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Smart Grid Load Forecasting Models Using Recurrent Neural Network and Long Short-Term Memory

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***Abstract*—** This paper presents two methods for managing electrical energy consumption and demand, with the objective of developing reliable and accurate forecasting models for smart electrical network energy consumption and optimization. The first method utilizes a recurrent neural network (RNN), while the second employs long short-term memory (LSTM) techniques. This approach builds upon previous studies that have explored the use of machine learning models for energy forecasting, but often with limited performance or the inability to capture long-term dependencies in the data. The study utilizes the Global Energy Forecast 2012 database - for the period from 2004 to 2008, with a focus on electricity consumption - to validate the performance of the proposed models. The R-squared (R2) score is used as the primary evaluation metric, with the LSTM model achieving a remarkable 90% R2 score, outperforming the RNN model's 80% R2 score. This is a significant improvement over previous studies, which have typically reported R2 scores in the range of 70-80% for energy forecasting models. Furthermore, the LSTM model demonstrates superior error rate performance, with a Mean Squared Error (MSE) of 4.345%, compared to the RNN model's 16.644% MSE. This highlights the ability of LSTM models to capture long-term dependencies in the data, which is crucial for accurate energy consumption forecasting, a limitation often observed in traditional RNN-based approaches. The findings of this study highlight the superior performance of the LSTM-based approach in accurately predicting energy consumption in smart grids, a crucial aspect for optimizing energy management and distribution. This contribution is particularly significant, as it showcases the advantages of LSTM models over traditional RNN techniques in the context of energy forecasting, providing valuable insights for researchers and practitioners in the field of smart grid optimization, where accurate forecasting is essential for efficient energy management and distribution.

***Keywords*—** long short-term memory technique; Simple recurrent neural network; Load forecast; Energy consumption; Smart Grid.

1. INTRODUCTION

The global shift towards sustainable energy practices has made the subject of energy usage in "smart grids," as they are often known, more and more significant. Modern technology is used by these networks to seamlessly integrate solar and wind energy sources into the electricity distribution network. This integration leads to both energy conservation and a decrease in greenhouse gas emissions. Nevertheless, the implementation of this state-of-the-art technology entails additional energy expenses for upkeep and functionality. Therefore, gaining a comprehensive understanding of how energy consumption in these systems may be improved and regulated is crucial to guaranteeing the long-term sustainability and usefulness of smart grids. The energy consumption of a smart grid presents a variety of challenges [1]. Firstly, the sophisticated technology used in smart grids, such as energy storage units, sensors,

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and smart meters, requires increased energy consumption for operation. Secondly, integrating renewable energy sources into the grid must ensure constant electricity access for customers. Thirdly, it's crucial to regulate electrical loads due to fluctuations in consumer demand and time of day. Effective management of production and distribution is essential for this purpose. Furthermore, greenhouse gas emissions from energy production and distribution are environmental concerns related to smart grid energy consumption. Lastly, the use of advanced technologies in smart grids raises issues regarding data security and the protection of consumer privacy when gathering and analyzing customer data.

The remainder of this paper is organized as follows: Section I provides an introduction that highlights the importance of accurately managing energy consumption in smart grids and addresses the challenges associated with energy consumption in smart grids and also provides a problem and motivation, also section 1 defines and describes a smart grid.

Section 2 describes extensive related work. Next, we describe data processing and model estimation in Sections 3 and 4 respectively. The overview of recurrent neural networks (RNN) and long short-term memory (LSTM) models used for electrical load forecasting is explained, with a discussion of their configuration and parameters, and the implementation of a recurrent neural network for load forecasting is detailed to understand how the models are implemented are detailed in section 5. The prediction results, which give an evaluation and comparison between simple LSTM and RNN models based on testing and training, are presented in sections 6 and 7, respectively. conclusions are drawn in section 8.

However, the difficulty with this paper in comparison to other people's is multifaceted. Model complexity [2], data collection, comprehending algorithms, and performance optimization are some of the special obstacles that may differ from other people's work. Implementing models based on RNNs and LSTMs might require extensive technical skills, which can be difficult for people who have not received specific machine learning training. Accurate, high-quality data might be challenging to get while training these models, especially in sparse or unstructured situations.

Those unfamiliar with deep learning principles may find it difficult to gain a thorough knowledge of the techniques underpinning RNNs and LSTMs. Furthermore, enhancing the efficiency of load forecasting models in smart grids may need precise tweaking and significant testing, which can be difficult for those with time or resource restrictions. To overcome these hurdles, specific training and practical expertise may be required. My work is motivated by a variety of factors, including technological innovation, environmental effect, and technical hurdles.

Working on sophisticated technologies such as recurrent neural networks and long-term memory neural networks is fascinating for individuals who want to keep ahead of the curve in energy management technology. Those concerned about the environment are motivated by the opportunity to improve energy efficiency in Smart Grids and optimize energy management. Technical problems, particularly load forecasting in Smart Grids, provide incentives for developing novel solutions. In conclusion, delivering novel solutions, having a beneficial influence on the environment, and overcoming interesting technological difficulties are all important sources of motivation for academics working on energy management and load forecasting in Smart Grids utilizing RNNs and LSTM.

The objective of this paper is to create accurate and trustworthy forecasting models for optimizing energy consumption in smart electrical networks. These models seek to increase energy efficiency, lower operational costs, and assure a reliable and sustainable energy supply. Using RNNs and LSTMs, the goal is to generate more accurate load predictions that can respond to complex fluctuations in energy demand, resulting in more efficient and intelligent energy management in smart grids.

This paper marks a significant technical leap in smart grid energy management through the use of RNN and LSTM. Using these neural network designs, we were able to dramatically increase the accuracy of load estimates, resulting in more effective energy management. Our RNN and LSTM-based models are notable for their capacity to adapt to complicated fluctuations in energy demand, resulting in improved real-time management even under shifting conditions.

Our study contributes to the energy efficiency of smart grids. By improving load projections with our models, we were able to optimize energy resources more precisely, lowering operational costs and encouraging more sustainable energy use. In summary, our technique is a big step forward in the field of smart grid energy management, providing substantial benefits in terms of efficiency, accuracy, and flexibility to current and future energy management difficulties.

In this context, intelligent networks, sometimes known as "smart grids" as shown in Fig. 1, are a significant advancement in energy delivery and management. These networks combine modern communication technology, automated measurement and control devices, and optimization algorithms to allow more efficient, dependable, and sustainable power management [3]. Smart grids provide real-time monitoring of energy demand and output, allowing for more efficient coordination of electricity flows. Smart grids employ modern sensors and control systems to identify outages faster, decrease energy losses, integrate renewable energy more effectively, and promote wiser power usage. In essence, smart grids have the potential to significantly enhance operational efficiency, cut carbon emissions, promote environmental sustainability, and enable more flexible and adaptable power grid management.

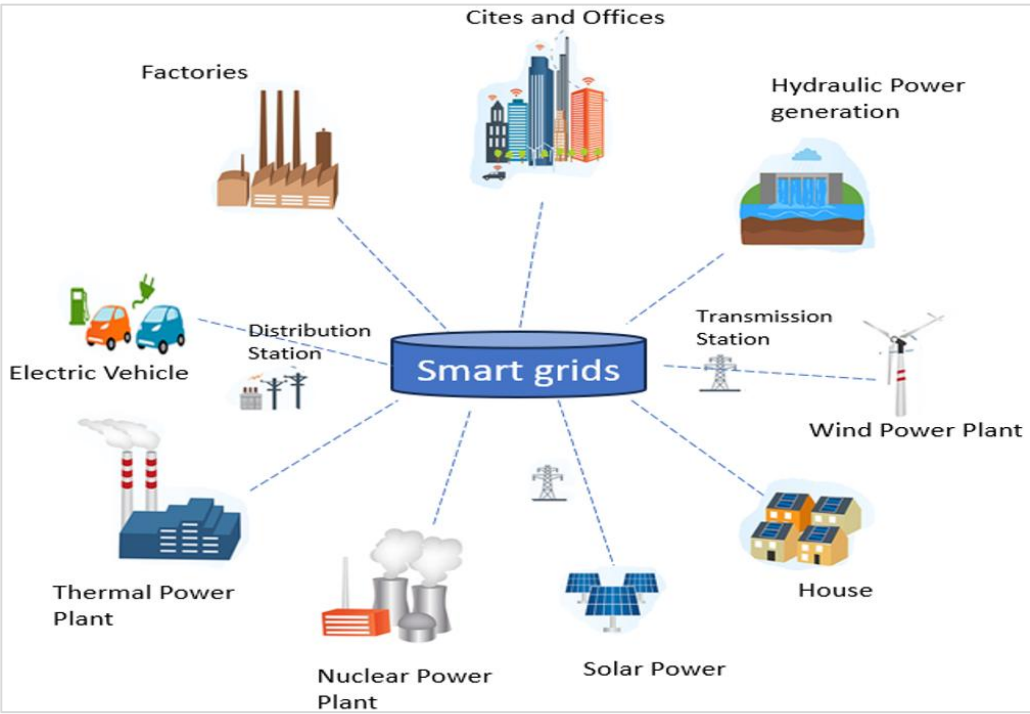

Fig. 1. Smart Grid.

2. RELATED WORKS

For efficient energy management, to avoid wasting precious resources, and to move toward an energy-efficient society, energy consumption forecasting is essential. Numerous techniques for forecasting electricity consumption have been developed because of the recent explosion in artificial intelligence and deep learning technologies. These techniques have been thoroughly investigated by researchers and e-commerce alike:

The study in [4] focuses on predicting power use using spatial similarity and deep learning. This work can help us understand how to enhance prediction models by considering geographical similarities and employing deep learning techniques. The author in [5] offers a study on predicting power use in office buildings. This article looks at how a gradient-boosting tree may be used to estimate monthly power use. This forecasting approach can help property managers and power suppliers improve the planning and control of energy use in office buildings. The paper [6] describes a study that used an artificial neural network to anticipate power use in China's Guizhou region. This study focuses on the use of artificial intelligence approaches for projecting power use, which has significant consequences for regional energy management and resource planning. The work in [7] focuses on research of the power demand in Qingyuan, China. The ANN-ARIMA (Artificial Neural Networks: Autoregressive Integrated Moving Average Model) model provides a predictive strategy for estimating short and long-term power usage. This technique combines the benefits of artificial neural networks for nonlinear modeling with the forecasting skills of ARIMA, a traditional statistical model. The study's findings may be useful for Qingyuan's energy planning and long-term growth. Reference [8] it presents a study on predicting home power use with a Back Propagation (BP) neural network. This forecasting approach is beneficial for monitoring residential power use trends and helping to improve energy management. Neural networks are strong tools that are used in a variety of industries to understand complicated data and anticipate outcomes. The study in [9] focuses on a strategy for estimating short-term power demand using hybrid cluster analysis. This study looks at how cluster analysis methodologies might be coupled to increase the accuracy of power consumption projections in a certain region. The findings and conclusions of this study may be valuable to energy planners, power suppliers, and other stakeholders involved in electricity demand control. The technique in [9] shows Hybrid cluster analysis utilizes several clustering approaches to increase the accuracy of regional electricity consumption projections. This study contributes to the subject of electricity demand forecasting and might be valuable to energy planners and power grid operators. The study in [7] focuses on employing deep neural networks to forecast short-term power demand. This discovery might have practical implications for power consumption control, allowing for more precise and efficient planning of electricity generation and delivery. Moreover, this study focuses on the various elements that might impact residential power use. This study analyzes and draws inferences from these characteristics using a multiple linear regression model. This study contributes to a better knowledge of household power consumption practices and can aid in the implementation of policies that encourage the efficient use of electrical energy in households. In [10] it focuses on utilizing an LSTM neural network to forecast power use. This method can help anticipate electricity usage, which is important for power network planning and management. The study [11] examines the effects of meteorological conditions in a Mediterranean location, emphasizing the need to take these elements into account when predicting power consumption. The findings of this study can help improve energy planning and promote more sustainable consumption patterns. The study in [12] employs an ABC-BP neural network to forecast power use. This sort of network combines the ABC (Artificial Bee Colony) algorithm and the BP (Back Propagation) neural network to increase prediction accuracy. This study's findings might have significant consequences for managing power use and developing energy saving techniques. [13] Describes a novel approach to assessing electrical energy measurement equipment. This approach is based on the gray model for vertical and horizontal cross-optimization. The paper looks at how this technique may be used to increase the accuracy of measuring device condition assessments, which is critical for providing dependable and accurate electrical energy consumption measurements. The authors investigate the prediction of home power usage using Bi-LSTM. This study demonstrates that Bi-LSTM can accurately anticipate home power usage, which might have significant implications in energy management and resource planning. In [14], the author suggests a mechanism for anticipating load curves at the home level. This approach employs data clustering to boost the accuracy of functional time series forecasts. The study focuses on intra-day load curves, providing intriguing possibilities for optimizing energy management at the home level.

To improve the accuracy of power consumption prediction, this paper presents two techniques: RNNs and LSTM. Both models take electricity consumption into account as a significant factor and forecast future consumption based on historical data. As shown in [5], the field of predicting electrical load using smart metering data at one-minute intervals is relatively new.

To predict the immediate future demand for electricity, short-term load forecasting has investigated a number of AI-based methods, such as wavelet neural networks, support vector machines, fuzzy logic, and artificial neural networks. RNNs are one of these techniques that have demonstrated noteworthy success in a variety of applications, including load forecasting. The study in [15] focuses on using an artificial neural network to anticipate short-term loads while accounting for meteorological variables.

This strategy can help improve the accuracy of power load projections by considering the influence of weather conditions on electricity consumption. In [16] uses deep neural networks for short-term load forecasting. Deep neural networks are a type of artificial intelligence that can examine complicated data and generate precise predictions.

The purpose of this research is to improve standard load forecasting methods by harnessing the capabilities of deep neural networks. The findings of this study may have significant consequences for the optimization of power distribution networks and energy demand management.

In [17] the paper presents strategies for projecting short-term power usage at the regional level. To create a useful forecasting model, the author used a hybrid cluster analysis technique. This method uses many cluster analysis techniques to increase the accuracy of power consumption projections. The findings of this study can help power grid management and energy policy makers better plan and manage short-term electricity demand.

In [18] the article examines the issues and solutions associated with smart grid energy use. The authors emphasize the challenges associated with managing smart grid energy use and provide ways to overcome them.

This study helps to the evolution of smart grid technology by highlighting current difficulties and suggesting solutions for improving energy efficiency.

In this paper, we present a deep learning-based load forecasting approach that uses a recurrent neural network (RNN) for prediction. We use different RNN models to compare load predictions accuracy in a methodical manner.

3. LOAD FORECASTS

In Smart Grids, there are many types of load predictions, each of which is influenced by distinct circumstances.

3.1. Weather-Based Load Forecast

Weather variables, including sunlight, wind speed, and temperature, all have an impact on this sort of load forecast. For example, fluctuations in sunshine have a significant influence on solar load forecasts in smart grids.

3.2. Load Forecast Based on Consumer Behavior

This form of prediction is influenced by variables connected to consumer behavior, such as spending patterns, holidays, and special events. For example, load forecasting for public holidays or events is dependent on user energy usage habits.

3.3. Load Forecast Based on Historical Data

This form of projection is affected by historical consumption statistics, consumption trends, and load patterns. Variables that influence this sort of projection include previous consumption patterns, seasons, growth trends, and so on.

4. MODEL OF THE LOAD FORECAST

Models for load forecasting are essential to efficient electrical energy management. They make it easier to predict future electricity demand by considering relevant variables such as seasonal fluctuations, past consumption trends, and weather. The strategic planning of energy production and distribution, cost reduction, and resource allocation all depend on these projections. Applications for load forecasting models are numerous and include energy production management, load optimization, electrical infrastructure planning, load pricing, and more.

In light of this, I propose using two methods: one that makes use of LSTM and another that makes use of a more straightforward RNN. Both approaches are intended to deliver accurate and timely estimates for the amount of electrical energy used.

4.1. RNN Model

An increasingly popular option for predicting patterns in electrical energy consumption is the RNN model. A recurrent cell is used in the simple RNN model, a more basic version of the RNN, to process inputs sequentially, one at a time. To produce an output, this cell combines the input from the present with the data from the past.

The cell uses the output to update its internal state after which it passes that state on to the subsequent input. Because it can effectively identify time-related patterns in the input data, the straightforward RNN model is a good choice for short-term electrical load forecasting.

However, because of the "vanishing gradient" problem, it has been observed to have difficulties when modeling long-term dependencies in the input data. When applied to longer-term forecasts, this can result in appreciable forecast errors. However, the straightforward RNN model has the advantage of being simple to use and efficient for short-term forecasting. To improve its functionality, it can also be easily expanded to include more layers, like hidden layers.

4.1.1. Forecast Model Configuration

The following factors affect forecasting in the basic RNN model. Firstly, Time Window Size: The length of the time window that the RNN model bases its predictions on is specified by this parameter. Depending on the intended forecast horizon and the data's sampling frequency, selecting the right time window size is essential. Secondly, Number of Recurrent Cells, this indicates how many cells the RNN model uses. By letting the model capture more complex temporal patterns, changing this value can improve prediction accuracy. Thirdly, the number of Hidden Layers, the number of hidden layers in the RNN model is indicated by this parameter. By raising this figure, prediction performance can be improved by helping to capture more intricate temporal trends. Additionally, the learning Rate, how quickly the RNN model adjusts the weights of its neuron's during training is determined by its learning rate. Choosing the right learning rate is essential to avoid problems such as underfitting or overfitting. Fourth, the activation Function, The RNN model's inputs and outputs are altered by this function. The ReLU function, the hyperbolic tangent function, and the sigmoid function are examples of common activation functions. Finally, the number of Iterations, this is the number of training iterations that the RNN model employs. Iterations must be sufficient in order to achieve high prediction accuracy.

The performance of the basic RNN model can be adjusted to guarantee accurate and trustworthy electric load forecasting.

The following are the forecasting parameters for the used simple RNN model:

- Two Simple RNN layers, each having a unit set at 1000 and one after the other
- Tanh, or the hyperbolic tangent function, is the activation function that is employed
- Adam is the optimization algorithm that is being used
- The loss function is computed using Mean Squared Error (MSE)
- Twenty iterations are required to generate prediction results.

Neural network group A in Fig. 2 takes input x_t and outputs the values of h_t. In this way, a loop is formed through which information can be sent from one network system to another.

Simple RNN is the most basic type of RNN, accepting input x_t and updating the value on a regular basis using a non-linear map. For a basic RNN, the recurrent unit f may be expressed as a summation of a linear transformation and a nonlinear activation, as shown by the following equation:

$$h_t = \tanh(w[h_{t-1}, x_t] + b) \tag{1}$$

where h_t shows the hidden state at time step t. This is the recurrent neural network (RNN) cell's output at the moment, and it will be utilized as input for the following time step, tanh represents the hyperbolic tangent function, an activation function that maps its input to a value between -1 and 1. It is used to add non-linearity to the model, w is a weight matrix holding the trainable network parameters that are used on the input data, $[h_{t-1}, x_t]$ represents the concatenation of the previous hidden state h_{t-1} with the current input x_t, x_t is the input vector at time step t, b is the bias vector that is added to the weighted inputs to stretch the activation function curve and give the model more flexibility, $w[h_t - x_t]$ is the matrix multiplication of the weight matrix w by the concatenated vector of the previous hidden state and the current input, $+b$ is the bias b is applied to the matrix multiplication results.

In conclusion, the equation explains how the hidden state h is disclosed in an RNN cell. The prior hidden state and current input are concatenated, multiplied by a weight matrix, and a bias is applied. The result is processed via the hyperbolic tangent function, resulting in the new hidden state. This technique is performed at each time step as the RNN processes an input sequence.

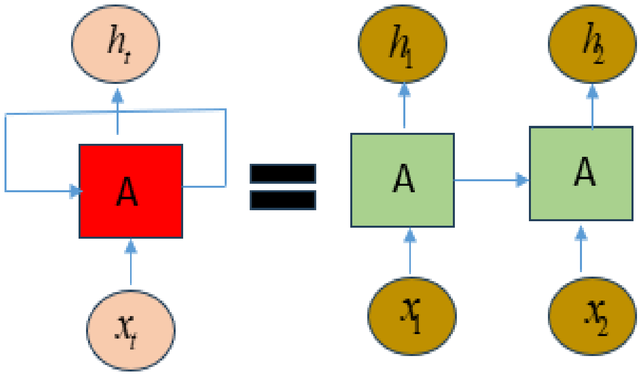

Fig. 2. Recurrent neural network.

4.2. LSTM Model

One more sophisticated version of the RNN model used in smart grid energy consumption forecasting is the LSTM neural network model. When it comes to predicting electric energy consumption over long periods of time, the LSTM model is superior to the basic RNN because it is better at capturing long-term dependencies within input data sequences. To control the information flow at each time step, the LSTM model includes gating mechanisms. The input gate, forget gate, and output gate are some examples of these gates. The forget gate controls how much information should be removed from the hidden state's memory, while the input gate controls how much new information can be added. The information flow to the model's output is managed by the output gate.

Additionally, the LSTM model exhibits the capacity to manage input sequences of different lengths, which is an essential characteristic for predicting electric energy consumption, considering the possibility of notable variations in consumption patterns over time. When it comes to long-term predictions of electric energy consumption, the LSTM model outperforms the RNN model due to its ability to identify non-linear relationships and capture complex temporal trends in the input data. It is important to keep in mind, though, that the LSTM model is more sophisticated and might require a bigger training dataset in addition to more processing time. To sum up, the LSTM model represents a cutting-edge method for predicting the amount of electric energy used in smart grids. It can produce accurate long-term forecasts because of its ability to comprehend intricate relationships and complex temporal patterns in input data.

4.2.1. Forecast Model Configuration

In the LSTM model for smart grid electric energy consumption forecasting, several key parameters play significant roles. Firstly, the time window size dictates the duration of the window over which the model is trained to make predictions. Similar to the RNN model, selecting an appropriate window size depends on factors such as data sampling frequency and the forecast horizon. Secondly, the number of LSTM cells integrated into the model impacts its ability to capture intricate temporal patterns, thereby enhancing prediction accuracy. Adjusting this parameter enables the model to accommodate varying levels of complexity in the data. Thirdly, the number of hidden layers in the LSTM model determines its depth and capacity to capture complex temporal trends, similar to the considerations in the RNN model. Increasing the number of hidden layers can improve the model's ability to extract relevant features from the data, potentially leading to better forecasts. Lastly, the learning rate governs the pace at which the LSTM model adjusts the weights of its neurons during training. As with the RNN model, selecting an appropriate learning rate is crucial to avoiding issues such as underfitting or overfitting, thereby ensuring the model's optimal performance in forecasting electric energy consumption for smart grid applications.

Adjusting these parameters is essential to improve the accuracy and reliability of LSTM-based electric load forecasting in smart grids. The LSTM model's specified forecasting parameters in this study are:

- Two LSTM layers, one consecutive unit and units set at 1000
- Tanh, or the hyperbolic tangent function, is the activation function that is used
- Adam is the optimization algorithm that's been used
- The chosen method for calculating the loss function is MSE
- Twenty iterations are required to generate prediction results

Figure 3 shows the mathematical equations for the LSTM model. Here is an explanation of the equations:

- $f_t = \partial(w_f.[h_{t-1}, x_t] + b_f)$: This equation depicts the computation of the Forget Gate in an LSTM model, where f_t is the Forget Gate value at time t, w_f is the weight associated with the Forget Gate h_{t-1} is the previous hidden state, x_t is the input at time t, b_f is the bias of the forget gate, and ∂ is the sigmoid function.
- $i_t = \partial(w_i.[h_{t-1}, x_t] + b_i)$: In an LSTM model, the Input Gate is calculated using the following equation: i_t is the value of the gate at the instant t, w_i is its weight h_{t-1} is the previous hidden state x_t is the input at time t, b_i is the gate's bias and ∂ is the sigmoid function.
- $g_t = \tan(w_g.[h_{t-1}, x_t] + b_g)$: This equation represents the calculation of an LSTM model's Update Gate, where g_t is the value of the update gate at time t, w_g is the weight associated with the update gate h_{t-1} is the previous hidden state x_t is the input at time t, b_g is the update gate's bias and tanh is the hyperbolic tangent function.

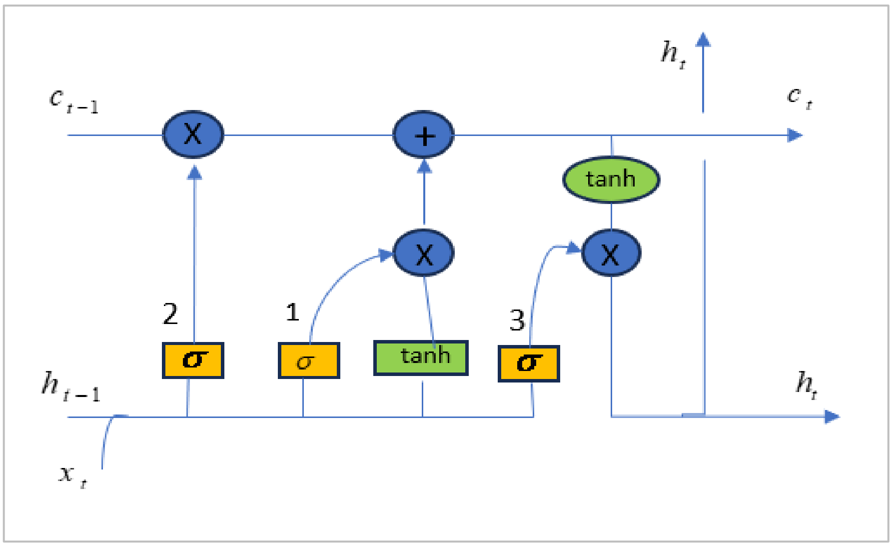

Fig. 3. The LSTM structure.

5. IMPLEMENTATION OF RNN

In this work, we used Keras on TensorFlow to forecast load using a RNN architecture. Python's Keras is a high-level library for neural networks that can be used with TensorFlow or Theano. TensorFlow is a popular machine learning library for creating deep learning models, but it might have some drawbacks. As a high-level interface built on top of TensorFlow, Keras, on the other hand, offers users a more straightforward and user-friendly interface.

5.1. The Two Models' Performance Evaluation

For an accurate assessment of the effectiveness of both my LSTM and Simple RNN models, the dataset must undergo a distinct division into two sections: the training dataset and the testing dataset. The training dataset serves as the foundation for the model's learning process, enabling it to adjust its parameters based on the provided data. Subsequently, the model's performance is evaluated using the testing dataset, which was not utilized during the training phase.

This separation is crucial as it ensures an unbiased evaluation of the model's predictive capabilities. By assessing the model's performance solely on the testing dataset, we can ascertain its ability to generalize to unseen data accurately.

This practice is fundamental in machine learning as it provides a reliable measure of the model's predictive accuracy and robustness in real-world scenarios.

5.1.1. The Performance Metrics Used

To compare the effectiveness of the LSTM and Simple RNN models, a quantitative analysis employing a variety of recognized performance metrics is necessary. When comparing the model predictions with the actual values, these metrics are useful tools.

The primary metrics utilized in this assessment are:

- The Root Mean Squared Error (RMSE) is a statistical measure that is computed by taking the square root of the average of the squared deviations between the predicted and actual values. It measures the difference between actual and expected values; better model performance is indicated by lower RMSE values.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

- Mean Absolute Error (MAE) is a difference between the values that were predicted and those that were observed is calculated using the mean absolute error (MAE) metric. As with RMSE, better model performance is indicated by a lower MAE value.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|e_i| = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \quad (3)$$

- Coefficient of Determination (R2): R2 quantifies the percentage of data variance that the model can account for. An R2 score of 1.0 indicates that the actual and predicted data are perfectly aligned, whereas a score of 0.0 indicates that the model is not predictive.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (4)$$

- Mean Squared Error (MSE): A popular metric for evaluating the effectiveness of neural network models, such as LSTM and Simple RNN models, is Mean Squared Error (MSE). The mean squared discrepancies between the expected and actual values are computed.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}e_i^2 = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

- Mean Absolute Percentage Error (MAPE): The average percentage of absolute differences between expected and actual values is calculated using this metric. It is frequently employed to evaluate load forecasting models' accuracy.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{y_i}\right| = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i - \hat{y}_i}{y_i} \quad (6)$$

To put it another way, to calculate the mean square error (MSE), each predicted value is subtracted from its matching actual value. The difference is then squared, and the average of all these values is obtained. When the MSE score is lower, the model is performing better, and the predictions are more closely aligned with the actual values.

where: y_i - the actual value of target variable at index I, $\hat{y}_i$ - the predicted value of target variable at index i, $\bar{y}_i$: average of the actual values of the target variable, n: Total number of observations, $e_i = y_i - \hat{y}_i$: errors are noted.

The calculated values for each performance metric are shown in Tables 1 and 2. When comparing the models' performance indicators, it becomes clear that the LSTM model performs better at predicting energy consumption in smart grids than the straightforward RNN model.

First, the average prediction error is measured using the MSE metric. A model with a lower mean square error performs better. Compared to the simple RNN model, which has an

MSE value of 16,644, the LSTM model has a lower MSE value of 4,345, indicating that it is more predictive.

Similarly, the average absolute difference between the expected and actual values is measured by the MAE metric. Once more, better model performance is indicated by a lower MAE value. In this instance, the LSTM model shows a lower MAE value of 3,943, whereas the simple RNN model records a value of 5,443, indicating even superior predictive accuracy on the part of the former.

Table 1. Calculated values of the performance metrics for the two models.

Model	RMSE [%]	R2-score [%]	MAE [%]	MSE [%]	MAPE [%]
LSTM	5 .042	90	3.943	4.345	9.6
Simple RNN	6.885	80	5.443	16.644	12.5

Table 2. Comparison between the test-based and learning-based performance metrics for the two models.

Model	Performance based on test		Learning based performance	
	MSE [%]	R^2-score [%]	MSE [%]	R^2-score [%]
LSTM	3.04	90	4.03	91
Simple RNN	6.03	85	6.14	83

Lastly, the square root of the average squared discrepancy between the actual and predicted values is determined by the RMSE metric. Like the preceding metrics, better model performance is indicated by a lower RMSE value. Once more, the RMSE of 5,042 for the LSTM model demonstrates its superior predictive ability compared to 6,885 for the simple RNN model.

As illustrated in Fig. 4, it is apparent that the LSTM model exhibits a reduced MSPE in contrast to the basic RNN. This indicates that the LSTM model is more accurate at predicting energy consumption than the basic RNN. Because LSTMs are designed to capture long-term dependencies within sequences, they are very useful for analyzing data on energy consumption that exhibits complex variations, seasonal patterns, and long-term trends.

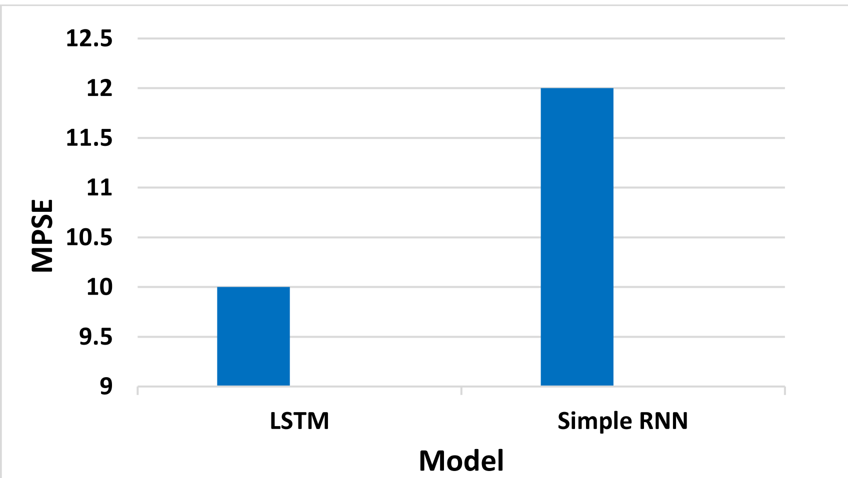

Fig. 4. MSPE of the models.

The ability of long sequences to selectively retain or discard information gives LSTMs their strength. This enables them to accurately simulate the complex temporal dynamics present in energy consumption, leading to more accurate forecasts. LSTM models can learn important lessons from past experiences, which allows them to provide accurate predictions about future variations in energy usage.

By contrasting the MSE values for energy consumption prediction between the LSTM and basic RNN models, we can determine how well each model captures underlying patterns and produces accurate forecasts in this specific scenario. Compared to the simple RNN, the LSTM model exhibits a lower MSE, as seen in Fig. 5. This difference suggests that the LSTM model performs better than other models at predicting energy consumption.

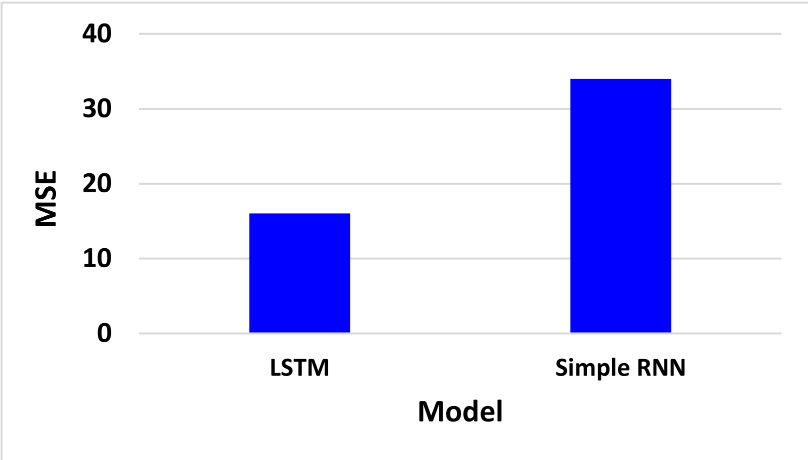

Fig. 5. MSE of the models.

We can determine how well the LSTM and basic RNN models perform in terms of prediction precision by comparing those using RMSE values for energy consumption prediction.

As seen in Fig. 6, the LSTM model exhibits a lower RMSE in comparison to the RNN. This suggests that the LSTM model is more accurate at predicting energy consumption than the basic RNN.

As such, comparing the LSTM and simple RNN models using RMSE values gives us a way to assess how well each model performs in terms of accurately predicting energy consumption.

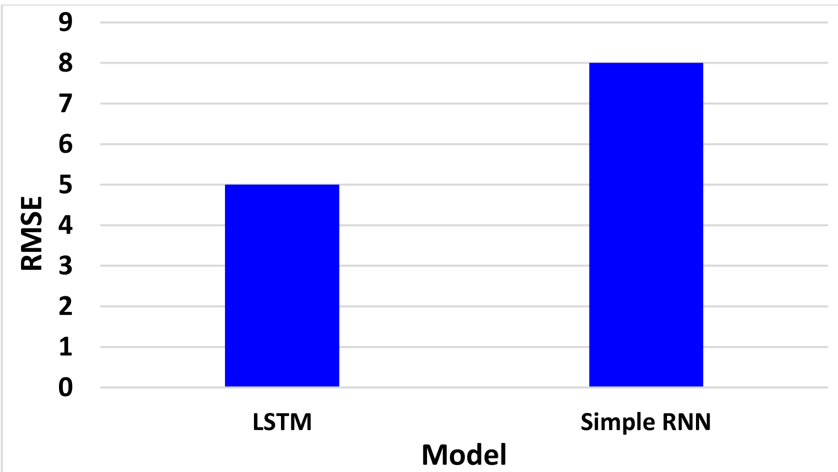

Fig. 6. Evaluating the models while considering their Root Mean Squared Error (RMSE) values.

6. EVALUATION RESULTS

One important tool for assessing a regression model's performance during training is the "model training and validation loss" curve. It shows how the model's loss varies as it goes through the training iterations for both the training and validation datasets, revealing the degree of error or deviation between the predicted values and the actual target variable values. A model with a lower loss value performs better.

The model's learning process as it adjusts to the training data is shown visually by this curve. Effective learning and adaptation to the training data is demonstrated by a steady reduction in loss with each iteration. On the other hand, overfitting might be indicated if the training dataset's loss keeps going down while the validation dataset's loss begins to increase. When a model is overly complex, it fits the training data too precisely, which reduces its ability to generalize to new data. This phenomenon is known as overfitting. To sum up, the "model training and validation loss" curve is an essential instrument for assessing a regression model's performance and identifying any indications of overfitting, which can improve the model's quality and generalizability. Given that both curves converge towards zero, the training and validation loss curves shown in Figs. 7 and 8 show that the LSTM and Simple RNN models successfully learned the patterns in the training and validation data. This suggests that both models have undergone effective training and have a promising degree of generalization. In Figs. 7 and 8, epochs (Epoch) refer to model iterations or training cycles. When training a machine learning model, each epoch represents one full pass through the training data set. As the model trains over several epochs, its parameters are adjusted to reduce loss and enhance its ability to generalize to new data.

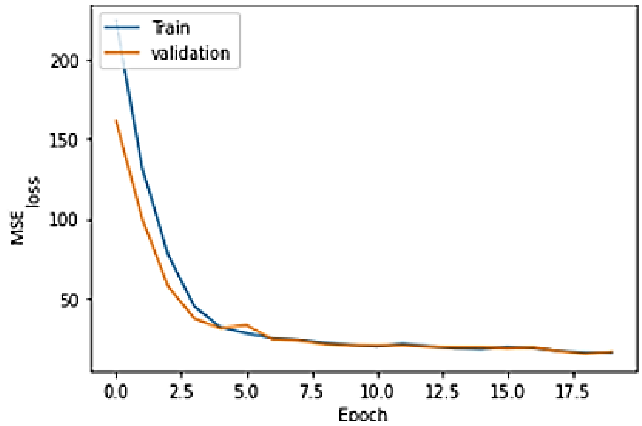

Fig. 7. LSTM model training and validation loss.

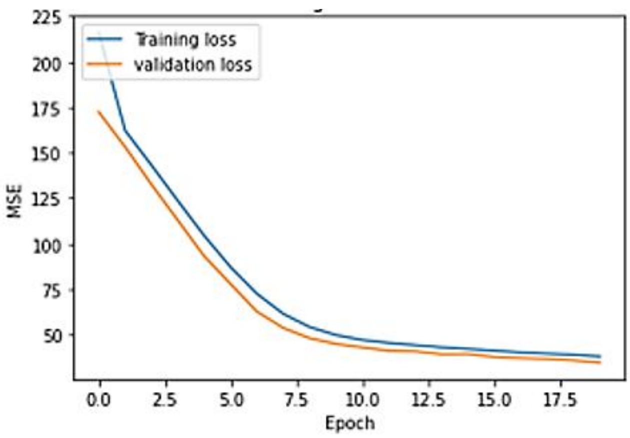

Fig. 8. Loss during training and validation of the simple RNN model.

7. PREDICTING FROM TIME SERIES

One method that is frequently used to predict future trends in temporal data is time series forecasting. LSTM and Simple RNN models have been used in the context of energy consumption in smart grids to forecast energy consumption values for future hours based on historical data.

Real-world energy consumption data was used for these models' evaluation and training, and the results were compared to the actual values.

The LSTM model performed better than the Simple RNN model, as shown by Figs. 8 and 9, which also show a stronger correlation between the predicted and actual values and a decrease in prediction errors.

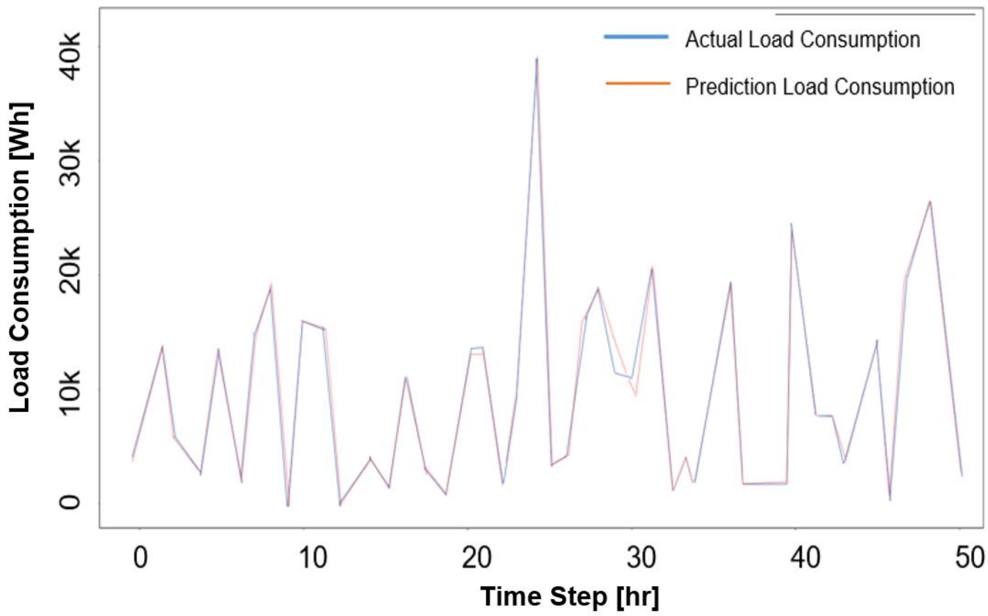

Fig. 9. LSTM load consumption.

However, both models showed a propensity to underestimate energy consumption during peak hours, indicating that more complex models might be required to improve predictions during these times.

The study's conclusions also highlighted the possible advantages of combining energy consumption data and extra weather data to improve model performance. Consequently, a more thorough examination of environmental variables like humidity, temperature, and meteorological conditions may be able to improve smart grid energy consumption predictions.

To sum up, both the LSTM and Simple RNN models demonstrated competence in predicting patterns of energy consumption in smart grids. However, depending on the environment and complexity of the data, these models' efficacy may differ.

Consequently, in order to improve energy consumption predictions in smart grids even further, future research projects may investigate the application of more sophisticated models and the integration of environmental factors.

In Fig. 9, the real energy consumption trend (blue line) over the 1000 hours under consideration is closely followed by the LSTM model (red line).

As we can see in Fig. 10, the actual trend of energy consumption (blue line) over the 1000 hours under consideration is closely followed by the Simple RNN model (red line).

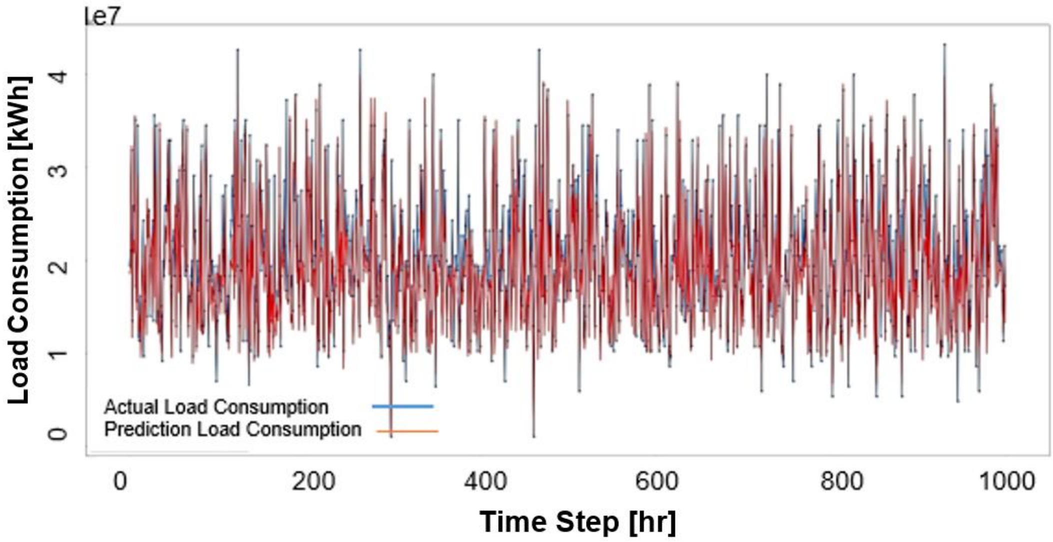

Fig. 10. Simple RNN load consumption.

8. CONCLUSIONS

This study presents two approaches for managing electrical energy consumption and demand, leveraging RNN and LSTM models. The primary objective was to develop reliable and precise forecasting models to optimize energy consumption in smart electrical networks. Through validation using the Global Energy Forecast 2012 database spanning the period from 2004 to 2008, with a focus on electricity consumption, the performance of both models was assessed using the R2 score metric. The results indicate a superior performance of the LSTM model, achieving a 90% R2 score compared to 80% for the RNN model. Additionally, the calculated error rates, measured by MSE, further support the superiority of the LSTM model with an error rate of 4.345%, compared to 16.644% for the RNN model. This study underscores the significance of LSTM models in accurately predicting energy consumption in smart grids, highlighting their potential for enhancing efficiency and optimization in energy management systems.

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