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Analysis and Prediction of Electric Energy Consumption Using a Deep Learning Approach: A Case Study of the Dessie District

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ABSTRACT

Predicting electric power consumption is essential for modern energy management, addressing challenges like cost optimization, resource allocation, and sustainability. This study offers a thorough analysis of power consumption prediction to tackle the prevalent issue of inaccurate energy usage forecasts. A real dataset from the Ethiopian Electric Utility in the Dessie district, covering the years 2019 to 2023, forms the foundation of this research. Using advanced deep learning models, specifically Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM. This study proposes a robust methodology based on cutting-edge neural network architectures. The research includes detailed experimentation in data preprocessing, feature extraction, model development, and evaluation to showcase the potential of these models to transform energy management. The findings highlight these models' capabilities to improve operational efficiency, reduce costs, and enhance grid management. Despite challenges such as model overfitting and the need for precise hyperparameter tuning, model performance is evaluated using metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Among the models, GRU demonstrated superior performance with minimal prediction error: 0.105 for MSE, 0.21 for RMSE, and 0.018 for MAE on testing data. This study emphasizes the potential of deep learning models to drive advancements in the energy sector, despite the existing challenges.

Keywords: Deep learning, Electric power consumption, Long short-term memory, Gated recurrent unit, Bidirectional long short-term memory

1. INTRODUCTION

Energy is the fundamental cornerstone driving the sustained economic success of both developing and developed nations. Over time, global energy consumption has seen a swift and continuous rise. Particularly, electric energy plays a pivotal catalyst in fostering economic progress. Its significance extends to bolstering industrialization efforts and enhancing living standards. Indeed, energy's pivotal role permeates our daily lives, facilitating essential tasks such as lighting and food preparation. Moreover, electric power finds extensive utilization across diverse sectors, including industries, manufacturing, organizations, institutions, and household applications. The International Energy Outlook 2023 (IEO2023) delves into the enduring energy patterns on a global scale. It thoroughly examines world energy markets over the long haul, encompassing 16 regions and projecting trends up to the year 2050 [1]. Full data sets are readily accessible starting from the year 2001, showcasing a total electricity consumption of 1388 gigawatt-hours (GWh) during that period. This consumption figure experienced a substantial increase, reaching 10,750 GWh by the year 2017. This growth trajectory is characterized by an impressive average growth rate of 13% throughout the observed years [2]. Annually, the generation capacity of electric power faces constraints even as global energy demand continues to escalate. Consequently, power providers are compelled to explore models that enhance the accuracy of energy consumption forecasts and planning. As energy consumption steadily rises, electricity shortages become a recurring issue. Therefore, one viable solution to this challenge is accurate energy prediction [3]. During Emperor Menelik II's reign in the late 19th century, Ethiopians were introduced to the electric power industry. The first generator was reportedly presented to Emperor Menelik II in 1898 to illuminate the palace. In 1956, the Ethiopian Electric Light and Power Authority (EELPA), a government-owned company responsible for providing electricity to Ethiopians, was established to centralize all electricity-related activities under one agency. However, in 1996, it underwent a split into two entities: The Ethiopian Electric Authority (EEA), which took on regulatory functions, and the Ethiopian Electric Power Corporation (EEPCo), managing activities from power generation to local distribution. Subsequently, in 2013, EEPC underwent further division into Ethiopian Elec., Power (EEP) and Ethiopian Electric Utility (EEU), as per Ministerial Council Regulation No. 302/2013 [4]. Ethiopian Electric Power (EEP) which covered generation and transmission activities and Ethiopian Electric Utility (EEU) which covered distribution [5]. Ethiopian electric customer data can be classified into two categories: self-connected and interconnected customers. Self-connected customers are also different types. Those are domestic, industrial, commercial, own consumption, retired staff consumption, and street lights. Interconnected customers are domestic, industrial, commercial, own consumption, active staff consumption, retired staff consumption, and street light [6]. Prediction is a method of estimating the unknown and it can be defined as the science of predicting future outcomes. Predicting should be highly reliable, accurate, timely, and meaningful. Predicting electric power consumption is critical in energy planning and strategy design. It affords strong support to efficient energy demand management [7]. Policymakers should make decisions and develop new strategies for meeting this growing energy demand. Energy consumption prediction is a task that enables energy supply firms to react to specific habits [8]. The support vector machine (SVM), Knearest Neighbors (K-NN), Artificial Neural Network (ANN), Naive Bayes, and Random Forest were previously well-known machine learning models for predicting electric energy [3]. The deep learning model, which is the subpart of the machine learning model, was developed to solve a complex problem with a huge volume of data [9]. Deep learning models have achieved significant success in handling sequential data, including text, audio, and video datasets. Examples of such models are Long Short-Term Memory, gated recurrent units, and Bidirectional LSTM, which are commonly used in deep learning applications [10]. Deep learning models have been employed for analyzing electric power consumption data due to their sequential nature. Industries frequently leverage deep learning algorithms to tackle complex problem-solving tasks. In this study, deep-learning algorithms such as LSTM, bidirectional LSTM, and GRU were employed. The primary objetive of this research is to analyze and forecast the electric power consumption among customers of the Ethiopian Electric Utility. Globally, insufficient electric power distribution has emerged as a widespread issue. The EEUl asked a predictive system for future power consumption, which is crucial for equitable and efficient electricity distribution among all customers. Furthermore, accurate prediction of customers' future power consumption aids in effective resource management for the organization. Therefore, there is a pressing need to conduct research aimed at addressing this significant challenge.

1.1 Previous studies

The research conducted by [11] utilized a hybrid data mining approach, focusing on the classification of customers based on power consumption to develop a prediction model using classification algorithms. The data spanned from January 2008 to January 2011 E.C. and encompassed all Ethiopian utility customer data, comprising 14 attributes and 85,849 instances. The study employed classification algorithms such as J48, bagging, and random trees to construct a predictive model. Results from the experiments indicated that the J48 algorithm outperformed the other models. The researcher advocates for the use of data mining methods to enhance customer classification. The study [12] introduced a novel Deep Learning (DL) framework designed for forecasting short-term grid load. Initially, the load data undergoes Box-Cox transformation, and the investigation focuses on two key parameters: electricity price and temperature. Parametric copula models are then employed to measure the tail-dependence of power load on these parameters, enabling the computation of the peak load threshold. Subsequently, a Deep Belief Network (DBN) is constructed to predict the hourly load of the power grid. Comparative analysis is conducted against classical neural networks, support vector regression machines, extreme learning machines, and classical deep belief networks within the proposed framework. The assessment of load forecasting performance is based on metrics such as mean absolute percentage error, root mean square error, and success rate. Computational results validate the effectiveness of the data-driven DL framework, showcasing superior prediction accuracy for both day-ahead and week-ahead forecasting compared to the tested algorithms. According to [13], the study examined five different methods for forecasting energy consumption in a residential building across various time horizons and resolutions. Notably, the study proposed the utilization of Deep Learning (DL), specifically Conditional Restricted Boltzmann Machines (CRBM) and Factored Conditional Restricted Boltzmann Machines (FCRBM), for energy consumption prediction. The analysis demonstrated that FCRBM emerged as a robust and powerful method, surpassing state-of-the-art prediction techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVM), Recurrent Neural Networks (RNNs), and CRBMs. It is noteworthy that as the prediction horizon extends, FCRBM and CRBMs exhibit enhanced robustness, with their prediction errors typically halving compared to ANNs. According to [11], the study focused on analyzing stock price data, which exhibit typical time series characteristics. Leveraging the advantages of LSTM's capability to analyze temporal data relationships through its memory function, the author proposed a stock price forecasting approach using CNN-LSTM. Additionally, the author employed CNN, RNN, LSTM, and other forecasting models individually to forecast stock prices. Initially, the study utilized CNN to efficiently extract features from the data, specifically from the preceding 10 days' data items. Subsequently, LSTM was employed to forecast the stock price using the extracted feature data. Based on the experimental outcomes, the CNN-LSTM model demonstrated the highest prediction accuracy, offering a reliable method for stock price forecasting. Hence, the aforementioned studies employ diverse methodologies, metrics, and data types to address various applications of machine learning algorithms. Many articles focus on comparing algorithms using data related to electric power consumption, while others delve into predicting stock prices. In Ethiopia, there hasn't been any research conducted on using either traditional machine learning algorithms or deep learning algorithms for analyzing and predicting power consumption. In contrast, our study utilizes authentic data from EEU to forecast and scrutinize electric power consumption. We leverage advanced and efficient deep-learning techniques to predict monthly and yearly power consumption for each customer. Furthermore, our analysis extensively examines electric power consumption patterns among different customer categories within the district. However, traditional ML algorithms exhibit subpar performance compared to the superior capabilities of DL algorithms [14]. DL, a subset of ML, has gained widespread use and is acknowledged for its superior performance in object detection and classification. Although DL needs a larger volume of data to train the network and enhance system performance, it has proven highly effective.

2. MATERIAL AND METHODS

A. Data Sources

An actual dataset was obtained from the Ethiopian Electric Utility Dessie district for this investigation. EEU's ERP system records client information, monthly power usage, and payment details, including the duration a payment remains active. The dataset covers the Gregorian calendar years 2019 through 2023. According to subject matter specialists, it includes monthly power usage data for hospitals, schools, museums, and residential clients. The active and retrieved datasets both contain monthly electricity use data for EEU staff, while the commercial dataset includes historical usage data from the manufacturing, food, beverage, wood, mill, microenterprise, and metalworking sectors. The company's power consumption statistics encompass station and office use. The dataset comprises postpaid customers in the EEU Dessie district, covering 28 service zones and 6 rate categories for all clients receiving the service.

B. Proposed research

The proposed study consists of four key components: data preprocessing, data splitting, model development and training, and prediction. Preprocessing prepares clean input data, data splitting identifies the training and testing sets, model development and training apply selected deep learning algorithms to create the model, and prediction ensures accurate power consumption forecasting based on the trained data. Together, these components form a cohesive framework for effective electric power consumption analysis. Figure 1 presents the comprehensive architecture of the entire proposed system.

Fig 1. Overview of the proposed study framework

Data Preprocessing involves cleaning, integration, reduction, and normalization. Irrelevant attributes are removed, and missing values are replaced with mean values using Python's pandas.drop() function. pandas.concat() is then applied to combine five years of data into a single CSV file for analysis. After integration, the resulting data includes [6,183,467*6] rows.

To reduce the data, dimensionality reduction was achieved by performing an aggregation function on the month and year attributes, resulting in 636,564 rows with 5 columns. A min-max normalizer was applied to normalize the dataset to a range between zero and one.

(i) Data splitting: Data splitting is essential to control overfitting and underfitting in the model. Overfitting occurs when a deep learning model fits the training data too closely, hindering its ability to generalize to new data. For this purpose, the dataset is divided into training and testing subsets, using an 80/20 percentage split. The training set comprises 80% of the total data, while the test set includes the remaining 20%.

(ii) Model Development and Evaluation: Leveraging the advantages of deep learning, this study employs LSTM, Bidirectional LSTM, and GRU techniques to predict power consumption. The dataset spans five years of historical electric power consumption data (2019-2023) from the Ethiopian Electric Utility Dessie district. The objective is to generate accurate predictions of energy consumption and to identify the most effective neural network structure through experimental evaluation. Model performance was assessed using metrics such as mean absolute error, root mean squared error , and mean absolute percentage error. Each model's performance, optimized with the required hyperparameters, is evaluated thoroughly.

(iii) Long Short-Term Memory (LSTM): LSTM is effective in mitigating vanishing and exploding gradient issues, particularly in continuous sequences where model values can grow indefinitely. For sequences with recurring patterns, LSTM's forget gate, with learned weights, regulates information retention within the memory cell. When input and output gates are inactive and the forget gate does not induce decay, the memory cell can retain its value, thereby stabilizing error gradients during back-propagation over extended intervals. This structure allows LSTM to retain information for potentially long durations, although it remains complex due to a higher parameter count in the hidden layer compared to a simple RNN with a similar hidden layer size [15].

(iv) Gated Recurrent Unit (GRU): GRU was designed to capture dependencies across various time scales by incorporating gating units that regulated information flow without distinct memory cells, as found in LSTM. Unlike LSTM, GRU revealed the entire state at each timestep, calculating a linear combination between the current state and the newly computed state.

(v) Bidirectional LSTM (BLSTM): BLSTM enhances the capacity of bidirectional recurrent neural networks (BRNNs) by stacking multiple layers of LSTM cells, a configuration known as deep BLSTM. This setup outperforms unidirectional LSTM networks by theoretically considering all information in input sequences, making it highly effective for applications requiring distributed representations, such as language understanding. BLSTM also effectively addresses the vanishing gradient problem, benefiting from the bidirectional RNN architecture.

(vi)Mean Squared Error: As shown in Equation 1, MSE measures the average of the squared differences between predicted and actual values.

$$\mathrm{MSE}(y,\hat{y}) = \frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N} \quad \text{---(i)}$$

(vii) Root Mean Squared Error: As illustrated in Equation 2, RMSE is the transformation between the values of the model predicted and the actual values measured by RSME.

$$\mathrm{RMSE}\ (y,\hat{y}) = \sqrt{\frac{\sum_{i=0}^{N-1}(y_i - \hat{y}_i)^2}{N}} \quad \text{---(ii)}$$

(viii) Mean Absolute Error: As illustrated in Equation

3, MAE is an average of the absolute variance among the actual and predicted values in the dataset.

$$\mathrm{MAE}\,(x, y) = \frac{\sum_{i=1}^{N} |x_i - y_i|}{N} \qquad \text{---(iii)}$$

Prediction: The performance of the model was evaluated, and prediction was conducted on the trained model using testing data to compare the actual electric power consumption with the predicted power consumption of the selected deep learning algorithms: LSTM, BILSTM, and GRU models.

3. RESULTS AND DISCUSSION

This section presents the experimental findings of electric power consumption prediction models based on LSTM, (GRU), and BILSTM architectures. Performance evaluation metrics, including MAE, Mean and RMSE were employed to assess the efficacy of each model.

A. Experimental dataset

A study was conducted to forecast the electricity consumption of the Ethiopian Electric Utility in the Dessie district using past customer data.The dataset encompassed customer information from 2019 to 2023 GC, including customer IDs (business partner codes), payment details for bills paid during the specified months and years, and the corresponding electricity usage by each client. Table I presents a comprehensive overview of the experimental dataset.

Table 1. Summary of the experimental data

S.no.	Attribute name	Details of the attribute
1	CSC Office	Dessie DST, service zone
2	Partner	2000447922, ID no.
3	Category	DOM, category of customer
4	Bill Month	05-02-2019
5	Month	02 (two-month bills)
6	Year	2020 (Financial year)
7	Consumption	111 kWh
8	Charge	100 (Electric charges as per tariff)

B. Data analysis and visualization

As shown in Figure 2, the analysis of electric power consumption in kilowatt-hours (kWh) revealed that power consumption in kilowatts (kW) was higher in 2020 compared to the range of the dataset covering 2019 to 2023. Consequently, electric power consumption increased each year. The maximum and minimum levels of power consumption in the Dessie district from 2019 to 2023 G.C. occurred in 2019 and 2020, respectively.

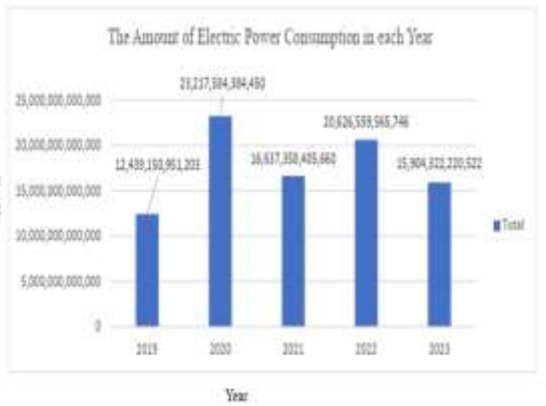

Fig 2. Power consumption analysis from 2019 to 2023

According to Figure 3, the Dessie district's share of total electricity consumption from 2019 to 2023 was 14%, 26%, 19%, 23%, and 18% for the respective years. This indicated fluctuations in the overall electricity usage, with a decrease anticipated in 2023. Such a decline may suggest a shortage of electric power or inconsistencies in service delivery. As illustrated in Figure 4, electric power consumption varied across different service zones based on the number of users and the living standards of the populations in those areas. Some service zones had fewer users and were organized earlier near 2023. However, Kombolcha Zone One, Kemissie, and Dessie Zone Two recorded the highest electric power consumption over the five-year period, while Dst, Densa, Mekoy, and Weynamba had the lowest consumption. As depicted in Figure 5, the distribution of electric power consumption varied inconsistently across the months in the EEU Dessie district. August, October, and September experienced the highest levels of electric power consumption, while January, February, and May exhibited the lowest levels. Therefore, the EEU-Dessie district required adjustments and special attention during high electric power demand.

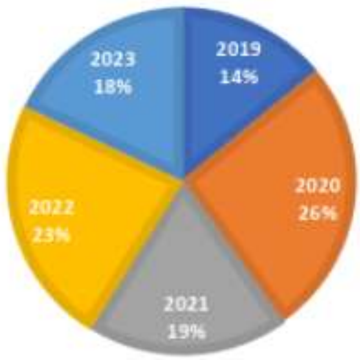

Fig 3. Percentage distribution of power consumption from 2019 to 2023

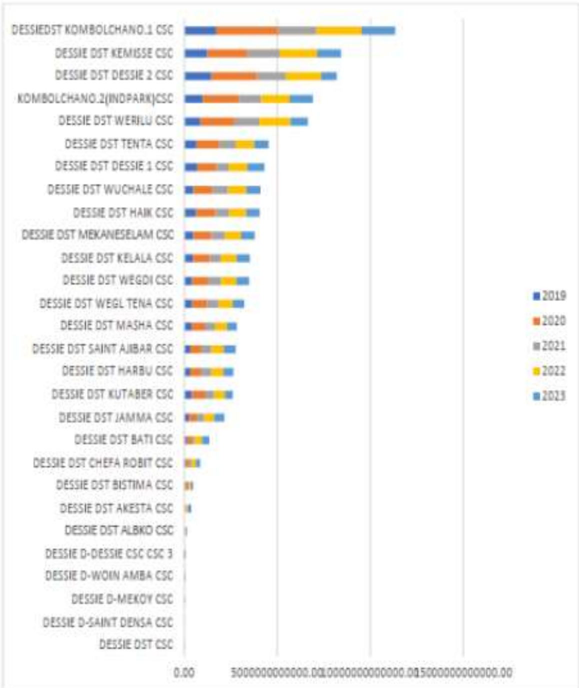

Fig 4. Power consumption across various service zones

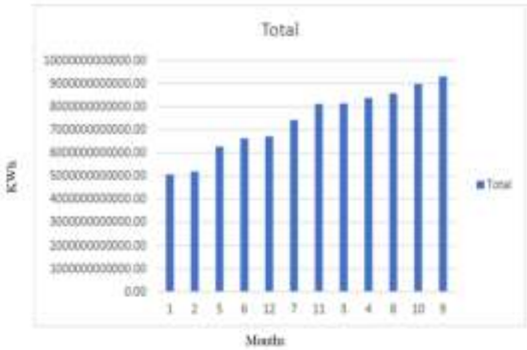

Fig 5. Monthly distribution of electric power consumption

C. Hyperparameters of the Trained Model

After compiling the model, it was essential to summarize it to visualize and generate each layer along with its corresponding output shape and number of parameters. Table II provided insights into the architecture of the model, including the total number of trainable and non-trainable parameters.

Table 2. Parameters of the Model

S.no.	Details of hyperparameter	Hyperparameter values
1	Number of layers	2
2	Number of neurons	100 and 50 for 1st and 2nd layers respectively
3	Dropout layers	0.2
4	Dense layer	1
5	Activation function	RELU
6	Optimizer	Adam
7	Loss function	MSE, RMSE, and MAE
8	Epoch	100
9	Batch size	1
10	Early stopping patience	10

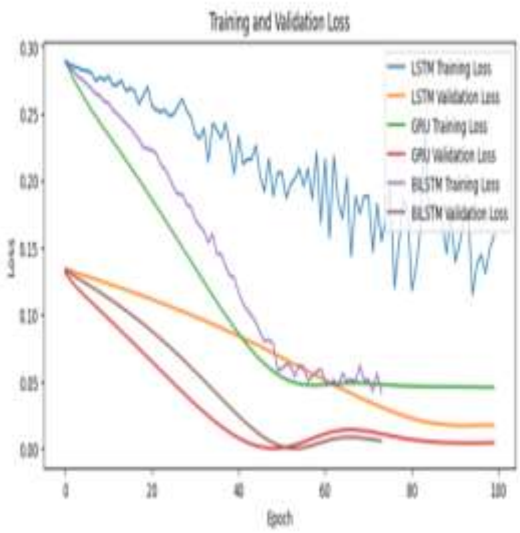

Fig 6. Training and validation loss for the three models

Figure 6 visualizes the training and validation loss throughout the training process. Typically, the training loss decreased as the number of epochs increased, indicating that the model was learning and improving its predictive capabilities. The results provided valuable insights into how the model learned and improved over time.

D. Test and prediction

The prediction graph of the three models—GRU, LSTM, and BILSTM—revealed a distinct order based on the magnitude of predicted values. Specifically, the BILSTM model yielded the highest prediction values, followed by the GRU model, with the LSTM model predicting the lowest consumption values. This observed hierarchy in prediction values suggested that the BILSTM and GRU models tended to overestimate power consumption, while the LSTM model tended to underestimate it. The prediction outcomes, along with the actual power consumption data for the EEU Dessie district, are illustrated in Figure 7.

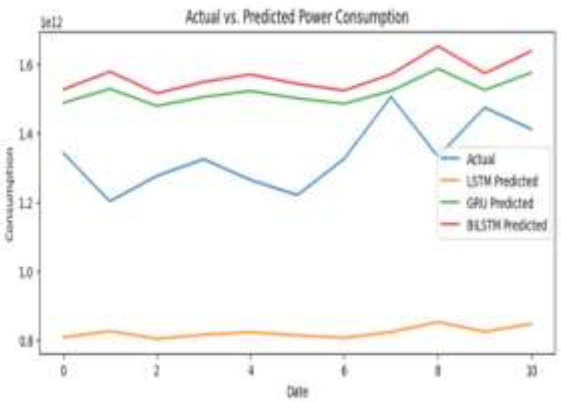

Fig 7. Comparison of actual and predicted power consumption

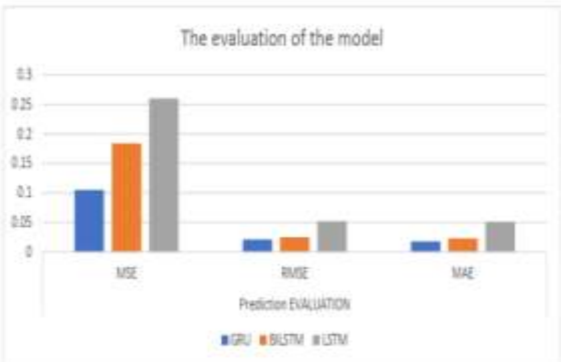

Fig 8. Summary of the model evaluation results

An energy consumption prediction model was developed using three deep learning algorithms. The performance of these algorithms—LSTM, Bidirectional LSTM, and GRU—was evaluated using MSE, RMSE, and MAE metrics. As shown in Table III and Figure 8, the evaluation summary indicated that the GRU model achieved lower MSE, RMSE, and MAE compared to the BILSTM and LSTM models, and the BILSTM model achieved lower MSE, RMSE, and MAE than the LSTM model.

Table 3. Performance results of model training and testing for the three models

Model name	MSE	RMSE	MAE
GRU	0.150	0.021	0.018
BiLSTM	0.184	0.025	0.023
LSTM	0.260	0.052	0.051

4. CONCLUSION

Energy is a key driver of economic growth worldwide, including in Ethiopia, where rising power demand has led to occasional shortages. To support sustainable energy management, this study developed a predictive model using deep learning and historical power data from Dessie.

Accurate power consumption forecasts can optimize costs, enhance grid stability, and support effective policy-making. Analyzing 2019–2023 data, the study found that the GRU model achieved the highest accuracy, outperforming both BILSTM and LSTM models, with MSE, RMSE, and MAE values of 0.105, 0.021, and 0.018, respectively. These findings underscore the GRU model's effectiveness for reliable power consumption prediction.

Recommendation: Although this study primarily focused on post-paid EEU-Dessie District customers, future studies should consider including prepaid (Card Meter) customers to enhance the accuracy of forecasting and support the achievement of organizational goals.

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