Explore and Analyze the Impact of Electrical Vehicles at a Substation and Feeder Level

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ABSTRACT

   With growing adoption of both residential and commercial electric
vehicles (EVs) and development of needed charging infrastructure in the
state of Tennessee, it is necessary to assess its potential impact on the
operation and planning of the power grid and identify measures to mitigate
such impacts if needed. In this project, Tennessee State University (TSU)
alongside Tennessee Valley Authority (TVA) and Nashville Electric Service
(NES) will predict the EV market penetration and analyze its impact in a
substation and feeder level on a substation of the NES service territory
in a 5, 10, 20, 30-year time frame. Then, apply EPRI DRIVE tool will be
utilized to study the potential impact on the substation's circuits and
to identify possible problems and propose mitigation measures. A
literature review is performed to identify the general trend of EV growth
in the state of Tennessee for the aforementioned time frame. As well as
its respective energy consumption forecast. According to the Tennessee
EV registration data, it is seen that the EV adoption in Williamson
County, TN is quite like the national low adoption scenario.

Keywords: Electrical vehicles, substation, Tennessee Valley Authority,
Electrical Power Research Institute.

INTRODUCTION

    A.   Problem Description

Balancing energy supply and demand on electrical power substations in the state of Tennessee will soon become a greater challenge considering the ongoing increase in transition from traditional fuel powered vehicles to new electric powered vehicles (EVs). The magnitude of this movement will depend heavily on society's adoption pace of EVs. This report explores the penetration rate of EVs for the future 5, 10, 20, and 30-year time frame. It will also assess its potential impact on operations and planning of the power grid at a substation/feeder level in a substation in the service territory of NES.

    B.   Need Analysis

Electric vehicles have seen their market share increase statewide in the past years and it is projected to continue increasing secondary to President Joe Biden Signing executive Order 14037 on August 05, 2023. Executive Order 14037 set forth the following goal: "by 2030 50% of all new passenger cars and light trucks sold in 2030 be zero-emission vehicles[1]." Consequently, it is expected that load demand in electrical power substations will increase in the years to come due to the integration of EVs to substations and feeders. The need of this project is to explore and analyze the potential impact of EV's energy consumption, at a substation and feeders' level. It is therefore essential that energy distributors make sure that substations and feeders can meet the increase in power demand. Consumers need a reliable supply of power today and in the coming.

    C.   Scope of Investigation

The approach to the analysis consists of three parts. One, market assessment; Where, EVs adoption model and energy consumption model will be used to forecast EVs energy demand in a substation and feeders; Two, process data obtained from NES, and feed it to a model to evaluate the hosting capacity of the substation transformer. The "hosting capacity" is the amount of distributed energy resources (DER), or load, that can be accommodated without adversely impacting power quality or reliability under existing feeder design and control configurations. Three, identify possible problems and propose mitigation measures.

Background of EVs

The first successful electric vehicle in the United States made its debut around 1890 thanks to William Morrison(2). As EVs came onto the market, so did a type of newly invented motor-powered vehicle available in steam or gasoline. Electric cars didn't have any of the issues associated with steam or gasoline. They were quiet, easy to drive and didn't emit a smelly pollutant like the other cars of the time. However, it was the introduction of Henry Ford's mass-produced Model T that dealt a blow to EVs. Introduced in 1908, the Model T made gasoline-powered cars widely available and affordable. 'By 1912, the gasoline car cost only $650, while an electric roadster sold for $1,750'(3). That same year, Charles Kettering introduced the electric starter, eliminating the need

for the hand crank and giving rise to more gasoline-powered vehicle sales. Furthermore, with the discovery of oil in Texas, gas became more affordable and readily available to rural America and gas stations began showing up across the country. In comparison, very few Americans outside of cities had access to electricity at that time. consequently, electric vehicles all but disappeared by 1935(4).

EV's are like an automatic car. They have a forward and reverse mode. When you place the vehicle in gear and press on the accelerator pedal these things happen:

1. Power is converted from the DC battery to AC for the electric motor.
2. The accelerator pedal sends a signal to the controller which adjusts the vehicle's speed by changing the frequency of the AC power from the inverter to the motor.
3. The motor connects and turns the wheels through a cog.
4. When the brakes are pressed or the car is decelerating, the motor becomes an alternator and produces power, which is sent back to the battery.

Charging EVs has two fundamental barriers to understand and analyze. First, starting at the EV Charger and working back to the power system. One of the barriers consumers and utilities must overcome is the facility power supply. Before analyzing the transformer supply, the EV charging power going through the power system in the home or business must be known. In the United States, there are three basic types of electric vehicle chargers:

1. Level 1 AC: 120-volt, simple household outlet. Low power long-time charging. Around 12-15 amps continuously and its typical home and business wiring charge is 12 hours per day.
2. Level 2 AC: 240-volt, hardwired or 240-volt outlet. It is the desirable home and business charger. Around 48 amps 240V and continuously.
3. Level 3 DC: 400-volt to 1,000-volt public stations.

This project will focus on level 1 and level 2 charging because that's the type of electric vehicle charging equipment that's installed in private homes and workplaces. DC fast charging equipment requires very high-power delivery which most residential buildings do not have access to. Also, the high cost of DC high charging is prohibitive for home installation even if the power were available.

The second barrier is a limited electrical panel capacity. How much power supply does the home or business have? EPRI did a 2022 "US Survey of Residential Electrical Panels" and found that about a third of the houses are likely under-powered for Level 2 EV Charging.

Design Goals and Objectives:
The goal of the project is to analyze if the substation has the capacity to host increasing energy demand due to the adoption of electric vehicles.

The objectives of the project are the following:

1. Forecast the county in TN with the biggest EV market penetration and energy consumption in the future 5, 10, 20, 30-year time frame.

2. Obtain, process, and feed substation data to a model to analyze the substation hosting capacity.
3. Compare the substation forecasted EVs energy demand to the hosting capacity; Last, identify possible problems and propose mitigation measures.

Design Specifications:

The model can be used by power distributing utility companies to be used as inputs for power plant units' planning commitment and substation's circuit upgrades. The design specifications related to the project are listed:

1. The model shall use market assessment to project EVs market penetration in the state of Tennessee.
2. The model shall use the county with the largest projected penetration.
3. The load demand projection shall be 5, 10, 15, 20, and 30-years.
4. The model shall use historical substation's data to generate an output.
5. The model's generated output shall be the electrical power hosting capacity in a substation.

System Decomposition:

Figure 1 shows the system decomposition of the main parts of the model. It consists of market assessment, data processing, output presentation, and output comparison and analysis. Market assessment focuses on literature review to identify the general trend of EV growth and energy consumption in the future 5, 10, 20, 30-year time frame. Whereas data processing focuses on the substation's circuits analysis to determine the hosting capacity.
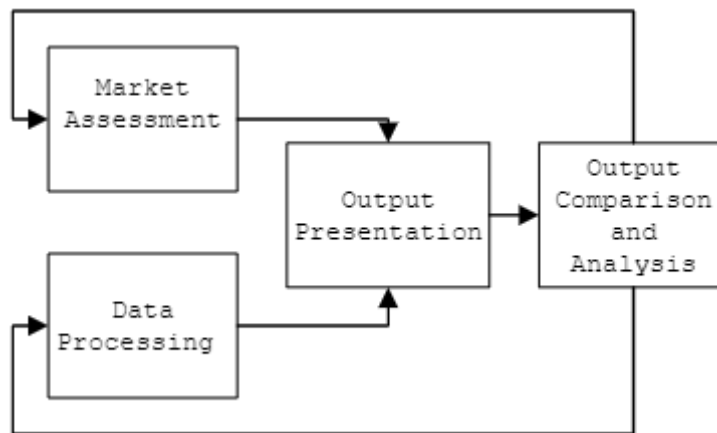

Figure 1
System Decomposition

A. Subsystem Decomposition.

Figure 2 shows the model's subsystem decomposition. The market assessment output, and data processing output will be compared and analyzed to determine if the substation's circuits are equipped to handle the increase in electrical power demand due to the integration of EVs. Figure 3 shows the market assessment subsystem decomposition, which

will be used to obtain EVs adoption data, forecast EVs penetration rate, and forecast EVs power consumption. The approach consists of obtaining present EVs registration data for Williamson County to determine the EVs to person ratio to calculate the penetration rate and forecast the population increase in the future 5, 10, 20, 30-year time frame. The model will be used to forecast the adoption of EVs in the same timeframe as the population forecast.
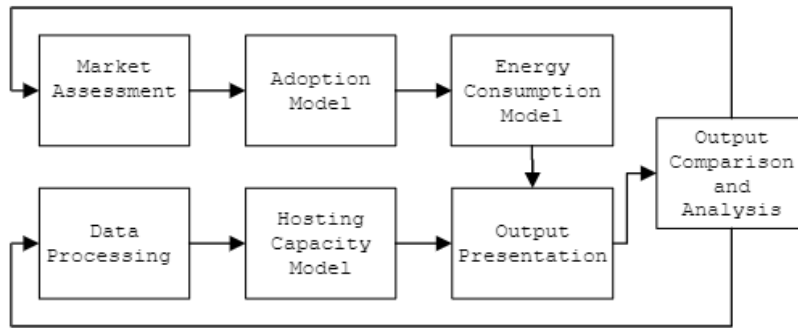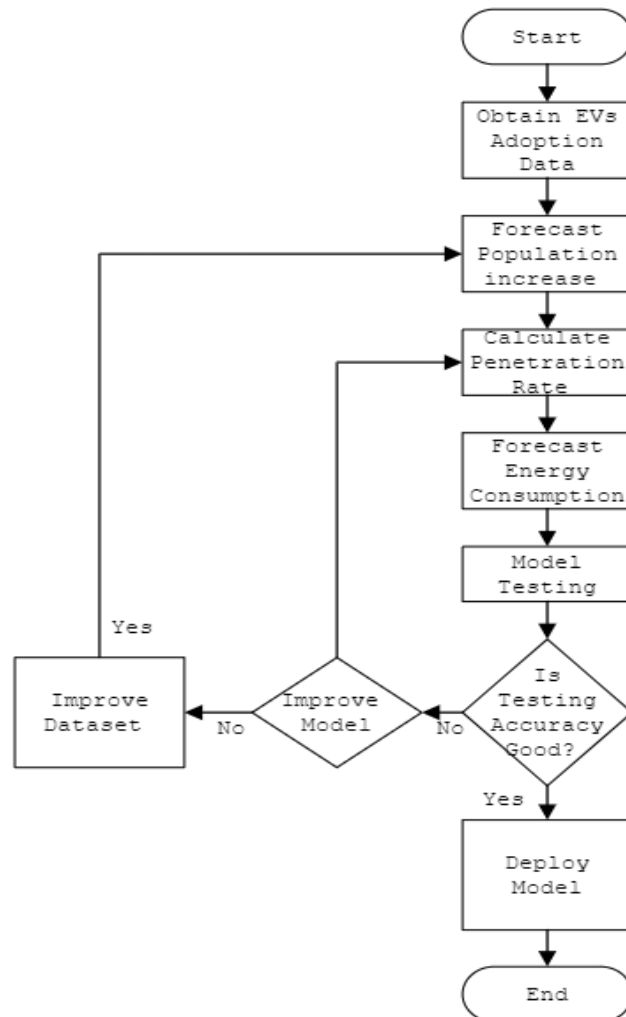

Figure 2 Subsystem Decomposition

Figure 3 Market Assessment Subsystem Decomposition

Figure 4 shows the data processing subsystem, which consists of preparing the data obtained from NES. Then, feeding the processed data to the substation hosting capacity model for testing. The accuracy of the model should be greater than 90%.
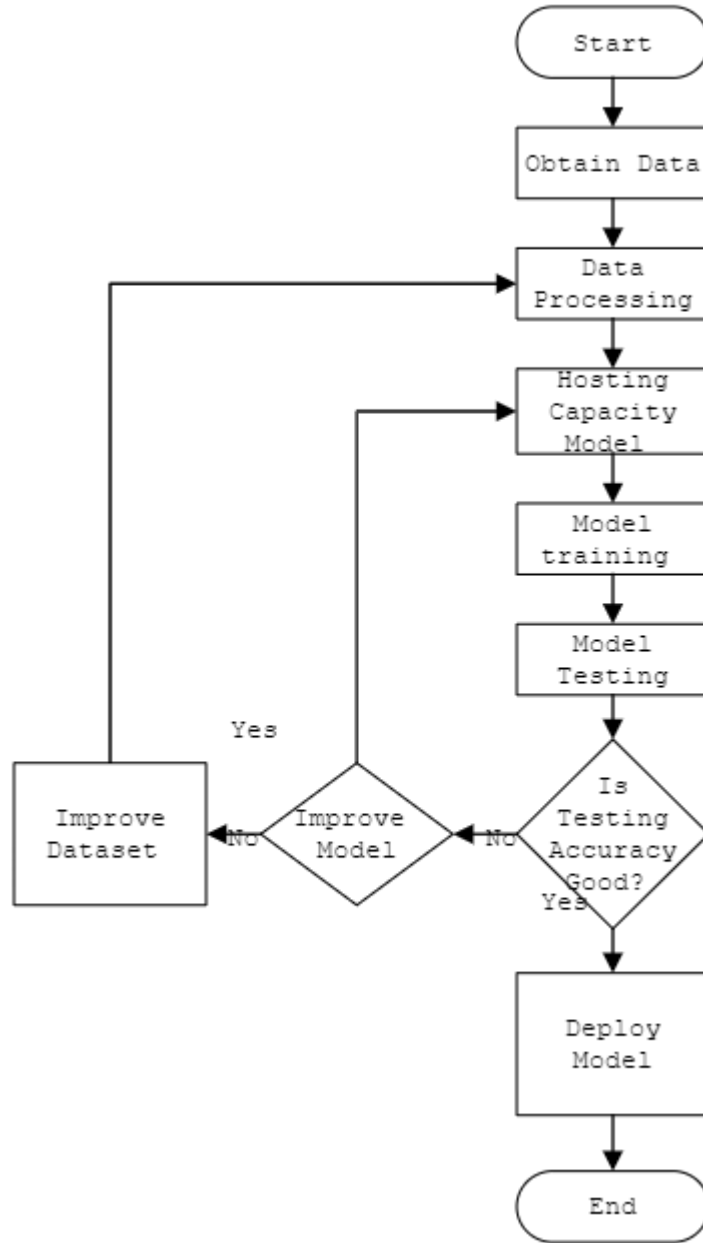

Figure 4 Hosting Capacity Subsystem Decomposition.

Implementation and Testing:
    A. EVs' Energy Consumption Forecasting Software Flowchart
    Figure 5 shows module I, II, & III in a software's flowchart. It consists of data import, feature extraction, user input selection, dataset to train the algorithm, dataset to test the algorithm, software deployment, and output presentation.
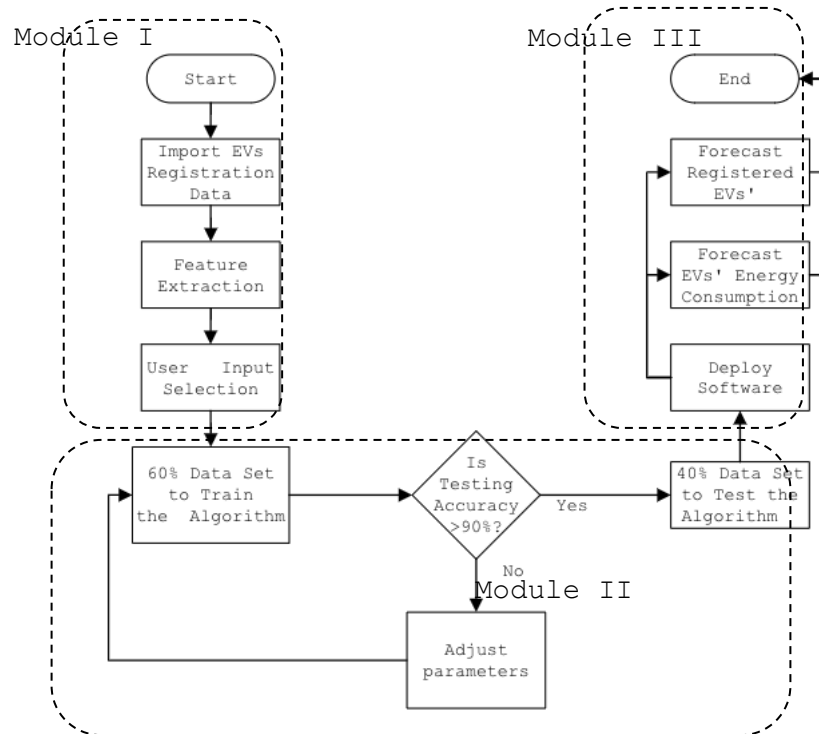

Figure 5. EVs' Energy Consumption Forecasting Software Flowchart

Module I: Software Development Environment Selection

Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda® Distribution that allows you to launch applications and manage Conda packages, environments, and channels without using command line interface (CLI) commands. The Jupyter Notebook, an extension from Anaconda Navigator, is an open-source web application used to create and share documents that contain live code, equations, visualizations, and text. It will be used to rapidly develop and test the code for the software one section at the time.

Module I: Development of Model EVs Registration Data processing

Step one is to import the vehicle registration data retrieved from **State EV Registration Data — Atlas EV Hub** into the Jupyter notebook environment. Figure A-1 shows the first five rows of the data after being imported.
Step two in data processing is to extract the features that will be used to train the model. In this design we will use the zip code, registration date, and vehicle count. All reminding columns will be dropped from the file. Figure A-2 shows the remaining matrix containing the desired features for the model.
Step three in data processing is user input and verification. The user must enter a valid zip-code in the state of TN for the code to move on to the next section. For this project the zip-code of interest is the one with the

highest number of registered EVs. Figure 3 is a screenshot from **State EV Registration Data – Atlas EV Hub** showing EVs on the road count per county in TN. It shows that 37062 in Williamson County is at the top of the list with the highest registered EVs in 2022. Therefore, data from a substation in this zip-code will be obtained from NES. Furthermore, 37062 will be used for the scope of this project for model testing, model training, and model output presentation.

Figure 6. EVs on the road in TN by County and zip code. Step four is to sort the rows by registration date starting from oldest to newest. Figure 7 shows features with the 37062 zip-code sorted from oldest to newest. Since the remaining rows are all in the 37062 zip-code, step five is to drop the zip code column and change the date format to one in which the model will understand what it is being fed. Figure 6 shows the vehicle count and registration date sorted by registration date.

Step six is to group the data by quarters meaning that each prediction will be made in a 3-month portion. The reason why the model will make quarterly predictions is because new data is published every quarter. And the data itself is arranged not by month but by quarters.

County	n	Lucid	Mercedes	Mini	Mitsubishi	Nissan	Polestar	Porsche	Rivian	Smart	Subaru	Tesla	Th!nk	Toyota	Volkswagen	Volvo	Total
⊞ Williamson County	5	1	21	9	3	144		74	9	1		2,806		67	17	84	4,061
⊞ Davidson County	1	4	32	11	10	325	10	57	17	8	1	1,859		188	43	104	3,952
⊞ Knox County	6		15	5	7	142	3	57	50	7	1	1,482		90	44	51	2,858
⊞ Shelby County	3		33	10	9	121	3	62	5	2		1,417		86	26	58	2,707
⊞ Hamilton County	9	1	6	5	8	94	1	27	7		1	431		54	43	44	1,233
⊞ Rutherford County	3		5	2	1	373		4	2	1		355		36	13	10	1,131
⊞ Wilson County	5		8	3	6	41	2	6	10	2		264		19	3	9	628
⊞ Sumner County	2		3		5	37		8	2			249		35	13	11	611
⊞ Montgomery County	5		2	3	2	27	1	3	1	3		216		27	6	14	577
⊞ Washington County	2	1	2		3	15		5	1			138		17	4	10	361
⊞ Sullivan County	1		1	2	5	15		7	1	2		116		17	7	18	344
⊞ Blount County			1	1	1	31	1	7	4	1		109		19	5	5	332
Total	1	8	146	58	82	1,615	25	352	125	38	5	10,677	1	901	262	486	22,663

Figure 6. Quarterly registration of the 37062 zip-code for the last 4 years.
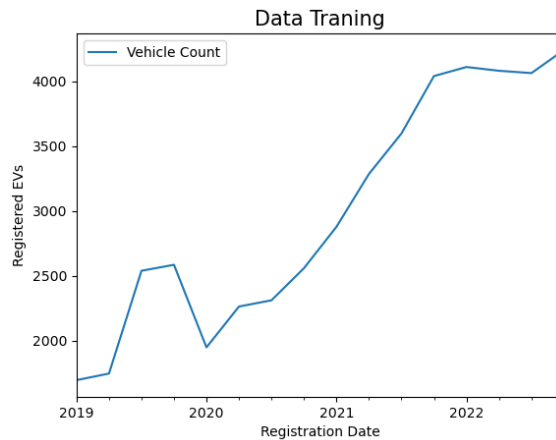

Figure 7. 2019–2020 EVs Quarterly Registration

Figure 7 is a graphical representation of Figure 6. It shows that the

registration of EVs is nonlinear. Meaning that further data processing is necessary to improve its quality and therefore improve the output. As discussed in Mathematics of RNN in chapter IIIA simple way to achieve that is to take the mean square error. The Mean Squared Error (MES) measures how close a regression line is to a set of data points. It is calculated by taking the average, specifically the mean, of errors squared from data as it relates to a function. Figure 8 shows the data after being normalized.
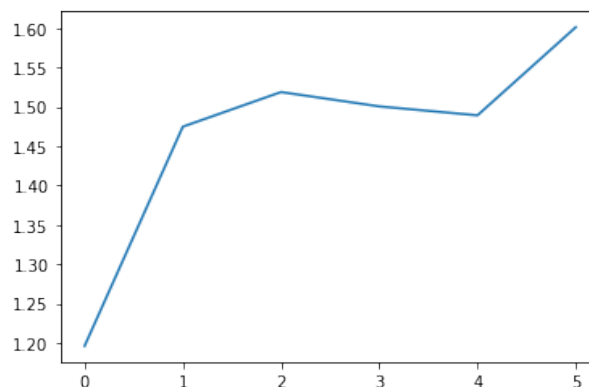

Figure 8. Normalized Data

Module II: Development of EVs Energy Consumption forecasting RNN Model

The first step is choosing a learning rate. In machine learning, the learning rate is a hyperparameter that controls the step size at which a model learns from the training data during the optimization process. It determines the size of the updates made to the model's parameters in each iteration of the training process. During training, the goal of the optimization algorithm is to minimize the loss function, which measures the difference between the model's predictions and the actual target values. The learning rate determines how much the model's parameters are updated in the direction of the negative gradient of the loss function. If the learning rate is too high, the optimization algorithm may overshoot the optimal values of the model's parameters and fail to converge to a good solution. On the other hand, if the learning rate is too low, the training process may be slow, and the algorithm may get stuck in a suboptimal solution. Therefore, selecting an appropriate learning rate is a crucial step in training a machine learning model. It is often tuned during the hyperparameter tuning process to find the optimal value that can help the model converge to a good solution.

The second step is choosing several epochs. An epoch refers to a complete cycle of training a machine learning model on a given dataset. During an epoch, the model is presented with the entire training dataset, and the model's parameters are adjusted to minimize the difference between its predicted output and the actual output for each example in the dataset. Typically, during an epoch, the training dataset is divided into multiple batches, and the model is updated after each batch is processed. The number of epochs is a hyperparameter that determines how many times the model will cycle through the entire dataset during training. Training a model for too few epochs may result in underfitting, where the model has not learned enough from the training data to make accurate predictions on new data. Training a model for too many epochs may result in overfitting, where the model has memorized the training data and does not generalize well to new data. Therefore, choosing the right number of epochs is an important aspect of training a machine learning model.

The third step is choosing several features. In this model there is one feature, which is the number of registered EVs each quarter.

The fourth step is building the input, hidden and output layer of the model. The proposed RNN model has a total of fifty neurons in the input layer, 25 neurons in the first hidden layer, 5 in the second hidden layer, and one neuron in the output layer.

The fifth step is choosing an algorithm to be the input. There are numerous algorithms that can be used for time series prediction, but the top three commonly used algorithms are:

Autoregressive Integrated Moving Average (ARIMA): ARIMA is a statistical model that is widely used for time series forecasting. It is a combination of three different models: Autoregression (AR), Integration (I), and Moving Average (MA). ARIMA models can capture the trend and seasonality in the data and can also handle non-stationary time series.

Long Short-Term Memory (LSTM) Networks: LSTM is a type of recurrent neural network (RNN) that is capable of handling long-term dependencies in time series data. LSTMs have a memory cell that can retain information for a long time, allowing the model to remember important patterns in the data. LSTMs are commonly used in time series forecasting for their ability to handle sequential data.

Prophet: Prophet is a time series forecasting library developed by Facebook. It is designed to handle time series data that has multiple seasonality and includes holidays or other events that can impact the time series. Prophet is easy to use and provides many options for tuning the model to improve its accuracy. It is widely used for forecasting sales, web traffic, and other time series data in the industry.

All in all, the algorithm that will best fit the model will be the Long Short-Term Memory (LSTM) Networks because the model is based in time series forecasting for their ability to handle sequential data.

Module II: Results

When training an RNN model, it is important to split the data into training, and test sets. This is done to evaluate the model's performance on data that it has not seen before and to prevent overfitting. The general guideline for splitting the data is to allocate about 80% of the data to the training set, and the remaining 20% to the test set.

The training set is used to train the model, while the test set is used to evaluate the final performance of the model after training is complete.

Figure 9 is a plot from the trained data. Referring to Figure 5, it is shown that the accuracy is greater than 90%. Figure 10 is a graph of the loss function. It shows that the model's parameters converge to an expected value close to zero.
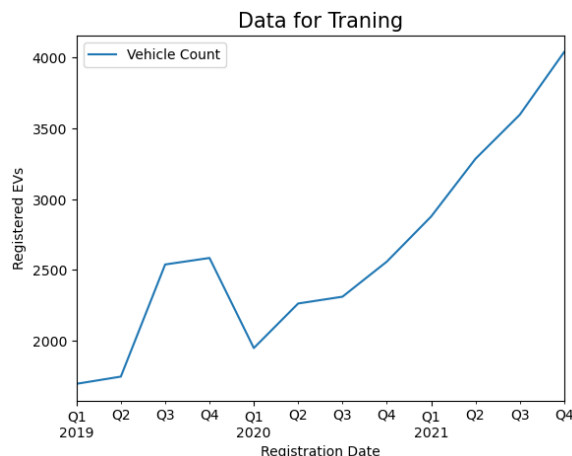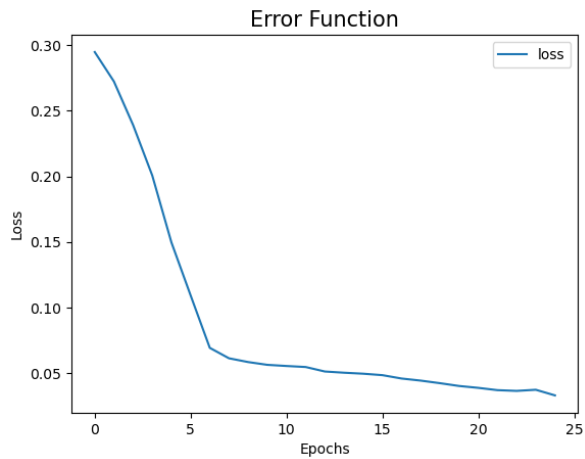

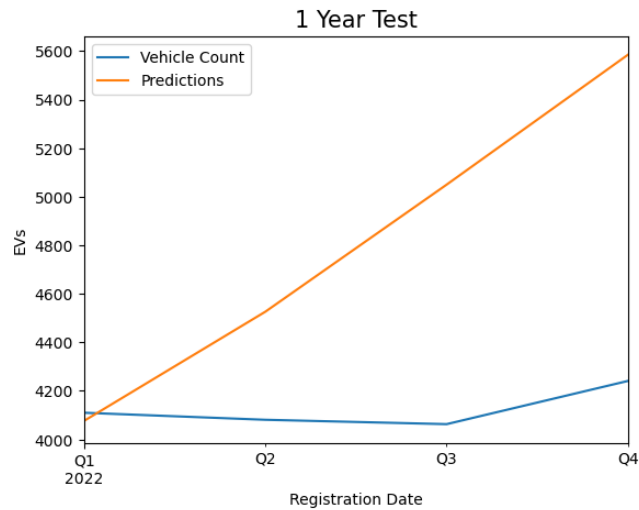Figure 9. RNN Training set Plot

Figure 10. Loss Function

Figure 11. 1-Year Prediction Test

Figure 11 shows a one-year forecast test. The test shows that the model is doing successful predictions and that the model is ready to be deployed in a full data forecast.

Module II: Model Testing and Evaluation

The next step is to make a 5-year forecast. Figure 10 shows the 5-year EVs registration forecast. Using the average anergy per calendar day of 8.44 [kWh] from "SmartCharge Nashville" the resulting EVs energy consumption forecast is shown in figure 12.
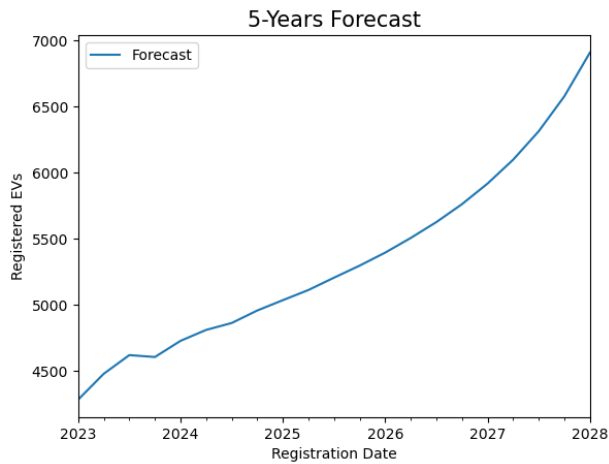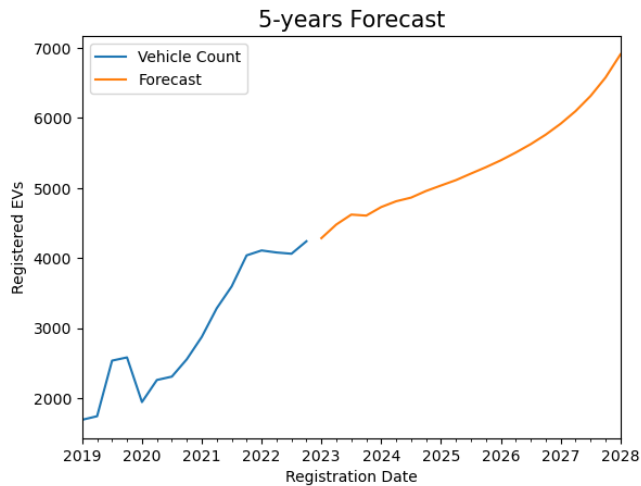
Figure 12. 5-years' Forecast
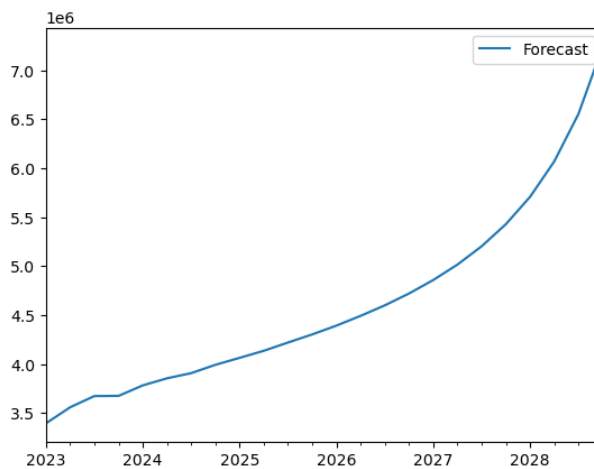

Figure 13. Aggregated EVs Registration

Figure 1. 5-years' Forecast EVs Energy Consumption

Module III: EVs Load Forecasting Software Interface

Step one is to save the weights from the trained model to incorporate them into the load forecasting software interface. The following is a description of the operation of the user interface. The user interface part of Module

III creates a window using PySimpleGUI library for a user to interact with. The window consists of the title "EVs 5-Year Registration & Energy Consumption Forecast", an image, a drop-down menu for selecting a county of interest, a "Forecast" button, and a canvas.

The image (image 14) serves as aesthetics in the interphase. The canvas is initially blank but will be used to display a plot after the "Forecast" button is clicked. The drop-down menu allows the user to select a county of interest, which will be used to filter and retrieve data related to the county. Once a county is selected, the "Forecast" button can be clicked to generate a 5-year forecast of EV registrations and energy consumption for the selected county.

When the "Forecast" button is clicked, the code retrieves the selected county features, filters the data for the county, normalizes the data, and generates a forecast using the pre-trained model. The resulting forecast is plotted and displayed on the canvas in the popup-window. Figure 13 shows the user interface when the code is executed. Image 15 shows two plots. The top plot represents the aggregated EVs registration. In red is the historical EVs registration dataset that was used to forecast the future 5 years EVs registration. The blue line represents the EVs registration 5 years' forecast. The second plot is located below the first plot. It shows the 5-years' EVs load forecast.
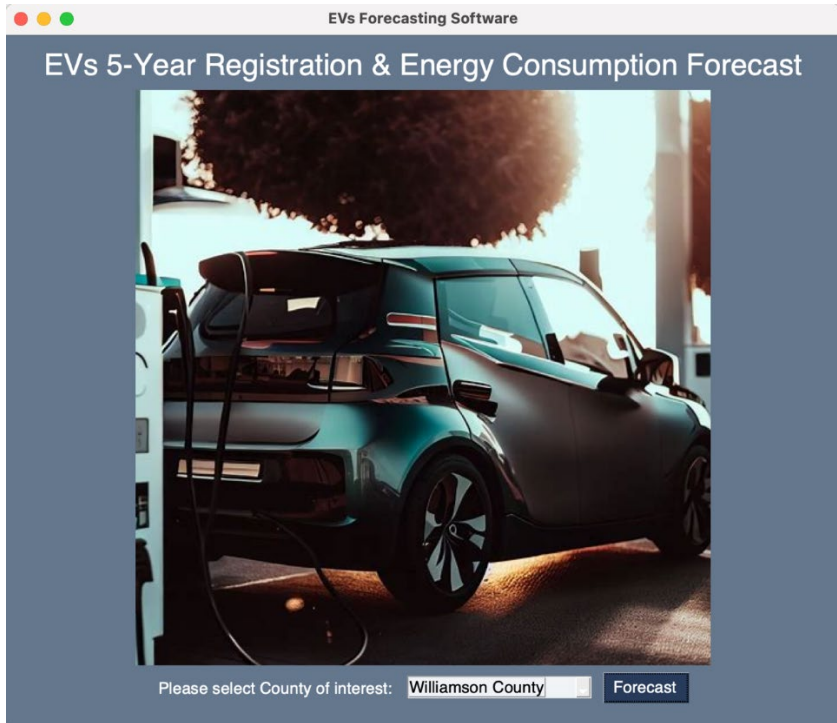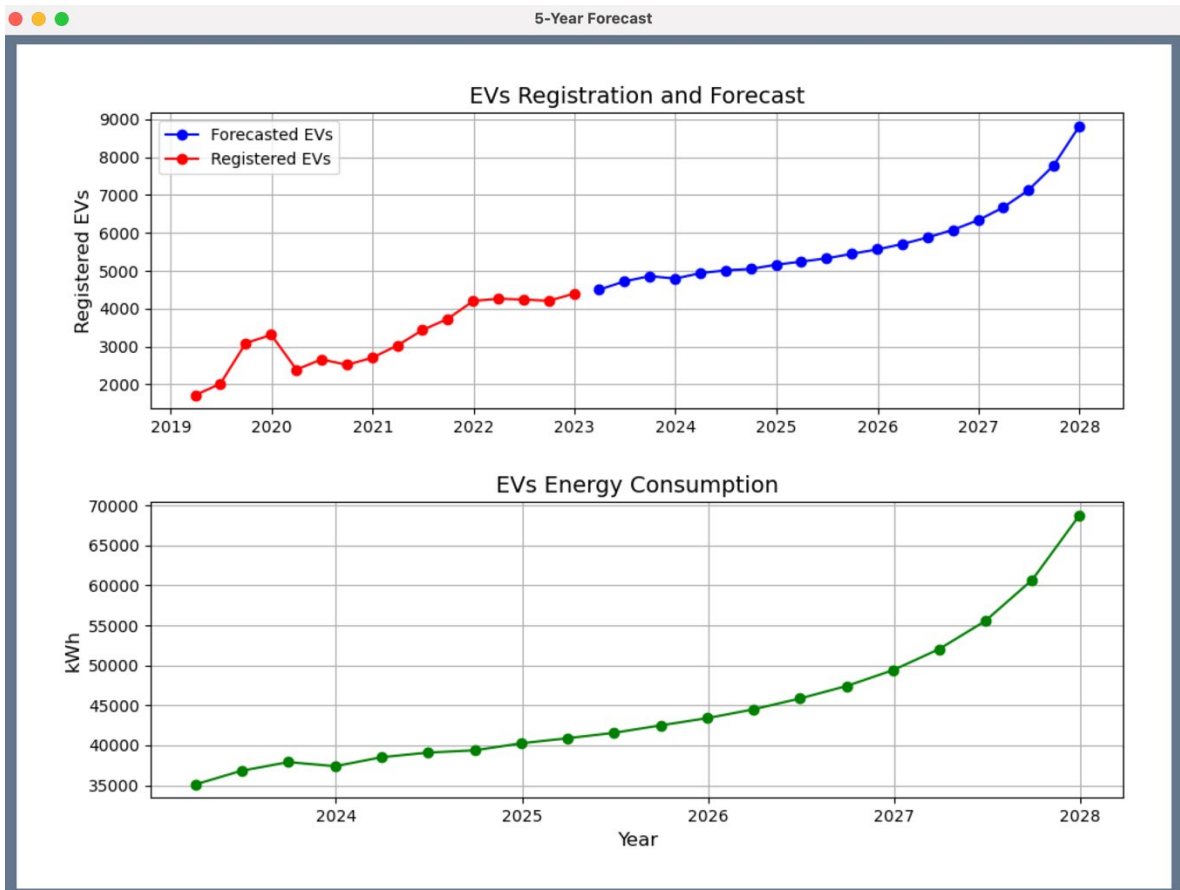
Figure 2. EVs Load Forecasting Software Interface

Figure 3. 5-Years' EVs Registration and Energy Consumption Forecast

EVs on the Road by County and ZIP Code   Warning: ZIP Code-level data is not valid for this state.

County	ma	Kia	Land Rover	Lexus	Lincoln	Lucid	Mclaren	Mercedes	Mini	Mitsubishi	Nissan	Porsche	Rivian	Smart	Tesla	Toyota	Volkswagen	Volvo	Total
⊟ Williamson County	2	24	5	2	25	2	1	34	10	3	147	76	24	1	2,930	68	26	102	4,398
37062	2	24	5	2	25	2	1	34	10	3	147	76	24	1	2,930	68	26	102	4,398
Total	2	24	5	2	25	2	1	34	10	3	147	76	24	1	2,930	68	26	102	4,398

Figure 4. EVs on The Road in Williamson County

Image 16 shows that the number of EVs registered in Williamson County for the first quarter of 2023 is 4398. Looking at the forecasted data from the EVs Load Forecasting Software the forecast is ±4500 hundred. Meaning that the software meets the specification of being greater than 90% accurate.

CONCLUSION AND RECOMMENDATIONS:

A. Conclusion

In conclusion, EVs load forecasting software is a valuable tool for utility companies due to its ability to accurately forecast electric vehicle registration and energy consumption demand. By using advanced algorithms and data analysis techniques, EV load forecasting software allows utility companies to anticipate and plan for the impact of EVs charging on substation infrastructure, energy generation, and load management strategies. This helps utility companies optimize their resources, provide robust power, and improve substations circuits and reliability. By leveraging the insights and predictions provided by the EVs load forecasting software developed in this project, utility companies can make informed decisions, enhance their operational efficiency, and better serve the needs of their customers and communities. As electric vehicle adoption continues to increase, EVs load forecasting software will play a crucial role in supporting the planning, management, and optimization of electric vehicle charging infrastructure for utility companies around Tennessee. With accurate and reliable EV load forecasting, utility companies can stay ahead of the curve and effectively meet the challenges and opportunities presented by the electric vehicle revolution. Therefore, investing in EVs load forecasting software is a strategic and wise decision for utility companies to stay competitive, sustainable, and resilient in the evolving energy landscape. The benefits of EVs load forecasting software are significant and far-reaching, making it an indispensable tool for utility companies in the era of electric mobility. As electric vehicles become more mainstream, the importance of EV load forecasting software will only continue to grow, making it an essential tool for utility companies in the 21st century.

B. Further Recommendations

Because the time constrain of the project, the following Modules were not completed:

- Module IV: Process NES Williamson County substation data.
- Module V: Feed Process NES Williamson County substation data to the DRIVE Software Tool.
- Module VI: Analyze Hosting Capacity of the NES Williamson County substation.

It is recommended to complete Modules IV, V, and VI to find the hosting capacity of NES Williamson County substation and make Circuits upgrades accordingly.