Unveiling Growth Patterns: Data Analysis and Prediction for Electric Vehicle Charging Stations

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Abstract: The analysis of Electric Vehicle (EV) charging station data has become increasingly vital due to rising electricity demand, reduced reliance on crude oil, and lower carbon emissions. This study collected EV charging station data from 2011 to 2020, focusing on transaction fees, charging levels, and methods of ending charging sessions. Furthermore, it utilized data visualization techniques to depict charging time, energy consumption, greenhouse gas (GHG) emission reductions, and gasoline savings annually. A decrease in energy consumption is noted in 2020 due to covid-19. Additionally, the SKTime algorithm is employed to forecast these attributes from 2021 to 2026, revealing significant growth in the average charging time, energy consumption, GHG emission reductions and gasoline savings. Also the forecast shows the total energy consumption by all charging stations.

Keywords: Electric vehicle, Charging time, energy consumption, Sktime, GHG saving

1. Introduction

Over the past 20 years, India's transport industry has experienced tremendous expansion and substantial economic benefits. Nonetheless, the threat of vehicle exhaust pollution to the environment is becoming more widespread. Today's trend towards high-speed EVs with longer range, lower costs, and zero emissions reflects a change towards sustainable transportation alternatives, driven by technology improvements and a growing environmental consciousness [1]. Since greenhouse gas emissions from human activity are main cause of unprecedented global warming, addressing the climate issue requires a swift and significant reduction in these emissions. The increasing use of electric vehicles (EVs) is a significant step towards sustainable mobility, a critical modern concern. But the transition from internal combustion engine (ICE) vehicle to EVs depends on building infrastructure that reduces range anxiety among early adopters and persuades potential buyers that EV performance can compete with that of ICE vehicles [2].

Worldwide, there is a strong push towards EV. According to projections, EV charging is expected to account for 5–7% of the world's electricity demand by 2030 [3]. In areas where there are many of EVs, grid and transportation planners need long-term forecasts of the power demand for charging. It is necessary to take into account several situations because EV consumption parameters are unpredictable. These scenarios must be produced by data-driven models that are scalable for millions of drivers [4].

Qualitative analysis and data visualisation were used to examine the Charge Point dataset. Which investigates the differences in the distribution of sessions over time, distributions of charge times across various charging locations, levels, and costs [5]. Precise assessment and forecasting of charging requirements are essential for organising infrastructure for charging, installing electrical grids, and guaranteeing effective functioning. Research on infrastructure design and the understanding of pricing behaviours affect on grid demand are based on this data. The gathering and application of EV data is made possible by developments in communication and vehicle networking. Data in the internet includes information about EVs, road networks, charging facilities, traffic, meteorological conditions, and environmental factors. Research prospects in infrastructure planning and charging demand forecasting are substantial which uses big data and AI algorithms [6]. Unorganised charging can cause problem and lengthy lineups at charging stations as EVs grow increasingly popular. In response, EV charging rights provide the option to reserve a particular charging service, cut down on wait times, and use pricing to incentivize the best possible charging practices [7].

Leveraging the flexibility of EV charging has become a desirable alternative for improving reliable and cost-effective power system operations due to the rise in popularity of EVs and developments in battery technology

[8]. EV charging systems are commonly divided into three categories: Direct Current Fast Charging (DCFC), Level 2 (AC slow to fast charging), and Level 1 (slow charging). Home charging—usually with Level 1 or Level 2 charger is the most popular option [9]. Researchers uses data from 500 EV charging events in Japan to present an ML-based EV charging time prediction model. For prediction, three machine learning algorithms are used: Extreme Machine Learning, Feedforward Neural Network, and Support Vector Regression. To improve accuracy and resilience, metaheuristic approaches such as Grey Wolf Optimizer, Particle Swarm Optimization, and Genetic Algorithm are used to optimise the parameters of the algorithms [10].

The use of various charger levels that are available at various locations will be the main focus. Our vision is to find disparities in charging habits by examining the charging habits of various EVs over a period of one week. Although there is no daily fluctuation in charging on many years, week days, month plays major role in the forecasting [11]. Comprehensive investigation of the factors influencing the length of time that EV connect to charging stations. Research indicates that studies focused on improving the deployment methods for charging infrastructure see EV charging demand largely as a spatial-temporal issue, highlighting the location and timing of the charging session's start [12]. EVs are widely regarded as environmentally friendly vehicles that offer reduced operational costs. Numerous studies have focused on evaluating the GHG emissions associated with EVs [13]. In order to assess GHG emissions from electricity generation and EV batteries by the year 2050, it is needed to examine the consequences of various charging procedures [14]. In order to estimate EV charging demand at the station level over the next few hours (1-4 hours), this study proposes an Long short term memory(LSTM) neural network and makes use of a special trajectory dataset of 76,000 private EVs from January 2018. The impact of input data structures, sample sizes, time spans, and intervals on prediction accuracy is examined and compares with two conventional time series models Autoregressive Integrated Moving Average (ARIMA) and Multilayer Perceptron (MLP) across four scenarios. LSTM beats ARIMA and MLP, demonstrating the superiority of time span and interval over input structures and sample sizes. Reduced time periods typically result in better LSTM performance [15].

To find the ideal sites for fast-charging Electric Vehicle Charging Infrastructures within the distribution system, use multi-objective particle swarm optimization (MOPSO), to reduce voltage variations and power loss. MATLAB and OpenDSS are used to do a time-series analysis of the distribution system and EV load fluctuations. Furthermore, an ARIMA model is utilized to forecast dynamic pricing patterns to evaluate the cost-effectiveness of EVCIs in real-time pricing conditions [16]. For predicting EV usage, researchers frequently employ recurrent neural networks (RNNs), artificial neural networks (ANNs), and their LSTM variation. ANN algorithms are used in a Building Energy Management System to forecast EV charging profiles. To predict 24-hour EV loads, Jahangir et al. used three different neural network techniques: a simple artificial neural network, a rough artificial neural network, and a recurrent rough artificial neural network [17]. In the data-driven world of today, time series forecasting is essential for making decisions in many different industries. Nevertheless, there are difficulties when working with different time series data and forecasting techniques. An inventive system for automated time series forecasting called auto-sktime to handle the data. This framework effectively creates forecasting pipelines by utilizing automatic machine learning, or AutoML. It automates the selection and building of pipelines that combine deep neural networks (DNN), machine learning (ML), and statistical models using Bayesian optimization [18]. As part of sktime, a brand-new open-source Python framework for time series forecasting, which contains instruments for creating, adjusting, and assessing composite models as well as specific forecasting algorithms. This reproduces and enhances key findings from the forecasting study by leveraging sktime [19].

2. Data

The dataset has various details such as charging station locations, available connector types, charging session durations, and energy consumption. Leveraging this data enables to assess charging infrastructure performance, identify trends, determine peak usage times, and devise data-driven solutions for enhancing the efficiency and accessibility of EV charging services. The data originates from Kaggle's Palo Alto EV charging station User open dataset, which provides valuable insights into the availability, utilization, and demand for electric vehicle charging infrastructure. The data analysis focuses on the information gathered from EV charging stations in spanning from July 2011 to December 2020 [20].

Data attributes of a charging station include the station's name and location, its unique MAC address assigned to the Network Interface Card, the type of charger port it has (e.g., Level 1 or Level 2), and the plug type specification. Additionally, data from various vehicles and charging attributes were used to enhance the analysis. Information such as charging, energy consumption in kilowatt-hours (kWh), greenhouse gas (GHG) savings in kilograms, and gasoline savings in gallons were collected from EV charging sessions. The attributes related to vehicle charging include the charging time in hours, minutes, and seconds format, energy consumption in kWh, GHG savings in kg, gasoline savings in gallons, transaction date of the charging event, start time, and end time of the charging event.

2.1 EV charging transaction Fee

The average EV charging transaction fee and the total EV charging transaction fee per year are key metrics that provide insights into the cost and usage trends of EV charging stations.

Fig. 1 and 2 depict the annual changes in transaction fees for all charging sessions at charging stations. In Fig. 1, the bar chart shows the yearly average transaction fee over the past decade, while Figure 2 illustrates the total transaction fees during the same period. It is important to mention that the transaction fee of 23 cents per kilowatt-hour started being enforced at the charging ports on August 1st, 2017. On average, an electric vehicle requires 8.5 kilowatt hours, which translates to approximately two hours of charging time. Consequently, each charging session costs around $2, and the vehicle continues to incur charges as long as it remains plugged in. Furthermore, there is a noticeable gradual increase in the average transaction fee between 2017 and 2020. The COVID-19 pandemic and subsequent travel restrictions resulted in a significant decrease in the demand for electric vehicle recharging, leading to a peak in total transaction fees in 2019 followed by a sharp decline in 2020 which is shown in Fig. 2.

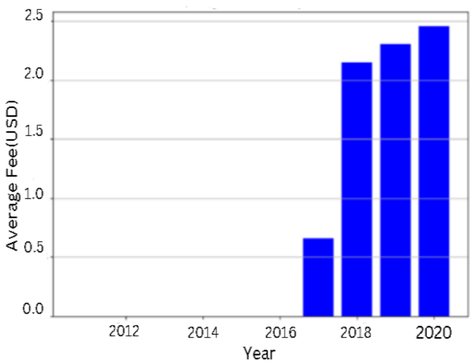

Fig. 1. Average Transaction Fee Per Year

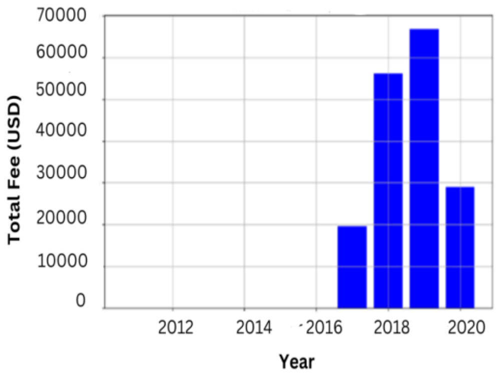

Fig. 2. Total Transaction fee per year

2.2 Electric Vehicle Charging Levels and Connector Types

Fig. 3 shows less than 10000 ports are Level 1 and 250000 ports using Level 2 charging. However, data from EV charging stations shows that Level 1 and Level 2 charging are predominantly utilized, with Level 2 being the most widely adopted.

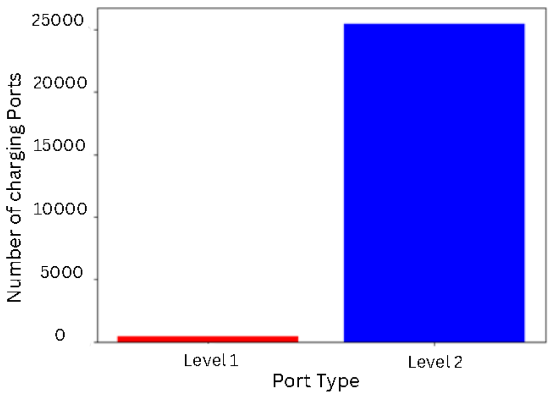

Fig. 3. Level 1 vs Level 2 Port types

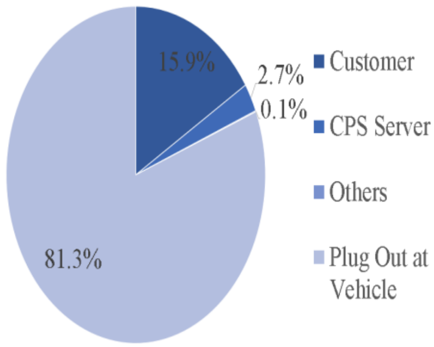

Fig. 4. Cause of Charging Session Termination

2.3 Understanding the Causes of Charging Session Unplugging

The data from Fig. 4 reveals that the majority of unplugging incidents during EV charging sessions, accounting for 81.3%, are triggered by actions at the vehicle itself. This includes scenarios like reaching the desired charge level and addressing technical issues. About 15.9% of unplugging events are initiated by customers, often due to personal scheduling and convenience factors. A smaller proportion, at 2.7%, is controlled remotely by the charging station's Global Positioning System server, usually in response to safety and operational concerns. The remaining 0.1% is attributed to various other sources. Understanding these percentages helps in pinpointing key areas for improving charging infrastructure, user interfaces, and overall system reliability.

3. Analysis for a decade

Analyzing charging station data over a decade is crucial to understanding the long-term trends, establishing standards for EV charging protocols, and analyzing adaptability.

3.1 Charging time

Charging time for EVs refers to the duration it takes to replenish the vehicle's battery. Average charging time is a measure of the typical time it takes to charge an EV in each charging session, calculated by averaging the charging times of multiple sessions. This provides valuable insights into EV usage patterns, charging efficiency, and user experience. Average charging time can help estimate how long a single charging session might take, while total charging time gives an overview of the total time spent charging over a longer period.

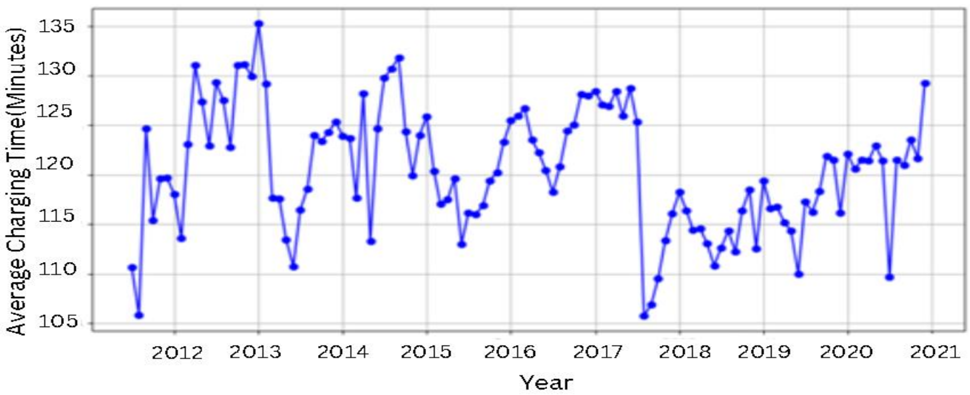

Fig. 5. Average charging time

Fig. 5. shows the average charging time varies between 105 min (1.75 Hr) to 135 min (2.25 Hr). This charging time varies based on the consumption of factors such as user preference, battery technology, charging rate, and charging infrastructure.

3.2 Energy Consumed

The energy consumption of an EV during charging is typically measured in kWh. This measurement represents the amount of energy the vehicle's battery pack receives while charging. This calculation provides an estimate of the average and total energy consumed by the EV over a year. Keep in mind that actual energy consumption can vary based on driving conditions, charging habits, and other factors. The average energy consumed gives you an idea of the typical energy usage pattern of the EV over a specific time frame, while the total energy consumed provides a complete picture of the overall energy usage without considering the time aspect. Both metrics are important for evaluating the energy efficiency and performance of an electric vehicle.

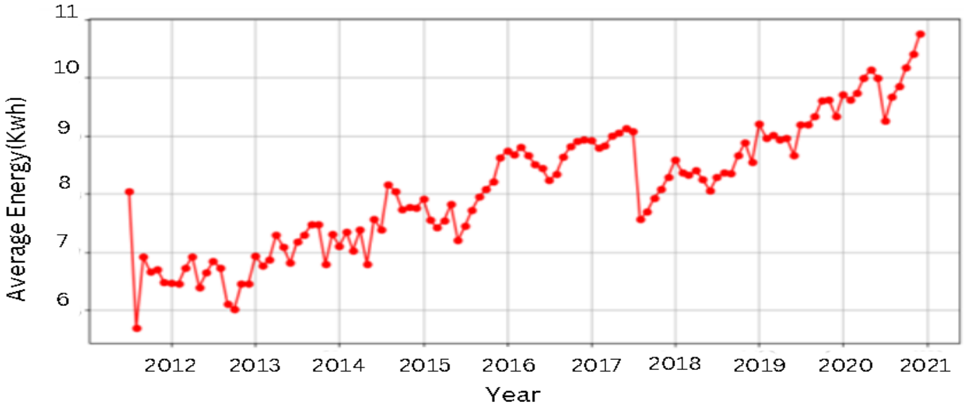

Fig. 6. Average Energy

Fig. 6 shows the average energy consumption varies from 5.78 kWh to 10.8 kWh depending on the specific circumstances of each charging sessions. This is essential to optimize the energy wage during charging routines.

Overall, the range of 5.78 kWh to 10.8 kWh represents a realistic variation in energy consumption for different EVs and driving conditions.

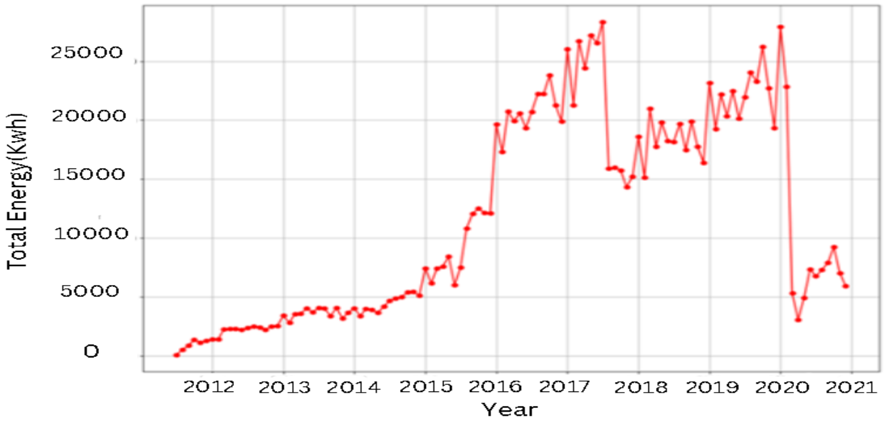

Fig. 7. Total Energy consumed from 2011 to 2021

Fig. 7 shows the total energy consumed by EV charging station for the decade. Is is observed four segments. First from july 2011 to December 2014, the energy consumed increases from 0 to 5000 kWh Slowly. Then between 2015 to 2017 July , the energy demand increased from 5000 kWh to 28000 kWh. A dip in energy consumed is observed in Aug 2017 and again during December 2017 enengy consumption started increases gradually and reached the peak of 27500 kWh during December 2019. Huge fall in energy consumed happened by February and march of 2020 because of covid lockdowns and then maintained between 5000 kwh to 9000 kWh during 2020.

3.3 GHG Saving

GHG savings refer to the reduction in emissions of gases like carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases. These reductions are often measured in terms of carbon dioxide equivalent (CO_2e), which converts the various greenhouse gases into a common unit based on their global warming potential.

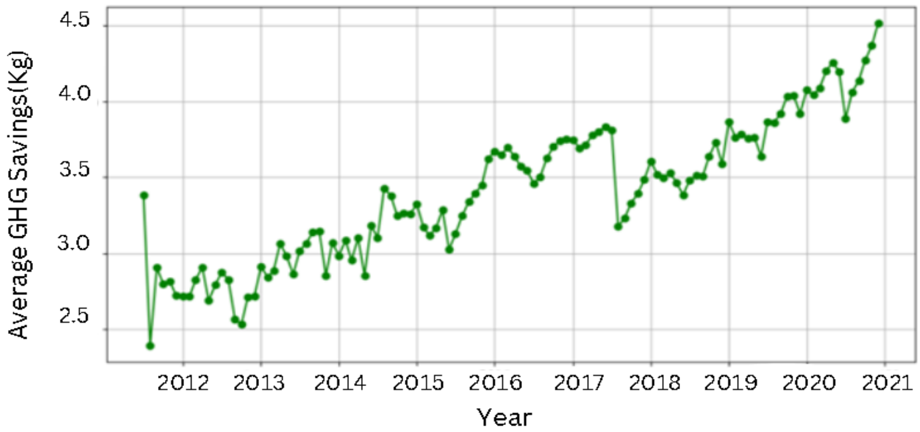

Fig. 8. Average GHG Saving

Fig. 8 shows the average GHG saving varies between 2.4 kg to 4.5 kg. This refers to the average reduction in greenhouse gas (GHG) emissions achieved by using an electric vehicle (EV) compared to a traditional internal combustion engine (ICE) vehicle over a specific distance traveled, such as per kilometer or per mile.

3.4 Gasoline Saving

EVs are powered by electricity stored in batteries, rather than relying on gasoline or diesel fuel. EVs do not use gasoline at all, leading to significant savings in fuel costs compared to traditional internal combustion engine vehicles with zero gasoline consumption.

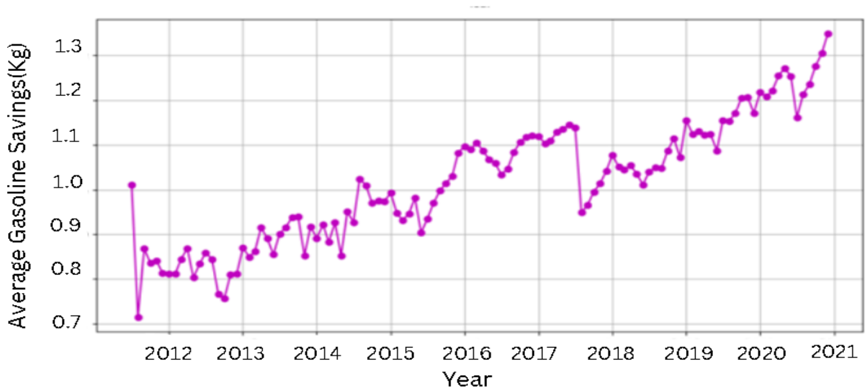

Fig. 9. Average gasoline saving

Fig. 9 shows the average Gasoline Saving varies from 0.7 gallons to 1.38 gallons. Electric Vehicles (EVs) having an average gasoline saving that varies from 0.7 gallons to 1.38 gallons shown in Fig.9 likely refers to the fact that EVs, on average, save a certain amount of gasoline compared to traditional internal combustion engine vehicles over a given distance or time frame.

Gasoline Saving refers to the amount of gasoline that is not used or consumed by an EV because it runs on electric power instead of gasoline.

4. Forecasting using sktime Algorithm

SKtime, short for "sklearn for time series," is a Python library designed for time series forecasting and machine learning tasks on time series data. It is built on top of scikit-learn and provides a unified interface for handling time series data, applying machine learning models, and performing various time series analysis tasks. SKtime offers a wide range of functionalities and algorithms tailored specifically for time series data, making it a valuable tool for researchers, data scientists, and practitioners working with time-dependent data.

To forecast EV charging demand using Sktime, start by preparing collected data with timestamps and corresponding charging demand values. Clean and preprocess the data, ensuring it is in a suitable format for time series analysis. Optionally, perform feature engineering to create additional relevant features from the timestamp data. Split the data into training and testing sets, with a larger portion for training. Choose an appropriate forecasting algorithm from Sktime, such as ARIMA, and train the model using the training data. Evaluate the model's performance using metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) on the testing data. Use the trained ARIMA model to generate forecasts for future EV charging demand based on new timestamps. Sktime's AutoARIMA implementation simplifies the process, as demonstrated in the code snippet provided earlier. Adjust the seasonal period and model parameters as needed for optimal forecasting accuracy.

Time series forecasting plays a pivotal role in a wide range of practical applications, including inventory management, economic growth prediction, and financial market analysis. This has been achieved through the utilization of both pure machine learning models and hybrid approaches.

Time series forecasting involves various crucial procedures, such as model development, calibration, selection, assessment, and implementation. Certain mathematical models, such as ARIMA or neural networks, are specifically tailored to cater to particular families of models. Furthermore, it should be noted that specific models may lack interoperability with commonly utilized machine learning toolboxes such as scikit-learn. Furthermore, certain toolboxes may possess restricted functionality, primarily focusing on the provision of feature extraction capabilities.
To address these limitations, Sktime's innovative Python forecasting system is introduced. This framework provides a comprehensive and intuitive interface for creating, enhancing, and evaluating forecasting models. The forecasting framework, integrated within Sktime, enhances the functionalities of scikit-learn by enabling it to perform forecasting tasks.

This enhances the effectiveness of machine learning models in forecasting time series data, highlighting its superiority over conventional statistical approaches. This aims to augment the open-source functionalities for time series forecasting in the Python programming language through the utilization of Sktime. This also will enhance the clarity and reproducibility of algorithmic performance ratings, while simultaneously optimizing the process.

Within the framework of code, specifically dealing with the traditional problem of forecasting a single variable using discrete time intervals. The objective is to use the observed values y = (y(t1), ..., y(tT)) from a single time series up to time point tT to create a forecaster f' that can accurately anticipate future temporal observations y'(hj) = f'(hj) for the specified time points h1, ..., hH inside the forecasting horizon. To assess the precision of predictions, utilize performance metrics, with mean absolute error (MAE) being a widely employed indicator.

Although assumed evenly spaced time intervals in this scenario, the forecasting system is adaptable to handle time series data with unevenly spread intervals. In addition, the main emphasis is on univariate forecasting, which involves using only one dataset for training. Unlike certain machine learning models that necessitate numerous series for training, this approach streamlines the process by just focusing on the single series provided.

This code snippet performs time series forecasting using the sktime library with a Prophet forecaster.

```
forecaster Prophet = (yearly_seasonality=True)
sktime_forecast(dataset=df, horizon 57, forecaster-forecaster, validation=False)
```

The code utilizes `sktime` for time series forecasting, employing Prophet as a forecaster with yearly seasonality. It evaluates forecast accuracy using MAPE and visualizes results through plotting.

Method Specification: This involves constructing and initializing models and configuring hyperparameters. The method used here is "Prophet."

Training: This phase focuses on optimizing model parameters using training data. The method employed for this is "fit()".

Forecasting: After training, the model produces predictions within or outside the sample using parameters that have been fitted. This is achieved through the "predict()" method.

Validation: Data is partitioned into separate training and testing sets, and the forecasting model's performance is assessed on data it has not been previously exposed to. The method used for temporal train-test splitting is "temporal_train_test_split".

Plotting: Once predictions are made, the program generates a plot displaying both actual and expected numbers. While not directly related to model training or prediction, this visualization is valuable for examining outcomes. The plotting method utilized is "plt.plot".

Confidence Intervals: The program calculates confidence intervals for the predicted values and displays them alongside the actual and expected values. This is facilitated by the method "forecaster.predict_interval".

Inspection: This involves obtaining hyperparameters and trained parameters for analysis. Methods such as "get_params" and "get_fitted_params" are used for this purpose.

5. Forcast for Next Five Years

5.1 Average Charging time forcast

Forcasting average charging time plays a crucial role in enhancement of user experience and enables better planning and shaping the future of EV Transportation. This shows that for many EV owners, 2 hour charging time maybe convenient. This allows users to change the vehicle without significantly disrupting their daily routines.

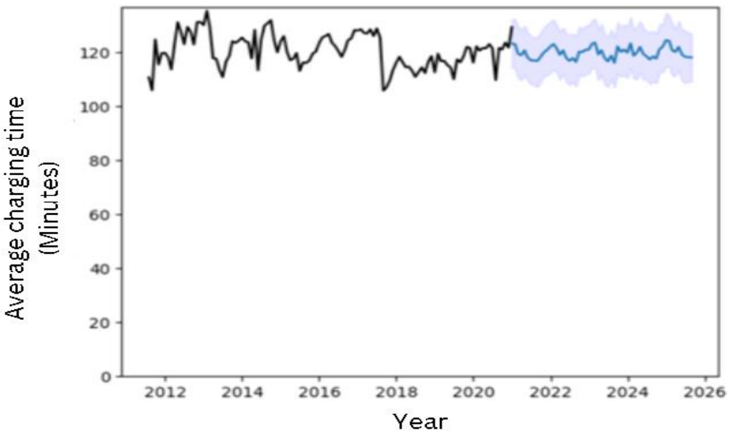

Fig. 10. Average charge time forecast

Fig. 10 shows the average forecasted energy consumption is around 2 hours for 5 years

5.2 Energy consumption forecast

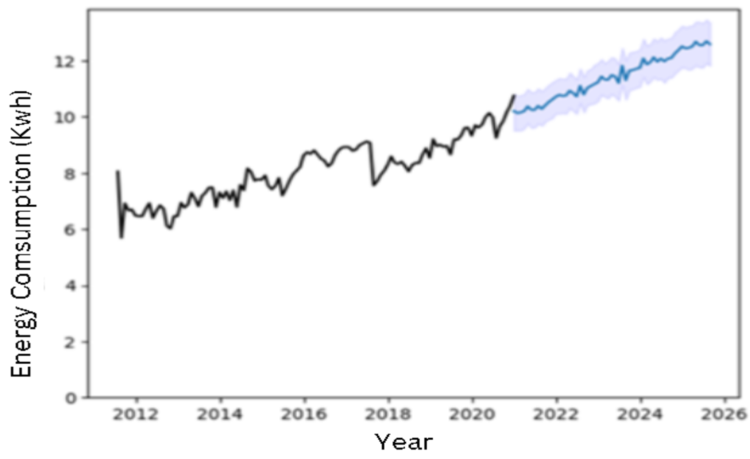

Fig. 11. Energy consumption forecast

Fig. 11 shows the energy consumption increased from 10 kWh to 12.2 kWh for 5 years. This energy consumption forecasting is crucial for resource planning, energy pricing, infastructure investments. The government and regulatory bodies use these forecasts to develop renewable sources which promotes sustainable energy while ensuring energy security.

5.3 Average GHG Saving forecast

The average GHG saving forecast helps in planning the policies and strategies for reducing GHG emissions.

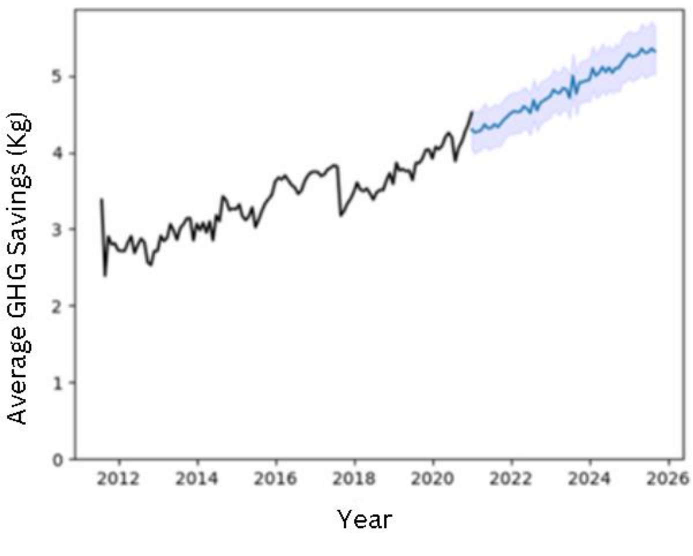

Fig. 12. Average GHG saving forecast

Fig. 12 shows the Avarage GHG saving varies from 4 kg to 5.2 kg in five years from 2021 to 2026.

5.4 Average Gasoline Saving Forecast

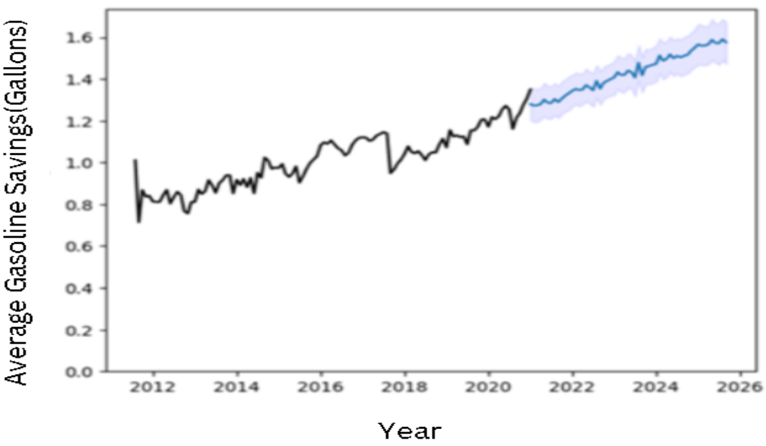

Fig. 13. Average gasoline saving forecast

Fig. 13 shows the gasoline saving increases from 1.2 gallon to 1.6 gallon in five years from 2021 to 2026. This gasoline savings forecast are needed for environmental reasons such as air quality improvement, conservation of natural resources and climate change mitigation. This leads to energy security and reduce economic and geographical risk.

5.5 Total Energy Forecast

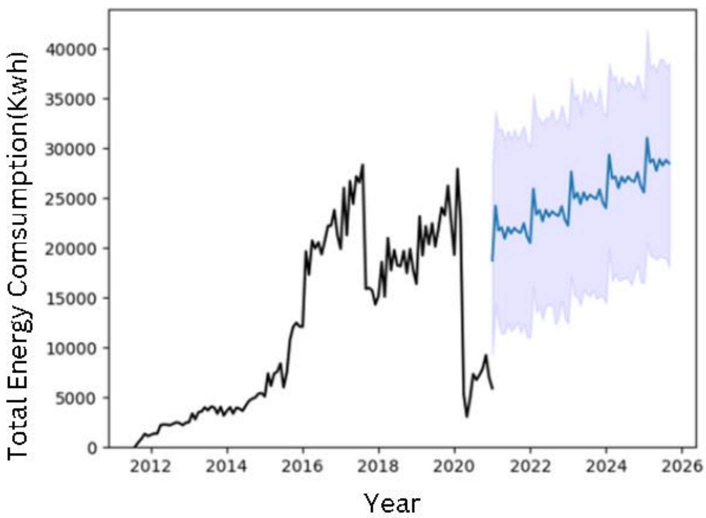

Fig. 12. Total energy consumed and forecast for 2021-2016

Fig. 12 shows the data for the decade 2011 to 2021 and the forecast for next half decade 2021-2026. This shows that EV charging resumed by 2021 which consumed 20000 kWh and in five years increases to 30000 kWh in 2026. Each year 2000 kwh additional power consumed as per forecast. This increase in total energy consumed might be attributed to increased EV adaption, expanded infastructure, technological advancements, governmental policies and inventives.

6. Conclusion

The analysis of Electric Vehicle (EV) charging station data spanning from 2011 to 2020 has provided valuable insights into the transformative impact of EV technology on energy consumption, environmental sustainability, and transportation trends. The findings highlight the increasing importance of EV charging infrastructure as a key enabler for reducing reliance on crude oil, mitigating carbon emissions, and meeting growing electricity demands. The observed dip in energy consumption in 2020, attributed to the COVID-19 pandemic's impact on travel patterns, serves as a reminder of the interconnectedness between societal events and energy usage trends. Furthermore, the use of the SK Time algorithm for predictive modeling has revealed optimistic projections for the years 2021 to 2026, indicating substantial growth in energy consumption and significant reductions in greenhouse gas emissions. These results underscore the urgency and potential of EV adoption in shaping a more sustainable and efficient transportation ecosystem. Continued investment in EV charging infrastructure, data analysis, and predictive modeling tools will be crucial for guiding policy decisions, optimizing resource allocation, and accelerating the transition towards a cleaner and greener transportation sector.

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