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Forecasting Energy Consumption from EV Station Charging Using RNN, LSTM and GRU Neural Network

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ABSTRACT

The increase in electric vehicles (EVs) has resulted in a substantial escalation in electricity consumption. This increased demand puts more stress on the overall power system. The current study offers a method to predict energy usage patterns by looking closely at when electric vehicles typically need to charge during the day. After that, the collected data were used to create a predictive model using three different deep learning methods: Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Gated Recurrent Units (GRUs). This study employs data pertaining to electric power consumption for EVs charging derived from Kamphaeng Phet Rajabhat University. The practical results show that the proposed model significantly outperforms in predicting power needs at the mentioned charging spots. This is evident in its precise prediction of the total power demands using the algorithm. Among the three types of deep learning structures studied, it's clear that the LSTMs type stands out as the best, achieving the most accurate results. This is supported by a Root Mean Square Error (RMSE) of 0.372 and a Mean Absolute Percentage Error (MAPE) of 11.508%. Additionally, the inquiry facilitates a comprehensive comparison between the dynamics of demand and the parameters of supply. This process yields data that offers valuable insights crucial for the strategic identification of potential electric vehicle charging stations. It also enables the prudent utilization of remaining electrical capacity derived from production processes. These combined efforts converge to ensure the utmost extraction of utility.

1. Introduction

The rapid progress in electrification technology presents a promising avenue for advancing electric vehicle (EV) systems. Concurrently, the Thai government is spearheading the integration of EVs, generating heightened public interest and a significant uptick in EV imports. At the crux of EV adoption lies the imperative for a robust battery charging infrastructure, pivotal for ensuring seamless consumer adoption and utilization. To tackle this challenge, the Faculty of Industrial Technology at Kamphaeng Phet Rajabhat University is leading a groundbreaking initiative, focusing on crafting a tailored prototype charging station for electric vehicle batteries. This strategic endeavor aims to cater to the diverse needs of students, teachers, and university personnel. Previous studies, as referenced [1-3], highlight that mismatches in electric vehicle charging needs can lead to issues like overloading, alterations in power flow, and premature aging of electrical equipment. An integral aspect of establishing and planning electric power systems involves precisely determining electricity requirements. This critical task necessitates meticulous forecasting models crucial for intelligent planning, cost evaluation, capacity determination, safety assurance, and overall system efficiency [4,5]. In this context, the development of forecasting consumption models is particularly significant, especially when considering power generation metrics and the essential calculation of battery charging requisites within the academic environment. While conventional methods for projecting energy demand often rely on statistical time series techniques, such as Smoothing Exponential (SE), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA), they are limited by linear historical frameworks. This limitation can pose challenges in estimating when nonlinear temporal patterns emerge in historical data. As a result, early prediction can be made in the short term. However, if the prediction is intended for a long-term forecast, the results may be highly inaccurate because this statistical model requires accurate past data to predict the future. Addressing this constraint, the contemporary landscape of machine learning introduces the prominence of deep neural networks, endowing them with the capability to navigate intricate temporal patterns [6,7]. An exemplary illustration among these deep neural network models, adept at capturing temporal characteristics, is the Recurrent Neural Networks (RNNs), as elucidated by Wan Muhammad [8]. A well-tuned RNN outperforms other models in predicting energy consumption. Subsequent enhancements to the RNN archetype result in the emergence of the Long Short-Term Memory networks (LSTMs) model [9], distinguished by memory cells and gate units contributing to enhanced learning capacities. Particularly noteworthy is the significant contribution by Zheng et al. [10], who employed the LSTMs paradigm to forecast electrical loads in buildings. The augmentation of the LSTMs model through additional memory cells leads to the enhanced LSTMs model, showcasing improved predictive capabilities. The intricate parametric architecture inherent in the LSTMs model has given rise to an alternative configuration known as the Gated Recurrent Units (GRUs). This innovative design involves a judicious reduction in LSTMs parameters, retaining only the update gate and reset gate. Investigative endeavors by Muhammad [11] underscore the strategic utilization of Convolutional Neural Networks (CNNs) and GRUs in predicting power consumption, yielding commendable results substantiated by comparative assessments against alternative learning models. Recognizing the gap in the current literature, the researcher introduces a novel aspect to the research by applying deep neural networks to aid in calculating electricity production from solar panels. Consequently, the study proposes a comprehensive comparative analysis involving RNNs, LSTMs, and GRUs models for estimating energy consumption within the university, marking a significant novelty in research. Moreover, this research distinguishes itself from prior works by diligently investigating and pinpointing the optimal hyper parameters crucial for precise energy consumption estimation. Unlike previous studies, which may have overlooked the nuanced intricacies of model configurations, our research delves into the meticulous identification of hyper parameters, seeking to enhance the accuracy and reliability of the energy consumption forecasts.

The primary objective is to discern the most suitable model for accurately estimating energy consumption associated with battery recharging within the university campus setting. This research aims not only to create a well-improved model, ready for smart planning, but also to play a key role in facilitating the steady progress of energy infrastructure, especially focused on solar arrays. Additionally, the forecasting model is useful for planning the expansion of battery charging stations and developing strategies to optimize extra electricity generated by these stations in various locations.

2. Material and Methods

2.1 Dataset

The present investigation leverages a dataset from the electric vehicle battery charging station situated within the premises of the Faculty of Industrial Technology at Kamphaeng Phet Rajabhat University, as in Fig. 1. This particular charging facility stands distinguished by its capacity to harness solar panel-generated electricity. The data collection endeavor spanned the temporal domain between November 2022 and May 2023, encompassing the meticulous compilation of electricity production metrics alongside the charging parameters associated with EVs. This dataset serves as a subject of analysis, as delineated in Fig. 2 and Fig. 3.

Fig. 1 shows the electric vehicle station, featuring a parking garage with solar panels, an EV wall charger, and power plugs for electric vehicles.

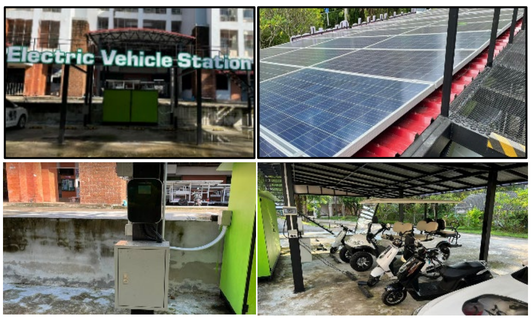

Fig.1 Kamphaeng Phet Rajabhat University electric vehicle station.

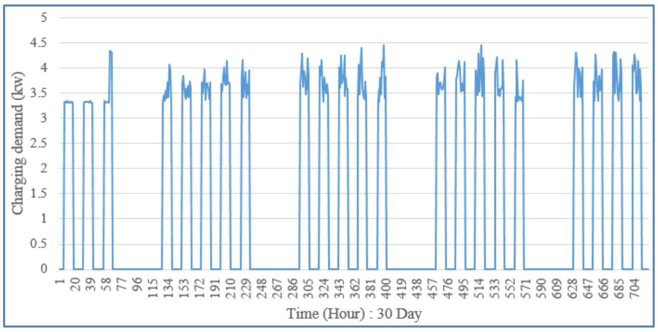

Fig. 2 Energy consumption across a span of 30 days.

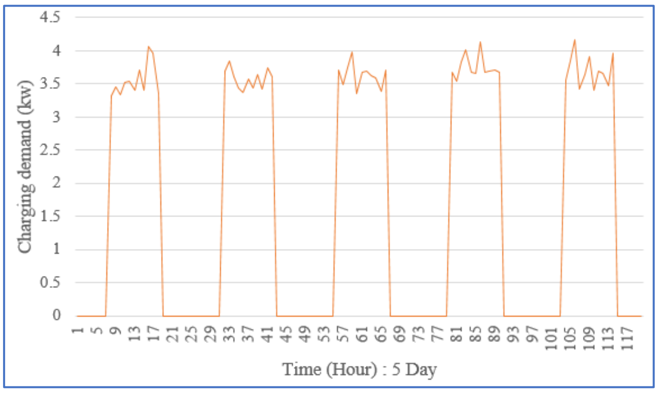

Fig. 3 Energy consumption across a span of 5 days.

Fig. 2 shows how much electricity was used in March 2023, not counting weekends. Similarly, Fig. 3 provides an intricate portrayal of the battery charging process for EVs, offering a detailed focus on a span of 5 specific days. These patterns unveil the temporal windows required for battery charging processes. Upon careful examination of both visualizations, a conspicuous semblance in data patterns emerges, underpinned by the prevailing operational rhythm of the university and the charging station. Specifically, this similarity arises from the temporal closure of the university during nighttime hours, resulting in a concomitant hiatus in electricity generation by the station. However, it is incumbent to recognize that the endeavor to glean maximal utility from the generated electricity necessitates a meticulous orchestration of data monitoring and collation vis-à-vis power generation and battery charging imperatives. This systemic scrutiny forms the crux of an analytical enterprise poised to ascertain avenues for optimizing electricity usage. In light of this, the exigency for a precision-engineered model for estimating power generation at charging stations becomes evident, constituting an indispensable tool in harnessing accurate insights for strategic decision-making.

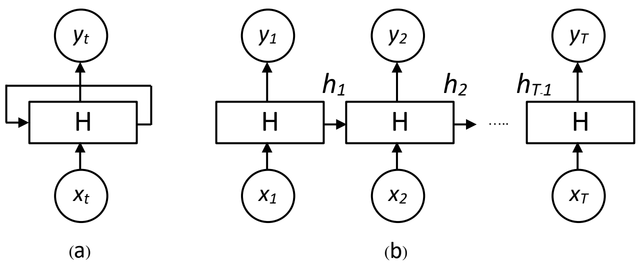

Fig. 4 The RNNs model.

2.2 The RNNs Model

The deep neural networks (DNNs) is characterized by a nested configuration comprising numerous strata of concealed networks, commonly referred to as multilayer perceptron [12]. The RNNs, one of the subclasses of the DNNs paradigm, operates on a foundational premise where the output of the preceding state is employed as input for subsequent states. This intrinsic mechanism engenders a sequential mode of data processing [13].

Fig. 4 illustrates the operational mechanism of the RNNs, a model characterized by two principal constituents: the antecedent hidden state and the temporal input data. In this context, *H* denotes the hidden layer, x_t signifies the input data at time *t* , y_t conveys the output emanating from the RNNs at time *t* and h_t collect the hidden state at time *t*. W_h is the weight matrix for the hidden state. b_h is the bias term for the hidden state. It is noteworthy that Fig. 4(a) visually encapsulates the iterative loop encompassing the neural network's hidden layer, thereby signifying the iterative reutilization of the prior hidden state. This recurrent loop essentially endows the RNNs with a memory-like trait, augmenting its modeling capability. To afford a comprehensive understanding of this intricate process, Fig. 4(b) expounds upon the constituents enclosed within image, thus revealing the nuanced interplay constitutive of the internal mechanism. The orchestration of parameter adjustments within the RNNs is inherently founded on the reverse input method, an approach poised to calibrate the model's parameters with the intent of computing the gradient. The operationalization of parameter adjustments finds expression through Equation 1-2.

$$h_t = f_h(W_h h_{t-1} + W_x x_t + b_h) \tag{1}$$

$$y_t = f_y(W_y h_t + b_y) \tag{2}$$

The adjustment of parameters for the hidden state, as delineated by the underlying equations, presents a notable challenge in the implementation of RNNs neural networks. This challenge manifests in scenarios involving extensive data sequences, giving rise to the issue of vanishing gradients. In essence, this phenomenon entails the gradual diminution of gradient values to an extent where discernible changes become imperceptible.

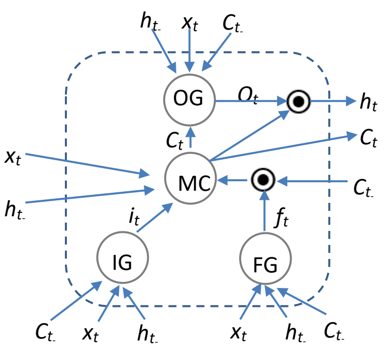

Fig. 5 The LSTM cell state.

2.3 The LSTMs Model

LSTMs are based on RNNs in deep learning and address memory issues found in RNN architectures. They are well-suited for tasks like classifying and predicting patterns in time series data. [14].

Fig.5 show that LSTM model where The MC is Memory Cell, IG is Input Gate, FG is Forget Gate and OG is Output Gate Owing to the memory constraints intrinsic to RNNs models, instances involving the concatenation of extended architectures tend to suffer from stagnated data updates, a phenomenon recognized as the "vanishing gradient" predicament. It becomes imperative to recalibrate the weights in order to compute the gradient of the loss function. This is underscored by the fact that the output y_t is not solely contingent upon the interval *t=t* but instead, it encapsulates a prolonged history ranging from *t*=*t*-1, *t*-2 and so forth. The hidden state h_t represents the output influenced by both the current input x_t and the memory cell state C_t.This multiplicative extension along the temporal continuum engenders a progressive degradation in the gradient's magnitude along the sequence length, potentially impairing the convergence of optimal weights. To redress this limitation, the LSTMs architecture was conceived. This remedial framework is visualized in Fig. 5, wherein an LSTMs cell is portrayed. A pivotal element within the LSTMs framework is the "state," an entity that encapsulates the memory cell's status and finds representation within the cell as denoted by equations (3)-(6).

$$i_t = \sigma(W_{x,i}x_t + W_{h,i}h_{t-1} + W_{c,i}C_{t-1} + b_i) \tag{3}$$

$$f_t = \sigma(W_{x,f}x_t + W_{h,f}h_{t-1} + W_{c,f}C_{t-1} + b_f) \tag{4}$$

$$C_t = f_t * C_{t-1} + i_t * \tanh\,(W_{x,c}x_t + W_{h,c}h_{t-1} + b_i) \tag{5}$$

$$O_t = \sigma(W_{x,o}x_t + W_{h,o}h_{t-1} + W_{c,o}C_{t-1} + b_o) \tag{6}$$

Where i_t is the input gate, f_t is the forget gate, O_t is the output gate, C_t is the cell stage , and h_t is the hidden stage

2.4 The GRUs Model

The GRUs, constituting yet another evolutionary stride in the realm of neural network models, emerged as a responsive solution to the prevailing challenges associated with RNNs. GRUs encompass a distinctive toggle mechanism designed to facilitate state updates within the contours of an RNNs architecture, analogous in nature to the internal functioning of the LSTMs model, albeit featuring a distinct "forget gate" characteristic. However, in contrast to the LSTMs, GRUs are endowed with a more parsimonious parameter configuration, owing to their exclusive reliance on the "update gate" and "reset gate" components [15]. The mathematical formulations underpinning the update gate and reset gate are elegantly articulated through equations (7)-(8).

$$r_t = \sigma(W_{r,x}x_t + W_{r,h}h_{t-1} + b_r) \tag{7}$$

$$u_t = \sigma(W_{u,x}x_t + W_{u,h}h_{t-1} + b_u) \tag{8}$$

Where r_t is reset gate, and u_t is update gate. The components encapsulated within the vector *r* are confined within the interval [0, 1] through the mediation of a sigmoid function. This transformation is contingent upon the hidden state *h* originating from the prior temporal iteration, in conjunction with the contemporary input *x*. Both of these elements are subject to weighting through the matrices denoted as *W*. Furthermore, an additive inclusion is made in the form of a bias term *b*.

Fig. 6 shows that the operational disparities the GRUs neural network, manifesting through the distinctive trait wherein the GRUs cell refrains from retaining the state stemming from preceding computations for subsequent analysis.

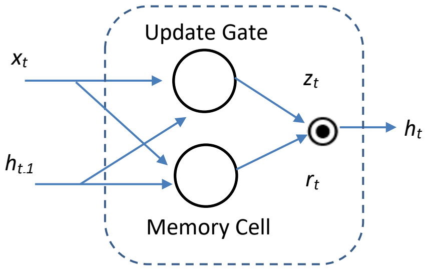

Fig. 6 The GRUs cell state.

2.5 Methodology

This section expounds upon the methodology employed to appraise the power generation emanating from the solar panels affixed to the charging station.

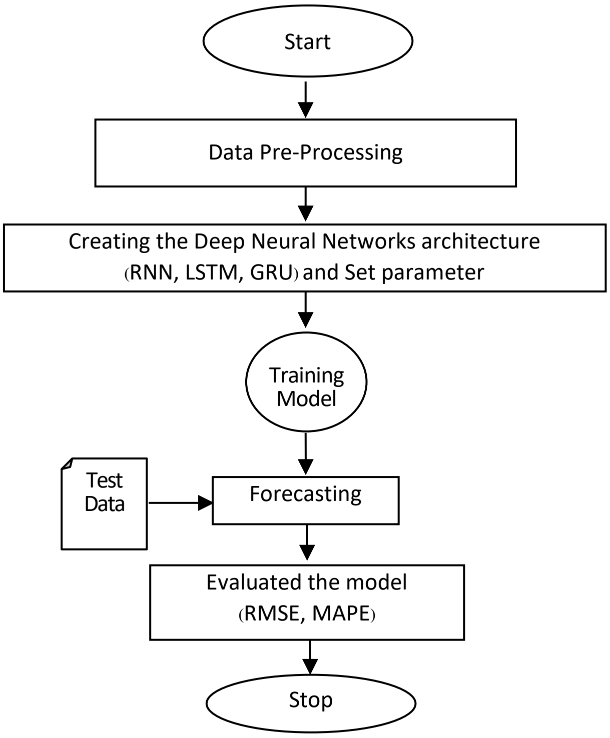

Fig. 7 The Proposed Methodology.

Fig. 7 presents an experimental approach delineated in the subsequent exposition. Commencing with data preparation in the CSV file format, the subsequent stages entail the formulation of the DNNs architecture, alongside the specification of requisite parameter values. Subsequently, the dataset is subjected to training processes, giving rise to the instantiation of the RNNs, LSTMs and GRUs model, which is subsequently assessed through testing procedures utilizing a designated test dataset.

2.5.1 Data Pre-Processing

Charging station data inaccuracies may emanate from charger malfunctions or errors introduced during data storage and transmission, thus compromising the integrity of volume forecasting for electricity consumption. As a precautionary measure, the evaluation of consumption entails the examination of electric train usage, meticulously culled from the log file. In this context, specific consideration is accorded to the omission of both the initial and terminal data points for each day, corresponding to instances of null consumption. This meticulous curation is instrumental in furnishing a foundation of utmost accuracy for subsequent estimation processes. Subsequently, this curated dataset is encapsulated within the comma-separated values (CSV) format, making it suitable for a tabular structure. This column-based delineation, segregated by commas, ensures the dataset is compatibility with a structural framework that is readily interpretable by deep neural network models.

2.5.2 Creating the Deep Neural Networks Architecture

The construction of a deep neural network learning model is undertaken using the Python programming language. This endeavor is accompanied by the execution of the subsequent experimental configuration:

Table 1 Parameters Setting.

Parameter Type	Parameter Values
Hidden Neurons	20,30
Hidden Layer	1,2,3
Optimizer	Adam,SGD
Epoch	50,100,150,200

Table 1 delineates the parameter configurations for constructing a deep neural network learning model in Python. It encompasses specifications such as the range of hidden neurons (20 to 30), the number of hidden layers (1, 2, or 3), and the choice between optimizers Adam and SGD (Stochastic Gradient Descent). Additionally, the table outlines epoch values ranging from 50 to 200. These parameters are systematically varied to explore their impact on the model's performance and learning dynamics. Concurrently, Table 2 presents a compilation of sample outcomes corresponding to each parameter, encompassing a cumulative total of 48 distinct experimental iterations.

2.5.3 Model Evaluation

RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) serve as fundamental metrics for evaluating the performance of predictive models. RMSE quantifies the average deviation between predicted values (Y_i) and actual values ($\hat{Y}$) through the formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2} \tag{9}$$

This calculation involves squaring the differences between predicted and actual values, averaging them, and taking the square root to yield the overall error. Lower RMSE values reflect greater accuracy in model predictions. Where N is the number of observations. (Y_i) is the actual value of the *i*th observation. ($\hat{Y}$) is the predicted value of the *i*th observation.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - \widehat{Y_i}}{Y_i}\right| * 100 \tag{10}$$

The MAPE formula computes the absolute percentage differences between actual and predicted values, which are then averaged across all observations, providing insights into the model's performance in terms of relative error. Lower MAPE values signify higher accuracy in prediction. Where *N* is the number of observations. (Y_i) is the actual value of the *i*th observation. ($\hat{Y}$) is the predicted value of the *i*th observation.

3. Result and Discussion

3.1 Comparative Analysis of Forecasting Models

The presented data assumes the structure of root mean squared error (RMSE), reflecting the divergence between actual values and their corresponding estimations derived from the training dataset. The RNNs model attains its lowest MSE value at parameter configuration 20,2,ADAM,150, with a recorded train loss of 0.28 and test loss of 0.34. For the LSTMs model, optimal performance is achieved at parameter configuration 20,2,ADAM,100, showcasing a train loss of 0.28 and a test loss of 0.32. Similarly, the GRUs model attains its minimum MSE at parameter configuration 20,2,ADAM,100, accompanied by a train loss of 0.28 and a test loss of 0.32. Upon a meticulous scrutiny of the power consumption estimation outcomes for each model, it becomes evident that the RNNs model, characterized by 20 hidden neurons, a hidden layer size of 2, an Adam optimizer, and 150 epochs, emerges as the optimal performer. Correspondingly, akin traits are discerned in the optimal parameter configurations for the LSTMs and GRUs models, as detailed in Table 2.

Table 2 The result.

Forecasting Model	Parameter Values	RMSE (kW)	MAPE (%)
RNNs	20,2,ADAM,150	0.385	12.439
LSTMs	20,2,ADAM,100	0.372	11.508
GRUs	20,2,ADAM,100	0.377	11.993

Table 2 illustrates the optimal architectural configurations for three distinct forecasting models: RNNs, LSTMs, and GRUs. Each model is characterized by 20 hidden neurons, 2 hidden layers, and the utilization of the Adam optimizer. Notably, LSTMs exhibit superior performance, particularly when trained over 100 cycles. They achieve the lowest RMSE of 0.372 kW and MAPE of 11.508%, outperforming RNNs and GRUs. Despite RNNs showing competitive performance based on RMSE after 150 cycles, LSTMs consistently excel in both RMSE and MAPE. These findings underscore the effectiveness of LSTMs in accurately forecasting power consumption, highlighting their practical advantage. The convergence of values across architectures reinforces the robustness of the results, offering valuable insights into the efficacy of different neural network structures for forecasting tasks. The distinct performance metrics enable a comprehensive comparison of the models, aiding in the selection of the most suitable approach for power consumption estimation. Ultimately, LSTMs emerge as the preferred choice for achieving precise and reliable forecasts in real-world applications, based on the provided data and analysis.

Fig. 8 depicts a visual representation in which the forecasting values are contrasted with the actual values, enabling a thorough comparative analysis. The discernible proximity between the forecasting curves and the actual data points is conspicuous, resulting in the attainment of notably low error values for both Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). This convergence into the lower error range collectively signifies the efficiency exhibited by all three deep neural network models.

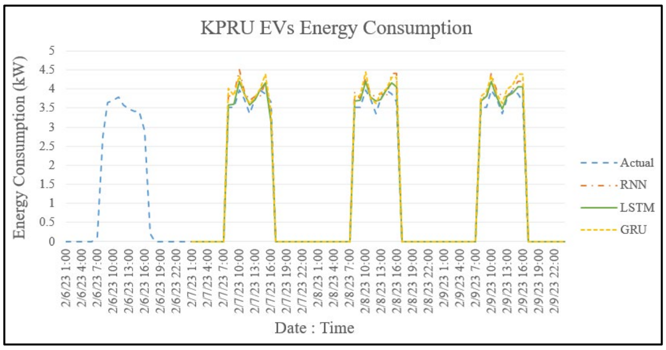

Fig. 8 Forecasting performance of the deep neural network models over test data.

3.2 Discussion

An examination of the data, as delineated in Fig. 2 and Fig. 3, underscores a discernible pattern of electricity demand. Concentrated in the time span from 8:00 a.m. to 5:00 p.m. This distinctive temporal trend fortifies the capacity of the experimental model to acquire knowledge and effectuate accurate estimations. Remarkably, the LSTMs model engenders a Root Mean Square Error (RMSE) divergence from actual data, dwindling to an impressively low threshold of 0.37 kW. This concordance with the study by [16], corroborates the model's robustness. It is imperative to acknowledge that the two alternative models may occasionally yield more favorable outcomes. For instance [17]. Discerned the heightened performance of GRUs within a volatile dataset. In the context of this experiment, it is noted that the LSTMs model marginally outperforms the GRUs, all while demonstrating enhanced computational efficiency compared to the latter. The selection between short-term and long-term forecasting methods introduces distinctions in performance based on certain characteristics. Statistical approaches like ARIMA excel in capturing short-term dependencies and patterns within stable trends or seasonal fluctuations. In contrast, deep learning methods, notably RNN, LSTM and GRU, are tailored for long-term dependencies, proving more effective in handling intricate, non-linear patterns over extended durations. Data volume plays a pivotal role, statistical methods like ARIMA shine in limited datasets or simpler patterns, while data-intensive deep learning methods, including RNN, LSTM and GRU, demonstrate proficiency in learning complex patterns with larger datasets. Regarding model complexity, ARIMA, with its fixed structure, may encounter challenges with highly non-linear patterns. On the other hand, the flexibility of RNN, LSTM, and GRU allows them to adeptly capture intricate temporal dependencies, demonstrating resilience in handling complex patterns. Hence, the suggested approach is apt for long-term estimation of electricity production at the Kamphaeng Phet Rajabhat University electric vehicle station.

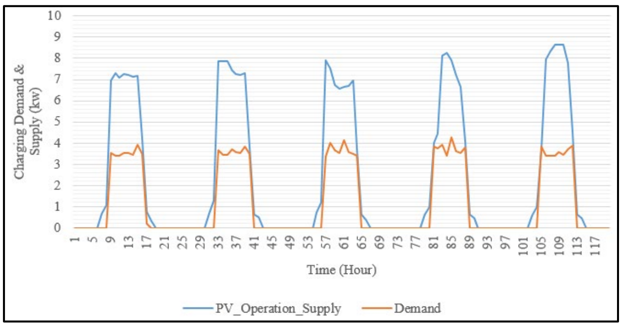

Fig. 9 Changing demand and supply.

4. Conclusion

This experiment is a conceptual framework aimed at forecasting the electricity consumption associated with EVs charging stations, thereby appraising the sufficiency of both electricity generation rates and demand for meeting this exigency. The experimental path begins with data preparation, which leads to designing architectural frameworks for three separate deep neural networks. These architectural designs set the stage for the training phase, where individual models undergo testing using training data. After successfully training the models, they undergo a series of testing procedures to develop the capability to predict electricity consumption rates. The evaluation of these models is undertaken through the lens of the Root Mean Square Error (RMSE), discerning the differential magnitude between actual and estimated values, and the Mean Absolute Percentage Error (MAPE), gauging the magnitude of percentage error. Remarkably, the outcomes underscore the superior performance of the LSTMs model, which yielded optimal results based on parameters including hidden neurons, hidden layer count, architecture, and optimizer (adam), and the number of training sets across 100 epochs. An analysis pertaining to the equilibrium between demand and supply surfaces. In the current context, the charging stations for electric vehicle batteries within the university environs exhibit the capacity to accommodate a substantial fleet of EVs, a phenomenon explicated in Fig. 9.

This research holds significance for the university as it contributes to the realm of accurate estimation pertaining to electricity consumption rates. The precise models developed through this study can serve as valuable tools for informing managerial decision-making processes. Furthermore, this research underscores the potential for advancing the management system dedicated to battery charging stations for EVs within the university setting. In conclusion, our research benefits alternative energy knowledge by providing precise electricity consumption estimates for EV charging stations. The identified optimal LSTMs model becomes a valuable forecasting tool for industry professionals, improving managerial decision-making processes and overall station management. These insights contribute to strategic planning, promoting efficient infrastructure expansion and surplus electricity optimization, thereby advancing sustainability within the alternative energy sector.

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