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POWERING UP EFFICIENCY: A DEEP LEARNING MODEL FOR ACCURATE ELECTRICITY CONSUMPTION FORECASTING

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ABSTRACT

The evolution of intelligent power methodologies has emerged recently. This evolution is based on extracting smart grids` information for electricity management. One of the key challenges in electricity management is forecasting consumption. Forecasting electricity consumption provides the ability to utilize resources and reduce costs efficiently. This paper proposes a novel hybrid deep-learning model for short-term electricity consumption forecasting that combines traditional consumption data with other external features. The proposed model utilizes a time series dataset, climatic features (temperature, wind speed, and humidity), and specific holiday information. These additional features are intended to improve the accuracy of electricity consumption forecasting, thereby enabling more efficient resource utilization and cost reduction. The data pre-processing phase includes adjusting time units and adding new features. The proposed model for processing the data begins with a multi-convolutional neural network (CNN) for feature extraction purposes. Then, these extracted features are passed through stacked gated recurrent units (GRU) for electricity consumption forecasting. An additional dropout layer is introduced to avoid overfitting. Experiments are carried out to apply the proposed model to the real dataset. The performance of the proposed model is measured using accuracy metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to assess the deviation between actual and forecasted values. The experiments show that our proposed model outperforms the published results of other research using techniques such as Linear Regression (LR), Long Short-Term Memory (LSTM), CNN-LSTM, Bidirectional LSTM (Bi-LSTM), Stacked LSTM, and Stacked Bidirectional LSTM on the same dataset.

Keywords: *Electricity forecasting, Intelligent energy, Deep learning, Convolution neural network (CNN), Gated Recurrent Neural Networks (GRU).*

1. INTRODUCTION

IoT technology in smart cities plays a vital role in the development of energy management [1]. IoT technology aims to build interconnected networks of every smart object in smart cities to collect and transfer data to be analyzed further [2].

Smart energy has emerged recently in smart cities for better power resource allocation, energy management systems, and energy consumption forecasting [3].

In smart cities, time series forecasting is an essential approach to improving people's quality of life and urban services (e.g., energy forecasting [4], traffic flow forecasting [5], water forecasting [6], etc.). One of the key tasks presented in this paper was energy forecasting.

Energy time series data was the core of energy forecasting, used to better understand energy-related trends. Interpreting the energy time series data was challenging because it involved analyzing the flow of consumption data over time and the corresponding patterns that can be identified [7]. Optimizing energy consumption was a highly demanding goal for efficient resource allocation from the demand side and minimizing the economic impact on residents [8].

Research recently focused on developing intelligent models for electricity consumption forecasting. These models are based on applying artificial intelligence techniques such as machine learning and deep learning [9]. Earlier studies showed that there were different aspects of electricity consumption forecasting. The studies are divided into short-term, medium-term, and long-term forecasting [10]. Short-term forecasting estimated the electricity load value based on hours to one week. However, medium-term forecasting was based on periods that ranged from a week to one year. However, long-term forecasting for over a year [11] [12].

Electricity consumption forecasting was a key task in terms of energy time series forecasting because of its characteristics, which include 1) seasonality patterns (i.e., hourly, daily, weekly) observations and 2) trending patterns [13]. These trends may vary from long-term trends based on economic features like (holidays and population growth) or short-term trends like sudden changes in weather or special events. Accurate forecasting implies better inference of these characteristics for better decision-making [14].

Electricity consumption forecasting faces some vital challenges compared to other forecasting types. Since electricity consumption data showed a strong correlation with seasonal observations, it was necessary to be analyzed. Other special features (i.e., holidays, weather conditions, etc.) that may influence the performance of consumption forecasting models must also be studied. This paper's focus has been introduced in [15] [16]. Both time series analysis techniques and regression models apply artificial neural networks (ANN) [17]. This paper proposed a short-term hybrid deep learning model for electricity consumption forecasting. The approach of this paper is combining (CNN) for a better feature extraction technique with a stacked-gated recurrent neural network (GRU) for model forecasting.

We presented previous machine learning and deep learning models for forecasting electricity consumption. Then, we identified the challenges and limitations. After that, a hybrid deep learning model was proposed for electricity consumption forecasting using CNN-stacked GRU. Also, according to previous research, our model studied the impact of holidays and weather, which assumed that these external features would affect the forecasting accuracy [16] [13].

Finally, the proposed model was experimented with a real household dataset to assess the performance based on (MSE, RMSE, MAE, and MAPE) metrics.

The rest of the paper is organized as follows: Section 2 introduces the related work in electricity forecasting models. Section 3 shows the motivations and background concepts used in this study and the motivation of the proposed model. Section 4 presents the architecture of the proposed hybrid CNN-stacked GRU model. Section 5 shows the configuration settings, description of the data set and key features, experimental results, and performance evaluation. Finally, the conclusion and future work are discussed in the last section.

2. RELATED WORK

Previous efforts in electricity consumption forecasting are presented in Figure 1. These efforts mainly begin with optimizing electricity forecasting through statistical models [3]. These models have been effective with small datasets that exhibit time series patterns. However, the rise of smart meters and the vast amounts of data they generate, with varying structures and trends, have created a need for more advanced models capable of capturing complex relationships in the data. As a result, recent efforts have concentrated on developing machine learning and deep learning models to evaluate their impact on improving the accuracy of the forecasting process. [4] [5].

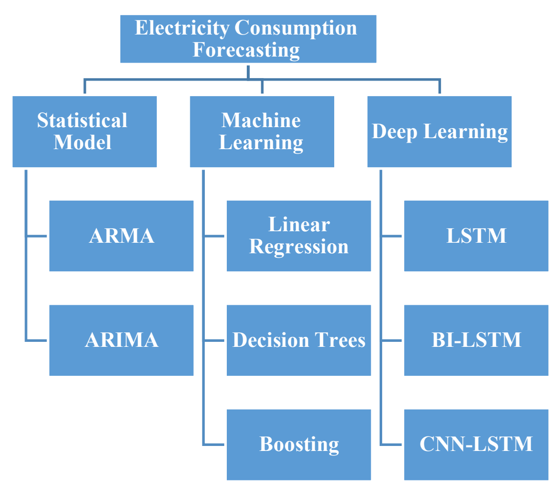

Figure 1 Electricity Consumption Forecasting Techniques

Past efforts have focused on optimizing forecast accuracy. Figure 1 summarizes previous

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works in electricity forecasting approaches [6]. They started with statistical models, machine learning, and deep learning techniques. These techniques are vital for enhancing smart cities' electricity and the whole energy forecasting sector [7]. Statistical time series techniques are used mainly to forecast energy demand. In [8], the authors introduced a spatial autoregressive moving average (ARMA) model.

To consider the dimensions of electricity demand based on the Markov chain Monte Carlo model for Japan demand data, the authors in [3] analyzed electricity consumption as a time series-based problem. They applied autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) to test the performance of each one on the forecasting level.

Also, the purpose of both [3] [8] was to find a suitable model to forecast electric consumption in a household and the most appropriate forecasting period (i.e., daily, weekly). Despite the ARMA model's simplicity in understanding and implementing the ARIMA model, the ARMA model can also be more efficient regarding performance concerning small-sized datasets.

However, unlike the ARMA model, the ARIMA model accounts for non-stationarity, which ARMA cannot manage. Additionally, ARIMA is better suited to capturing seasonality patterns than ARMA. Therefore, while the ARMA model is more appropriate for stationary data, ARIMA is crucial for analyzing non-stationary data, including seasonal, trend, and irregular patterns.

Both ARMA and ARIMA are statistical models used to predict future outcomes based on past time-series data. However, with the growing size of datasets, other contextual factors may complicate consumption forecasting. Recent efforts focus on developing advanced models to identify patterns between time series and related features. Given the increasing irregularities in electricity consumption forecasting, traditional methods have shown limitations. Consequently, the rise of intelligent electricity forecasting, driven by machine learning, has been encouraged to improve forecast accuracy, though this remains a challenging task.

To overcome this problem, the authors in [13] introduced XG-Boost as an ensemble model based on the extreme gradient boosting algorithm for estimating the individual household electricity consumption data. Also, in [1] The authors test the accuracy of the random forest model for classifying load patterns onto numerical levels.

However, in [2] The authors introduced genetic algorithms as an approach for a more accurate feature selection process. After that, researchers showed the effect of applying ANN as authors in [3] Presented the recent trends and models in electricity consumption forecasting and the performance evaluation of each. Also, in [4] The authors focus on forecasting electricity consumption based on the level of appliances, besides peak demand for the residential lifestyle.

This work applied the CLARA clustering model technique with a support vector machine and artificial neural networks to predict electricity consumption. The rapid development of the generated data and the increasing need to better understand the correlations between consumption features are considered key challenges. Hence, the impact of deep learning models, especially recurrent neural networks (RNNs), has been studied massively to overcome this challenge.

As in [13], the authors presented the performance of the long-short-term memory (LSTM) model to forecast individual household power consumption. The LSTM model can potentially offer better forecasting accuracy, as in [14]. In addition, authors in [15] tested the importance of applying a hybrid deep learning model for better performance by adding a convolutional neural networks (CNN) layer for better feature extraction besides the LSTM layer for forecasting.

Also, [19] proposed an electric energy consumption forecasting model for combining CNN and Bidirectional Long Short-Term Memory (Bi-LSTM) to forecast household electricity consumption. On the other hand, in [16], the authors considered multiple smart meters attached for recording household electricity consumption. This model emphasized a hybrid model of CNN and BI-LSTM for feature extraction and model prediction.

Finally, previous work noticed several drawbacks concerning input data and model performance. Most of the earlier efforts only considered the numeric features for consumption. However, testing additional features may have a major impact on electricity consumption.

Moreover, enhancing the model`s performance metrics will remain an issue of concern. One of the limitations of LSTM neural network architecture is the high memory requirement based on multiple cells in its structure. Finally, several drawbacks were noticed in previous work, starting from the traditional time series forecasting model, where the performance of the model defects against stationarity data in the ARMA model or cannot catch patterns between other special features with time series data.

Even though machine learning-based research mainly obtained LSTM models as a best practice for time series analysis, it was thought that LSTM adds more complications to the model performance. Also, most previous research only considered the features of the available dataset. However, testing additional features will have a major impact on electricity consumption.

Moreover, enhancing the model`s performance metrics will remain a concern. To overcome these drawbacks, we propose a deep learning model based on stacked gated recurrent neural networks for model forecasting combined with convolutional neural networks for feature extraction.

3. PROBLEM STATEMENT AND MOTIVATION

This section will present the research problem, the motivations for the proposed model, and a brief background for common Deep Learning architectures in electricity consumption forecasting.

Electricity forecasting is a critical component of effective energy management, especially as demand fluctuates due to factors such as weather changes, economic activities, and consumer behaviors. Traditional forecasting methods often struggle to capture the complex, non-linear relationships inherent in electricity consumption data. With the advent of smart meters and the resulting increase in available data, there is an opportunity to leverage deep learning techniques to enhance the accuracy and reliability of short-term electricity consumption forecasts [5]. This research aims to develop a hybrid deep learning model that incorporates both historical consumption patterns and external variables to improve forecasting performance.

We have targeted issues with the following questions: how do deep learning models affect the accuracy of consumption? What external factors (e.g., weather conditions, holidays, economic indicators) significantly impact short-term electricity consumption?. And how can they be effectively integrated into deep learning models?.

Extensive research has been conducted to forecast aggregated consumption. Nonlinear approaches, including those based on fuzzy models, expert systems [6], and deep neural networks. These models have demonstrated progressive performance by extracting the best features. The principles of electricity forecasting were recently built on the idea of recurrent neural networks (RNNs).

As the RNN was considered one of the rising deep learning techniques, it was found suitable for processing sequential or time-series data. Using features learned through memorizing previous inputs, RNN seeks to predict future data based on past and current data, as shown in [16]. Yet, RNN was limited to processing input data because of gradient vanishing or gradient exploding issues.

These concerns initiated the idea of the LSTM long-short-term memory technique, which enabled the ability to hold a long sequence of data based on extra gates added to the basic architecture of RNN to keep the important data, if needed, through forget gate structure [17]. Despite LSTM being a promising technique over RNN, the three-gates architecture requires a high memory structure even if the processed dataset's size is small.

Accordingly, the gated recurrent units have been exposed with only two gates` structures (Reset and Update) and only one hidden state, which keeps only long- and short-term dependencies instead of the two states in LSTM [18]. The GRU was on track to exceed other RNN techniques for analyzing time-series data because of its speed and similar accuracy.

However, enhancing performance depends on building a suitable model and preparing the input data, which aims to reach the best set of features, called feature extraction [15]. Because of the unsupervised deep learning problem, the feature extraction process was vital in providing training data with the best features to increase the model`s accuracy and reduce dimensions [7]. By applying dimensionality reduction, we can decrease or bring down the number of columns [8].

As [9] Approved, CNN was one of the recommended techniques for extracting the most significant feature vector. It consists of several layers (i.e., convolution, max pooling, and rely), which optimize neurons and weights efficiently until the fully connected output layer is built [10].

4. PROPOSED MODEL

The proposed model consists of two main stages: data preparation and model building. The

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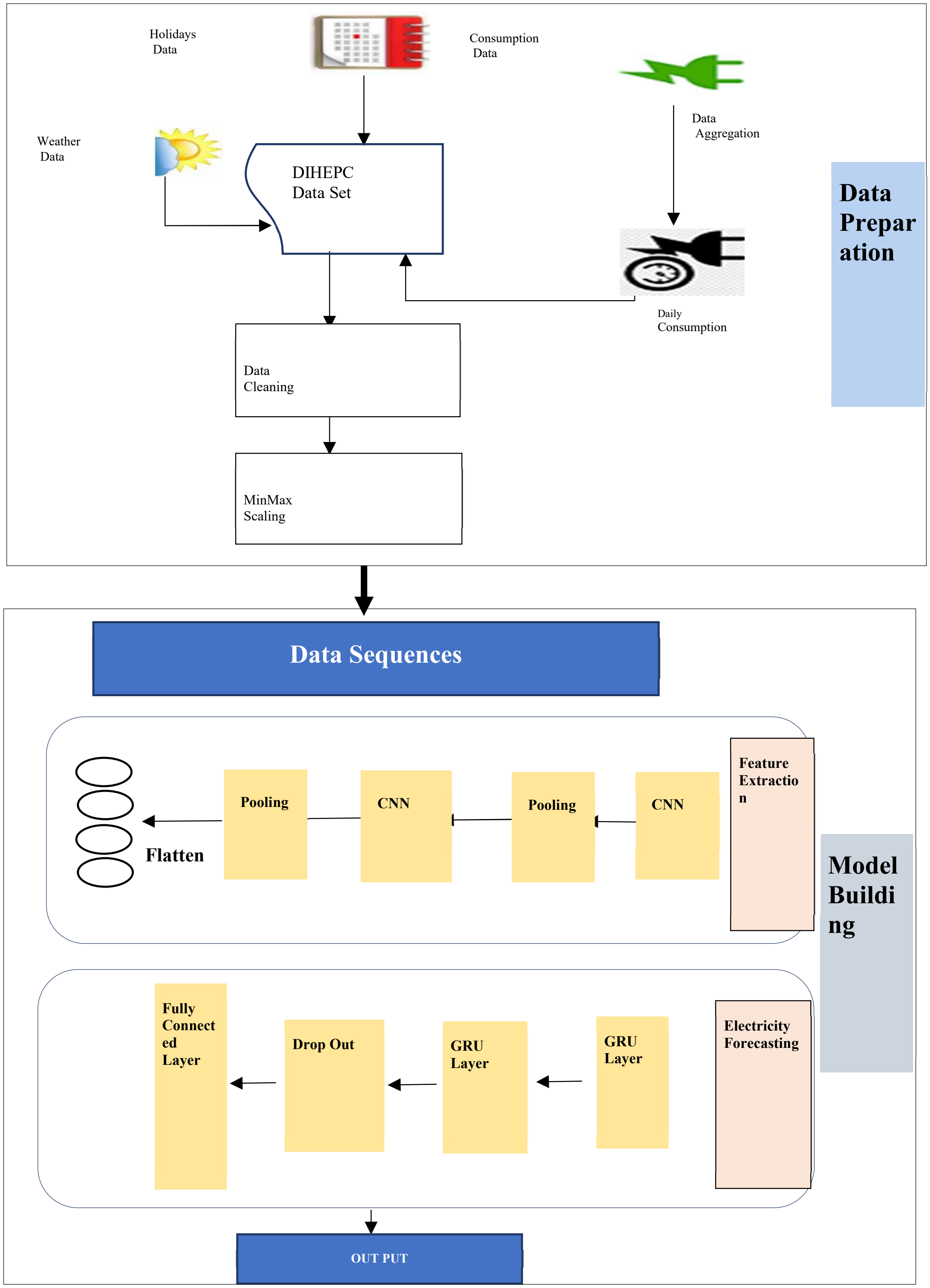

Figure 2 The architecture of Proposed Model

first stage holds the input data description based on

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the individual household electricity

consumption data set. The second stage considers the principles of deep learning architectures for CNN. CNN is applied as a feature extraction layer to find the best feature set based on [15] [21], as shown in Figure 2.

The proposed model also uses GRU for consumption forecasting. Considering contextual and consumption features is a challenging problem, as mentioned in [15] [22]. Therefore, our proposed model aims to enrich the model's performance by considering not only the consumption data but also weather and holiday information. The accuracy metrics are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentile Error (MAPE). These metrics are used to test the model performance.

4.1. Stage 1: Data Preparation

4.1.1. Dataset Description:

The individual household electricity consumption dataset (IHEPC) [23] used is considered a benchmark dataset based on [14] [24] in the field of electricity forecasting. This dataset holds electric power consumption measurements for individual households with a time unit of one minute. IHEPC is a time series dataset containing an archive of electrical measurements gathered in a house in Sceaux (7km from Paris, France) between December 2006 and November 2010 (47 months).

Table 1 lists different quantitative features describing the consumption patterns for this house over almost four years, observed with 2075259 samples. These attributes are composed of consumption features, shown in attributes 1-9, with weather data and holidays from attributes 10-16.

Moreover, based on aggregation calculations, the IHEPC dataset can be divided into multiple datasets using the time domain (i.e., minutely, hourly, daily, weekly, monthly, quarterly, and every year). Hence, this paper aggregated the IHEPC dataset based on a daily and weekly basis.

We obtained the data available in [25] [26] to identify the weather and holiday information related to the exact time and location dimensions listed in the original description of IHPEC.

4.1.2. Dataset Preprocessing:

In this step, the input data is refined before being applied to our CNN-stacked GRU model. The dataset is pre-processed by aggregating it to daily consumption observations by taking mean values daily. In addition to daily numeric features, we concatenated the daily consumption data (i.e., submeters, voltage, global active power, etc.) with external information to include data from different sources rather than time series, like the weather and holidays. This combination is based on each day's date and spatial information.

So, each data record describes a particular day`s electricity consumption data, weather conditions, and type of day (a working day or holiday). We enriched the proposed model with these external features to improve our model's accuracy. Then, the collected data is scaled through a min-max scaler from 0 to 1 range. This is described in Equation (1).

$$X_{new} = \frac{X - X_{min}}{X_{Max} - X_{Min}} \quad (1)$$

Where X_{new} was the new value after scaling and X was the old values and X_{min}, X_{max} was the minimum and the maximum values in each column. We can formulate the energy forecasting problem in this research as follows. Given the electricity consumption time series observations, X can be represented every time step T, every X_{T+1} would be obtained from past observations combined P. Where P denotes the external parameters (weather, holiday) information as Equation (), which describes the context of this consumption behavior along with the description of the day (e.g., working day, an official holiday, weekends). This information has been thought to improve model accuracy and add more value to better understanding the individuals` pattern of consumption.

$$X=X1, X2,\ldots\ldots,Xm \ + (P) \quad \text{where } 1<T<m \quad (2)$$

Then, a refinement process for handling missing data with mean value is implemented. Later, the data is pre-processed through the min-max scaler technique to a normalized daily dataset of time series electricity consumption sequences. This step was decomposed into subtasks described as follows:

Data Preparation: This model includes additional features, such as weather data (e.g., temperature, humidity, wind speed) and holiday information, collected from relevant sources [29] [30] and then concatenated with the time series features.

Feature engineering: the consistency of the data was guaranteed between time series data and other features through the time domain. These features

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are selected and combined with time series features to be used as predictors.

4.2. Stage 2: Model Building

The model-building stage includes the CNN model used for feature extraction and a description of the forecasting model.

4.2.1. CNN for Feature Extraction:

Our main intention is to extract the best features set from the input data described in Stage 1. Several models perform the feature extraction process to select the best subset of features from the entire set. According to [27] [19], the CNN model is selected in the feature extraction phase by processing the input data based on two convolutional layers.

Research has shown that using CNNs for time series forecasting has several advantages over other methods. They are highly noise-resistant models, and they can extract very informative, deep features independent of time. In addition, CNNs incorporate feature engineering in one framework and eliminate any need to do it manually: they can extract features and automatically create informative representations of time series.

We also added max pooling and flattened layers to produce the sequences of time series data that will be passed to the forecasting step. These sequences describe the dataset as a stream of observations that help the model learn to forecast future forecasting.

4.2.2 Electricity Forecasting:

In this step, we select the gated recurrent neural network (GRU) by stacking multiple layers for forecasting purposes. Furthermore, the dropouts are added for best-practice performance according to the evaluation metrics.

The dropout layers achieved regularization. This regularization avoids overfitting during training by randomly turning off neurons and their corresponding connections. Also, the stacking concept for GRU layers has been adopted since it is observed that the deeper the model, the better accuracy is achieved [28].

The proposed model outperforms the current techniques (LSTM, BI-LSTM, and LR). This step of electricity forecasting can be decomposed into the following sub-tasks:

Model selection: The CNN-stacked GRU model is proposed based on the dataset generated from stage 1, which contains daily electricity consumption data for a single household. Our model integrates the daily features of weather conditions and type of day to add more dynamics to the forecasting model by including time series and external features.

Model Fitting: Then, the model is trained through both features to minimize the error between output and actual values with an 80-20 strategy for training and testing purposes. The dimensionality of the data was around (1433) samples and (15) features as a daily observation.

Model Forecasting: Forecasting is generated after the model is trained. The weather, holiday, and past observations are used as inputs.

Model Evaluation: The proposed model's accuracy was measured using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentile Error (MAPE).

Table 1 Dataset Attributes

ID	Attribute Name	Description
1	Date	Format: dd/mm/yyyy
2	Time	Format: hh:mm: ss
3	global_active_power	Global active power in average (Kilo Watt).
4	global_active_power	Global reactive power is measured in an average of minutes (Kilo Watt).
5	Voltage	The minute-averaged voltage (in volts).
6	global intensity	The household global minute-averaged current intensity (in ampere).
7	sub_metering_1	This variable corresponded to the kitchen devices (in watt-hours of active energy).
8	sub_metering_2	This variable corresponded to the laundry room (in watt-hour of active energy).
9	sub_metering_3	This variable corresponded to an electric water heater and air conditioner (in watt-hour of active energy).
10	Tavg	This variable describes the average temperature of the day.
11	Tmin	This variable describes the minimum temperature recorded the day.

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ID	Attribute Name	Description
12	Tmax	This variable describes the temperature recorded the day.
13	Wdir	This variable described wind direction.
14	Wspd	This variable described wind speed.
15	Prcp	This variable described the perception.
16	isHoliday	the holiday information as numeric weekend, or national holiday.

The proposed CNN-Stacked GRU model configuration is described as a convolution layer that takes the input data dimension with the pooling layer for feature extraction. This configuration can discover hidden patterns between data samples and features through the many parameters produced. This model combines convolutional layers, recurrent layers (GRU), and fully connected layers. The GRU layers capture the sequential dependencies, and the convolutional layers likely extract hierarchical features. The model ends with fully connected layers for final predictions—the Dropout to prevent overfitting during training.

Table 2 Proposed Model Summary

Layer (Type)	Output shape	Number of Parameters
CONV_Layer1	(None, None, 6, 64)	192
Pooling Layer	(None, None, 3, 64)	0
CONV_Layer2	(None, None, 2, 64)	8256
Pooling Layer	(None, None, 1, 64)	0
Flatten Layer	(None, None,64)	0
GRU_1	(None, None,64)	24960
GRU_2	(None, None,32)	9408
GRU_3	(None, 16)	2400
Dropout	(None, 16)	0
Fully Connected Layer	(None, 128)	2176
Output	(None, 1)	129
CONV_Layer1	(None, None, 6, 64)	192
Pooling Layer	(None, None, 3, 64)	0
CONV_Layer2	(None, None, 2, 64)	8256
Pooling Layer	(None, None, 1, 64)	0
Flatten Layer	(None, None,64)	0

Layer (Type)	Output shape	Number of Parameters
GRU_1	(None, None,64)	24960
GRU_2	(None, None,32)	9408
GRU_3	(None, 16)	2400
Dropout	(None, 16)	0
Fully Connected Layer	(None, 128)	2176
Output	(None, 1)	129

The Initial CNN layers help extract basic features from the input, followed by the Pooling layers for down sampling the feature and the CNN layer to capture the complex patterns in the data. Then, a flattened layer is added to pass data as a 1-D array of sequences.

After that, GRU layers offer to capture sequential dependencies in the data. It has 64 units, allowing it to learn complex temporal patterns. The dropout layer introduces a regularization technique during training by randomly deactivating portions of the neurons, helping prevent overfitting. The output layer consists of a single unit to produce the final prediction for the target variable.

5. EXPERIMENTS AND RESULTS

The experiment settings are as follows: the hardware is an i7-10750H Core with 16 GB DDR4 RAM and a 64-bit operating system programmed in a Python environment. The dataset is split into 80% training and 20% testing data. The model configuration was built using Kera's (2.9.0) [29] and Tensor Flow (2.9.1) open-source libraries [30] for deep learning purposes.

The experiments in this paper illustrate the accuracy of the proposed model. This model proposes a hybrid deep learning model, combining convolutional neural networks with gated recurrent neural networks for forecasting electricity consumption. The model is applied to a real dataset, tested, and used for performance metrics. The original data set is a minute basic observation of a single household based on [12].

We aggregated the original data set daily and weekly for our model to meet our comparing research. In this section, we show the results of experiments that would prove the performance of our proposed model. Experiment results are evaluated using the four common performance metrics for time series forecasting, including Mean

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Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentile Error (MAPE).

These are mainly brought to prove the convergence of the best results quantitatively. The architecture is proposed and tested with other models, including (LR, LSTM, E-LSTM, CNN-LSTM, Bi-LSTM, Stacked-LSTM, and Stacked BI-LSTM) in [31] [32] [33] [34].

The experiments illustrated the idea of this research. First, we obtained the hybrid model results by adding external information (weather, holidays) against traditional approaches. Then, we applied other experiments to prove the robustness of the model by eliminating the external features one at a time. For that, another experiment was made to test the model's performance without weather data and another test without holiday information. The proposed model is based on daily consumption, and the errors observed are recorded in Table 3.

Table 3 Performance Measures For The Proposed Model Are Based On Daily Data.

Model	***MAE***	***RMSE***	***MSE***	***MAPE***
Linear Regression [11]	0.392	0.503	0.253	52.69
LSTM [11]	0.413	0.491	0.241	38.72
E-LSTM [12]	0.43	0.62	0.38	-
CNN-LSTM [11]	0.191	0.255	0.065	19.15
Stacked LSTM [13]	0.290	0.391	0.152	20.23
Stacked BI-LSTM [14]	0.310	0.350	0.21	-
Proposed Model.	**0.184**	**0.243**	**0.059**	**19.00**
Proposed Model With Holiday	**0.024**	**0.03**	**0.001**	**19.00**
Proposed Model With Weather	**0.022**	**0.03**	**0.001**	**19.02**
Proposed Model With weather and Holidays.	**0.023**	**0.03**	**0.001**	**17.42**

Equations of the accuracy metrics MSE, RMSE, MAE, and MAPE used in the experimental results are also presented in Equations 3-6 [14].

$$MSE = \frac{1}{n}\sum_{1}^{n}(y - y`)^2 \tag{3}$$

$$RMSE = \frac{1}{n}\sqrt{\sum_{1}^{n}(y - y`)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|y - y`| \tag{5}$$

$$MAPE = \frac{100\%}{n}\sum_{1}^{n}\left|\frac{y - y`}{y}\right| \tag{6}$$

AS MSE shows the average distance values between each predicted yˆ actual y value in Equation 3. However, the square root of that difference enhanced the distance value, especially in forecasting problems, called RMSE in Equation 4. In addition, the error values should be tested regardless of direction. We enriched the experiments with MAE to take the absolute value of the error. Furthermore, to compute the error values in terms of percentages, the MAPE was added as a measure for prediction accuracy in our model.

The proposed model achieved the best results based on experiments emphasizing the daily dataset with contextual weather-holiday information. These experiments, presented in Table 3, prove the model`s robustness. The model performance was tested in different situations.

Figures 3 to 7 show an improvement in prediction accuracy with the proposed model compared to compared models. Fig. 3 indicates that the proposed model enhanced the performance metrics MSE, RMSE, and MAE against compared models in daily datasets without adding contextual features. The effect of adding all external features to the proposed model was measured, and the results in Fig. 6 showed that the proposed model outperformed the compared models.

Figures 4 and 5 showed a 15% decrease in the importance of combining contextual features that add more explanation to consumption values. Metric values were reduced by 95% for MSE, 87% for both RMSE and MAE, and 15% for MAPE, as shown in Figs. 6.

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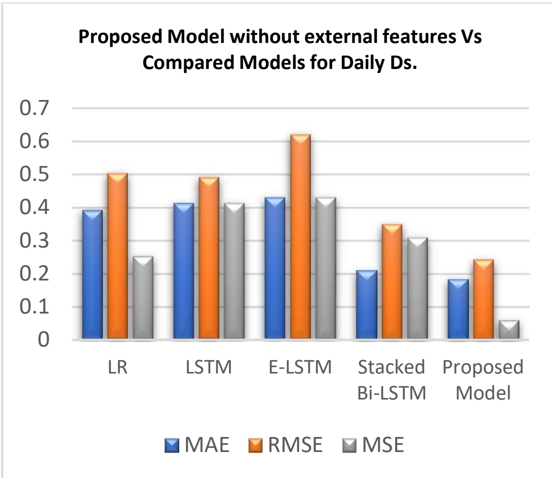

Figure 3 Performance without external data for Daily Data

the extra contextual information, including the weather and holidays data that were presented in Table 3, has enriched the proposed model`s accuracy as the MSE metric measured 0.001, RMSE value was 0.030, in addition to MAE with a value of 0.022 and MAPE value was 17.43 %. Figure. 7 shows the model`s performance of the MAPE metric, which proved a significant decrease in prediction error, as in Table 3.

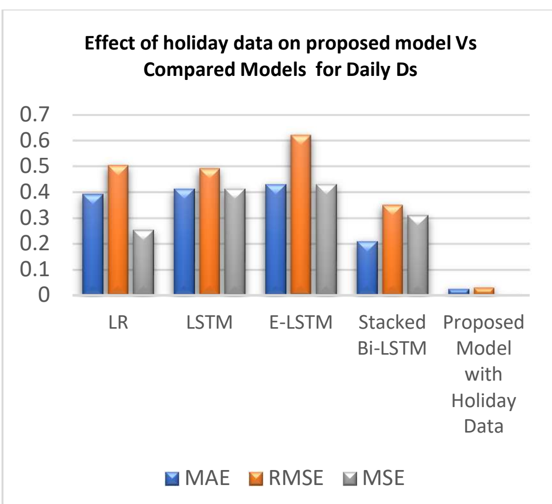

Figure 4 Performance with Holiday data for Daily Data

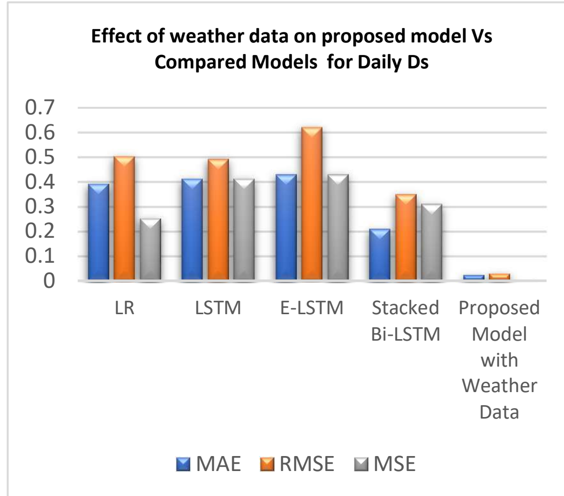

Figure 5 Performance with Weather for Daily Data

Despite the better accuracy that has been proven against previous models in electricity forecasting in daily datasets, the proposed model-enriched testing accuracy based on weekly data also improves accuracy results against [31], as shown in Table 4.

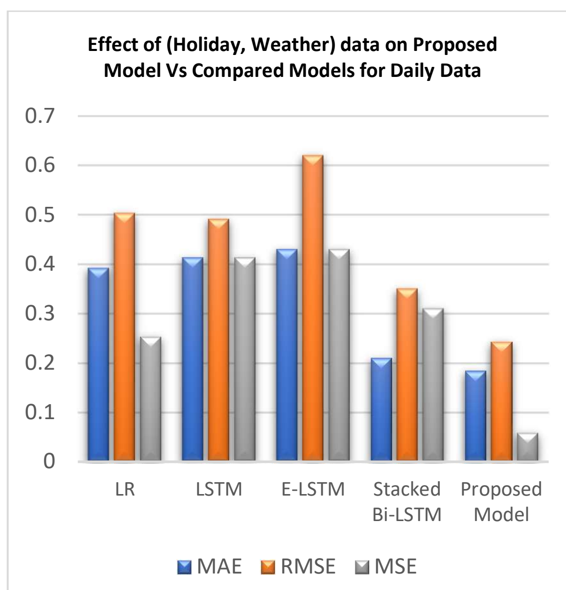

Figure 6 Model Performance Results for Daily Data

In addition, Figure. 7 displays the proposed model's performance to prove the enhancement in

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prediction accuracy according to the weekly data set. Figures 8 to 10. show the error metrics values for the weekly test. They illustrate the proposed model's significant performance compared to the compared models.

These enhancements were 40 % for the MSE, RMSE, and MAE values. In addition, the second experiment that measured the effect of the aggregated weekly observations combined with weather and holiday data showed that MSE enhanced by 95%, a cut down in RMSE and MAE by 88%, as illustrated in Figures 9 to 10.

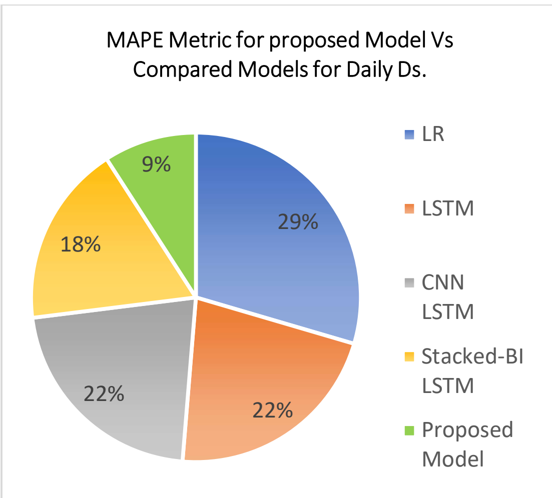

Figure 7 MAPE Evaluation for Daily Data

Also, the model`s stability was a major challenge in each experiment, as we focused on how the system would be affected when adding extra features, which indicated more complexity. However, the model proved its efficiency when compared with other models with and without the impact of contextual information.

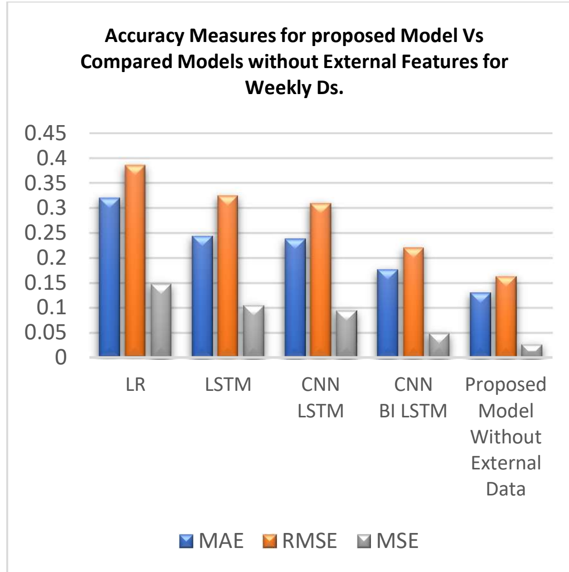

Figure 8 Performance without external features for Weekly Data

Finally, the MAPE was reduced by 26%, as shown in Figure 10 and Table 4. The training time compared to [31] was 8 and 10 seconds for the daily dataset and weekly data training time and 0.3 and 0.4 seconds for both the daily and weekly dataset regarding the prediction time.

Table 4 Metrics Evaluation of Proposed Model Based on Weekly Data

Model	MAE	RMSE	MSE	MAPE
LR [11]	0.320	0.385	0.148	41.33
LSTM [11]	0.244	0.324	0.105	35.78
CNN-BI-LSTM [11]	0.177	0.220	0.049	41.33
Proposed Model	**0.130**	**0.163**	**0.027**	**14.939**
Proposed Model With Weather	**0.016**	**0.02**	**0.004**	**12.313**
Proposed Model With Holiday	**0.015**	**0.019**	**0.0003**	**11.243**
Proposed Model (Holiday, Weather)	**0.015**	**0.019**	**0.0004**	**11.161**

We summarized the MAPE metric to prove the enhancement of the proposed model for assessing forecasting accuracy because of its simplicity, interpretability, and focus on percentage errors. The weekly observations were generated by summarizing the mean value of the consumption features along with the weather data and holidays to be evaluated, as shown in Table 4.

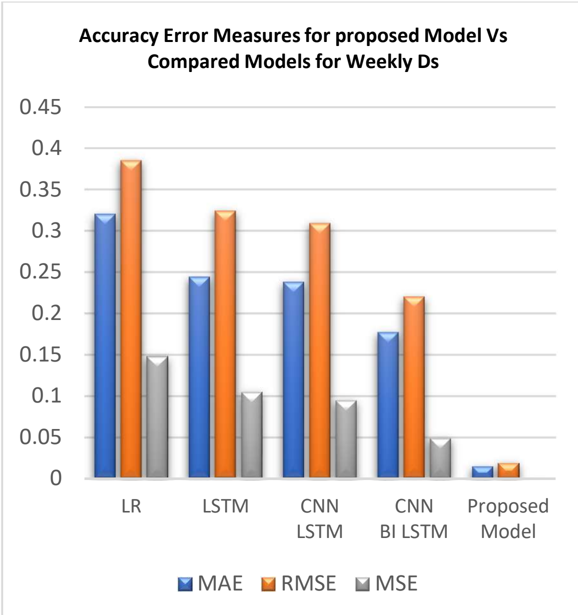

Figure 9 Accuracy Metrics for Proposed Model for Weekly Data

These experiments are implemented against benchmark techniques, starting from regression [15]. And other traditional machine learning models. These techniques faced several challenges regarding sense of seasonality and lack of non-stationarity handling, in addition to the difficulty of capturing the patterns of time series data and external information. Also, LSTM-based techniques may not outperform when the amount of data is not too large, as a large scale of data is required to be reserved for training, in addition to requiring much memory usage.

Finally, experiments presented in this section proved the research point of view, as the impact of the external information might directly correlate with the time series data for electricity consumption. The effect of combining weather data and holiday information with individual consumption enhanced model performance and decreased the error rates compared with [11] [12] [13][14].

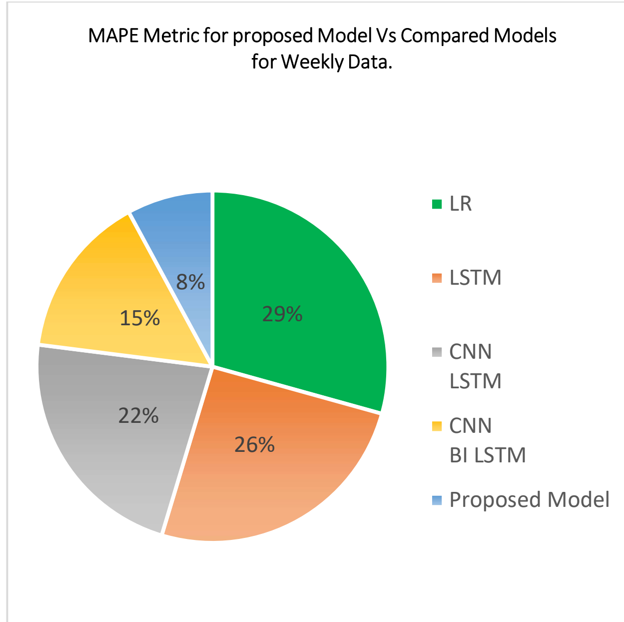

Figure 10 MAPE Evaluation for Weekly Data

6. CONCLUSION AND FUTURE WORK

This paper introduced a hybrid deep-learning model for short-term electricity forecasting. The model leverages a convolutional neural network for feature extraction and employs multiple stacked gated recurrent units (GRUs), an advanced, recurrent neural network architecture, to improve forecasting accuracy. Regularization with dropout layers was used to prevent overfitting during training and validation, based on a dataset of individual household consumption recorded by multiple smart meters over specific dates and times.

The model, utilizing the daily and weekly dataset structure, outperformed previous methods by incorporating external weather and holiday data. Experimental results demonstrated superior performance compared to other machine learning and deep learning models (e.g., LR, LSTM, CNN-LSTM, Bi-LSTM, Stacked-LSTM, Stacked BI-LSTM), as evaluated using common error metrics like MSE, RMSE, MAE, and MAPE. These metrics provide different perspectives on the gap between predicted and actual values, which is essential in forecasting tasks.

For future research, it is important to analyze consumption behavior patterns to gain insights into user attitudes and potentially create common user profiles. Additionally, the impact of economic and housing characteristics on the model's performance should be explored, along with the

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potential use of textual data to improve consumption predictions.

REFERENCES

[1] Y.-T. Chen, E. Piedad Jr and C.-C. Kuo, "Energy Consumption Load Forecasting Using a Level-Based Random Forest Classifier," symmetry, vol. 11, no. 8, 2019.

[2] Z. Li, D. Friedrich and G. P. Harrison, "Demand Forecasting for a Mixed-Use Building Using Agent-Schedule Information with a Data-Driven Model," Energies, vol. 13, no. 4, pp. 780-800, 2020.

[3] J. Runge and R. Zmeureanu, "Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review," Energies, vol. 12, no. 17, pp. 3254-3279, 2019.

[4] F. Z. Abera and V. Khedka, "Machine Learning Approach Electric Appliance Consumption and Peak Demand Forecasting of Residential Customers Using Smart Meter Data," Wireless Personal Communications, vol. 111, no. 1, pp. 65-82, 2020.

[5] S. Haben, S. Arora, G. Giasemidis, M. Voss and D. V. Greetham, "Review of Low Voltage Load Forecasting: Methods, Applications and Recommendations," Applied Energy, vol. 304, no. 2, pp. 11798-11835, 2021.

[6] K. M. Tarwani and S. Edem, "Survey on Recurrent Neural Network in Natural Language Processing," International Journal of Engineering Trends and Technology (IJETT), no. 48, pp. 301-304, 2017.

[7] M. Attia, M. Mahmoud, M. Farghaly and A. M. Idrees AMI, "A Statistical-Mining Techniques' Collaboration for Minimizing Dimensionality in Ovarian Cancer Data," Future Computing and Informatics Journal, vol. 6, no. 2, pp. 52-71, 2021.

[8] M. Jogin, M. M. M S, D. G D, M. R K and A. S , "Feature Extraction using Convolution Neural Networks (CNN) and Deep Learning," in 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT-2018), 2018.

[9] M. Jogin, M. M. S. Madhulika , G. D. Divya , R. K. Meghana and S. Apoorva , "Feature Extraction using Convolution Neural Networks (CNN) and Deep Learning," in Feature Extraction using Convolution Neural, 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT-2018), 2018.

[10] S. Dara and P. Tumma, "Feature Extraction By Using Deep Learning: A Survey," in Proceedings of the 2nd International conference on Electronics, Communication and Aerospace Technology, 2018.

[11] T. Le, M. T. Vo, B. Vo and E. Hwang, "Improving Electric Energy Consumption Prediction Using CNN and Bi-LSTM," applied science, vol. 9, no. 20, pp. 4237-4249, 2019.

[12] R. Chinnaraji and P. Ragupathy, "Accurate electricity consumption prediction using enhanced long short term memory," IET Communications, vol. 16, no. 8, pp. 830-844, 2022.

[13] D. SYED, H. ABU-RUB and S. S. REFAAT, "Household-Level Energy Forecasting in Smart Buildings Using a Novel Hybrid Deep Learning Model," in IEEE ACCESS, 2021.

[14] M. I. and S. K. , "Short-term energy forecasting framework using an ensemble deep learning approach," IEEE Access, vol. 9, no. 1, pp. 94262-94271, 2021.

[15] H. M. A. H. S. A. A. A. S. M. . H. M. and S. D. , "A Hybrid Machine Learning Method with Explicit Time Encoding for Improved Malaysian Photovoltaic Power Prediction," Journal of Cleaner Production, vol. 382, no. 1, pp. 134979-135013, 2023.

[16] [Online].Available:https://www.tensorflow.org/.

[17] Y. Zheng, H. Yu, Y. Shi, K. Zhang, S. Zhen, L. Cui, C. Leung and C. Mia, "Pids: An intelligent electric power management platform," in roceedings of the AAAI Conference on Artificial Intelligence, 2020.

[18] Y. Yu, X. Si, C. Hu and J. Zhang, "A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures," Neural computation, vol. 31, no. 7, pp. 1235-1270, 2019.

[19] P. YAN , A. ABDULKADIR , P.-P. LULEY, M. ROSENTHAL , G. A. SCHATTE, B. F. GREWE and T. STADELMANN, "A Comprehensive Survey of Deep Transfer Learning for

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Anomaly Detection in Industrial Time Series: Methods, Applications, and Directions," IEEE Access, vol. 12, no. 1, pp. 3768-3780, 2024.

[20] K. Wang, X. Qi, H. Liu and J. Song, "Deep belief network based k-means cluster approach for short-term wind power forecasting," Energy, vol. 165, no. 1, pp. 840-852, 2018.

[21] T. Viering and M. Loog, "The shape of learning curves: a review," in IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, 2022.

[22] K. Venkat, T. Gautam, M. Yadav and M. Singh, "An XGBoost Ensemble Model for Residential Load Forecasting," in In Proceedings of International Conference on Intelligent Computing, Information and Control Systems, 2021.

[23] D. SYED, H. ABU-RUB and S. S. REFAAT, "Syed, Dabeeruddin, et al. "Household-level energy forecasting in smart buildings using a novel hybrid deep learning model.," IEEE Access, vol. 9, no. 1, pp. 33498-33511., 2021.

[24] M. Raju and A. J. Laxmi, "IOT based Online Load Forecasting using Machine Learning," in Third International Conference on Computing and Network Communications (CoCoNet'19), 2020.

[25] M. Ordouei, A. Broumandnia, T. Banirostam and A. Gilani, "Optimization of energy consumption in smart city using reinforcement learning algorithm," International Journal of Nonlinear Analysis and Applications, vol. 15, no. 1, pp. 277-290, 2024.

[26] X. Ma , M. Wang and C. Li, "A Summary on Research of Household Energy Consumption: A Bibliometric Analysis," sustainability, vol. 12, no. 1, pp. 316-334, 2019.

[27] J. Liu, R. Zhou, H. Zhao and P. Xu, "Electricity Price Forecasting Based on Transfer Learning and CNN-LSTM," Frontier Academic Forum of Electrical Engineering, vol. 1048, no. 1, pp. 9133-924, 2022.

[28] J.-Y. Kim and S.-B. Cho, "Electric Energy Consumption Prediction by Deep Learning with State Explainable Autoencoder," energeis, vol. 12, no. 4, pp. 739-753, 2019.

[29] T.-Y. Kim and S.-B. Cho, "Predicting the Household Power Consumption Using CNN-LSTM Hybrid Networks," in International Conference on Intelligent Data Engineering and Automated Learning, 2018.

[30] J.-Y. Kim and S.-B. Cho , "Explainable prediction of electric energy demand using a deep autoencoder with interpretable latent space," Expert Systems With Applications, vol. 186, no. 1, pp. 115842-115853, 2021.

[31] J.-Y. Kim and S.-B. Cho, "Predicting Residential Energy Consumption by Explainable Deep Learning with Long-Term and Short-Term Latent Variables," Cybernetics and Systems, pp. 1-16, 2022.

[32] K. Kakamu, T. Oga and K. Kakamu, "Forecasting electricity demand in Japan: A Bayesian spatial autoregressive ARMA approach," Computational Statistics and Data Analysis, vol. 54, no. 1, p. 2721–2735, 2010.

[33] . A. Jakoplić, . D. Franković, . J. Havelka and . H. Bulat, "Short-Term Photovoltaic Power Plant Output Forecasting Using Sky Images and Deep Learning," energies, vol. 16, no. 14, pp. 5428-5446, 2023.

[34] H. Habbak, M. Mahmoud, . K. Metwally, M. M. Fouda and M. I. Ibrahem, "Load Forecasting Techniques and Their Applications in Smart Grids," energies, vol. 16, no. 3, pp. 1480-1913, 2023.

[35] P. Chujai, N. Kerdprasop and K. Kerdprasop, "Time Series Analysis of Household Electric Consumption with ARIMA and ARMA Models," in Proceedings of the International MultiConference of Engineers and Computer Scientists, 2013.

[36] F. T. M. Ayasrah, H. J. Abu-Alnadi, K. Al-Said, D. G. Shrivastava, G. K. Mohan and E. Muniyandy, "IoT Integration for Machine Learning System using Big Data Processing," INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING, vol. 12, no. 14, pp. 591-599, 2024.

[37] F. A. Almalki, S. H. Alsamhi, R. Sahal, J. Hassan, A. Hawbani, N. S. Rajput, A. Saif, J. Morgan and J. Breslin, "Green IoT for Eco-Friendly and Sustainable Smart Cities:Future Directions and Opportunities," in Mobile Networks and Applications, 2021.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[38] M. ALHUSSEI, K. AURANGZEB and S. I. HAIDER, "Hybrid CNN-LSTM Model for Short-Term Individual Household Load Forecasting," IEEE Access, vol. 8, no. 1, pp. 180544-180557, 2020.
[39] R. E. Alden, H. Gong and C. Abab, "LSTM Forecasts for Smart Home Electricity Usage," in International Conference on Renewable Energy Research and Application, 2020.
[40] X. Jin, . X. Y. X. Wang, Y. Bai, T. Su and J. Kong, "Prediction for Time Series with CNN and LSTM," in Proceedings of the 11th international conference on modelling, identification and control (ICMIC2019), 2020.
[41] Z. P. J. Y. . L. C. Z. L. W. T. T. T. and K. X. , Frontiers of Environmental Science & Engineering, vol. 17, no. 22, pp. 22-36, 2023.
[42] M. A. "Smart city urban planning using an evolutionary deep learning model," Soft Computing, vol. 28, no. 1, pp. 447-459, 2024.
[43] L. J. W. Z. S. L. a. B. X. "The optimization of carbon emission prediction in low carbon energy economy under big data," IEEE Access, vol. 12, no. 1, pp. 14690-14703, 2024.
[44] D. M. "Artificial Intelligence and Machine Learning for Energy Consumption and Production in Emerging Markets: A Review," energies, vol. 16, no. 2, pp. 745-762, 2023.
[45] "Metostate," [Online]. Available: https://meteostat.net/en/place/fr/sceaux?s=07156&t=2006-02-08/2010-02-04.
[46] "Machine Learning Repository," [Online]. Available: https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption.
[47] "Global Holidays," [Online]. Available: https://publicholidays.fr/.
[48] [Online]. Available: https://keras.io/.