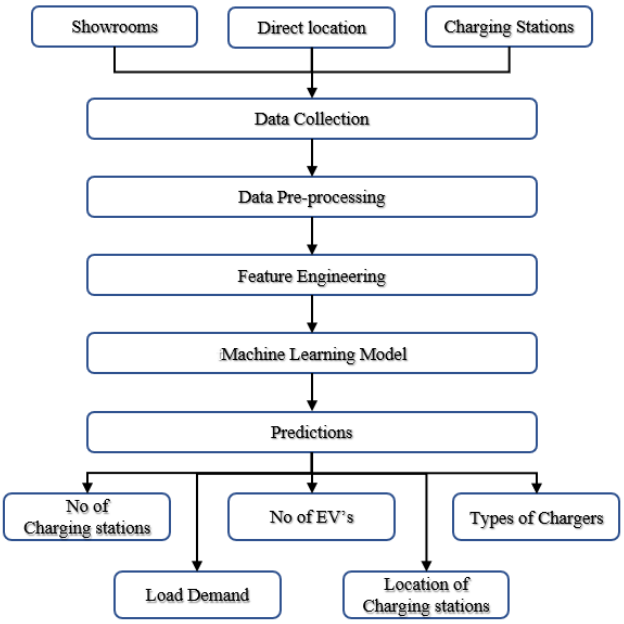

Fig. 3. Block Diagram of the proposed system

- *Collecting Data from Charging Stations*

This way means working with electric vehicle dealers or stores to keep watch over the selling and recording of new EVs. It gives a more immediate look at EV use in the area, and facts can be changed as new cars are bought. It can save money and be correct for keeping an eye on new EV registrations.

- *Collecting Data from Charging Stations*

Getting information straight from the people who make things can help us know more about production and supply. However, it might not show how many items are actually sold or used locally [21]. Makers might not know where each car is or who owns it after they are sold from the store.

B. Data Pre-Processing

Before going into implementation should use our records about electric-powered vehicles (EVs), it should be cleaned. Searching and eliminating any repeated facts, so data is not more than once. When a few details were missing, it is stuffed within the gaps with good predictions. It was additionally checked the records to make certain it all made feel and became correct [22]. This made EV information neat and sincere. Now it was ready and make smart predictions approximately what number of EVs will be and in which to position charging stations for them.

C. Feature Engineering

Feature engineering is like finding important portions of information in a large pile of records. In electric vehicle task, enables the dataset to apprehend and predict things like how many electric vehicles there can be and in which need to put charging stations. Techniques are used to make information easier to work with, like simplifying numbers and locating patterns. This helps our applications make better guesses and plan for the future of electrical vehicles.

D. Algorithms

For electric vehicle venture, a math tool referred to as ARIMA (Autoregressive Integrated Moving Average) to look at destiny. ARIMA is a crystal ball for records that modifications through the years, just like electric-powered cars do. It assesses what came about in the beyond, like how many electric-powered motors were sold or charged, and spots styles and developments [23]. This enables to make predictions approximately how many electric automobiles there may be in the future and whilst human beings will want to charge them. So, ARIMA is one of the best time series forecasts, supporting us to see into the future of electric cars.

E. Predictions

Model has given us five important predictions about electric cars. It tells how many more electric cars will be on the roads, so we can plan for them. It also helps to figure out what kinds of chargers these cars will need, so we can be ready for different charging needs. Additionally, it predicts when these cars will need electricity and how much so that we can get ready with enough power. It also tells us we'll need more charging stations as more people use electric cars, and it helps us put them in the right places. These predictions are like a map for a future with more electric cars, making charging easy for everyone and helping keep our planet clean.

IV. METHODOLOGY

The first step in the process is approximately making predictions on older record sets after which growing accurate and horrific outcomes for those forecasted values. Using the ARIMA (Autoregressive Integrated Moving Average) version with set values of p, d, and q [24], forecasts are made for 2024 and 2025. Simulations add random noise to the predictions. This helps locate each first-class and worst-case condition by looking at tops among made-up forecasts. After that, while we do visualization steps it is about making pictures for every set of statistics [26]. These can include old data and anticipated destiny values in addition to what ought to appear if the whole lot goes very speedy or not so excellent [26]. The predicted numbers and large guesses for each statistic set assist us in understanding adjustments and doubts.

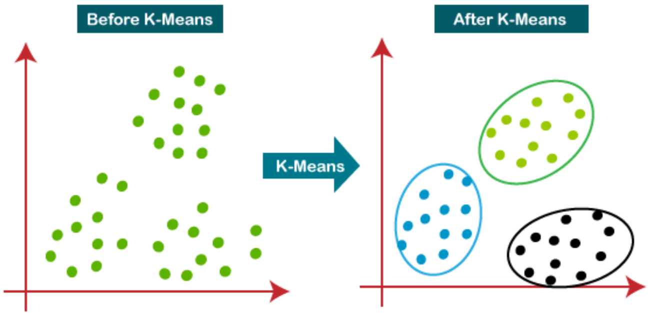

Fig. 4. Visualization of K-means Clustering Process

The K-means clustering is used for grouping data [27] so this will help in grouping the electric vehicles so that maximum demand can be at the nearby charging station shown in Fig 4. The aggregated daily load data is saved to a new CSV file, enabling further analysis or visualization. Line plots are generated for each station, comparing daily load patterns over 30 days. The focus then shifts to calculating the average daily load for each station [28]. A bar graph represents the charging stations and their average daily load, aiding comparisons and energy management decisions. By using this data we can improve the infrastructure of the charging station system to meet the required load demand

V. RESULTS AND DISCUSSION

The model like ARIMA is used to forecast how many electric cars we think will be around in 2024 and 25 for the area shown in Fig 5 & 6. These predictions give important clues about how much demand there will be in the future for places to charge cars. Another problem found is about big change in people wanting more. This is because there are now many electric cars being used. As the electric car market keeps growing, we expect a big increase in the need for places to charge them. This increase shows the need for smart planning of infrastructure to meet the growing needs of electric vehicle users.

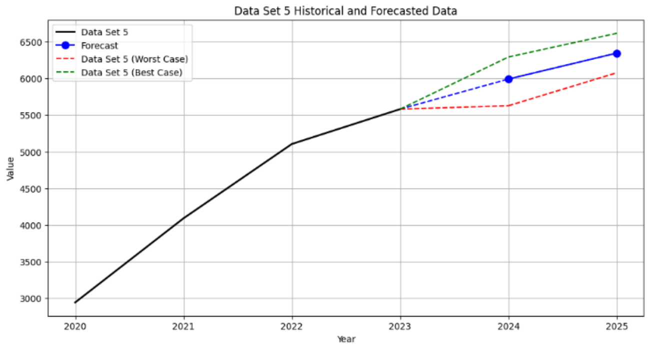

Fig. 5. ARIMA predictions for a state

The studied how electric vehicle users charge their cars each day is done and found some interesting facts. Some places where you can charge electric cars are always very busy, showing that people use them often and need more charging stations shown in Fig 7.

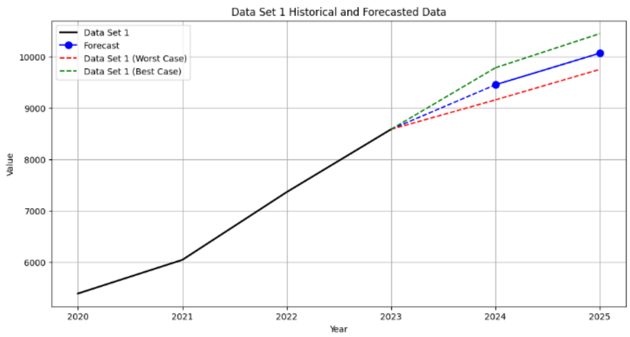

Fig. 6. ARIMA predictions for another state

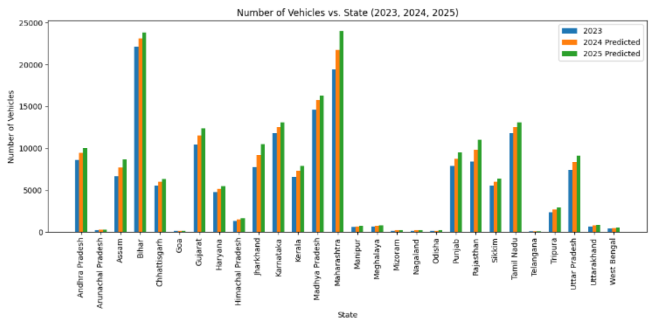

Fig. 7. Bar graph of ARIMA redictions for all states

In Fig 8 & 9 the forecasted growth of EVs is given in different states so that we can identify which state is adopting more EVs in the respective states. Using K-means clustering, we can identify ten capacity places for charging stations. These cluster centers constitute areas with excessive concentrations of vehicles, suggesting they're appropriate for charging infrastructure placement shown in Fig 10. The places had been selected based totally on the density of electrical cars, ensuring that stations are readily reachable to a tremendous part of the electrical vehicle user population.

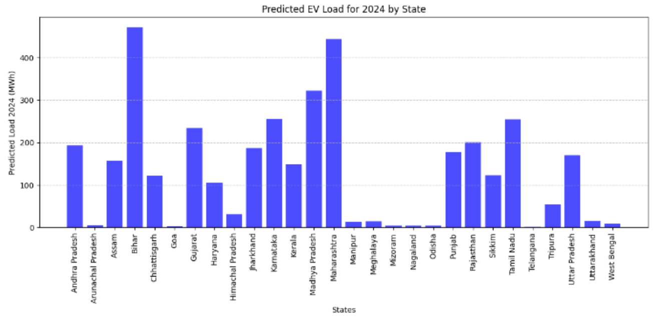

Fig. 8. Forecasted Load for 2024

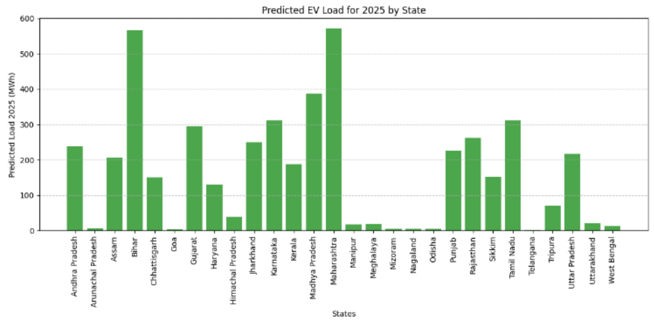

Fig. 9. Forecasted Load for 2025

In contrast, others displayed sporadic or low load patterns, suggesting less frequent usage, which might influence resource allocation decisions. The analysis of daily load patterns revealed interesting insights into the charging behavior of electric vehicle owners.

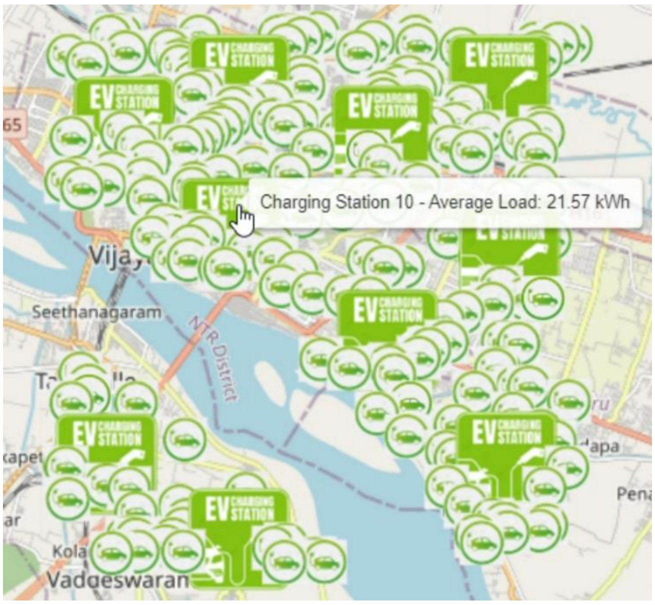

Fig. 10. EV and Charging Station Locations with Load Averages

Some charging stations consistently exhibited high-demand profiles, indicating frequent electric vehicle usage and the need for robust charging infrastructure. In contrast, others displayed sporadic or low load patterns, suggesting less frequent usage, which might influence resource allocation decisions shown in Fig 11. Then the average daily load for each charging station, providing a quantitative measure of their expected power consumption shown in Fig 12. This information is crucial for prioritizing charging stations based on their anticipated load requirements. Stations with high average loads may necessitate additional charging units or advanced technologies to meet the demand effectively. Meanwhile, stations with lower averages might require further evaluation to assess their viability and determine optimal resource allocation.

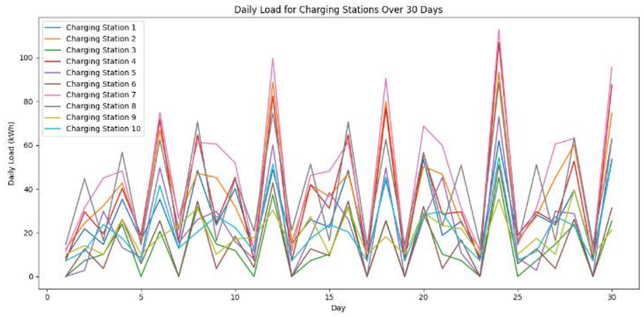

Fig. 11. Daily Load analysis of each Charging Station

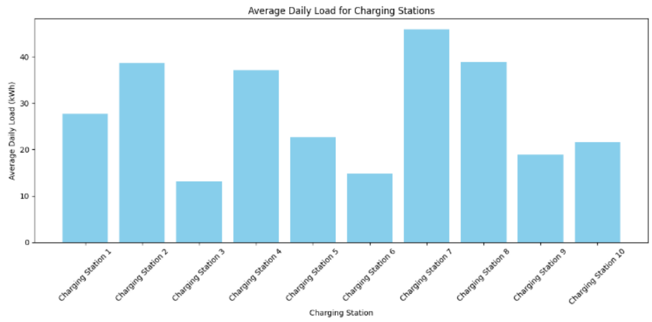

Fig. 12. Daily Load analysis of each Charging Station

These suggestions are made by thinking about how each station is used and what electric car users require. The aim is to make sure there are enough charge points of the right kind at every station so electric car owner's needs can be met shown in Table 1. The plan includes looking at things like the kind of station, where it's placed, and how many people use it. This helps to choose the best way to give out chargers across the charging system.

TABLE I. CHARGER TYPE DISTRIBUTION IN EV CHARGING STATIONS

Charging Station	Car Count	Type A	Type B	Type C	Universal
Station 1	24	2	2	1	1
Station 2	29	2	2	1	1
Station 3	13	1	1	1	1
Station 4	28	2	2	1	1
Station 5	24	2	2	1	1
Station 6	15	1	1	1	1
Station 7	36	3	3	2	1
Station 8	24	2	2	1	1
Station 9	16	1	1	1	1
Station 10	21	2	2	1	1

Big charging stations have different chargers to fit many types of electric cars. The chosen spots for charging stations should be well thought out to make them as useful as possible. You need to think about a few things like how close it is to busy roads, business zones, and homes when deciding where you want it. Checking if quick-charge stations are possible at places with lots of demand will make the charging experience even better. Our daily load study helps us understand how to handle heavy things better. Busy charging spots might get help from extra chargers or quicker ways to charge. This can cut down the time people wait and make sure things run smoothly. Stations with less average use can be checked to see if they are a good fit in the charging network. This might help make better use of resources too.The study's results can be used in making electric vehicle systems better. Putting charging stations and checking how much use they get can greatly change electric car owners' feelings about it.

This helps support the spread of using electric cars around here too. The details we have here are important for people who make rules, run electricity networks, and everyone interested in using electric cars. Future studies could look into models that forecast daily weight load. This would take factors like time of day, weather, and special happenings into account. Watching and gathering data at charging spots will give useful comments for always improving, and changing slowly. Also, checking if it's possible to mix in renewable energy and use storage options will make the charging set-up greener. It also makes sure it stays reliable all the time.

VI. Conclusion

In conclusion, we have taken a comprehensive approach to predicting the growth of electric vehicles, utilizing means clustering algorithms strategically in addition to relying on reliable time series models such as ARIMA. By using these two approaches, we have been able to plan for the increase in EV adoption and group cars into clusters that make it easier to set up an efficient charging network. We ensure that charging stations are positioned strategically to meet the changing demand across various clusters by classifying vehicles according to growth patterns and geographic locations. Furthermore, charging stations receive the knowledge necessary for efficiently handling due to our analysis of average load and daily load patterns. This helps to guarantee that the necessary infrastructure, like the right number of chargers. In short, our data-driven methodology establishes the foundation for a neat, flexible charging infrastructure in addition to projecting the growth trajectory of electric vehicles. By adopting a comprehensive approach, charging stations can remain ahead of the curve, meeting the varied demands of the growing electric vehicle market and promoting an eco-friendly and well-functioning charging ecosystem.

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