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Deep Learning Model for Electrical Load Forecasting Considering Meteorological Effect

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***Abstract*—Accurate electric demand forecasting has become increasingly crucial with the advent of smart grids, since it may assist energy distribution and providers in better load scheduling and decrease surplus electricity generation. Many studies have focused on developing accurate load forecasting models to attain the maximum possible prediction accuracy. However, designing and choosing precise sequential approaches is relatively difficult to achieve because it necessitates training several different models considering intermittency and the unpredictable nature of temperature, humidity, solar radiation, and wind speed. Research often overlooks data preparation procedures, leading to poor prediction performance. Deep learning approaches are used to develop short to medium-term aggregate load forecasting models. Hourly residential load data and location-specific weather data are collected, evaluated, and tested for optimal performance. The findings suggest that the GRU model has higher accuracy than the LSTM model, where the overall accuracy of the GRU and LSTM models is 98.06% and 96.46%, respectively. The mean average percentage error of the GRU model was lowest at 1.93%, which subsequently produced an accurate forecast of the projected value compared to the LSTM model, which had a higher error percentage at 3.53%.**

***Index Terms*—Time-series analysis, Forecasting, Deep Learning**

I. Introduction

Energy generation and distribution continue to raise their building sizes mutually with rocketing economic development, and the incorporation of electrical grid infrastructure and operating modes is increasingly diversifying [1], [2]. Utility companies can model and anticipate power loads using load forecasting to maintain the steadiness between the energy supply chain and energy demand chain, cut production costs, determine realistic energy pricing, and control scheduling and long-term capacity planning. Accurate load forecasting is also important in the design and handling of power plants, manufacturing materials, and the efficient functioning of power grid networks. A time-series dataset is a compilation of inspections made at routinely distributed time interruption and includes both linear and nonlinear components [3].

This paper focuses on creating an optimal deep-learning model for hourly electrical load forecasting. The development of this system requires careful consideration of factors such as the number of layers, cells, batch size, and activation type. The chosen parameters can impact the training process, model under-fitting, over-fitting, and final model accuracy. However, this complex and time-consuming task is challenging and error-prone. The paper aims to develop a deep-learning model that is accurate and efficient in predicting electrical consumption.

The several approaches to load forecasting may be broadly divided into two categories: data-driven methods and engineering methods [4]–[8]. Meteorological criteria are utilized in engineering methodologies, also known as physics-based models, to calculate and evaluate energy use, primarily based on contextual information like building structure and HVAC system data. In load forecasting over several periods, namely short, medium, and long term, it is becoming more and more attractive to adopt data-driven methodologies as a substitute to physics-based procedures due to the comparatively huge chunk of energy data accessible [9]. Since it may be used for peak load anticipation, energy consumption, energy storage operation, electricity demand management, energy scarcity risk reduction, and other purposes, short-term load prediction, or STLF, has become more and more common in smart grids, microgrids, and buildings [6]. The Box-Jenkins model was beaten by the adaptive auto-regressive moving-average (ARMA) model proposed by the authors in Ref. [10], for day- and week-ahead load forecasting. These multivariate time-series approaches have a direct description of the temporal domain, but they are limited by their dimensions, lose accuracy with time, and require constant training. Other techniques for energy demand forecasting have included simple linear regression, multivariate linear regression, non-linear regression, artificial neural networks (ANN), and support vector

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machines (SVM); they have been used more in the short-to-medium term [11]–[13] and less in the long term [14]. Random walk prediction showed that SVMs outperformed the benchmark model, although they were not far off from the ARMA-GARCH econometric method. To estimate pricing for the next day, a combination of evolutionary algorithms and wavelet transform neural networks was used. The combination above produced a more precise and stable forecasting model [6], [15].

The research aims to enhance the maturity of deep learning in solving load forecasting problems by expanding the number of works with different prediction model designs, considering factors like meteorological intermittency, input type, significance, deep learning version, and validation process. The key objectives of this research are as follows:

1) To prepare the raw collected data, reshape them according to the model needs, and analyze them to understand the dispersion and probabilistic distribution for better understanding.
2) To develop a sequential model using the TensorFlow framework by using both LSTM and GRU methods and testing the validity using prepared data.
3) To predict future hourly data and validate those predictions using the current data.

Such models are being increasingly used for energy load forecasting due to their ability to manage the complexities of energy data, thereby improving efficiency and cost reduction.

II. Problem Formulation

The proposed methodological approach shown in Fig. 1 consists of four core operational sections: data preparation, model selection, LSTM training model, forecasting data, and visualization. It validates the sample and visualizes the final output, with model parameters adjusted as an auxiliary operation.

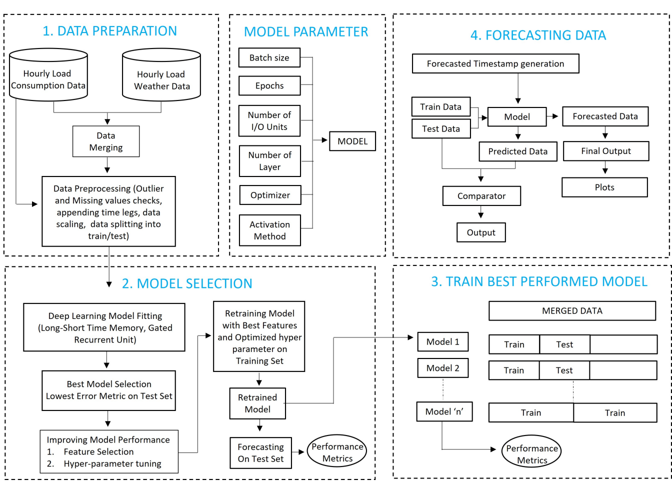

Fig. 1. Proposed Model.

A. Data Preparation

A neural network model is trained using the Khulshi Substation electricity use data set from the Power Grid Company of Bangladesh (PGCB) as shown in Fig. 2 [16]. When a model is trained with data, it learns from an input set to provide predictions or carry out particular tasks. Neural networks are a type of computational learning paradigm that uses a dataset to execute specified operations. They are inspired by the structure and operation of the human brain.

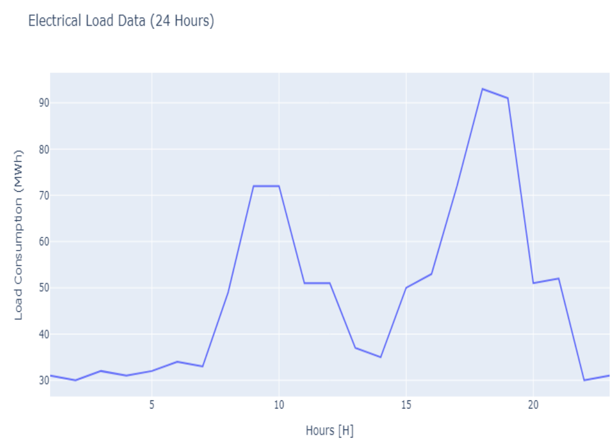

Fig. 2. Hourly Load Data

The neural network is trained using a labeled dataset containing input data and desired results. It adjusts its biased and weighted variables to minimize errors between forecasts and results. The model is trained using hourly electrical data with 8760 samples, covering 24-hour data for 365 days. The 8:2 ratio of the data sample is used to split the entire data set for training and validation.

1) Window size & Batch size: The window size, or look-back of data, is crucial in the RNN prediction model as shown in Fig. 3, determining the cutout length from a 24-hour data set for a year.

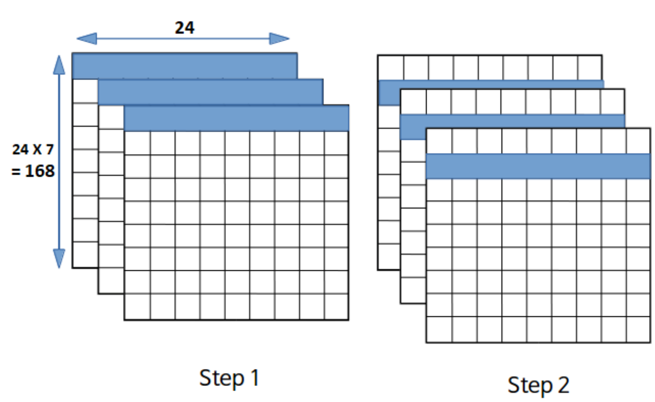

Fig. 3. Look Back windows and batch size of dataset

This text explains how a look-backk size of 24 is crucial for sequential data processing jobs, particularly in predicting time series, such as predicting electrical load for the future. It emphasizes the importance of considering 24-hour data, as hourly changes in load consumption can still maintain a consistent pattern over multiple days.

The batch size is for each sample considered 7 for selecting data samples for 7 days as shown in Fig4. The total training dataset of 7008 data points is split into 42 batches where each batch size is defined as $24 \times 7 = 168$.

1 day's data
Window Size (Lookback) =24

Batch Size = 7 (1 Week's data)	t=1	t=2	t=...	t=24
	t=25	t=26	t=...	t=48
	...	...	...	...
	t=144	t=145	t=...	t=168

Fig. 4. Batch Window

2) Train and Test Split: Cleaning data is crucial for RNN models as it removes unwanted errors or missing values, enhancing model performance. An electrical dataset of 8760 samples, covering 24-hour data for 365 days with a 60-minute resolution, is selected for training and validating the model. The 8:2 ratio splits the data set for training and validation. 80% of the total data points, 7008, are used for training, while the remaining 20%, 1752, are used for validation.

B. Deep Learning Layer

The research focuses on hourly load demand forecasting, aiming to determine future electrical load demand data. The choice of a neural network model is crucial as different data types require different approaches. Performance standard evaluation is crucial to determine the model's efficacy. Sequential models are more suitable for this situation, as they are simple stacking layers with a single input and output. However, sequential models are not suitable for systems with multiple inputs or outputs or a non-linear topology. Therefore, the choice of a sequential model is crucial. A time series generator's objective is to generate a synthetic or simulated data set that resembles the attributes of practical time series data. The hyper-parameter used to develop the LSTM-GRU model is shown in Table I.

a) LSTM: LSTM layers in machine learning models as shown in Fig. 5, maintain long-term relationships in sequential data using memory cells, input, forget, and output gates, enabling individuals to retain or forget understanding.

b) GRU: GRU layer's cell structure as shown in Fig. 6, demonstrates its fewer parameters, resulting in shorter training times. It's suitable for limited computational resources or large datasets and may be more resilient against excessive fitting in short datasets.

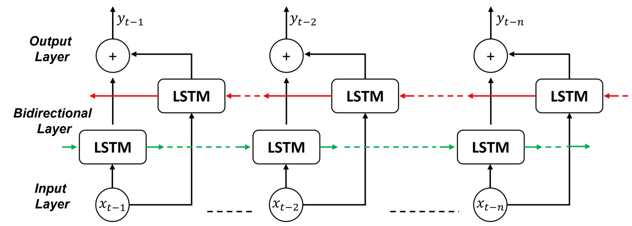

Fig. 5. LSTM Layers

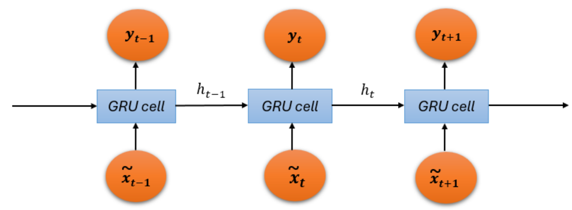

Fig. 6. GRU Layers

1) Activation Method: Deep learning models use activation processes to stimulate hidden nodes, with ReLU (Rectified Linear Unit) being a popular non-linear function that incorporates non-linearity for learning complex data correlations. The mathematical representation of the ReLu function is expressed in (1) [6].

$$f(x) = max0, z \tag{1}$$

In other words, it outputs the input value x if it is positive, and otherwise, it outputs zero. This means that ReLU sets all negative values to zero while leaving positive values unchanged. The function is piecewise linear with a positive slope for positive inputs.

$$f(x) = \begin{cases} 0 & \text{for } x \leqslant 0 \\ x & \text{for } x > 0 \end{cases} = max\{x, 0\} = x1_{x>0} \tag{2}$$

$$f'(x) = \begin{cases} 0 & \text{for } x \leqslant 0 \\ 1 & \text{for } x > 0 \end{cases}; \quad (0, \infty) \tag{3}$$

When compared to alternative activation functions such as sigmoid or tanh, the function of ReLU is more efficient in terms of computation.

2) Optimizer: An optimizer modifies neural network properties to reduce loss and improve precision. Adam, Adaptive Moment Estimation, is a popular optimization approach for neural network training, suitable for large-scale challenges and demonstrating strong converging qualities in various settings. This necessitates the setting of a pair of critical variables: the learning rate (α) and the exponential decay rates (β_1) for the first and subsequent moments estimates (β_2). The standard values for (β_1) and (β_2) are 0.9 and 0.999, accordingly [6]. The step size in each update is determined by the learning rate.

TABLE I
MODEL PARAMETER

Data Point	**Total**	**Split Ratio**	**Train Sample**	**Test Sample**
	8760	8:2	7008	1752
Window Sizing	**Window size (Lookback)**	**Batch size**	**Total number of batch**	**Number of Epochs**
	24	168	42	25
Deep learning model	**Neuron layer**	**Dense layer**	**Optimizer**	**Learning rate**
	164	5	adam	0.01

Adam calculates the initial and next instances for each parameter in the neural network during learning. The first moment is the average of previous gradients, while the following instant is the mean of previous gradients twice. The following formulae are used to determine these moments shown in EQ. (4).

$$\begin{aligned} m_t &= \beta_1.m_{t-1} + (1-\beta_1).g_t \\ v_t &= \beta_2.v_{t-1} + (1-\beta_1).g_t^2 \end{aligned} \tag{4}$$

Because periods are initially set to zero, they are skewed towards zero, particularly during the early training phases. Adam implements a bias adjustment to compensate for this bias by producing distortion-corrected approximations of the moments calculated using the EQ. (5) [6]. The bias-corrected values are used for determining the amended value of the parameters. The updated parameter values for each moment are estimated using $W_{t+1} = W_t - \alpha.\frac{\hat{m}_t}{\sqrt{(\hat{v}_t)+\epsilon}}$, where, W_{t+1} is the parameter, α is the learning rate and ϵ is the constant that added to the denominator for numerical stability.

$$\begin{aligned} \hat{m}_t &= \frac{m_t}{1-\beta_1^t} \\ \hat{v}_t &= \frac{v_t}{1-\beta_2^t} \end{aligned} \tag{5}$$

3) Performance Evaluation: The efficiency of a neural network is the most basic statistic used for classifying jobs, calculated by dividing the proportion of correctly categorized instances out of every instance. However, unbalanced data sets may limit the precision of this analysis. The main metric that evaluates the performance of the deep learning model is shown in Table II.

TABLE II
MODEL PERFORMANCE EVALUATION

Approach	Equations
MAPE	$\frac{1}{N}\sum_{n=1}^{N}\left\lvert\frac{\hat{x_i}-x_i}{x_i}\right\rvert \times 100\%$
MAE	$\frac{1}{N}\sum_{n=1}^{N}\lvert x_i - x_i\rvert$
RMSE	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}(x_i-x_i)^2}$
R^2	$1-\frac{\sum_{n=1}^{N}(\omega_i-\sigma_i)^2}{\sum_{n=1}^{N}(\omega_i-\bar{\omega}_i)^2}$

4) Forecasting Window Generation: A time series generator for forecasting windows is a tool or method that generates a dataset suitable for time series forecasting tasks. Forecasting Window is shown in Fig. 7. Time series forecasting predicts future values based on historical patterns in a sequential dataset. A predictive frame time series generator creates a simulated dataset using Python's datetime library. The generator sets start and end dates and determine the sampling frequency, such as hourly, daily, weekly, or monthly, to test forecasting models without relying solely on historical data.

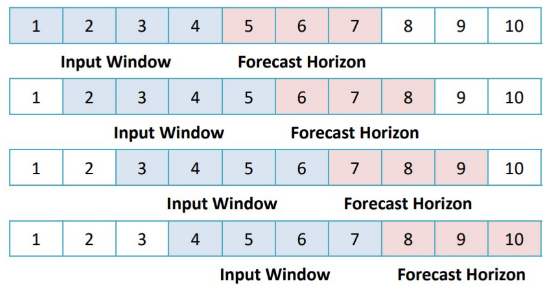

Fig. 7. Forecast Window

III. ANALYSIS CONDITIONS

The hourly meteorological data from the Chittagong, Khulshi area are shown in Fig. 8 [17].

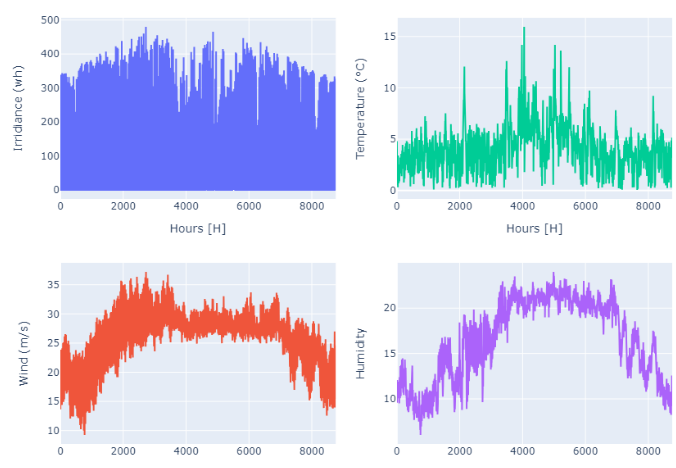

Fig. 8. Meteorological data.

A time series generator generates a synthetic data set that resembles practical data, allowing forecasting without relying solely on historical data.

IV. Results and Evaluations

The figure illustrates residential load distribution throughout the day, with peak demand hours from 5:00 PM to 7:00 PM. The data shown in Fig. 9 merged with electrical and meteorological data, is stored in a panda's database for data manipulation and analysis before neural network operation.

	count	mean	std	min	25%	50%	75%	max
Load	8760.0	47.935160	18.843504	30.00	33.00	43.500	52.0000	94.00
Irridiance	8760.0	95.518669	130.531259	0.00	0.00	3.240	188.7325	479.88
Temperature	8760.0	25.682441	4.839392	9.26	23.04	26.800	28.7600	37.20
Wind	8760.0	4.139000	1.972636	0.06	2.76	3.940	5.1700	15.94
Humidity	8760.0	16.479014	4.492432	6.04	12.45	17.365	20.5700	23.99

Fig. 9. Data-set in Panda Data frame

The training set, validation set, and test set are data sets used in a model's training phase. The model's parameters are modified using input data and output labels. The validation set as shown in Fig. 10, evaluates the model's efficacy and high-level parameters. The model is trained for 200 iterations, with each iteration reducing training and validation loss in RMSE and MAE scales.

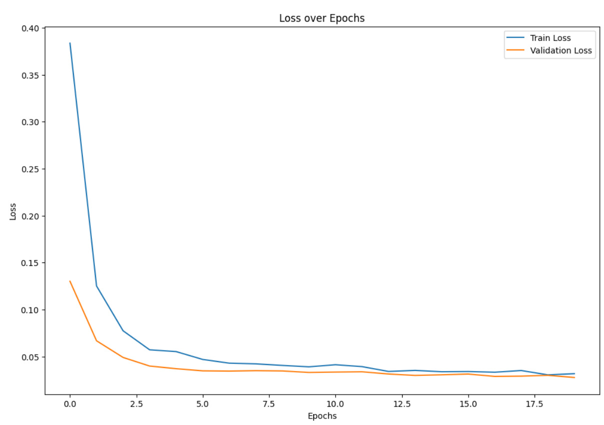

Fig. 10. Training progress

During the training phase, both the training loss and the validation loss to evaluated as shown in Fig. 10, how the model is learning and if it is over-fitting or under-fitting the data. The performance comparison between two developed deep learning model is shown in Table III, where both approach shows accuracy over 96%. However, the GRU performed relatively better than the LSTM scoring over 98% accuracy.

The performance of two constructed deep-learning models are compared in Fig. 11, both of which have accuracy levels, and due to their simplified structure, GRU often converges faster during training. This is advantageous when one wants to reduce training time.

TABLE III
Performance Comparison between GRU and LSTM

Model	Overall Accuracy	MSE	RMSE	MAE	MAPE (%)
GRU	98.06 %	1.49	1.22	0.86	1.93%
LSTM	96.46%	3.49	1.86	1.45	3.53%

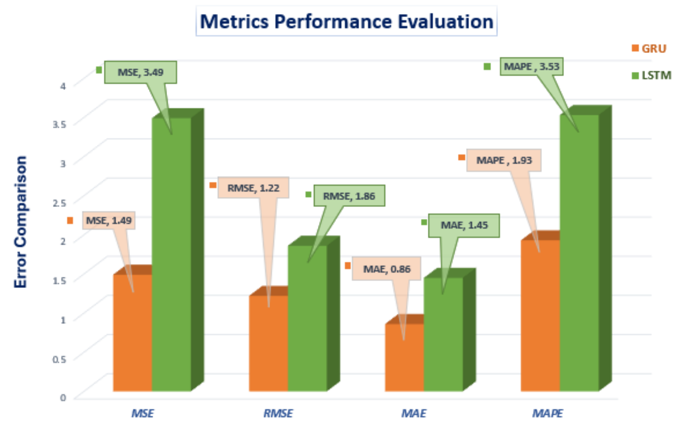

Fig. 11. Error Performance Metrics Comparison

The comparison between originally input data (used for training), predicted data, and testing data (data used for validating) is plotted in Fig. 12. The data collection is crucial to assess the persuasiveness of the model and offer accurate load estimations throughout the day.

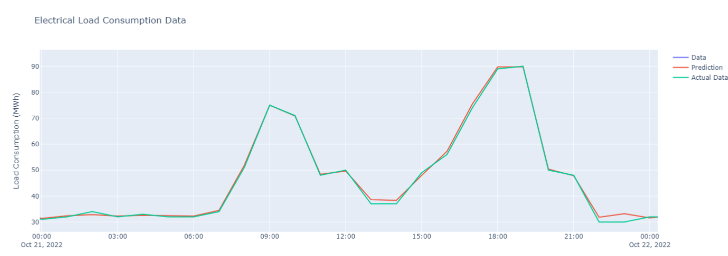

Fig. 12. Actual Vs Predicted Load Curve

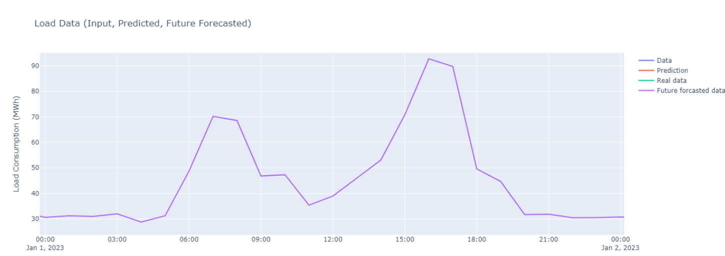

Fig. 13. Future Forecasted data (24 hours)

The comparison between historical data and future forecasted data is a fundamental aspect of assessing the performance of predictive models, the actual response of the best-performing model is emphasized in Fig. 13. The GRU model accurately predicted future load demand and household electrical power consumption patterns, influenced by human activity, weather, and other variables. Utility firms use a GRU model for residential load forecasting, trained on historical data, to accurately anticipate electricity use for each hour of the day.

A. Comparative analysis

Comparison with previously studied work is depicted in Table. IV.

TABLE IV
COMPARISON WITH SIMILAR WORKS

Name	Approach	Accuracy matric
This study	LSTM & GRU layer forecasting using location specific intermittent weather data & on site collected load samples.	365 days (throughout the year): MSE=1.49 (GRU), 3.35(LSTM) RMSE=0.86 (GRU), 1.85 (LSTM) MAPE=1.49 (GRU), 3.350 (LSTM)
Ref. [18]	SVR forecasting model with the ambient temperature of two hours before DR event as input variables.	1 day ahead (eight hours on working days): MAE = 1.57
Ref. [19]	A ensemble method based on wavelet transform, ELM and partial least squares regression	1 h ahead: MAPE = 1.27 (winter), 1.52 (summer) 1 day ahead: MAPE = 1.43 (winter), 2.82 (summer)
Ref. [20]	Fuzzy prediction interval models	1 day ahead (PINC=90%): LF nRMSE=6.73, LF nMAE=4.53, LF NAW=19.08

V. CONCLUSIONS AND RECOMMANDATION

This research uses RNN-based deep learning models, LSTM and GRU, to forecast residential electrical loads using the Google Tensorflow framework and Keras library. The GRU model outperformed the LSTM model with an accuracy of over 98%, while the LSTM model had an overall accuracy of around 96%. The best-performing model was used to train data for future load response. The study highlights the difficulty in estimating electrical consumption due to the unpredictability and variability of power load patterns. Previous research has mainly focused on predicting electricity consumption patterns using a one-fold forecasting paradigm, which has drawbacks.

The proposed model for power consumption forecasting has limitations, including the difficulty of capturing continuous relationships in data, short memories due to vanishing gradients, and complexity in computation and training. To address these limitations, future works should focus on developing more sophisticated RNN variations like LSTM and GRU, which can solve the vanishing gradient issue and accurately represent longer-term relationships. Combining RNNs with other methodologies like feature technology, outside factors, and ensemble approaches can enhance the accuracy and resilience of load prediction methods.

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