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Research Article

MEDIUM-TERM RESIDENTIAL ENERGY CONSUMPTION PREDICTION USING TCN AND TCN-LSTM MODELS

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Abstract: *Prediction of electricity consumption is important for energy management and efficient use of energy resources. Accurate prediction of electricity consumption provides benefits to consumers and distribution companies in terms of correct management of electricity demand, electricity usage cost and waste control. This article proposes Temporal Convolutional Network (TCN) and Temporal Convolutional Network with Long Short-Term Memory (TCN-LSTM) models for medium-term electricity consumption prediction with an open access dataset in individual household electricity consumption prediction. An individual household's 5000-hour electricity consumption prediction is made with the proposed models. The performance of the proposed models is compared with different prediction algorithms. The performance of all models used in the study is evaluated with three evaluation metrics commonly used in prediction model performance evaluation. When the prediction performances of TCN and TCN-LSTM models are compared with the performances of other prediction algorithms, it is seen that they have lower error rates and are more successful in medium-term electricity consumption prediction.*

Keywords*: Electricity consumption prediction, TCN, TCN-LSTM.*

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1. Introduction

In the last decade, due to the rapid development of technology and widespread use of electrical devices, electricity consumption has increased significantly. The increasing demand for electricity, which has a wide range of uses, negatively affects the supply-demand balance. In order to achieve this balance, it is important to predict the electricity used in industries and households in particular. With accurate prediction of electricity consumption, consumers become conscious about reducing their costs and waste. Electricity distribution companies become conscious about adjusting the supply-demand balance of distributed electricity and energy management. Various methods, especially machine learning, deep learning and time series analysis methods, are used to predict electricity consumption. In the literature, these methods have been used in short-term, medium-term and long-term electricity consumption prediction. In the study [1], the Light Gradient Boosting Machine (LightGBM) model was used to predict building heating and cooling loads on the office building dataset created with EnergyPlus. The model showed high accuracy by obtaining 6.95% Mean Absolute Percentage Error (MAPE) in cooling load prediction and 7.09% MAPE in heating load prediction in office buildings. In the study [2], hybrid deep learning model was used to predict energy consumption on residential energy consumption data. The proposed hybrid model exhibited high prediction performance by achieving a low error rate of 0.37 Mean Square Error (MSE) in electrical energy consumption prediction. In the study [3], an integrated model was proposed to predict short-term energy consumption of educational buildings.

Considering the spatial features in time series data, the model was tested in an educational building in China and the results provided high prediction accuracy with low error rates compared to other energy consumption prediction models. In the study [4], a granular deep learning approach including Maximum Overlap Discrete Wave Transform (MODWT) and Long Short-Term Memory (LSTM) network was proposed to predict energy consumption in different sectors at the macro level. The proposed hybrid model showed superior performance when compared with six different algorithms and achieved more successful results especially in predicting energy consumption in commercial and transportation sectors. In the study [5], Support Vector Regression (SVR) method was used to predict building energy consumption in China. Multiple parameters such as annual mean temperature, relative humidity were used to improve the performance of SVR in building energy consumption prediction. The model achieved high accuracy with MSE below 0.001 and correlation coefficient (R^2) above 0.99 when compared with datasets from National Bureau of Statistics of China. In the study [6], a hybrid model combining Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) network is proposed to predict household energy consumption. The model was tested on individual household electricity consumption dataset in France and outperformed other models with 0.038 MSE, 0.072 Mean Absolute Error (MAE) and 8.23% MAPE. The proposed method successfully models dynamic user behavior and changes in weather conditions, especially thanks to the Bi-LSTM layer that can process both forward and backward data flow, providing high accuracy in energy consumption prediction. In the study [7], a model combining deep learning and Stationary Wavelet Transform (SWT) is proposed to predict household energy consumption. In particular, deep learning models such as LSTM, Gated Recurrent Unit (GRU), Bi-LSTM were studied on data that was denoised using bior2.4 wavelet filter together with the deep learning models. The model gave successful results in predicting electricity consumption in 1 minute, 15 minutes and 1 hour time intervals. In the study [8], a new hybrid model combining CNN, LSTM and Bi-LSTM models was proposed to simultaneously predict short-term and long-term energy consumption. The model was tested on residential energy consumption data and achieved high accuracy rates in short-term and long-term predictions. The model outperformed existing models in metrics such as MSE and MAE. In particular, it was found to have lower error rates compared to LightGBM and other traditional models. In the study [9], an LSTM-based model was used for both electricity consumption prediction and anomaly detection. The LSTM-based model was trained on one year electricity consumption data of 21,623 users in China. The model reduced the prediction error by 22% compared to the Auto Regressive Integrated Moving Average (ARIMA) model. In the study [10], LightGBM, Artificial Neural Networks (ANN) and linear regression models were used to predict the hourly energy consumption of buildings. The LightGBM model performed better with lower Root Mean Square Error (RMSE) values compared to other models. In the study [11], a model combining transfer learning and LSTM models was proposed to predict multiple electricity consumption profiles in smart buildings. The model grouped similar consumption profiles using the k-means clustering algorithm and reduced the computational time by applying transfer learning on these groups. The model was applied to data from two smart buildings in South Korea and it was observed that the model made faster and more accurate predictions compared to traditional methods. In the study [12], three different deep learning models, namely LSTM, GRU and Drop-GRU, were used to predict energy consumption. The models used on real-time data were compared and the Drop-GRU model performed better than the others. While the GRU model was successful in predicting high consumption values, the LSTM model gave more stable results in long-term predictions.

2. Material and Methods

In this study, deep learning-based TCN and TCN-LSTM models were developed to perform the electricity consumption forecast of individual households. The deep learning-based models provided end-to-end automatic categorization without requiring feature extraction or selection processes at any point in the time series data [13]. In addition, medium-term forecasting was performed with traditional forecasting models such as LightGBM, K-Nearest Neighbors (kNN), Random Forest (RF), SVR and XGBoost. First, hourly resampling was performed after filling the missing data in the time series data of the individual household. The resampled data was normalized to the 0-1 range using MinMaxScaler. Then, the time series data was prepared for training the models using a custom function that generates input-output sequences based on a selected number of previous time steps. These data were divided into training and testing subsets. Then, training and forecasting steps were performed with each developed model. The block diagram of the method used in the study is given in Figure 1.

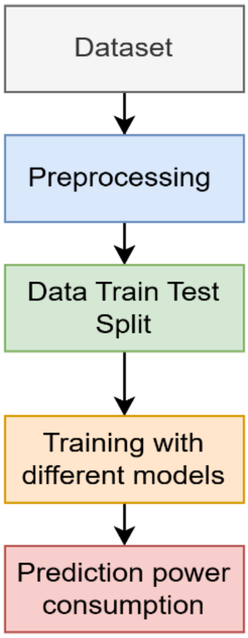

Figure 1. Flowchart of the proposed method.

2.1. Dataset

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.

2.2. Proposed TCN Model

This study proposes a new model using TCN to predict the electricity consumption of an individual household. In the first layer of the model, 1D convolution is performed with 128 filters having a kernel size of five. This convolution layer creates feature maps by extracting temporal dependencies in the signal. Causal convolution is used in the model to prevent future information from affecting the prediction process. In the next stage of the model, dilated convolution layers working with increasing amplitudes are used. Dilation factors are determined as 1, 2, 4, 8, 16 and 32. This structure allows the model to capture long-term correlations by allowing feature extraction from a wider area. After the convolution layers, the outputs are denoised with dropout layers before being fed to a dense layer and overfitting is prevented. In order to organize the learned representations of the model and create a more generalizable model, 200 and 100-unit dense layers using the ReLU activation function are added. The last output layer of the model consists of a single unit that gives the output value of the electricity consumption of an individual household. MSE was used as the loss function of the model and the Adam algorithm was preferred as the optimizer. The parameters of the proposed TCN model are given in detail in Table 1.

Table 1. Detailed layers and parameters of the proposed TCN model.

Layer	Layer name	Kernel × unit	Other layer parameters	Output shape
1	TCN	5 × 128	Dilations=[1,2,4,8,16,32], Causal Padding, Activation=None	(None, 40, 128)
2	Dense	200	Activation=ReLU, L2 Regularization=0.01	(None, 200)
3	Dropout	-	Rate=0.2	(None, 200)
4	Dense	100	Activation=ReLU, L2 Regularization=0.01	(None, 100)
5	Dropout	-	Rate=0.2	(None, 100)

2.3. Proposed TCN-LSTM Model

In this study, a hybrid TCN-LSTM model is proposed for time series prediction. The model consists of a combination of TCN and LSTM networks. TCN uses dilated causal convolutions with dilation rates [1,2,4,8] to learn long-term dependencies in time series data, while LSTM layers improve prediction performance by capturing sequential dependencies over time. The input of the proposed model is time series data containing 100 time steps, scaled using Min-Max normalization.

First, two TCN layers form the TCN block of the model. These layers extract features from the input using 3 × 128 filters, and each TCN layer returns sequences to maintain the temporal structure. The model applies Batch Normalization and Dropout (0.2) after each TCN layer to enhance generalization.

After the TCN block, there are two consecutive LSTM layers. The first LSTM layer contains 128 units and is set to return_sequences=True, passing the sequence to the next LSTM layer. The second LSTM layer contains 64 units. To mitigate overfitting, Dropout (0.2) is applied after each TCN and LSTM layer.

Finally, the model has a Dense layer with a single neuron, which produces the predicted value. The model is trained using the Adam optimizer (learning rate = 0.001) and MSE loss function. During training, Early Stopping, ReduceLROnPlateau, and ModelCheckpoint are utilized to optimize performance. Table 2 provides detailed information on the proposed model's architecture.

Table 2. Detailed layers and parameters of the proposed TCN-LSTM model.

Layer	Layer name	Kernel × unit	Other layer parameters	Output shape
1	TCN	3 × 128	Dilations=[1,2,4,8], Return Sequences=True, Input Shape=(100,1)	(None, 100, 128)
2	BatchNormalization	-	-	(None, 100, 128)
3	Dropout	-	Rate = 0.2	(None, 100, 128)
4	TCN	3 × 128	Dilations=[1,2,4,8], Return Sequences=True	(None, 100, 128)
5	BatchNormalization	-	-	(None, 100, 128)
6	Dropout	-	Rate = 0.2	(None, 100, 128)
7	LSTM	128 Unit	Return Sequences = True	(None, 100, 128)
8	Dropout	-	Rate = 0.2	(None, 100, 128)
9	LSTM	64 Unit	-	(None, 100, 64)

3. Experimental Results

In the study, 7 different models, namely LightGBM, KNN, RF, SVR and XGBoost, TCN and TCN-LSTM, were trained to predict the first 5000 hours of global active power on 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. The TCN and TCN-LSTM models proposed for the study were optimized in the best way to obtain the lowest error rates in predicting the most energy consumption. The performances of the models used in the study were evaluated with MSE, RMSE and MAE performance evaluation metrics.

The TCN model used the Adam optimizer and a batch size of 64. The first 5000 hours of global active power were predicted on the test data of the TCN model trained for 100 epochs. The predictions were made on the test data using time series sequences of 100 time steps. The first 5000 hour forecast graph of the TCN model is shown in Figure 2.

The TCN-LSTM model used the Adam optimizer and a batch size of 32. The first 5000 hours of global active power were predicted on the test data of the TCN-LSTM model trained for 100 epochs. The predictions were made on the test data using time series sequences of 100 time steps. The first 5000 hour forecast graph of the TCN-LSTM model is shown in Figure 3.

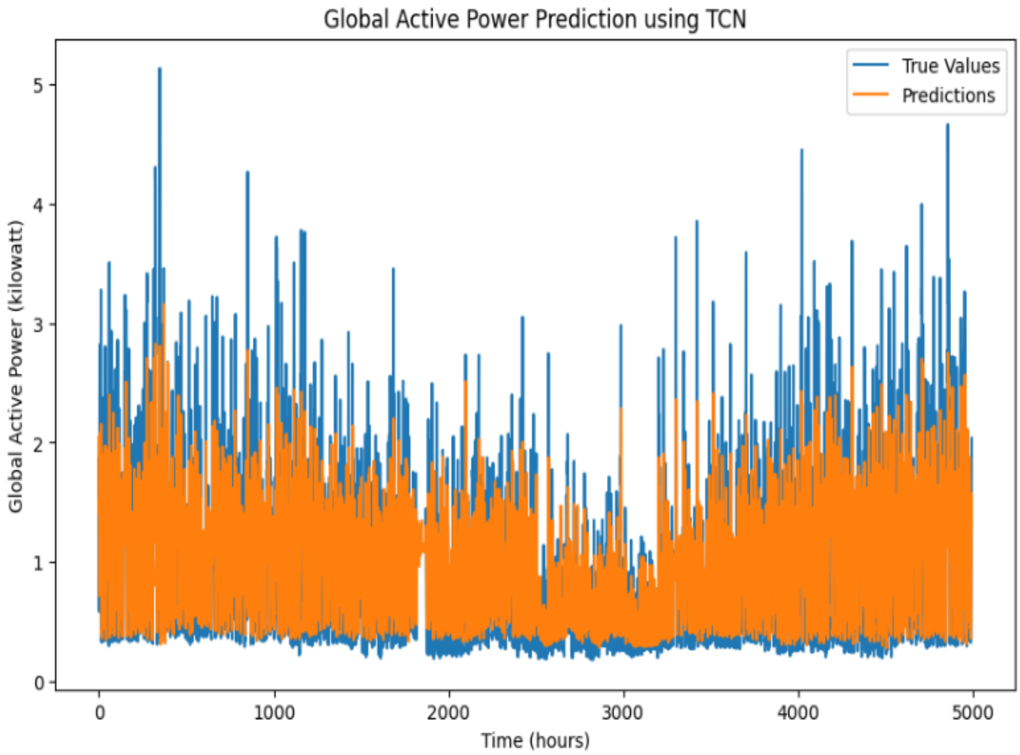

Figure 2. Line plots of the predicted and actual values of TCN model on the test set.

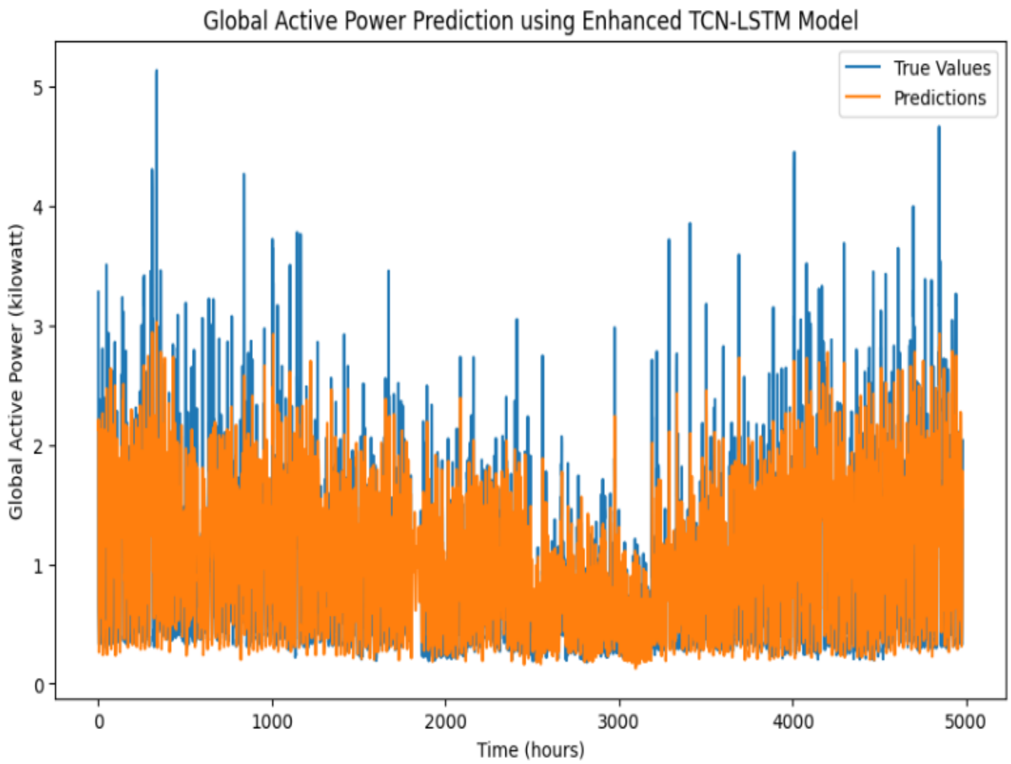

Figure 3. Line plots of the predicted and actual values of TCN-LSTM model on the test set.

In the study, the performances of all models used for electricity consumption prediction were evaluated with three different error metrics and the models with the best prediction performance were

TCN and TCN-LSTM models. MSE is 0.214, 0.23 for TCN-LSTM, TCN, respectively. RMSE is 0.463, 0.479 for TCN-LSTM, TCN, respectively. MAE is 0.312, 0.332 for TCN-LSTM, TCN, respectively. Among the models with the best prediction performance, TCN and TCN-LSTM, the TCN-LSTM hybrid model exhibited relatively better performance than TCN. The comparative table of the performances of different models used in the study is given in Table 3.

Table 3. Evaluation results of different models.

Model	**MSE**	**RMSE**	**MAE**
LightGBM	0.337	0.58	0.408
kNN	0.485	0.696	0.493
RF	0.368	0.606	0.451
SVR	0.474	0.688	0.523
XGBoost	0.355	0.596	0.427
TCN	0.23	0.479	0.332
TCN-LSTM	0.214	0.463	0.312

4. Conclusions

In this study, electricity consumption prediction was performed using the IHEPC dataset. Seven different prediction models, one of which is hybrid, were used in medium-term residential energy consumption load prediction. The performances of the models were evaluated with error metrics, which are metrics used to evaluate the prediction performance, and graphs showing the predicted time. In the examinations made with error metrics, the TCN and TCN-LSTM models proposed in the study showed close performance to each other in 5000-hour prediction and showed the best performance compared to the other five models. Among the proposed models, the hybrid model TCN-LSTM model showed the highest prediction performance with low error metrics. The TCN-based models proposed in the study showed effective and fast performance in residential electricity consumption prediction.

Ethical statement

The authors declare that this document does not require ethics committee approval or any special permission. This review does not cause any harm to the environment and does not involve the use of animal or human subjects.

Conflict of interest

The author declares no conflict of interest.

Authors' Contributions

M. G: Conceptualization, Methodology, Formal analysis, Writing - Original draft preparation
Ö. Y: Resources, Investigation, Formal analysis.
Y. D: Resources, Investigation, Formal analysis.
All authors read and approved the final manuscript.

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