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A Novel CNN-GRU-Based Hybrid Approach for Short-Term Residential Load Forecasting

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ABSTRACT Electric energy forecasting domain attracts researchers due to its key role in saving energy resources, where mainstream existing models are based on Gradient Boosting Regression (GBR), Artificial Neural Networks (ANNs), Extreme Learning Machine (ELM) and Support Vector Machine (SVM). These models encounter high-level of non-linearity between input data and output predictions and limited adoptability in real-world scenarios. Meanwhile, energy forecasting domain demands more robustness, higher prediction accuracy and generalization ability for real-world implementation. In this paper, we achieve the mentioned tasks by developing a hybrid sequential learning-based energy forecasting model that employs Convolution Neural Network (CNN) and Gated Recurrent Units (GRU) into a unified framework for accurate energy consumption prediction. The proposed framework has two major phases: (1) data refinement and (2) training, where the data refinement phase applies preprocessing strategies over raw data. In the training phase, CNN features are extracted from input dataset and fed in to GRU, that is selected as optimal and observed to have enhanced sequence learning abilities after extensive experiments. The proposed model is an effective alternative to the previous hybrid models in terms of computational complexity as well prediction accuracy, due to the representative features' extraction potentials of CNNs and effectual gated structure of multi-layered GRU. The experimental evaluation over existing energy forecasting datasets reveal the better performance of our method in terms of preciseness and efficiency. The proposed method achieved the smallest error rate on Appliances Energy Prediction (AEP) and Individual Household Electric Power Consumption (IHEPC) datasets, when compared to other baseline models.

INDEX TERMS CNN, CNN-GRU, deep learning, energy forecasting, electricity consumption prediction, GRU, LSTM, short-term load forecasting.

I. INTRODUCTION

Since last two decades, electricity consumption has overwhelmingly increased around the globe due to economic developments and growing population. In terms of social and economic development of a region, energy is considered as the most important factor, which contributes incredibly to its advancements and an improved economy. Accurate electricity consumption prediction is essential for appropriate energy supply, its capacity expansion, revenue analysis, capital investment and market research management. However, the large number of uncertainties such as long-term prediction for last two decades have impaired the interest of scientists and the continuous development of new approaches for more accurate and reliable future energy consumption predictions.

Future energy consumption prediction is a time series problem, comprising of univariate or multivariate features. The data is recorded from smart sensors including redundancy, missing values, outliers and uncertainties [1]. Due to the seasonal variation in time series data patterns and irregular trend components, traditional machine learning techniques fail to learn data sequential patterns for accurate energy forecasting in [2]. Thus, traditional machine learning techniques

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are imperfect for complex real-world scenarios. In contrast to machine learning based techniques, deep learning models yield eventually better accuracy, which are widely studied in different data science domains such as video summarization [3], image classification [4], action and movies characters' recognition [5], [6], etc. In the last few years, researchers from diverse domains are thriving to achieve higher accuracy and enhanced performance by integrating several deep learning models for effective data analysis [7]. Similarly, for electricity consumption prediction a number of strategies based on deep learning and hybrid models have been presented in the related literature. However, their performance in terms of practical trustworthy implementation and accurate prediction is still questionable. Although the hybrid models achieved state-of-the-art results, but they do sacrifice the computational efficiency and pose short-term forecasting delays, where its practical usage is a huge liability in real-world scenarios.

To this end, in this research, we proposed a hybrid (CNN-GRU) electricity consumption prediction model and evaluated its performance over several benchmark datasets. After extensive experiments on several machine learning and deep learning models, finally, we selected CNN-GRU model for short-term future electricity consumption prediction. We achieved state-of-the-art accuracy by applying several data refinement techniques, followed by its training using our fine-tuned hybrid model. The CNN in our proposed model extracts spatial features and the multilayered GRU is used to model the temporal features corresponding to its output CNN features. The main contributions of the proposed work are mentioned below:

1. Experimenting on a number of solo and hybrid machine learning and deep learning models over various datasets in terms of prediction accuracy. These models include Linear regression, SVR, Tree prediction, CNN, Long Short-Term Memory (LSTM), CNN-LSTM and CNN-GRU. Thus, after a deep analysis of these models, we advocate the usage of CNN-GRU as optimal model, that is applicable for real-world energy prediction problems.
2. A unique CNN-GRU based hybrid model for hourly electricity consumption prediction is presented in this article. To achieve a flexible and generalized model, we employ CNN features for sequence representation followed by a multi-layered GRU for its effective learning. Thus, the proposed hybrid model is demonstrated to be the best option while considering short-term residential load forecasting, as evident from experiments.
3. The proposed hybrid CNN-GRU model is evaluated on AEP and IHEPC benchmark datasets and achieved satisfied results as compared to other baseline models. Experiments over AEP dataset witnesses 4% reduced error rates for MAE and RMSE, while the results over IHEPC dataset are promising when compared to recent state-of-the-art methods.

II. LITERATURE REVIEW

A number of studies have been conducted in literature for electricity consumption prediction i.e. ARIMA [7], SVR [8], time series modeling [1], linear regression and neuro fuzzy models [9], ANN [10], sequence to sequence learning [11], Deep Recurrent Neural Network (DRNN) [12] and a number of hybrid models [13]–[16]. The statistics presented in [17] show different methods' utilization for energy consumption prediction where 47% methods utilize ANN and rest of the researchers employ SVM, decision tree and other models with percentage of 25, 4 and 25, respectively. The ANN models are mostly employed for building energy consumption, as in [18] an EnergyPlus based electricity forecasting system is developed, where EnergyPlus refers to a simulation software which integrate equipment's, system models and energy load. Mohammadi *et al.* used LSTM and an autoencoder to predict solar energy consumption by using weather data and also test several other deep learning models for optimal model selection [19]. Muralitharan *et al.* suggested various approaches for short, medium and long duration-based forecasting. For instance, an ANN based genetic algorithm for mid-term/short-term energy prediction and neural network based particle swarm optimization algorithm is suggested for long-term energy prediction and also compared these models with CNN and achieved comparatively better results [20]. Some studies compared the usage of regression and classification models with ANN. For instance, Ahmad *et al.* compared their decision tree with ANN model, where ANN achieved best results by using previous weather data, comprising of temperature (indoor and outdoor), wind speed, humidity and temporal information [21]. In a followed research [22], time series, SVM, ANN and the combination of these models are tested and compared against each other. The combination of ANN with SVM performed better as compared to other models. Daut *et al.* integrate BPNN, SVM and ANN with swarm intelligence, where SVM performed better than ANN. Similarly, some recent studies compared the results of deep learning models with machine learning models [23]. In most cases the results of deep learning models performed well as compared to machine learning models. Paterakis *et al.* achieved good results on a multi-layer perceptron and compared the results with ensembled boosting, linear regression, gaussian regression, regression tree and SVM [24]. In [25], several deep learning models are compared with traditional models where deep belief network achieved highest performance among these models. Fan *et al.* used SVM and random forest for electricity consumption prediction which outperformed the MLP generated output results [26]. The research in [27] proposed MLP based electricity forecasting model and achieved state-of-the-art results. Also, they compared the results with SVM, random forest, linear regression and gradient boosting machine.

Concluding the overall related literature, there are three types of baseline models for electricity consumption prediction: (1) machine learning, (2) deep learning and

(3) hybrid models. In machine learning models, linear regression, SVR and decision tree are mostly used to predict electricity consumption. N. Fumo *et al.* used linear regression and multiple regression for short-term load forecasting and also performed analysis referencing to time resolution [28]. K. Amber *et al.* used multiple linear regression through genetic programing [29]. Similarly, in [30] and [31], multiple regression models are developed. Bogomolov *et al.* [32] used random forest regressor based on human dynamics analysis for weekly electricity prediction. Y. Chen *et al.* proposed SVR model for electricity forecasting by using office building energy consumption and temperature data [33]. Similarly, Y. Yaslan *et al.* developed a hybrid model which is the combination of Empirical Mode Decomposition and SVR for electricity consumption prediction [34]. Machine learning models performed well but due to multicollinearity in independent variable correlation of electricity consumption, these models have inadequate electricity consumption prediction potentials. On top of this, these models often pose overfitting problem with increase in data. Similarly, several sequential learning based deep neural networks are developed for electricity consumption prediction. For instance, LSTM based electricity forecasting model is proposed in [35], where the input electricity data is preprocessed through autocorrelation graph to extract hidden features and then fed to LSTM network. In the same way [36] and [37] also developed deep learning models, but modeling the temporal and spatial features of electricity data is difficult for generalization. Next, the hybrid models performed well for the aforementioned problem and attained the baseline results. Kim *et al.* developed CNN-LSTM model for electricity prediction and recorded the lowest error rates as compared to other baseline models, because CNN-LSTM model learned from both spatial and temporal features [38]. Similarly, Ullah *et al.* developed a hybrid model by integrating CNN with multilayer bi-directional LSTM [13]. In hybrid deep learning models, CNNs are used to model spatial features and recurrent models are used to model temporal features but still the error rate is much higher. Therefore, in this work we developed a hybrid model by employing CNN for spatial features representation and multi-layered GRU for temporal features representation to achieve the lowest error rates when compared to the mentioned models.

III. PROPOSED ELECTRICITY CONSUMPTION PREDICTION FRAMEWORK

Accurate electricity consumption prediction improves energy usage rates that help the building administration to make better decisions for energy management and thereby saves a handsome amount of energy. However, due to noisy and random disturbances, the accurate energy consumption prediction is a difficult task. To obtain accurate results for energy consumption prediction, a unique framework is developed in this paper as shown in **Figure 1.** and explain in subsequent section. The proposed framework has two basic steps (1) data refinement (2) training.

A. DATA REFINEMENT

The input data is refined before training our CNN-GRU model because the neural networks are sensitive to diverse data. So, in this work we employ data preprocessing strategies to remove outlier and missing values and normalize the input data. The proposed method is evaluated on two benchmark datasets AEP and IHEPC. The AEP dataset standard transformations are employed to transform the input data into a specific range. The features range in AEP dataset lies between 0 to 800 as shown in **Figure 2a**, by applying standard transformation the features range is converted into −4 and 6 and as shown in **Figure 2b**. The basic operation of standard transformation formula is shown in equation 1. IHEPC dataset includes some null, outlier and redundant values. All the non-significant values are removed and bring each feature is converted into a specific range by applying minmax scalar. The range of features in IHEPC dataset lies between 0 to 250 as shown in **Figure 2c**, after applying minmax transformation the range of these features are converted

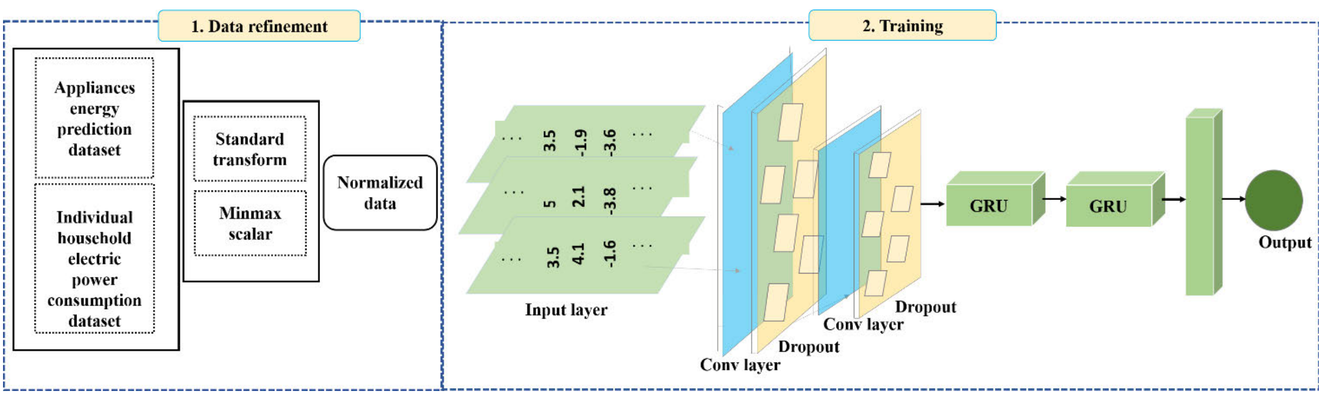


FIGURE 1. Proposed CNN-GRU model-based framework for short-term energy consumption prediction. The input data is preprocessed in the first step by applying standard and minmax scalar to convert it into a specific range of values; in second step the normalized data is fed into CNN-GRU model for training.

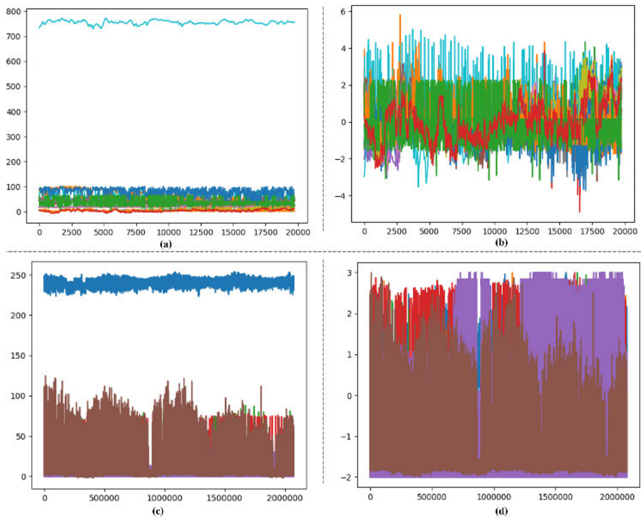


FIGURE 2. Original and normalized data visualization before and after applying minmax and standard transformation.

into -2 and 3 as shown in **Figure 2d**. The basic operation of minmax scalar is shown in equation 2. The experiments over AEP dataset produce good results for standard transformation while experiments over IHEPC dataset gave good results on minmax scalar.

$$Y = (X - U)/S \tag{1}$$

$$Y = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Here in "X" represents the actual input data in the dataset, "U" represent the mean, "S" is the standard deviation, "X_{min}" and "X_{max}" signify the minimum and maximum value in the dataset.

B. PROPOSED CNN-GRU ARCHITECTURE

In this research, we developed a two-step framework for short-term electricity consumption prediction. In the first step the input data is preprocessed to remove outliers, missing and redundant values. We employed standard and minmax scalar techniques to normalize the input datasets into a specific range. The processed input data is then fed to training stage. Next, we performed experiments on Linear regression, SVR, Tree prediction, CNN, LSTM, CNN-LSTM and CNN-GRU. Inspired by the results of CNN-GRU, we developed a hybrid model incorporating CNNs with multi-layered GRU model and achieved up-to-date results. The architecture of the proposed hybrid model is shown in the training step of **Figure 1** which is composed of two main neural network models, CNN and GRU.

CNN is particularly designed for image classification tasks, where the network accepts two-dimension data. CNNs are also used for time series analysis which is one-dimensional data. The weight sharing concept is used in CNN [39]–[41] that provide high performance on non-linear problems such as time series prediction, electricity consumption prediction, stock price prediction etc. The internal operation of convolution and pooling layers is shown in **Figure 3**. Applying the convolution on input data x1, x2, x3, x4, x5 and x6 transforms then into transformed to f1, f2, f3 and f4 feature maps, as shown in **Figure 3**. After the convolutional layer, a pooling layer is employed to model the acquired feature maps and convert them into features to a more abstract form between hidden layers and memory cells. Unfortunately, the RNN suffers from exploding and vanishing gradient problem. Exploding gradients refers to an issue in recurrent neural networks, where the norm of the gradient for "long-term" temporal components grows exponentially faster than the short-term [42]. GRU and LSTM are the most commonly used type of Recurrent Neural Network (RNN). Unlike CNNs, RNNs have a backward connection that vastly influence the model accuracy in a negative manner, these issues are tackled by LSTMs [43]. That is in advanced architecture of RNN, particularly developed for long range dependency in temporal features. The internal structure of LSTM includes cell blocks. The cell state and hidden state are transferred from one block to another while the memory block is used to remember the state through gates. The LSTM architecture includes three gate the input, forget and output while the GRU has only two gates layers: the reset (Y) and an update (Z) gate. The update gate checks the memory of the earlier cell to stay active and the reset gate is used to combine input sequence of next cell with preceding cell memory. However, LSTM is a bit different in some ways: firstly, the GRU cell consists of two gates as a substitute LSTM are three. Secondly, the input and forget gate in LSTM are merged to update gate and for hidden state reset gate are directly applied. The general equations of GRU cell are shown in equation 3-6. We choose multi-layer GRU by considering that they train faster due to a smaller number of parameters. The general architecture of RNN, LSTM and GRU are shown in **Figure 4**.

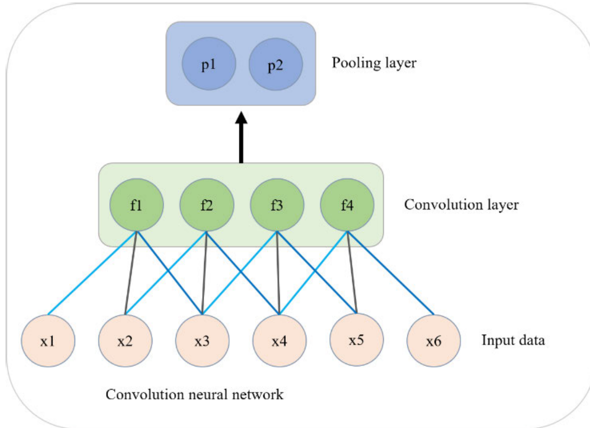


FIGURE 3. Simple convolution and pooling layer architecture.

$$z_t = \Theta\left(W_z.\left[h_{t-1}, x_t\right] + b_z\right) \tag{3}$$

$$r_t = \Theta\left(W_r.\left[h_{t-1}, x_t\right] + b_r\right) \tag{4}$$

$$\hat{h}_t = tanh\left(W_h.\left[r_t \cdot h_{t-1}, x_t\right] + b_h\right) \tag{5}$$

$$h_t = \left(1 - z_t\right) \cdot h_{t-1} + z_t \cdot \hat{h}_t\Big) \tag{6}$$

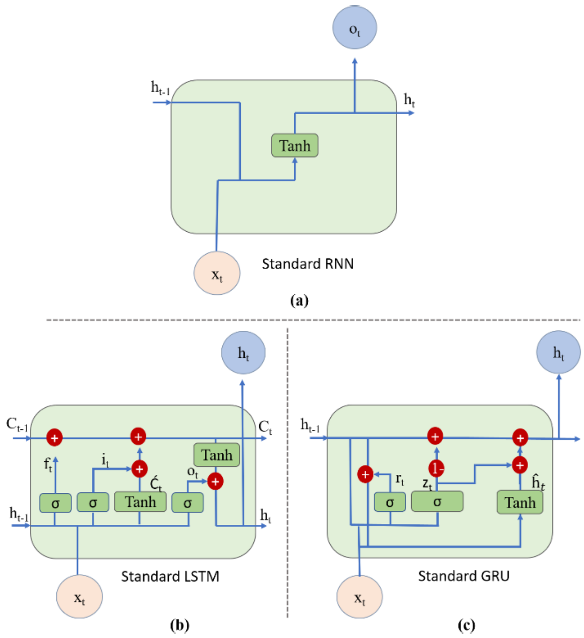


FIGURE 4. Standard architecture of RNN, LSTM and GRU.

In the proposed framework, we employ CNN features for sequence representation followed by a multi-layered GRU for its effective sequence learning. The CNN layers are used for spatial features extraction from input refined data, and then fed into multilayer GRU. In this paper, we used two CNN layers with Relu activation function and kernel size of 2 while the filter is 1×16 and 1×8 for the first and second layer, respectively with. After extracting the spatial features, they are then input into GRU layers. Two GRU layers are used to model temporal features and finally, a dense layer is used to predict future energy consumption. The proposed model is evaluated using AEP and IHEPC datasets which are available on UCI repository. For training and testing purposes the datasets are split into 75%, 5% and 20% for training, validation and testing, respectively.

IV. EXPERIMENTAL RESULTS

This section includes the system's configuration, dataset description, evaluation metrics, experimental results over several traditional machine learning and deep learning models tested on AEP and IHEPC datasets and comparisons with other baseline models.

A. SYSTEM CONFIGURATION

The effectiveness of the proposed CNN-GRU model is confirmed using AEP dataset [44] and IHEPC datasets [45] available on UCI repository. The model was trained over TITAN GPU with Core i5 processor, 64 GB RAM and Ubuntu. The implementation was performed in Python3 Keras with TensorFlow at the backend and Adam optimizer [46].

B. DATASETS

The proposed method is evaluated on AEP dataset [44] and IHEPC dataset [45]. The AEP dataset is recorded in ten-minutes resolution for about 4.5 months. The dataset includes 29 different parameters related to weather information (dew point, temperature, wind speed, humidity and pressure), light and appliances energy consumption etc. The data is gathered from wireless sensor networks from both indoor and outdoor environments. The outdoor data is collected from a nearby airport. The dataset collected from a building includes 9 indoor and 1 outdoor temperature sensors, 9 humidity sensors in which 7 are integrated with the indoor environment and one is in outdoor environment. Outdoor da including temperature, humidity, dew point, visibility, pressure and visibility are collected from nearest airport. The house temperature is collected from different locations where T1, T2, T3, T4, T5, T6, T7, T8, and T9 is recorded in kitchen, living room, laundry room, office room, bathroom, outside building, ironing room, teenager room and parent room, respectively. Similarly, the house humidity is also collected from the same locations in the house where RH_1, RH_2, RH_3, RH_4, RH_5, RH_6, RH_7, RH_8 and RH_9 is collected from kitchen, living room, laundry room, office room, bathroom, outside building, ironing room, teenager room and parent room, correspondingly. The outside temperature, pressure, outside humidity RH_out, wind speed and visibility is collected from weather station.

The IHEPC dataset includes 9 parameters which includes date, time, voltage, global-active-power (GAP), intensity, global-reactive-power (GRP) and submetering 1-3. Where GAP is the current average minute power in kilowatt, GRP is the current average minute power in kilowatt, average voltage in volt, current global intensity in ampere and submetering 1, 2 and 3. Submetering indicate electricity consumption in kitchen, laundry room and air-conditioner and electric water heater, respectively. The dataset is recorded between 2006 and 2010 in residential house in France in one-minute resolution.

C. EVALUATION METRICS

The proposed CNN-GRU model is assessed on RMSE, MAE and MAE metrics where the mathematical equations are shown in equation 7-9. Basically, these metrics calculate the variance between predicted and actual values. For instance,

$$MSE = \frac{\mathbf{1}}{\boldsymbol{n}} \sum\nolimits_{\mathbf{1}}^{\boldsymbol{n}} (y - \hat{y})^2 \tag{7}$$

$$MAE = \frac{1}{n} \sum\nolimits_{1}^{n} |y - \hat{y}| \tag{8}$$

$$RMSE = \sqrt{\frac{1}{n} \sum\nolimits_{1}^{n} (y - \hat{y})^2} \tag{9}$$

MSE calculates the average square value between ground truth and the predicted values. MAE demonstrates the percentage difference between predicted variables, while RMSE computes percentage difference between actual and predicted value.

D. COMPARATIVE ANALYSIS OF MACHINE LEARNING AND DEEP LEARNING MODELS

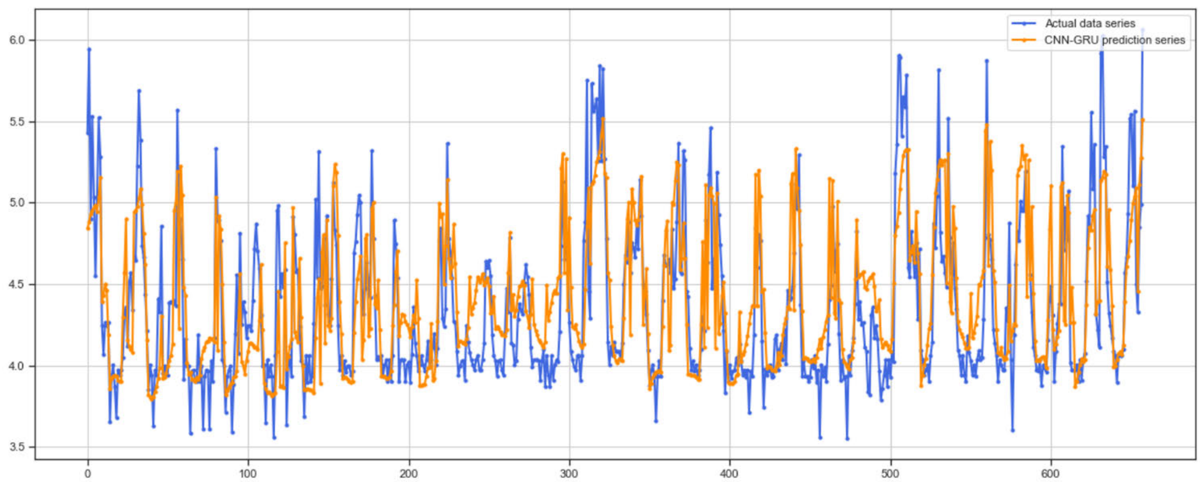
1) IHEPC DATASET

In this article, we investigated several machine learning and deep learning models to find an optimal paradigm for short-term electricity consumption. First, we performed experiments over machine learning models that include Linear regression, SVR and Tree prediction. The performance of SVR model is quite good when compared to other two models. For instance, linear regression achieved 0.16, 0.41 and 0.30 MSE, RMSE and MAE, decision tree attained 0.17, 0.41 and 0.33 MSE, RMSE and MAE and SVR achieved 0.12, 0.35 and 0.27 MSE, RMSE and MAE, correspondingly as demonstrated in **Table 1.**

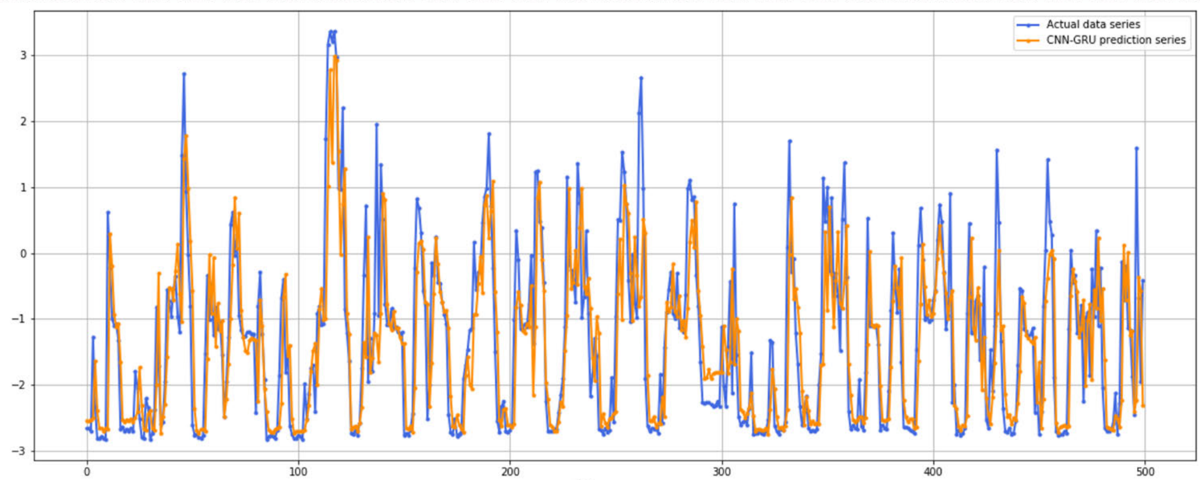
After extensive experiments on machine learning models and noticing their behavior for energy time series data, we perform evaluated several deep learning models, and noticed comparatively improved results. Among various choices of deep learning models, we performed experiments on CNN, LSTM, CNN-LSTM and CNN-GRU. From experiments, we conclude that CNN attained 0.17, 0.41 and 0.32 values for MSE, RMSE and MAE, correspondingly.

TABLE 1. Performance of different machine learning and deep learning models for AEP dataset.

Method	MSE	RMSE	MAE
Linear regression	0.16	0.41	0.30
Decision tree	0.17	0.41	0.33
SVR	0.12	0.35	0.27
CNN	0.17	0.41	0.32
LSTM	0.25	0.50	0.36
CNN-LSTM	0.14	0.38	0.30
Proposed	**0.09**	**0.31**	**0.24**



(a)



(b)

FIGURE 5. Prediction performance of the proposed CNN-GRU model over test data, where (a) shows the prediction over AEP dataset and (b) demonstrates the prediction over IHEPC dataset.

LSTM achieved 0.25, 0.50 and 0.36 MSE, RMSE and MAE, respectively, while CNN-LSTM attained 0.14, 0.38 and 0.30 MSE, RMSE and MAE, respectively. Finally, CNN-GRU achieved 0.09, 0.31 and 0.24 MSE, RMSE and MAE, correspondingly. The proposed model attains the smallest error rate as compared to CNN LSTM and CNN-LSTM models. The prediction performance of these models over AEP test data is shown in **Figure 5a.**

2) IHEPC DATASET

After performing experiments over AEP dataset next, we evaluated the proposed model on IHEPC dataset, where as expected, the machine learning techniques showed the inadequate results as compared to deep learning models. Linear regression attained 0.60, 0.77 and 0.55 MSE, RMSE and MAE, respectively, decision tree achieved 0.59, 0.77 and 0.54 MSE, RMSE and MAE, correspondingly, while SVR achieved, 0.59, 0.77 and 0.49 MSE, RMSE and MAE respectively. For MSE the results of linear regression and SVR are better than the decision tree, while for MAE the SVR model attained the lowest error rate. The RMSE for the tested machine learning models are almost similar.

In a similar way, we test the deep learning models over IHEPC dataset and obtained satisfactory results. The CNN achieved 0.37, 0.67 and 0.47 values for MSE, RMSE and MAE correspondingly. The LSTM model reduced the rate up to 0.41, 0.64 and 0.40 MSE, RMSE and MAE, respectively. Similarly, CNN-LSTM scored 0.43, 0.65 and 0.40 MSE, RMSE and MAE, correspondingly. In contrast, the proposed hybrid CNN-GRU model attained 0.22, 0.47 and 0.33 MSE, RMSE and MAE, respectively as demonstrated in **Table 2**. The prediction performance of the proposed model over IHEPC test data is shown in **Figure 5b.**

TABLE 2. Performance of different machine learning and deep learning models over IHEPC dataset.

Method	MSE	RMSE	MAE
Linear regression	0.60	0.77	0.55
Decision tree	0.59	0.77	0.54
SVR	0.59	0.77	0.49
CNN	0.37	0.67	0.47
LSTM	0.41	0.64	0.40
CNN-LSTM	0.43	0.65	0.40
Proposed	**0.22**	**0.47**	**0.33**

E. COMPARISON OF PROPOSED HYBRID CNN-GRU MODEL OVER AEP DATASET WITH OTHER BASELINE METHODS

The proposed hybrid CNN-GRU model was also compared with other baseline models by performing experiments on AEP [44] dataset. These models include XGBoost [49], Gradient boosting machine [50] and AIS-RNN [51].

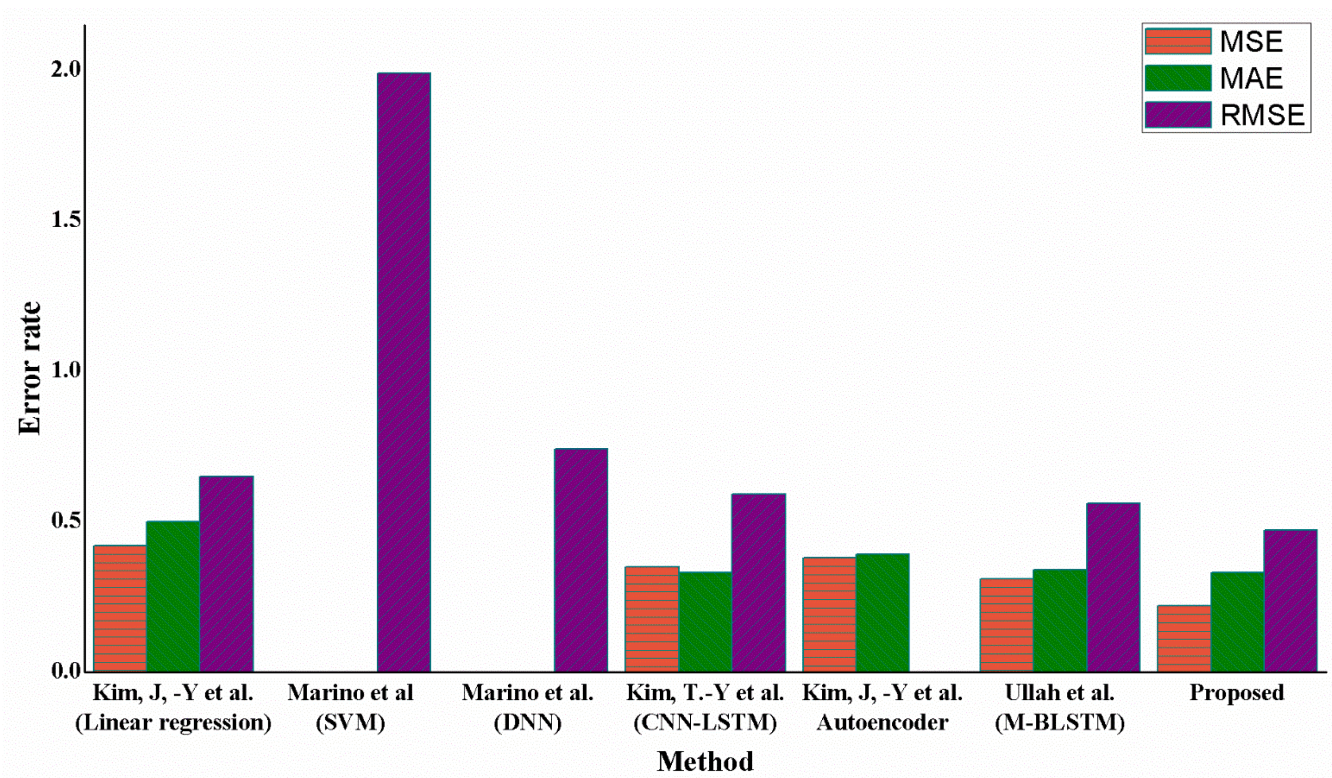


FIGURE 6. Comparison of the proposed hybrid CNN-GRU model with Kim T, -Y et al [38], Kim, J, -Y *et al.* [47], Marino *et al.* [48] and Ullah *et al.* [13].

The comparison of our proposed model using different evaluation metrics with baseline models in the related literature is shown in **Table 3**. As evident from **Table 3**, XGboost model attained 0.26 MSE and 0.59 RMSE, while Gradient boosting machine achieved 0.66 MAE and 0.35 RMSE and AIS-RNN attained 0.59 RMSE. In contrast, the proposed CNN-GRU model achieved 0.09, 0.31 and 0.24 MSE, RMSE and MAE, respectively, which are the lowest error rates when compared to other models.

TABLE 3. Comparison of the proposed model over AEP dataset with other state-of-the-art techniques.

Method	MSE	RMSE	MAE
XGBoost [49]	-	0.59	0.26
Gradient boosting machine [50]	-	0.35	0.66
AIS-RNN [51]	-	0.59	-
Proposed	**0.09**	**0.31**	**0.24**

F. COMPARISON OF PROPOSED CNN-GRU MODEL OVER IHEPC DATASET WITH BASELINE METHODS

In this section, the performance of the proposed CNN-GRU model over IHEPC dataset is compared with baseline models. The results are compared with, linear regression [47] SVM [52], CNN-LSTM [38], autoencoder [47], multilayer bi-directional LSTM (MLBD_LSTM) [13] and deep neural network (DNN) [48] as shown in **Figure 6**. For instance, linear regression attained 0.42, 0.65 and 0.50 MSE, RMSE and MAE while SVM achieved 1.99 RMSE respectively. The CNN-LSTM model attained 0.35, 0.59 and 0.33 MSE, RMSE and MAE, correspondingly while the autoencoder achieved 0.38 and 0.39 MSE and MAE, respectively. MLDB_BLSTM achieved 0.31, 0.34 and 0.56 MSE, MAE and RMSE, respectively while DNN attained 0.74 RMSE. The proposed CNN-GRU model attained the lowest values of 0.22, 0.47 and 0.33 for metric MSE, RMSE and MAE, respectively as compared to other models.

V. CONCLUSION

In this work, we proposed a hybrid CNN-GRU model to predict electricity consumption in residential buildings. The proposed model is tested on AEP and IHEPC datasets which are publicly available. Due to the non-linearity in the input data, first we normalized it by applying a standard minmax scalar then fed the normalized data for further training processes. Next, we investigated several machine learning and deep learning models and optimally developed a hybrid model in which we combined CNN with GRU. First, we extracted spatial features through CNN and then fed them into our multi-layered GRU to model temporal features corresponding to the input time series data. The proposed model work well as compared to other baseline models, indicating the real-world implementation of our proposed model for residential buildings.

In future work, we aim to will test the proposed CNN-GRU model on different datasets and will improve the performance of the model by adding fuzzy logic concepts. Currently the model is tested on residential building data we will also test the model on commercial datasets. In this work, we predicted short term electricity, in the future our target is to test the model performance for medium term and long-term electricity consumption prediction.

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