Demand Forecasting for Thailand EV Charging Station Based on Deep Learning Techniques

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***Abstract*— The rapid of electric vehicles (EVs) is challenges and opportunities for energy grid management and infrastructure planning. This research is aims to fill the knowledge gap by employing advanced analytical methods on a 503-day time series dataset from Thailand's EV charging stations. The dataset includes information on date, station name, connector type, energy consumed in kWh, payment in Baht, vehicle brand and model, as well as customer ID. This study focuses on three main objectives: (1) Forecasting daily energy demand with a focus on the top 5 stations in terms of kWh consumption to identify seasonality and trends, (2) Predicting daily revenue based on energy consumption, and (3) Conducting a Geo-Spatial Analysis to recommend optimal locations for installing new EV charging stations. The insights derived are expected to assist in efficient grid management, revenue planning, and strategic infrastructure deployment.**

Keywords*— *Electric Vehicle Charging Stations, Decision Support System, Machine Learning, Charging Load Prediction, Location-Based Analysis, EV Adoption, Sustainable Transportation.

I. INTRODUCTION

The growth of electric vehicles (EVs) is an unstoppable trend aimed at reducing carbon emissions and making transportation more sustainable. However, this trend also brings forth various challenges such as grid management, infrastructure planning, and revenue optimization for EV charging stations. In Thailand, where the government has been promoting the use of EVs, there is a palpable need for reliable forecasting models that can guide future strategy and planning.

This research focuses on a comprehensive analysis of a 503-day dataset from Thailand's EV charging stations. The dataset comprises variables such as the date of charging, the station name, the type of connector used, the amount of energy consumed (kWh), the payment made (Baht), the brand and model of the vehicle, and the customer ID. Based on this dataset, the study aims to achieve the following objectives:

Predict Daily Energy Demand: To anticipate the strain on the electrical grid and to facilitate its efficient management, the first objective aims to predict the daily demand of energy in kWh. The focus will be on the top 5 stations with the highest kWh consumption to uncover any seasonality and trends.

Revenue Forecasting: The second objective is to predict the daily revenue in Baht that could be generated from the energy consumed at these stations. Understanding the revenue patterns can help in strategic pricing and offers, ultimately leading to optimized revenue streams.

Geo-Spatial Analysis: The third objective is to conduct a Geo-Spatial Analysis to identify potential areas where new charging stations can be installed. This prediction will be based on factors such as demand, customer clustering, and proximity to existing infrastructure like roads or power grids.

The studies are expected to have a significant impact on both public and private stakeholders involved in the EV ecosystem. The predictions and insights will assist grid operators, policy-makers, and station owners in efficient grid management, revenue planning, and strategic location selection for new stations.

By achieving these objectives, this research aims to contribute substantively to the literature on EV charging stations, offering empirical insights that can be generalized or adapted to similar markets or scenarios.

II. RELATED WORKS

A. Demand prediction of electric Energy and revenue prediction for charging station

The station charging for EV provide to user that enough or not, this question is one objective for research. When charging a car, the station will provide one plug to one car that take time depends on user car. Currently, the station charging in Thailand provide all over the country. We will observation on station that have many of user and load. To predict load in future to support plan for maintenance, reduce or increase the station or plug. The charging load of electric in working day and weekend are difference. Prediction use be concern about peak time of traffic, daily and the rest day. The multiple linear regression can use to prediction compare in situations [1].

Type of day effected to demand of energy, we can find pattern from the behavior of users. Learning machine can learn with Short-term load prediction [2]. The paper collect data from power grid in China to analyze the demand and show accuracy and effectiveness of proposed method is verified by analysis and comparison results with traditional load prediction method.

The electric load can define to demand of energy, focus on EV owner. The load scale analysis found that the peak load of private cars will be mainly around the suburbs During the time when they are about to leave work and return home [3].

Accurately predicting Electric Vehicles (EVs) load have two primary challenges: missing values and outliers significantly affect predictions. Paper present data generation method based on a Generative Adversarial Network (GAN) mitigates with Long Short-Term Memory (LSTM) network, enhancing its prediction [4].

B. Location and geo-spatial of charging station

The charging station locate all over in Thailand. When we travel in long distance, we must think about the next station we can charge our car. In EV model have difference capacity and ratio to use energy. So, how long distance we can go? The prediction of driving range is interesting. Multiple regression machine learning algorithms are used to predict the range [5]

A spatial-temporal distribution prediction method for urban EV charging load. Researcher present Monte Carlo simulation method is used to calculate the probability of charging demand of the EV load at each time point and order the demand made guidance to user select location charge avoid peak demand or high prices [6].

Multiple factors impact the choice of charging station locations, including the spatial and temporal patterns of charging demand, as well as the financial considerations and interests of various stakeholders. The mesh grid method to analysis the spatial distribution of charging load and can planning model is established to maximize the social benefits [7].

Electric vehicle charging facility location planning is a vital aspect of long-term strategic planning. This process involves a unique blend of considerations, as it requires a deep examination of both the electric grid and transportation networks. The paper, classical methods are well-suited for addressing the coverage of charging networks, which relates to the average time or distance required to reach a charging station when needed [8].

III. METHODLOGY

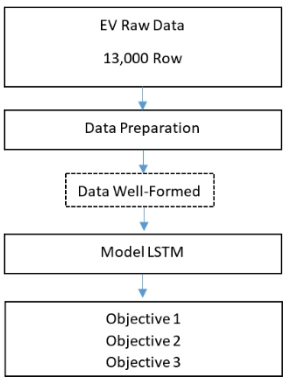

Fig. 1. Top 5 station highest Energy use in kwh

A. Data Source

The primary source of data for this research is an expansive dataset from Thailand's PEA Volta network, which consists of 130,000 electric vehicle (EV) charging transactions. This dataset provides an in-depth view into various aspects of EV charging station operations, including variables such as station ID, connector type, energy consumption in kWh, and payments made in Thai Baht.

B. Data Preparation

Data integrity is critical for any analytical research, and as such, the initial phase of data preparation involved identifying and rectifying gaps and anomalies. The dataset initially contained missing values, primarily due to testing stations, as well as entries from mockup tester stations. These were purged to maintain the quality of the data. The remaining data was then converted into a time-series format. This involved summing up the 'payment' and 'energy' variables, grouped by charging time, and then aggregated into daily values. The resulting dataset was then sorted chronologically, providing a robust dataset spanning 503 days.

To enable a more comprehensive Geo-Spatial Analysis, additional geographical data specific to Thailand was integrated into the dataset. This included mapping POSTCODES to province names, thereby facilitating a richer, contextual analysis of demand and potential locations for new EV charging stations.

C. Well-Formed Format

The refined dataset, prepared for model creation, includes the following key variables:

- Date: The dataset spans from September 2021 to January 2023.
- Station_ID: A unique identifier for each EV charging station.
- Energy (kWh): Captures the amount of energy consumed during the charging process.
- Payment (Baht): Denotes the amount of money spent on charging, expressed in Thai Baht.
- Payment/Energy: This index measures the profitability of a station by comparing the revenue generated against the unit cost of energy.

D. Model Selection

Justification: The selection of an LSTM-based deep learning model assumes paramount importance in addressing the inherent complexities of our dataset, which are further compounded by the introduction of an additional dimension represented by day names. Within this section, we provide a comprehensive exposition of our chosen LSTM-based model, delineating its precise configuration and its fundamental purpose in the accurate prediction of the "Payment/Energy" index, while adeptly accommodating the temporal dynamics associated with weekdays and weekends.

Model Configuration: Our approach hinges upon harnessing the formidable computational prowess intrinsic to LSTM (Long Short-Term Memory) networks, meticulously tailored to contend with the intricate idiosyncrasies enmeshed in our dataset. The configuration of our deep learning model, devised for the task of revenue prediction, is meticulously defined as follows:

- Training Data Allocation: A substantive 80% of our dataset is thoughtfully apportioned for the explicit purpose of model training, ensuring that our model is adequately exposed to a diverse range of data patterns.
- LSTM Layer Architecture: The architectural underpinning of our model is distinguished by a superlative stack comprising 100 LSTM layers, an astute choice meticulously calibrated to apprehend and encapsulate the subtle yet intricate temporal dependencies that reside within our dataset.
- Epochs of Training: The model undergoes an extended training regimen spanning 100 epochs, a judicious strategy that facilitates a holistic and comprehensive exploration of the dataset, ensuring the acquisition of profound insights.

E. Objective of Experiment

Objective 1: Seasonality and Trends for Efficient Grid Management.

For this objective, the dataset was filtered to include only the top 5 stations with the highest energy consumption in kWh. The final dataset for this objective includes a date index and daily energy consumption values for these 5 stations.

Objective 2: Predict Daily Revenue (in Baht) Based on Energy Consumption between Weekdays and Weekends.

The dataset was further manipulated to create an index termed "Payment/Energy," which gauges the profitability by comparing the revenue (in Baht) with the unit cost of energy (kWh) over the span of 503 days.

Objective 3: Geo-Spatial Analysis to Predict Optimal Locations for New Charging Stations Based on Demand.

For this part of the study, external geographical data on Thailand's provinces was mapped to the existing dataset. The aim was to identify zones or main cities with the highest "Payment/Energy" index values. The dataset revealed that Chonburi Province recorded the highest values for this index. As a result, this province's data will be used to predict the "Payment/Energy" index for the next 30 days.

This comprehensive approach to data preparation ensures a robust foundation for each of the study's objectives, enabling precise and reliable analysis and predictions. Analytical Experiments Method.

IV. EXPERIMENT AND REULT

A. *Objective 1: Seasonality and Trends for Efficient Grid Management*

For the first objective, the analysis focused on the top 5 stations with the highest energy consumption in kWh in figure 1. According to initial observations, these were Station IDs 6, 35, 38, 56, and 60. Each station's identification, name, and province are tabulated in Table 1.

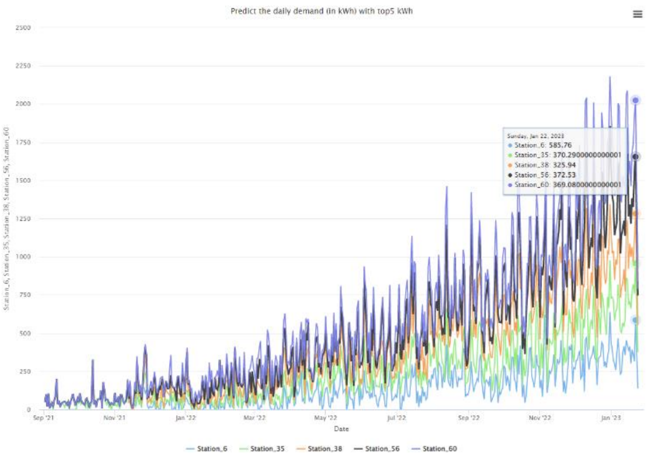

Fig. 2. Top 5 station highest Energy use in kwh

Table 1. Infomation of Station_ID

Station_ID	Station name	ProvinceName_E
6	PEA VOLTA บางจาก นาเกลือ #1	Chon Buri
35	PEA VOLTA บางจาก เมืองระยอง #2	Rayong
38	PEA VOLTA พัทยาใต้	Chon Buri
56	PEA VOLTA บางจาก เมืองชลบุรี #1	Chon Buri
60	PEA VOLTA บางจาก เมืองระยอง #1	Rayong

Due to the complex nature of the dataset, Deep Learning was chosen over traditional methods like Linear Regression for its higher predictive ability. Specifically, a neural network model with 100 hidden layers and 10 training epochs was utilized.

The model was trained 80% to forecast the growth in energy usage, and its performance was validated using the Root Mean Square Error (RMSE) metric to ensure the reliability of the predictions.

By employing this robust analytical method, the study aims to provide accurate and actionable insights into the demand for EV charging stations, assisting stakeholders in making informed decisions for efficient grid management, revenue optimization, and strategic infrastructure planning.

An Energy Prediction next 30 days

- Station 6 : Predict value: 418.47, RMSE : 0.250
- Station 35: Predict value: 318.83, RMSE : 0.250
- Station 38: Predict value: 432.64, RMSE : 0.29
- Station 56: Predict value: 400.06, RMSE : 0.271
- Station 60: Predict value: 271.10, RMSE : 0.299

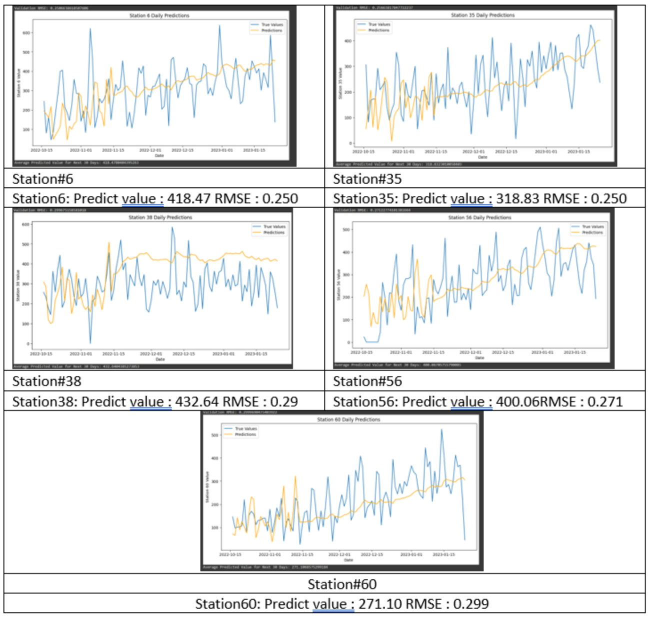

Fig. 3. An Energy Prediction next 30 days from Top 5 station

For the top 5 stations with the highest energy usage, the analysis shows that these stations can serve as a representative sample for other stations, thus providing a basis for efficient power grid management. Currently, the energy usage rate for EV charging stations ranges between 390-400 kWh. According to the 30-day forecast generated by the deep learning model with 100 hidden layers and 10 epochs, there is an expected average increase in energy consumption to around 410 kWh. The model's prediction was validated using the RMSE score, providing a reliable forecast.

B. Objective 2: Predict Daily Revenue (in Baht) Based on Energy Consumption between weekdays and weekends.

For the second objective, the aim is to predict daily revenue based on energy consumption at EV charging stations while considering the day of the week to differentiate between weekdays and weekends. The metric of interest remains the "Payment/Energy" index, which gauges profitability by comparing the Baht revenue against the unit costs of energy (kWh). In addition to the existing variables, the dataset has been augmented to include the type of the day (e.g.,Weekday, Workday). This addition allows us to investigate the trends in customer behavior and revenue generation between weekdays and weekends.

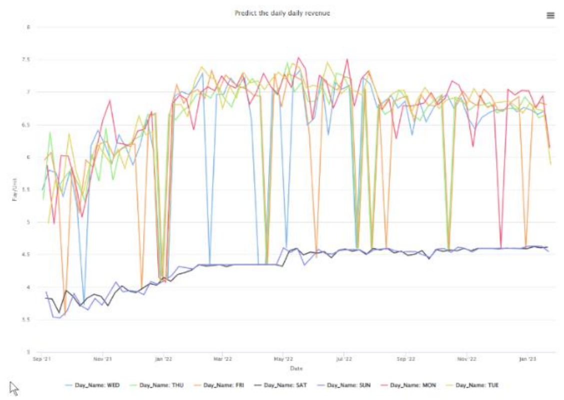

Fig. 3. The trends in customer behavior and revenue generation between weekdays and weekends

The 30-day revenue prediction shows an increase in the "Payment/Energy" index, with a slight growth in profitability on workdays compared to weekdays. The index may grow from an average of 6.5 on workdays and 4.3 on weekdays to 6.539 and 4.319, respectively. The model, validated with an RMSE of 0.017, forecasts a profit increase of approximately 0.600% on workdays and 0.442% on weekdays over the next 30 days.

Table 2. The 30-day revenue prediction

Mode	Workday	Weekday
Original	6.5	4.3
Prediction	6.539	4.319
Compare growth	0.600%	0.442%

Model Validation

The model is evaluated using the Root Mean Square Error (RMSE) metric, providing a reliable measure of its predictive accuracy. This will ensure that the model's predictions are robust, and it will identify any scope for further tuning.

By adding the day of the week to the analysis, this objective will yield more nuanced insights into daily revenue patterns. This could enable station owners and policymakers to develop more targeted pricing and promotional strategies based on customer demand during weekdays versus weekends.

- Revenue Predict value: RMSE: 0.017
- Average Predicted for Workdays: 6.53 Baht/Unit(kwh)
- Average Predicted for Weekdays: 4.31 Baht/Unit(kwh)

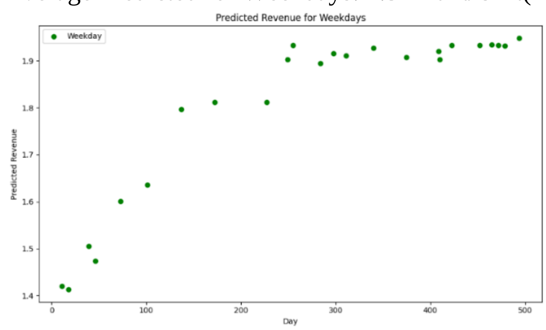

Fig. 4. The Prediction result of Daily Revenue (in Baht) Based on Energy Consumption for weekday

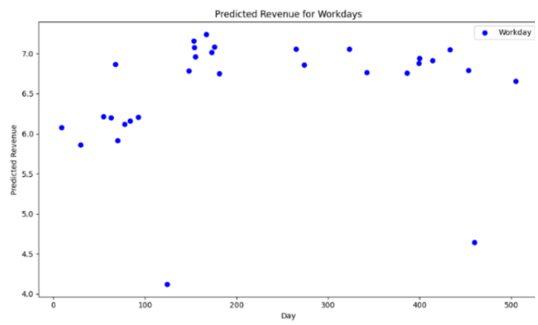

Fig. 5. The Prediction result of Daily Revenue (in Baht) Based on Energy Consumption for workday

C. *Objective 3: Geo-Spatial Analysis to Predict Optimal Locations for New Charging Stations Based on Demand.*

The third objective aims to utilize Geo-Spatial Analysis to predict the most favorable locations for installing new EV charging stations in Thailand. This objective is essential for aligning infrastructure investment with areas of high demand for EV charging, thereby optimizing both utility and profitability.

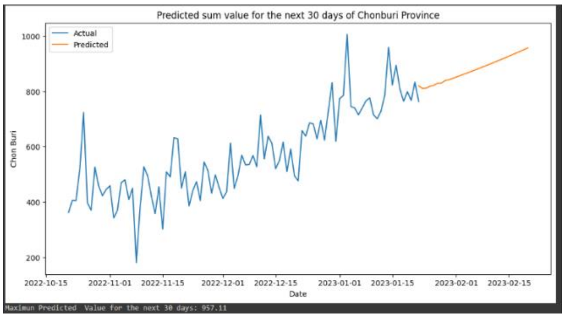

Fig. 6. The result of demand prediction of EV charging in Chonburi.

For this objective, the dataset used includes all the charging transactions from the EV stations across Thailand. This data is then mapped to the 76 provinces by their respective IDs, providing a more regionalized context for the analysis.

Geo-Spatial Analysis

Using advanced Geo-Spatial Analysis techniques, the data is analyzed to predict the demand for EV charging stations across the provinces. Two main variables are considered for this prediction:

1. Energy Consumption (kWh) - This metric provides insights into how much energy is being used in each province, thereby reflecting the level of demand.

2. User Payment (Baht) - This reflects the revenue potential of each province and is a crucial factor in deciding where the next station should be established.

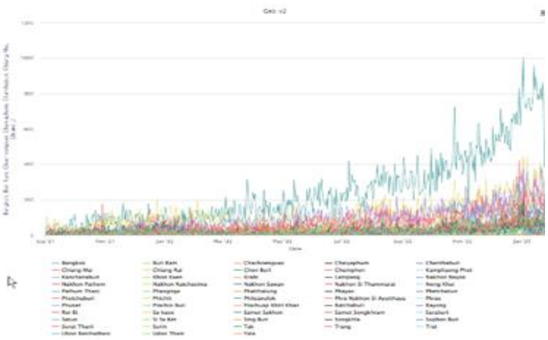

Fig. 7. The demand for EV charging stations across the provinces

Prediction and Optimization

The analysis aims to identify the provinces that show the highest levels of both energy consumption and payment in Baht. By combining these two metrics, the model predicts which province would be the most profitable and efficient location for a new EV charging station.

Result Interpretation

The result of the Geo-Spatial Analysis provides a ranked list of provinces where the installation of a new charging potential. The top-ranked province is identified as the most optimal location for the next EV charging station.

Geo-Spatial Analysis revealed that the highest number of transactions occur in Chonburi Province. The 30-day prediction indicates that this province could yield a revenue load index exceeding 900 units, whereas other provinces hover around an index of 400 units. This information serves as a strong decision-making tool for investing in new stations, with Chonburi Province emerging as the most lucrative location.

V. Conclusion

The research effectively employed time-series analysis and deep learning models to address three key objectives focused on optimizing EV charging stations in Thailand. Objective 1 gave insights into energy consumption patterns, paving the way for better grid management. Objective 2 provided nuanced revenue predictions for weekdays and weekends, giving a more complete picture of profitability. Finally, Objective 3 used Geo-Spatial Analysis to identify Chonburi Province as the optimal location for new charging station investments, based on both demand and revenue load potential.

The findings of this study offer a data-driven roadmap for efficient energy management and revenue optimization in the burgeoning field of electric vehicle infrastructure. It serves as a valuable resource for policymakers, city planners, and investors in making informed decisions for the expansion and efficient operation of Thailand's EV charging network.

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