Investigating the performance of RNN model to forecast the electricity power consumption in Guangzhou China

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ABSTRACT

The project initiatives to create a reliable prediction model for power loads in Guangzhou, China. The power industry is facing issues due to rapid market growth and the necessity for better grid management, prompting this response. In developing the models, conventional machine learning models have been used so far, but in this study, the performance of deep learning is investigated. Therefore, the recurrent neural network (RNN) was selected for the prediction of electricity consumption. Later, the performance of the model was compared with autoregressive integrated moving average (ARIMA), long short-term memory (LSTM), and RNN. The experimental results show that the RNN outperforms ARIMA and LSTM, with an R^2 value of 0.92, an RMSE of 0.13107 and an MAE of 0.0176. The project improved power resource planning and management, selected an acceptable forecasting model RNN and contributed to forecasting technology developments. The study identified limits in historical data availability and quality, as well as external influences affecting the studies. RNN models can help optimize resource allocation and improve energy planning.

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1. INTRODUCTION

Significant demand growth, a strong reliance on fossil fuels, and rising carbon emissions define China's energy system. The nation's dependence on oil imports exceeds 50% by the end of 2009, and it was projected to 60% in 2015 and predicted up to 70% in 2030 [1]. Power grid businesses face issues in meeting load needs due to the dynamic energy environment, where accurate forecasting of electrical load is crucial for informed decision-making. An effective tool for resolving uncertainty is required for better cost and energy efficiency decisions such as generation scheduling, system reliability, power optimization, and economic operations [2]. Establishing datasets and records for a project is crucial, especially in the energy, water, and environmental sectors. From data there are many important aspects that can be viewed from the data analytics perspective. Numerous techniques have been employed for data acquisition, such as the internet of things and the Scada system. These two concepts are similar, serving as data sources for the purposes of monitoring and control. The basic idea is simple, which is derived from the development of grid construction with the sensor connections that are placed at important node, microcontroller, and computer system. Figure 1 shows a basic block design of an electrical grid with an internet of things system. In this grid, the sensor is connected to the controller and then to the computer system or either to gateway or run in the docker.

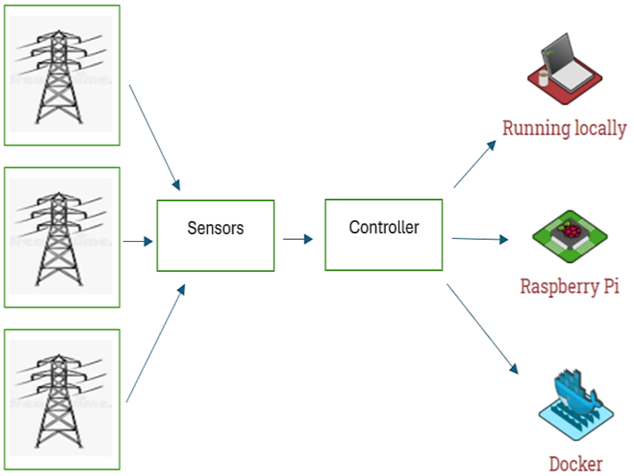

Figure 1. Illustration of power generation with internet of things system

The development of this system is not limited to data acquisition, but the resulting data is also stored in the storage system for a specific purpose. The development of today's technology with artificial intelligence makes the data found in a system developed to another level. As shown in Figure 2, shows a sample of works in prediction based on deep learning analysis. The workflow begins with dataset acquisition, followed by data annotation. The input will then be augmented to various sizes and divided into training and test sets based on a predetermined ratio. The training and test sets will then be fitted and trained using a detection algorithm. After the training is completed, the best model will be saved. Finally, the best model will be utilized to estimate the test dataset or new data for evaluation. The process for assessing will be based on the chosen metrics, such as mean average precision (mAP) and average precision (AP). If the model performs well, it can be applied to a real-world problem [3].

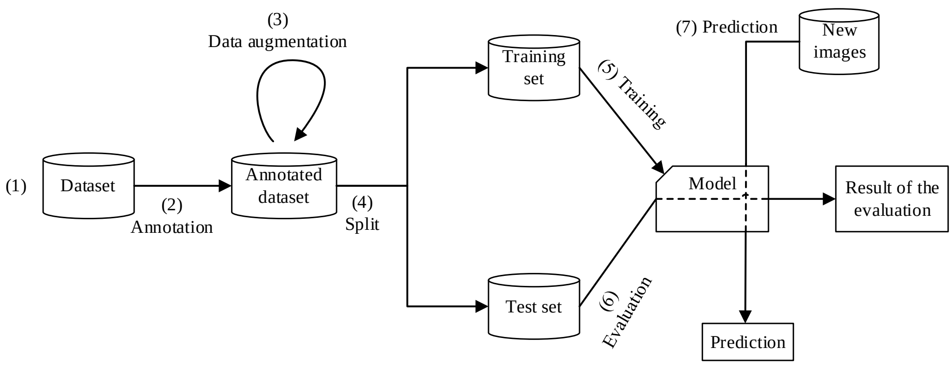

Figure 2. Workflow for prediction [3]

In recent decades, a scientific method known as power load forecasting has been developed [4]-[9]. In other countries, forecasting technology has been studied and is now being applied. Load forecasting is currently divided into two phases. During the first phase, which lasted from the 1960s to the 1980s, conventional methods were used. Regression analysis and time series were two of the economic forecasting techniques used in this stage [10]. In the second phase, which spans the 1990s to the present, load forecasting developed to include sophisticated algorithms. Expert systems, artificial neural networks, and fuzzy logic systems are the three main categories into which modern artificial intelligence approaches can be divided [11]. Load forecasting was the eventual application of these concepts. Intelligent load forecasting systems have replaced conventional economic forecasting techniques in the field over time. Artificial neural networks and expert systems are two instances of artificial intelligence-powered load forecasting methods. The necessity to address the power grid's short-term load capacity has grown more critical as the power market continues to change. In the upcoming years, long-term forecasting will assist plans for power system expansions and enhancements, which will ultimately increase the power system's benefits to society and the economy [11]. As a result, it is clear that load forecasting for power systems using data mining and others techniques has to be researched immediately [12], [13].

Regression analysis is a solid method for forecasting load using historical data because of its mature assumptions, simple computations, and speedy processing. However, its limitations become apparent in real-time applications and nonlinear effects, where it may struggle to represent dynamic interactions [14]. The time series analysis method organizes historical load changes by time, indicating variations over time and the evolution of the rule. This approach can estimate future load fluctuations over time and is also employed in routine operations. In a typical power grid operation, the time series method's prediction accuracy is good, but its smoothness requirements are too high. The technique may no longer have the desired 1 impact due to unusual occurrences [15]. An expert system is a computer programming system designed to mimic human load forecasting competence. It processes load data and makes appropriate forecasting predictions by utilizing artificial intelligence and a database of past load changes. To predict short-term load in the Mumbai area, REL used an expert system technique [16].

Positive outcomes have been obtained when the impact of a load on holidays and other uncertainty is assessed using human experience. Nonetheless, the power environment varies by region, which leads to a complicated computer program and a lot of data are required. An intelligent information processing technique that imitates the workings of the human brain is the artificial neural network. It is proficient at handling complicated non-linear interactions between input variables and predicted output, learning the best parameters, and assessing and resolving stochastic uncertainty and complex non-linear relationship problems [17], [18]. The approach is limited to small sample learning and is based on empirical risk minimization. The study aims to analyze the efficiency of time series models, that are autoregressive integrated moving average (ARIMA), long short-term memory (LSTM), and recurrent neural network (RNN) models in predicting power consumption by gathering electricity load data and applying them. Metrics including mean square error (MSE), mean absolute precision (MAP), and root mean square error (RMSE) are used to assess the models' performance. The main objective is to determine which model is most appropriate for this investigation. In the meanwhile, the issue of the illogical distribution of electricity demand can be resolved and energy waste can be prevented by integrating short-term load forecasting techniques with demand response of electricity consumption. The power grid business can select the most appropriate model based on the study's findings. Additionally, there is a lot of room for improvement in the power grid's efficiency and dependability through the integration of short-term load prediction and demand response technologies. With this strategy, electrical resources can be used more effectively, and the system can react quickly to variations in demand. Moreover, it gives consumers the ability to take an active role in controlling their power usage, empowering them to make knowledgeable decisions and help create a more sustainable energy future [17], [18]. Organizations can help promote sustainable development in Guangzhou City and offer useful information for energy management by developing a simplified and accurate power demand forecasting model.

A few electrical companies have successfully used artificial neural network to modify internet load. In comparison to the standard predictor, the experimental data demonstrate that the technique reduces error by 41% and training time by 66% [19]. Use the genetic algorithm (GA) to find the optimal time lag and number of layers to maximize the performance of LSTM models. Findings: with a CV (RMSE) of 0.56% on average and 0.61% over the short term, LSTM-RNN shows reduced forecast errors. Higher prediction accuracy can be achieved by optimizing features, lags, layers, and LSTM configurations. This approach not only allows for better utilization of power resources but also enables the grid to respond promptly to fluctuations in demand [20]. The study finds that the mean absolute error (MAE) and RMSE of medium- and long-distance forecasts were reduced [21]. The mean absolute percentage error (MAPE) measure is used to assess models. For autoregressive moving average (ARMA), ARIMA, and autoregressive integrated moving average with explanatory variable (ARIMAX), the forecast error levels are 17.7%, 4%, and 3.6%, correspondingly. In terms of forecast accuracy, ARMA performs worse than ARIMA and ARIMAX models. Research suggests that ARIMAX models outperform ARIMA models by a little margin [22]. Under ideal weather conditions, the RMSE accuracy can approach 4.62% and the LSTM model accuracy can reach 4.62%. The recommended method achieves a high degree of forecast accuracy and effectively captures the dynamic characteristics of less-than-ideal weather conditions [23].

Utilizing a deep neural network, quantile regression is utilized to predict power consumption according to probability density. The error value is at its lowest when deep learning is used. Three values have been identified [24]: 3% for MAPE, 6% for mean relative percentage error (MRPE), and 594 for MAE. The experimental results show that the deep learning strategy performs better than the random forest and gradient boosting machine methods in terms of prediction error. The deep learning model suggests that the most important variables for the feature selection problem are those linked to temperature, weekly, and monthly cycles. considering consumption is most affected by summer highs. substantial impact on power consumption [25]. The paper suggests using LSTM, chaotic time series, intelligent optimization algorithms, mapping, and short-term power load forecasting to reduce manual debugging, improve prediction accuracy, and extend load forecast duration. When compared to LSTM prediction, the method used in this study increases prediction accuracy by 61.87% in terms of RMSE. There are times when the forecast error is reduced by 50% within the 40-time prediction window [26]. Residential loads in urban areas, commercial loads, rural loads, industrial loads, and other sorts of loads are among the several kinds of power system loads. Different loads have different characteristics and rules [27]-[29].

2. METHOD

This paper's approach includes collection of datasets, preprocessing of those datasets, model selection, and performance testing using RMSE, MAE, and MSE to compare and contrast three models: ARIMA, LSTM, and RNN. Figure 3 shows the flow of research methodology.

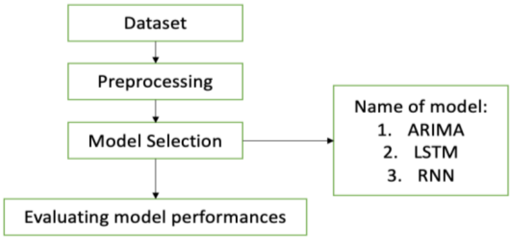

Figure 3. Research methodology

2.1. Dataset

The study collected three datasets, the first dataset is a regional electrical load dataset recorded at 15-minute intervals as shown on Table 1. The second dataset is an average electricity consumption dataset for different industries as shown in Table 2. The third dataset (as shown in Table 3) is a dataset on meteorology, which records attributes such as temperature and wind speed. The first dataset is recorded from January 2018 to August 2021, it has two attributes. And the second dataset is recorded from year 2019 to 2021, it has four attributes.

Table 1. A 15-minute intervals regional power load dataset (dataset)

Attribute name	Attribute type
Datatime	Date
Total power usage (kw)	Numeric

Table 2. Average power load dataset for different industries (dataset)

Attribute name	Attribute type
Sector type	Categorical
Datatime	Date
Average power max (kw)	Numeric
Average power min (kw)	Numeric

Table 3. Climate dataset (dataset)

Attribute name	Attribute type
Date	Date
Weather	Categorical
Max temperature	Numeric
Min temperature	Numeric
Daytime wind	Categorical
Night wind	Categorical

2.2. Preprocessing

To predict the future load with historical load data, accuracy and integrity of the data is the first condition. Due to the external or internal random fault, communication signal interference and artificial recording, there is part of the time node data missing or abnormal. So that it is necessary to analyze and correction of historical data was needed before establishing the prediction model.

2.3. Model selection

The ARIMA model is a time series analysis method used to model and predict time series data. It consists of two parts: autoregressive and moving average. The model decomposes time-series data into autoregressive components, moving mean components, and random error terms. The autoregressive component represents the correlation between current and past observations, the moving average component represents the correlation between current and past errors, and the random error term represents fluctuations that cannot be explained by these components. LSTM is a variant of traditional RNN that effectively captures semantic associations between long sequences and reduces the phenomenon of gradient disappearance or explosion. Its main feature is the control of gate structure, including forgetting, input, cell state, and output gates, which adds a "processor" to judge information utility, enabling better time series tasks and solving long-term dependence issues caused by RNN backpropagation during training. A RNN is an artificial neural network with internal ring connections used for processing sequence data. Its key feature is its loops, allowing information to circulate and facilitate the storage and processing of sequence information.

2.4. Evaluating model performances

The best model for predicting power consumption data was selected after each model had been evaluated using RMSE, MAE, and MSE. One way to measure the accuracy of a prediction is by looking at its MAE. This scale-dependent metric minimises the gap among both negative and positive errors in order to properly reflect prediction error. In (1) may be used to determine MAE [28].

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | yi - \widehat{yi} | \tag{1}$$

The mean squared error (MSE) is a measure of the average squared deviation between the expected and actual values [29]. It is determined by (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n} | yi - \widehat{yi}|^2 \tag{2}$$

The RMSE measures these prediction mistakes. RMSE as shown in (3). The residuals, a measure of the dispersion of the data points around the regression line, should be considered first. An indicator of the dispersion of these residuals is the RMSE. In order to validate the experimental models, this statistic is often calculated and utilised in regression analysis, climatology, and forecasting [18].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} | yi - \widehat{yi}|^2} \tag{3}$$

3. RESULTS AND DISCUSSION

This section provides an in-depth look at the evaluation and results of three different models (ARIMA, LSTM, and RNN) used to forecast electricity load data. The analysis covers regional power load datasets at 15-minute intervals (Dataset) and a combined dataset (Merged Dataset) focusing on average maximum power loads for large industrial power. Dataset is a single variable input and a single variable output for research purposes. The merged dataset is a research purpose containing external variable input and single output. Using, RMSE, MAE, and MSE as performance metrics, hyperparameter configurations, and models were placed into grid search for automated searches for selected optimal model hyperparameter configurations while training the models, followed by predictions. Each model's optimal parameters and subsequent performance metrics were explored to gain a comprehensive understanding of their predictive capabilities. Overall result dataset as shown in Table 4.

Table 4. The results of using three models in the dataset

Model	RMSE	MAE	MSE	R^2
ARIMA	9950.35	5518.96	99009397.03	0.42
LSTM	0.12563	0.0509	0.004737	0.485
RNN	0.13107	0.0176	0.000512	0.92

From Figure 4, the RNN model outperforms the LSTM model in terms of R^2, indicating a better fit. The LSTM model has a slightly lower RMSE, suggesting slightly better accuracy in predicting the target variable. The RNN model significantly outperforms the LSTM model in terms of R^2, MAE, and MSE, indicating better accuracy and predictive performance. RNN score 0.92 and LSTM score 0.485. Table 5 shows a result of using three models in the merge dataset for large industrial power usage. Based on this table, the output are stable and the algorithm, can be considered. Figure 5, blue represents the original data, yellow represents the LSTM model prediction, and pink represents the RNN model prediction. It is obvious from the figure that the RNN model predicts better than the LSTM model. Figure 5 illustrates that the RNN model has better accuracy and prediction performance. As can be seen from Figure 6, blue represents the original data, yellow represents the LSTM model prediction, and green represents the RNN model prediction. It is obvious from the figure that the RNN model predicts better than the LSTM model.

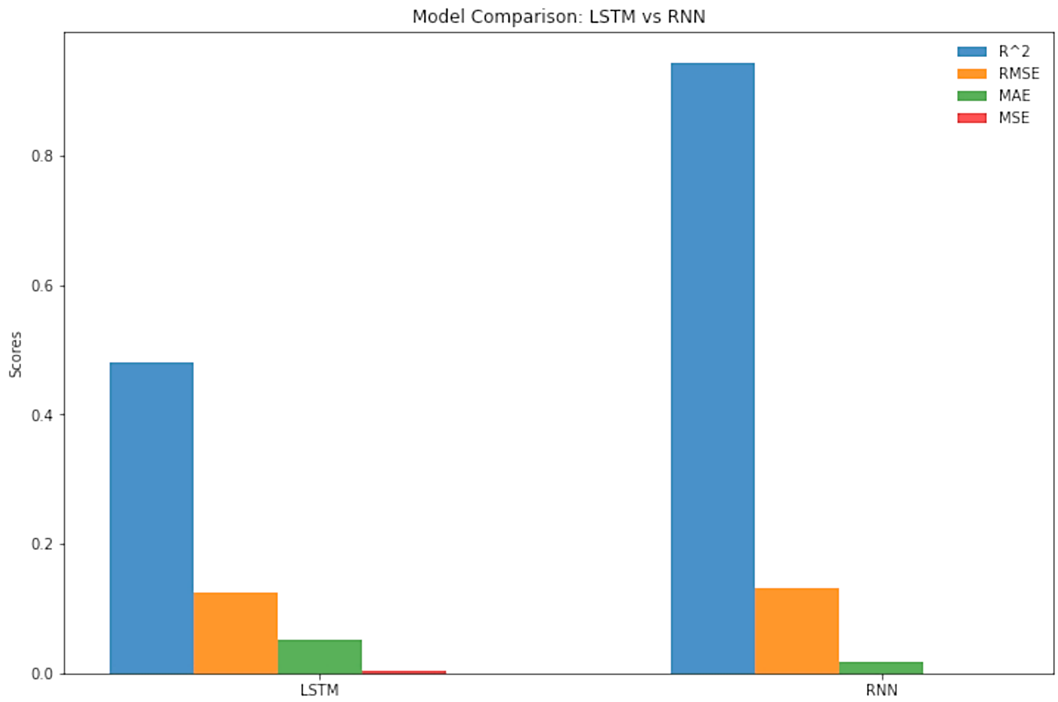

Figure 4. Compare RNN model and LSTM model performance index in the dataset

Table 5. Compare RNN model and LSTM model performance index in the merged dataset (large industrial electricity average power max)

Model	RMSE	MAE	MSE
SARIMAX	11869.72	8452.04	140890218
LSTM	0.06871	0.04986	0.0047
RNN	0.06507	0.049748	0.0042

As can be seen in Tables 4 and 5, the RNN outperformed both LSTM, ARIMA, and seasonal autoregressive integrated moving average with explanatory (SARIMAX). The reason for the good performance of RNN could be related to the nature of the datasets themselves. In the context of regional electricity load forecasting, it uses high-frequency data which is recorded at 15-minute intervals. The forecasting performance of a model is closely linked to its ability to capture the temporal dependencies inherent in the data. Electricity demand is usually characterized by strong local, short-term dependencies, where the load values of the last few hours have a greater influence on future consumption than the long-term historical values. RNNs are particularly well suited to such scenarios, as their architecture allows information to be passed sequentially through hidden states, preserving the immediate context of the past without making the model unnecessarily complex.

In contrast to LSTM networks, which are designed to capture long-term dependencies through gating mechanisms and memory cells, RNNs effectively capture short-term patterns that dominate high-frequency load forecasts. In addition, the relatively small number of attributes in the datasets, including electrical load, industrial consumption and meteorological variables, hence further reduces the need for complex storage architectures. External factors such as temperature and wind speed typically have an immediate impact on electricity demand, highlighting the suitability of RNNs that can efficiently model these short-term cause-and-effect relationships. The superior performance of RNNs in this context can therefore be attributed to the match between the model's ability to capture local dependencies and the short-term, high-frequency nature of the load forecast data.

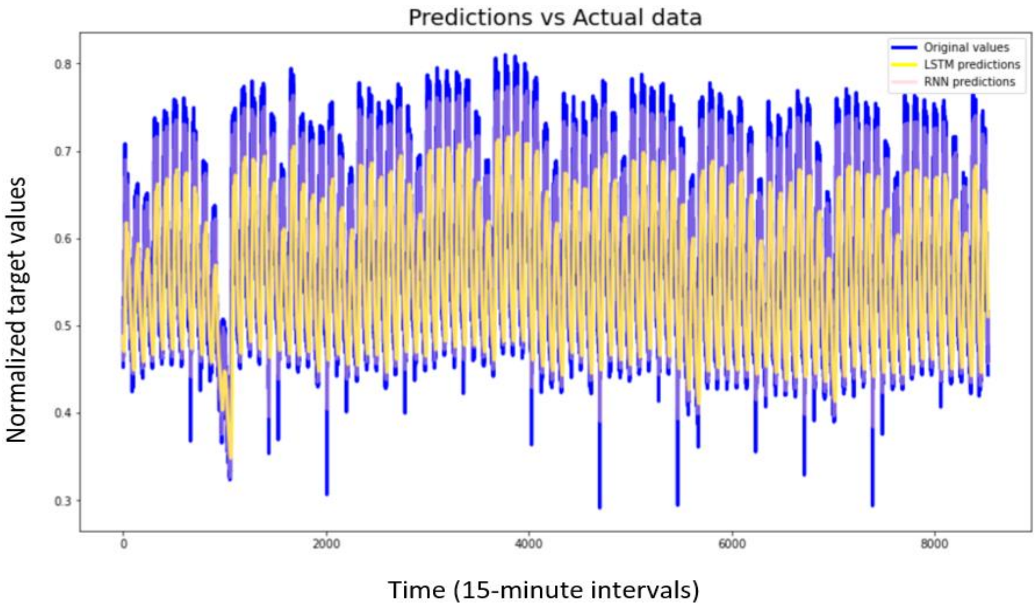

Figure 5. Compare RNN model and LSTM model in the 15-minute intervals

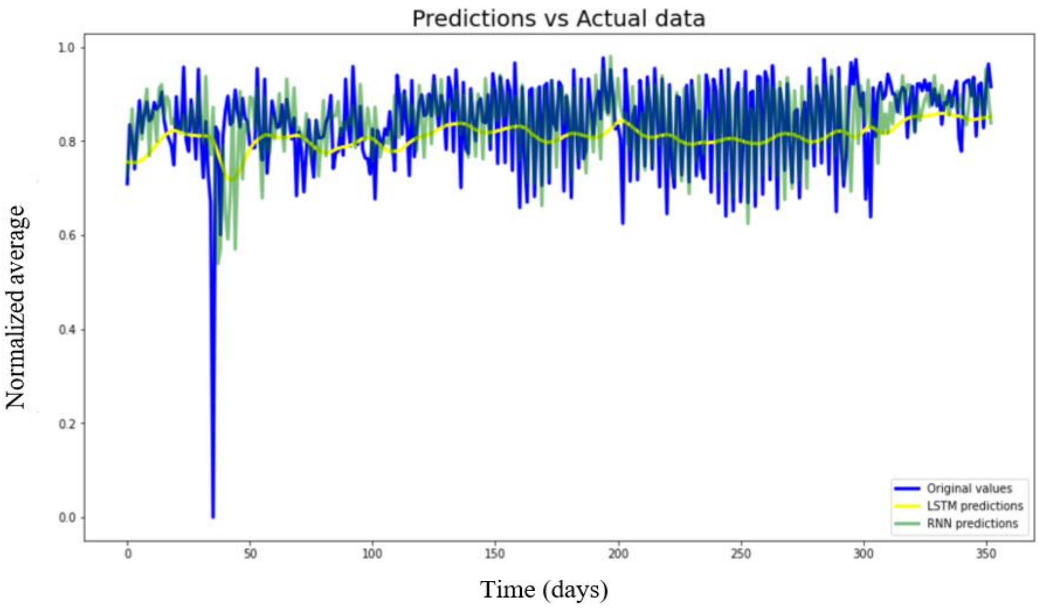

Figure 6. Compare RNN model and LSTM model in the merged dataset (large industrial electricity average power max)

Figure 7 is the use of RNN model to predict the usage of electricity load at 15 minutes apart over 10 days. As can be seen from the figure, the power use area is from low to high and gradually tends to a stable value. Figure 8 is the use of RNN model to predict the usage of electricity load within 30 days in the merged dataset. The average maximum power consumption of large industries predicted using the RNN model is above 12,000 and the average minimum power consumption is within the range of 90,000 and 95,000.

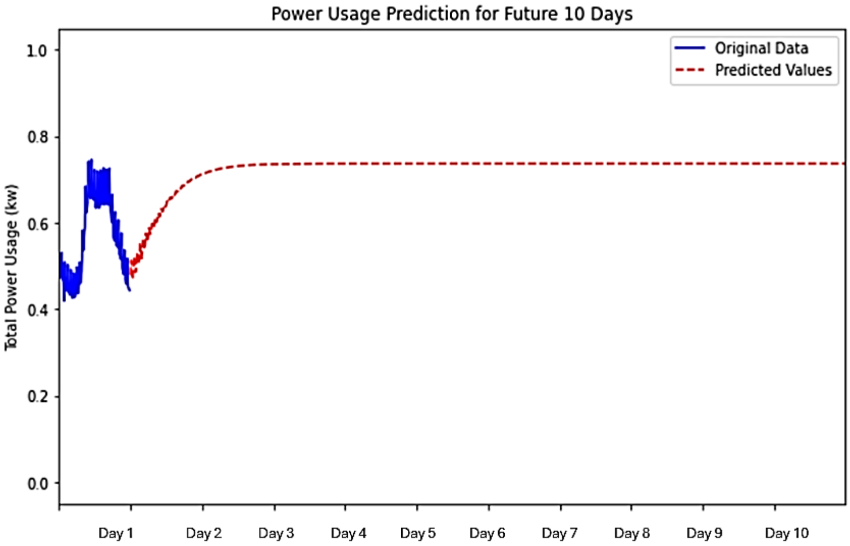

Figure 7. Using RNN model for future 10 days in the 15-minute intervals regional power load dataset

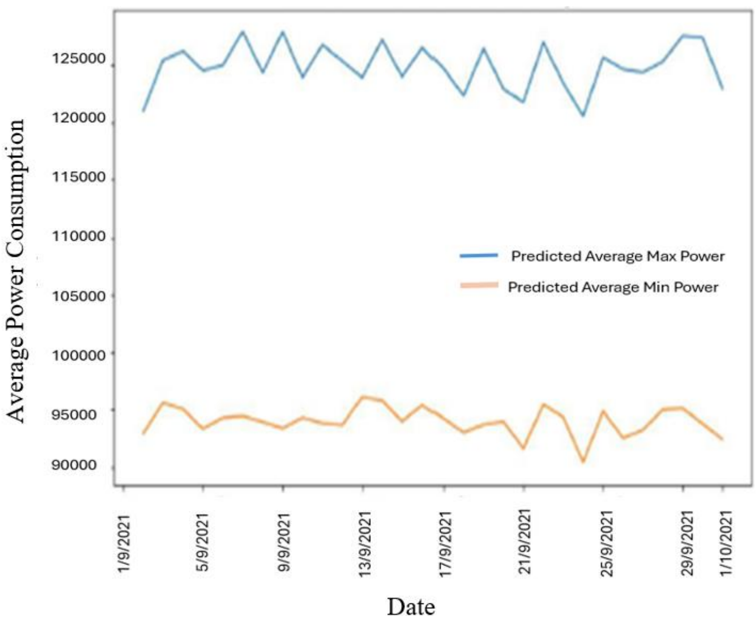

Figure 8. Using RNN model for 30 days in the merged dataset (large industrial electricity)

4. CONCLUSION

This study investigates the performance of deep learning models on two difference dataset, namely dataset and merged dataset by using three models, ARIMA, LSTM, and RNN. Dataset is featured by the indexing of date time, a single input variable that is the value of electricity consumption, and a single target variable that is a single predicted value. The merged dataset is featured by the presence of external variables to explore the effect of temperature factors on electricity consumption load. Therefore, the SARIMAX model is required to analyze the external variables. According to the characteristics of dataset, four models, ARIMA, SARIMAX, LSTM, and RNN models were applied and evaluated on different datasets, demonstrating their advantages and disadvantages. RNN consistently outperforms LSTM, demonstrating its superiority in accuracy and predictive performance. Using RNN for short-term and long-term forecasting demonstrates its potential applicability in forecasting electricity loads. Hyperparameter tuning is a key step in this research project. It finds the optimal values of the model hyperparameters to maximize its performance and prediction accuracy. This study employed a grid search technique for hyperparameter tuning, where a grid of hyperparameter values is defined and the model is trained and evaluated for each combination of values. This exhaustive search evaluates the model's performance under different hyperparameter settings and determines the optimal configuration. During the hyperparameter tuning process, evaluation metrics such as MSE, MAE, RMSE, and R^2 to assess the performance of the model. By comparing the performance metrics of different hyperparameter combinations, it can be able to determine the optimal set of hyperparameters that produced the best results. This leads to improved model performance and better predictions. By carefully tuning the hyperparameters, it can improve the accuracy and effectiveness of the model in predicting power load data and supporting decision-making in the grid industry. For future recommendations, we would like to explore hybrid modeling approaches for electricity consumption forecasting, by combining the strengths of different modeling techniques, such as statistical, machine learning, and deep learning models to improve prediction accuracy and robustness. In addition, the Transformer models, also can be taken into consideration, as it has the ability to capture long-range dependencies and complex temporal patterns. This will offer significant potential in modeling electricity usage trends, especially in scenarios with high variability or non-linearity. These approaches may provide more accurate and generalizable forecasts, supporting better energy management and planning decisions.

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