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Deep Learning-Based Approaches for Short-Term Residential Electricity Consumption Prediction: A Comparative Study of LSTM, CNN-LSTM, and CNN-GRU Models

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Abstract **-** The rapid increase in the world population has increased electricity consumption and demand for electricity. In order for electricity distribution companies to determine electricity demand, household electricity consumption must be predicted. In this study, an open access dataset was used to predict individual household electricity consumption. For this purpose, deep learning-based LSTM, CNN-LSTM and CNN-GRU models were developed and a comparative analysis was performed. The performance of the models was evaluated using four evaluation metrics commonly used in prediction model performance evaluation. According to the results obtained, it was seen that the models used in the study were successful in predicting short-term electricity consumption. In particular, the CNN-LSTM model was found to have a lower error rate compared to the other two models.

Keywords**:** deep learning, electricity consumption prediction, LSTM, CNN-LSTM, CNN-GRU.

1. Introduction

Electricity, one of the most important needs of people in modern life, is widely used in many areas such as transportation, health and communication, especially in industry. The widespread use of electricity increases the demand for electricity. The increasing demand for electricity has brought many difficulties, especially in the efficient use of energy resources and environmental sustainability. For this reason, monitoring electricity consumption and balancing electricity production and consumption are very important in energy management.

Electricity consumption forecasting is of critical importance to ensure the balance between energy production and consumption. Prediction of electricity consumption is effective in ensuring the sustainability of energy resources and the efficient use of energy resources. The increase in electricity consumption is related to factors such as population growth, economic development, and the increase in the number of electrical devices. Electricity consumption forecasting is widely used to determine energy demand fluctuations, optimize energy management systems, and prevent energy waste [1].

In recent years, deep learning and machine learning based models have achieved high prediction accuracy in studies on electricity consumption prediction. There are important studies in the literature using different data sets and methods on the subject. In [2], household energy consumption prediction was made using deep learning models using a data set including customer characteristics, weather information, and energy consumption profiles. The Recurrent Neural Network (RNN)-based Temporal Convolutional Network (TCN) model increased prediction accuracy with lower error rates compared to other models. In the study conducted in [3], electricity demand prediction was made with an Long Short-Term Memory (LSTM)-based model using the energy consumption data set taken from the Chandigarh region of India. Predictions were made on a daily, weekly, and monthly basis with the developed LSTM model. The LSTM model showed higher prediction performance compared to Artificial Neural Networks (ANN), RNN, and Support Vector Regression (SVR) models. In [4], a hybrid model based on Factored Conditional Restricted Boltzmann Machine (FCRBM) was developed to predict hybrid electricity energy consumption on the US electricity grid data. The proposed model was predicted with metrics such as Mean Absolute Percentage Error (MAPE), variance and correlation coefficient and successfully predicted energy consumption with 98.9% accuracy. In [5], three different models were developed for energy demand forecasting using the data set obtained from the Korea Power Exchange, namely Convolutional Neural Network (CNN), RNN, and CNN-RNN hybrid model. The performances of the models in energy demand forecasting were compared. The developed CNN model showed better performance in short-term power forecasting compared to RNN and CNN-RNN hybrid models. In [6], a hybrid model combining CNN and LSTM was developed for short-term energy forecasting. The hybrid model tested on five different datasets outperformed Auto Regressive Integrated Moving Average (ARIMA) and LSTM methods. In [7], various deep learning models were developed for electricity consumption prediction in buildings. LSTM based models outperformed Gated Recurrent Unit (GRU) in the evaluation with Root Mean Square Error (RMSE) metrics. In [8], a new hybrid model combining Bidirectional Long Short-Term Memory (Bi-LSTM) and Bidirectional Gated Recurrent Unit (Bi-GRU) models was developed for short-term load prediction. Various preprocessing techniques were applied to historical load and generation data taken from UCI dataset. Then, the model was evaluated using Mean Square Error (MSE), RMSE, Mean Absolute Error (MAE) and MAPE metrics and obtained lower error rate compared to other methods. In [9], a LSTM based hybrid model was proposed for individual household energy consumption prediction. The model stabilized energy consumption signals using Stationary Wavelet Transform (SWT) and increased the performance with multiple LSTM networks. The model tested on the real dataset UK-DALE provided superior results to existing methods in RMSE, MAPE and MBE metrics. In [10], a CNN-Bi-LSTM based model was developed to predict individual household energy consumption. The model was tested on one-minute energy consumption data in UCI dataset and showed superiority with lower prediction errors compared to other deep learning models. This approach aims to optimize power management with accurate prediction of energy consumption.

2. Deep Learning Methods

2.1. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM), a model based on Recurrent Neural Networks (RNN), is widely used in the analysis of time series due to its effective performance in learning long-term dependencies. LSTM effectively overcomes the gradient vanishing problem frequently encountered in traditional RNNs. LSTM consists of a cell state and various gates. The cell state is a memory unit that carries meaningful information and past information for prediction. The gates control which information will be stored, updated or deleted in the cell state with a sigmoid function [11]. The ability of LSTM to learn long-term and short-term dependencies simultaneously contributes to achieving high accuracy in time series analysis. LSTMs have achieved successful results by achieving high prediction accuracy in studies on nonlinear time series problems such as energy consumption data [12].

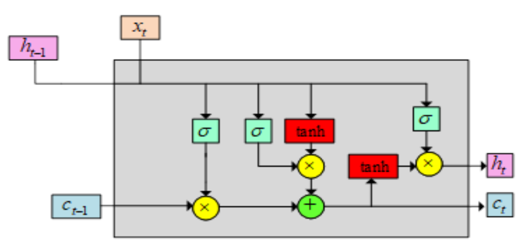

Fig. 1: LSTM architecture.

The LSTM architecture seen in Fig. 1 consists of a cell state, an input gate, a forget gate, and an output gate. The forget gate determines which information and which part will be forgotten, the input gate determines which part will be added to the cell state, and the output gate determines which part will be output from the cell. The cell state carries information from the past to make predictions and is controlled by gates.

2.2. Hybrid Network of CNN-LSTM

This hybrid model, which is a combination of Convolutional Neural Network (CNN) and LSTM, can learn both spatial and temporal features. CNNs are effective in learning patterns or spatial features in data sets, while LSTM layers are effective in learning temporal features in sequential data. This hybrid model has achieved high performance with high accuracy and low error rate, especially in the estimation studies on electricity consumption data consisting of time series [13]. The general architecture of the CNN-LSTM model is given in Fig. 2. CNN (Convolutional Neural Network) layers in the first part of the CNN architecture are used to extract spatial features in the data set. The features are extracted with the convolution layer in the CNN layers and the data size is reduced with the maximum max-pooling layer. Then, the outputs obtained with the flatten layer are transferred to the LSTM layers. LSTM layers are used to learn temporal features in the data consisting of time series and model future relationships from past data. In the last part of the model, the estimation is made using the flatten layer and activation function again.

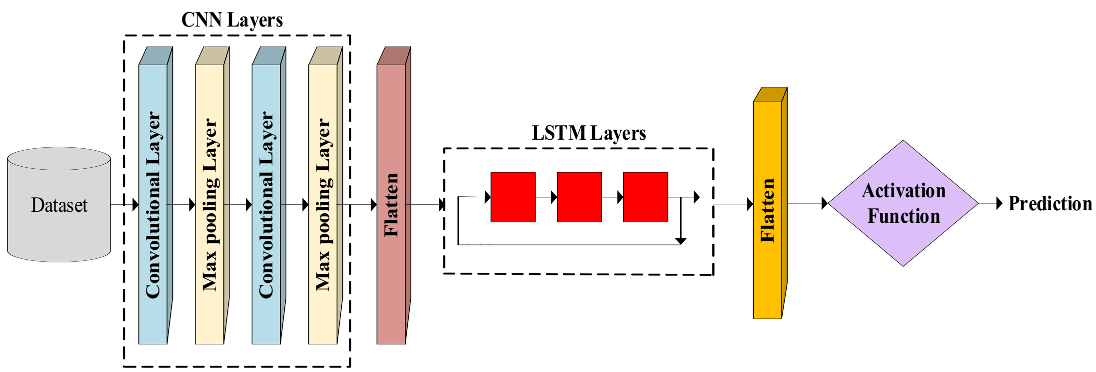

Fig. 2: CNN-LSTM architecture.

2.3. Hybrid Network of CNN-GRU

This hybrid model, which is a combination of Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU), can learn both spatial and temporal features. While the CNN layers in the hybrid model extract spatial features in sequential data, the Gated Recurrent Unit (GRU) layers extract temporal features. The architecture and working logic of GRU are similar to LSTM. However, since GRU has a simpler structure, it requires less computational cost. Due to the low computational cost in the CNN-GRU model, it is ideal for use in large data sets [14]. The general architecture of the CNN-GRU model is given in Fig. 3. In the first part of the CNN architecture, features are extracted with the convolution layer in the CNN and the data size is reduced with the maximum max-pooling layer. Then, the outputs obtained with the flatten layer are transferred to the GRU layers. GRU layers are used to learn temporal features in data consisting of time series and model future relationships from past data. In the last part of the model, prediction is made using the flatten layer and activation function again.

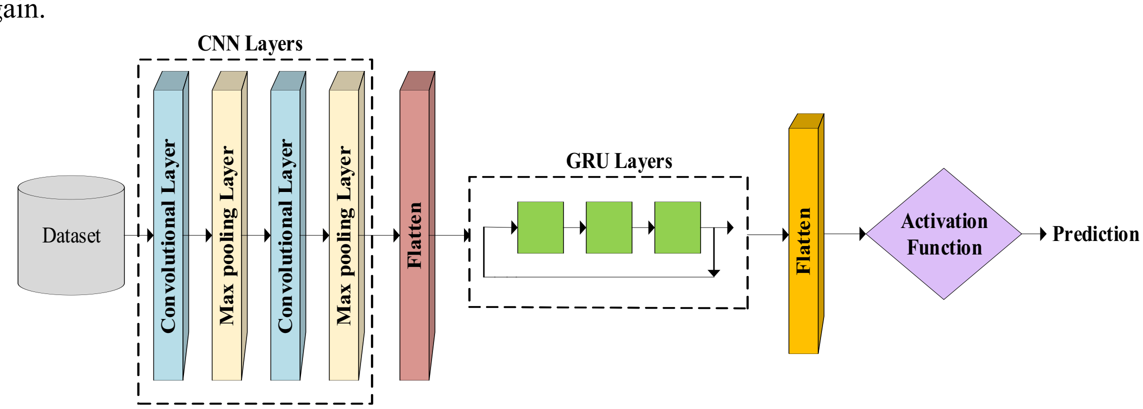

Fig. 3: CNN-GRU architecture.

3. Materials and Methods

3.1. Dataset and preprocessing

The IHEPC dataset used in this study is a publicly available dataset obtained from the UCI Machine Learning Repository [15], which contains data on electricity consumption in a household in Sceaux, France, between December 2006 and November 2010. The data is recorded over a period of about 4 years and contains a total of 2075259 measurements with a sampling rate of one minute. There are 25,979 missing data in the dataset. The dataset contains nine variables (day, month, year, hour, minute, global active power, global reactive power, voltage and overall intensity) and three variables (submetering 1, submetering 2 and submetering 3) collected from energy consumption sensors. In this study, the global active power (GAP) kW and time (date and time) columns from the dataset are used. Missing data in the dataset were replaced with the average values of the available data. The data was then resampled hourly. The data was normalized to the 0-1 range using MinMaxScaler.

3.2. Proposed Method

In this study, in order to predict the global active power in the dataset, firstly various pre-processing is performed on the dataset and 80% of the data is separated for train and 20% for test. Then, after the prediction process is performed on the three different models developed, the performances of the models are evaluated. These steps are shown in Fig. 4.

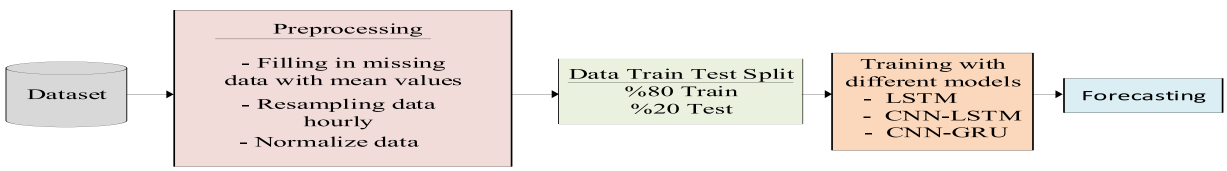

Fig. 4: Proposed method.

4. Experimental Results

In the study, three different models were trained to predict the first 500 hours of global active power in the hourly resampled dataset and the results were evaluated using error evaluation metrics. The models developed for the study were trained in the Google Colab environment using 16 GB memory, 1.59 GHz Intel Xeon CPU and NVIDIA K80/T4 GPU. 4 LSTM layers, Adam optimizer, and 32 batch size were used in the LSTM model. The first 500 hours of global active power were predicted on the test data of the LSTM model trained for 100 epochs. The first 500 hours prediction graph of the LSTM model is shown in Fig. 5.

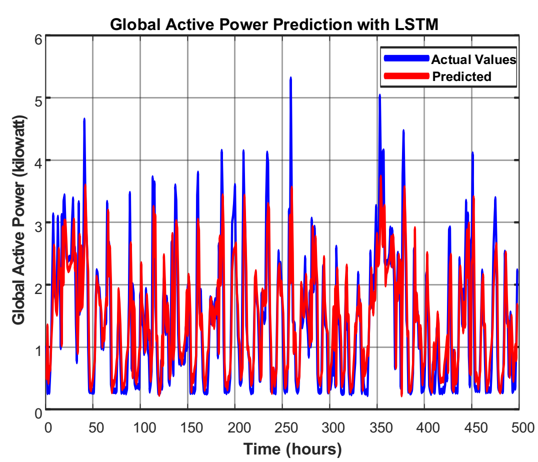

Fig. 5: Line plots of the predicted and actual values of LSTM model on the test set.

In the CNN-LSTM model, 2 convolution layers, 2 maxpooling layers, 2 LSTM layers, Adam optimizer, and 16 batch size were used. The first 500 hours of global active power prediction were performed on the test data of the CNN-LSTM model trained for 50 epochs. The prediction graph of the first 500 hours of the CNN-LSTM model is shown in Fig. 6.

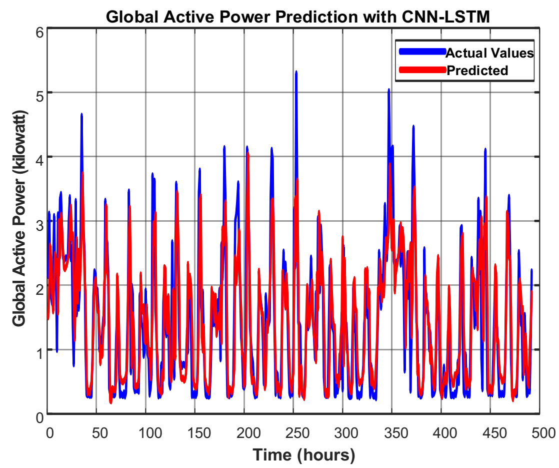

Fig. 6: Line plots of the predicted and actual values of CNN-LSTM model on the test set.

In the CNN-GRU model, 2 convolution layers, 2 maxpooling layers, 2 GRU layers, Adam optimizer, and 16 batch size were used. The first 500 hours of global active power prediction was performed on the test data of the CNN-LSTM model trained for 50 epochs. The prediction graph of the first 500 hours of the CNN-LSTM model is given in Fig. 7.

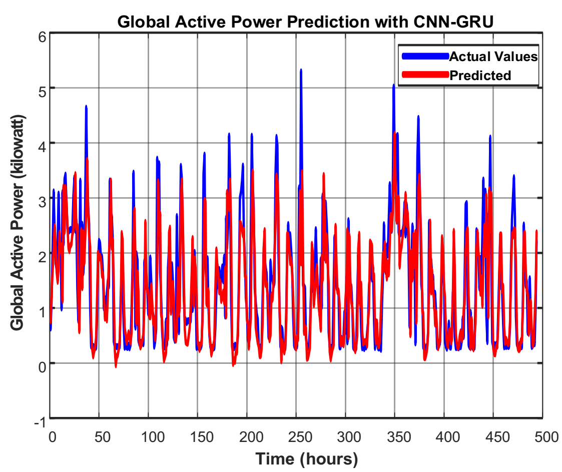

Fig. 7: Line plots of the predicted and actual values of CNN-GRU model on the test set.

The performances of the LSTM, CNN-LSTM and CNN-GRU models were evaluated with the error metrics MSE, RMSE, MAE and MAPE and the evaluation results are given in Table 1.

Table 1: Comparative analysis of models with four different error metrics.

	Evaluation metrices			
Models	**MSE**	**RMSE**	**MAE**	**MAPE**
LSTM	0.4874	0.6982	0.5005	56.584
CNN-LSTM	0.4149	0.6441	0.4336	41.648
CNN-GRU	0.4218	0.6494	0.4519	43.842

5. Conclusion

Three different deep learning-based models, two of which are hybrid, were used in the short-term load forecasting of residential energy consumption. The performances of the models were evaluated with error metrics, which are metrics for evaluating the forecast performance, and graphs showing the forecasted time. In the study, the CNN-LSTM model has lower error rates than the other hybrid model CNN-GRU and the LSTM model. The CNN-LSTM model proposed in this paper shows effective and fast performance in the forecasting of irregular electricity consumption patterns and residential electricity consumption forecasting.

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