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An Optimized Hybrid Deep Learning Model for Appliance Energy Prediction in Smart Homes

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Abstract

The increased energy consumption due to industrial machines and household appliances affectenergy sustainability as well as economic stability. To meet the energy demand various practices are followed worldwide. Research on sustainable energy production is at peak meanwhile research towards reducing the cost of energy generation is gaining more interest in recent times. one of the key points considered to reduce the power generation cost is energy consumption prediction. Future demands can be predicted, and necessary power can be generated or delivered to meet the demand. Specifically, prediction model is essentially required for smart homes as they utilize multiple devices for smart connectivity. Machine learning algorithms are widely used for energy prediction applications. However, the performance of machine learning models needs manual selection of features and is still complex in data analysis and decision-making process. Recently deep learning (DL) techniques are used in various classification and prediction applications. DL superior performance is incorporated for energy prediction for smart home appliances. This research work presents a hybrid optimized DL model using Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) network. Additionally, to improve the prediction performances, the parameters of the hybrid DL model is fine-tuned using canonical particle swarm optimization algorithm. Experiments of the proposed model utilizes UCI Household power consumption dataset to evaluate the performances in terms of RMSE, MAPE, MAE and R2-score. The proposed model attained RMSE of 26.2154W, MAPE of 2.965%, MAE of 18.65W and R2-Score of 0.9989 which is much better than existing linear regression, extreme learning machine and diverse LSTM models.

Keywords: Energy prediction, smart homes, Deep learning, CNN, BiLSTM, Canonical particle swarm optimization

1 Introduction

The annual report of International Energy Agency (IEA) states that the global energy demand will increase 1.3% every year which emphasize the necessity of introducing energy efficiency initiatives [1]. In the overall world electricity consumption, around 27% of power is used for residential uses. Specifically smart home users have a comfortable lifestyle using different types of home appliances. Comfort comes with cost associated with home appliances and in recent years, the utilization of home appliances in smart homes are gradually increased due to IoT devices [2]. As the number of devices increases in smart homes, eventually it will increase the energy usage. The recent development of IoT applications and wireless sensor networks [3] specifically as smart home appliance is more affordable and efficient in monitoring and assisting the users. IoT devices in smart homes can be used to monitor appliance condition, weather control, etc., Users can control the appliance through IoT devices from anywhere so that the smart home appliances can be monitored remotely [4]. Also, user can perform real time monitoring for energy optimization without any manual helps.

The increasing population faces increased energy demand, thus the step towards reducing energy consumption in smart homes becomes essential.
It is necessary for a smart home to identify the possible ways to reduce energy consumption. However, it is challenging due to the systems and processes used in smart home appliances. Consumption data-based prediction can be done to obtain effective solution for the energy efficiency problem. The technological advancements allow artificial intelligence to control the home appliances. ML techniques are used in smart applications for process and analyse the consumption data to improve the energy utilization [5-6]. However, the time series forecasting of energy consumption is extremely difficult as the energy consumption patterns are non-linear and complex. DL techniques provided better performances in handling time series data and it visible in forecasting stock indices, solar irradiance forecasting, wind speed prediction, etc., Thus DL techniques can be used in power consumption forecasting problem of smart homes. The significant layers in the DL techniques can effectively solve the power consumption prediction problems.

This research work presents a hybrid DL model for energy consumption prediction of smart homes. The complex temporal correlations and consumption patterns can be effectively captured and analysed through the hybrid DL model. The hybrid model combines CNN and BiLSTM for precise energy consumption forecasting. The architecture of DL techniques is similar for every application and the only way to change the architecture is selecting the optimal parameter or fine tuning the network to obtain better performances. Thus, in this research work, the optimal parameters for the hybrid DL model is obtained using

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canonical particle swarm optimization algorithm. The CPSO selects the optimal parameters by fine tuning the network parameters. The contributions made in this research work is summarized as follows.

1) Presented an optimized hybrid DL technique for energy consumption prediction in smart home appliance. CNN and BiLSTM are used to obtain the hybrid model for energy prediction.
2) Presented an optimization algorithm canonical particle swarm optimization (CPSO) for fine tuning the network parameters.
3) Benchmark household energy consumption dataset based experimental evaluation is presented for the proposed model and the prediction performances are analyzed using RMSE, MAPE, MAP and R2-Score metrics. ‘
4) Presented a detailed comparative analysis with existing ML and DL techniques to present the proposed model better prediction performances.

The remaining arrangements in the article are presented as follows. Section 2 presents a brief literature review of existing energy management and forecasting models. The proposed optimized hybrid DL model is presented in section 3. Results and discussion are presented in section 4 and concluded the findings in section 5.

2 Related Works

A brief literature review of different energy management approaches is presented based on the application, methodology and features. In energy consumption forecasting, ML and DL techniques are widely used [7]. The detailed survey presented in [8] provides a clear insight into different learning-based approaches evolved in recent times for energy forecasting in wind turbines, solar panels, and electric power loads. Using different DL techniques, a simple experimental analysis is also presented to compare the prediction performances of learning-based approaches. The comprehensive comparison shows that the learning-based approaches shows better prediction accuracy and supports energy management effectively.

The cost minimization approach presented in [9] for smart homes considers the uncertainties present in the energy management models and its operational constraints. The challenging energy management for temperature control was selected as a smart home application and utilized Markov decision methodology to formulate the problem. Further using deep deterministic policy gradients, the solution for energy management is provided. The limitation like prior knowledge and parameter uncertainty are overcome by the presented model. The ML based energy prediction in IoT application presented in [10] utilizes hidden Markov models and compare the prediction performances with traditional models like artificial neural network, support vector machine and regression tree models. The comparative results confirm the superior performance of hidden Markov models over other ML models with high precision and accuracy.

The predictive control procedure for smart home is presented in [11] using unsupervised quadratic programming model. The presented approach considers the binary and continuous constraints to calculate the global optima. The predictive controller forecasts the disturbances, occupancies, and user weights for control scheme effectively, so that the importance of global optimization in complex energy management control schemes are managed effectively compared to existing methodologies. The energy forecasting model presented in [12] utilizes modified mutual information technique and restricted Boltzmann machine for accurate prediction performances. The abstractive features in the energy data is extracted using the modified mutual information technique and fed into prediction which includes restricted Boltzmann and genetic optimization algorithm. The prediction model parameters are optimized through the genetic optimization algorithm to attain better prediction performances over conventional Neural network models. A comparative analysis presented in [13] includes techniques like ANN, SVM, DNN, multiple regression and genetic programming models for energy consumption forecasting in administration building. The comparative analysis utilizes different parameters like humidity, temperature, solar radiation, weekday index and wind patterns for prediction process. The results of comparative analysis depicts that the performance of ANN is better than other models with better MAPE.

DL techniques are used in various applications in different domains [14-15]. In energy prediction applications, the performance of DL techniques is better than ML models. In addition to prediction accuracy, the computation speed of DL is higher than ML models [16]. A series of DL models are used in an energy prediction model presented in [17] for better predictive performances. DL techniques like convolutional autoencoder, fully connected autoencoder and generative adversarial network are used in the prediction model for building energy prediction. The experimental results presents that the combined approach effectively extracts the features and classifies to attain better performances.

The energy management system reported in [18] provides a demand response algorithm for smart homes which predicts the prices to reduce the energy consumption. Multi-agent reinforcement learning algorithm is used in the prediction model for decision making and the simulation experimental results confirm the presented approach better performances over conventional decision-making methodologies. To manage the temporal and spatial constraints in application energy consumption prediction deep reinforcement learning is used in [19] which effectively predicts the consumption details with better precision over conventional ML based prediction models. The energy consumption prediction model presented in [20] includes federated learning and edge computing to develop a centralized learning machine for future forecasting. The federated learning model managesdiverse types of energy consumption data to train the DL network and attains better prediction results over ML models. However, to develop a final model multiple parameters are used in the research work which increases the computation complexity.

An online adaptive recurrent neural network (RNN) based forecasting model is presented in [21] which continuously learns the arriving data and adapts to new patterns. The time dependencies in the online data handling are effectively managed by adjusting the weights of RNN. The continuous performance evaluation modifies the hyperparameters adaptively based on the evaluation results. Experiments of the presented model is performed based on the data obtained from five different smart homes and comparatively analyzed with existing methodologies to validate the better performances. An optimized recurrent neural network-based energy prediction model presented in [22] analyzes the energy consumption patterns and predicts the future demands. The preprocessing steps includes data imputation methods to fill the missing values in the energy consumption dataset and analyzes the patterns using RNN with minimum error compared to conventional neural network-based prediction models

The energy demand prediction model presented in [23] includes CNN and optimization models like genetic algorithm, particle swarm optimization algorithms. The presented approach selects the optimal features from the energy consumption data using an optimization algorithm and then predicts the future demands based on selected features using CNN with better precision. The energy forecasting model presented in [24] utilizes CNN for feature extraction and fed the extracted data into GRU for final prediction. The hybrid model effectively manages the time series dependencies of energy consumption patterns and attained better prediction performances over ML models like support vector machine, extreme learning machine, gradient boosting regression and artificial neural networks. A similar prediction model presented in [25] includes 2D-CNN for feature extraction and classification. To improve the prediction performances of learning model, attention layers in included in the presented model which improves the prediction accuracy over conventional methods.

A combination of LSTM and stationary wavelet transform is presented in [26] for energy consumption forecasting. The ensemble model effectively manages the data dimensional complexities using stationary wavelet transform and improves the prediction performance of LSTM over conventional methodologies. Similar LSTM based prediction model presented in [27] manages the long-term data dependencies effectively over ML approaches. The presented model experiments results confirmed the superior prediction performance compared to traditional artificial neural network, support vector regression and recurrent neural networks. From the literature review, it can be observed that ML based energy prediction model exhibits poor prediction performance over DL based prediction models. The combination of optimization algorithms with DL based prediction models will improve prediction accuracy. Thus, in this research work an optimized hybrid DL model is presented to attain maximum prediction performances in energy consumption prediction.

3 Proposed Work

The proposed smart home appliance energy prediction using optimized hybrid DL model incorporates DL techniques like CNN and BiLSTM for energy prediction. To attain better prediction performance and to select optimal parameters for hybrid DL model, canonical particle swarm optimization (CPSO) is used in this research work. The optimal solutions of CPSO are used to fine tune the network parameters. A simple illustration of the proposed energy prediction model is presented in figure 1.

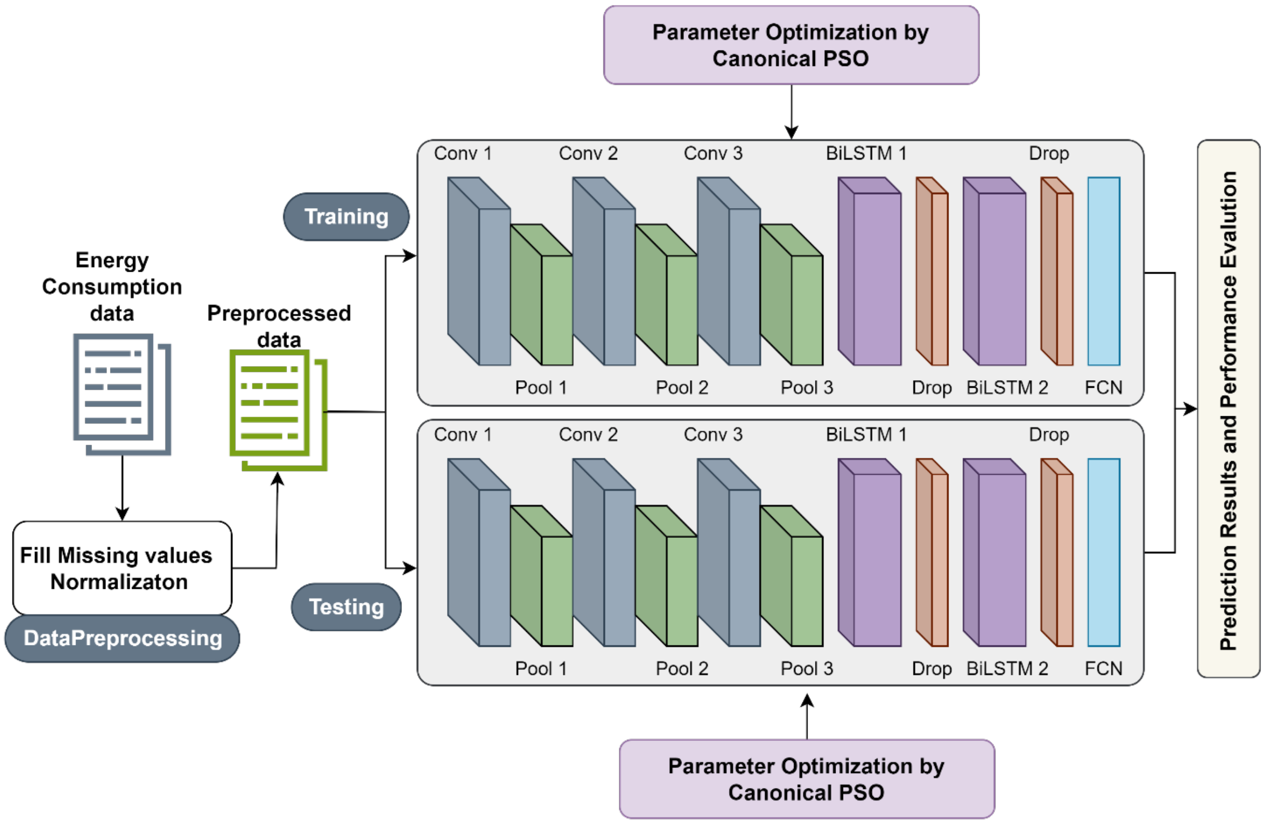

Fig. 1. Proposed Energy prediction model

The hybrid model CNN-BiLSTM used for energy prediction includes series connection of CNN and BiLSTM networks. The complex features from the appliance energy consumption data are extracted to predict the energy demands. The initial CNN layers process the variables which cause energy consumption. The input variables are processed through an input layer and the outputs are provided to BilSTM network. In between the hidden layers present in the CNN has convolution layer, activation function ReLU and pooling layers. The incoming multivariate time sequence data is processed through convolution layer and the results are passed to the next layer.

The convolution operation in the prediction model is mathematically formulated as

$$y_{ij}^{l} = \sigma\left(b_j^l + \sum_{m=1}^{M} w_m^l, j x_{i+m-1,j}^{0}\right) \quad (1)$$

where the output of l^{th} convolution layer is given as y_{ij}^{l}, kernel weight is represented as w_m^l, filter index value is given as m, and j^{th} feature map bias factor is represented as b_j^l. The activation function is represented using σ. Next to the convolution layer pooling layer is used in the architecture which reduces the feature size and number of parameters. The computation cost of the network is reduced due to the feature dimension reduction and minimizing the parameters. Max pooling is used as the pooling layer in proposed work which effectively avoids overfitting by selecting maximum value for each neuron. The stride rate in the architecture is used to define the movement across the input data. Considering the stride, pooling size, the mathematical expression for pooling operation is given as

$$p_{ij}^{l} = \max_{r \in R} y_{i \times T + r, j}^{l-1} \quad (2)$$

where R indicates the pooling size, T indicates the stride. After convolution and max pooling layers BiLSTMnetwork is used in the proposed work. LSTM has the feature to store the key features of information so that it can be used to update the previously hidden states. Thus, the temporal relationship on long term sequence can be understood easily. The CNN layers output is passed through LSTM gates to predict the power demand. The architecture of LSTM has three gates like forget gate, input gate and output gate. Thegates in the LSTM architecture are updated using the memory cells and each gate are controlled by an activation function with values between 0 and 1. In each step, the LSTM cell hidden state is updated and using the present and previous hidden states, the gate functions are mathematically expressed as

$$i_t = \sigma\left(b_i + w_{hi} h_{t-1} + w_{ci} c_{t-1} + w_{pi} p_t\right) \quad (3)$$

$$o_t = \sigma\left(b_o + w_{ho} h_{t-1} + w_{co} c_{t-1} + w_{po} p_t\right) \quad (4)$$

$$f_t = \sigma\left(b_f + w_{hf} h_{t-1} + w_{cf} c_{t-1} + w_{pf} p_t\right) \quad (5)$$

The equations given above describes the input, output and forget gates in which the notation f indicates the forget gate, i indicates the input gate and o indicates the output gate. The hidden state(h) and cell state(c) in the architecture are mathematically expressed as

$$c_t = f_t c_{t-1} + i_t \sigma\left(b_c + w_{hc} h_{t-1} + w_{pc} p_t\right) \quad (6)$$

$$h_t = o_t \sigma(c_t) \quad (7)$$

where the activation function tanh is indicated as σ and its range is given as [-1,1]. Each gate weight matrix is represented through w and each gate bias vector is represented using b. The features of energy consumption present the output of CNN final pooling layer is used as input to the LSTM network which is indicated using p_t. The combined architecture will provide better performance in predicting information for energy consumption.

The fully connected layer in the proposed architecture is used to generate the power consumption details. The LSTM output is flattened and used as input to fully connected layer. The prediction process used in the proposed model is mathematically expressed as

$$d_i^l = \sum_j w_{ji}^{l-1}\left(\sigma(h_i^{l-1}) + b_i^{l-1}\right) \quad (8)$$

where σ is the non-linear activation function, for layer l and $l-1$ nodes weight function is indicated using w and b_i^{l-1} indicates the bias. The layer details of the proposed CNN-BiLSTM are presented in table 1.

Table 1. Architecture details of proposed model

Type	Output Shape	Parameters
Convolution	(None, 1, 98, 64)	256
Pooling	(None, 1, 49, 64)	0
Convolution	(None, 1, 47, 128)	24704
Pooling	(None, 1, 23, 128)	0
Convolution	(None, 1, 21, 64)	24640
Pooling	(None, 1, 10, 64)	0
BiLSTM	(None, 1, 200)	592800
Dropout	(None, 1, 200)	0
BiLSTM	(None, 200)	240800
Dropout	(None, 200)	0
Total Parameters		883200

The architecture of CNN-BiLSTM can be modified based on the application and the parameters can be adjusted by adjusting the kernel size, filters, and number of strides. The parameter fine tuning is done to enhance the model learning speed and performance. To adjust the parameters of energy consumption prediction model, an optimization technique is incorporated in the proposed work. The hyper parameter optimization can be done through by modifying the hyper parameters without changing the architecture. In another way, the neural network architecture is fine-tuned nu adjusting the number of layers, learning rate, etc., In the proposed work, the hyperparameters of CNN layer parameters like kernel number, kernel size, padding and stride are fine tuned. Additionally, the pooling layer parameters like pooling method, padding and stride are fine-tuned using the optimization method. The parameter optimization is performed through Canonical Particle Swarm Optimization (CPSO) algorithm. Instead of traditional PSO, the proposed work utilizes CPSO to overcome problems like premature solution generation of PSO. Since training CNN architecture requires multiple iterations and the parameters like weights and biases need to be adjusted effectively. Practically this process requires more particles which would increase the CNN training instances instead of decreasing it. Thus, in the proposed work CPSO is used which utilizes few particles to find the optimal solution. CPSO performs better in high-dimensional spaces, which is essential for tuning multiple parameters in deep learning models. By reducing the number of particles, CPSO minimizes the computational load and improves the training process without compromising on solution quality. Also, CPSO considers particle evaluations as a time-series problem and provides better prediction by efficiently adapting the optimization requirement. Due to this, CPSO improves the stability and solution quality. Thus, the optimization model saves the time and computation resources of CNN in the training process. As the particles count is less in CPSO, the CNN training instances is reduced for each swarm generation.

To cut off the unnecessary iterations in CNN training, the final ranking solutions can be predicted using the proposed model. This can be achieved by utilizing a mini batch of dataset instead of an entire large dataset. This can potentially reduce the training time and requires minimum computation resources. CPSO considers the particle evaluation sequence as a time series problem and utilizes trend estimation to validate particle tendency by correlating the classification error rates.

The linear trend estimation of utilizes least squares to define the quality of the particles which can be described using a function

$$\widehat{C_{er}} = \sum_i \big(C_{er} - (ai + b)\big)^2 \tag{9}$$

where the classification error rate is indicated using C_{er} and to minimize the C_{er} the parameters a and b are used. The particles are ranked based on the predicted C_{er}. Further to observe the stability, the ranked particles at the top and worst are not changed over iterations. Further the linear trend is considered to determine the particle quality over iterations. The number of evaluations is reduced using the function given below.

$$p = \begin{cases} 1 & i \geq e_i > e_{t+1} - 1 \\ \sum_{i=1}^{i_{max}} \delta(i - e_i) & otherwise \end{cases} \tag{10}$$

where the unit impulse function is indicated using δ and the evaluation frequency is indicated using e_i. The first two occurrences of e_i are set empirically as the particles ranking are expected to be dynamic in the initial stage of CNN training. Further the velocity update process in CPSO is mathematically expressed as

$$v_{id}(t+1) = wv_{id}(t) + c_1 r_1 (p_{ld} - x_{id}(t)) + c_2 r_2 \big(p_{gd} - x_{id}(t)\big) \tag{11}$$

where particle velocity is indicated using v_{id}, the acceleration coefficients are given as c_1 and c_2. The real numbers r_1 and r_2 range is given as (0,1). The inertia weight is given as w, the local best and global best are indicated using p_{ld} and p_{gd} respectively. The particle position is indicated using x_{id}. In the proposed work, the velocity of particles in CPSO is modified as follows.

$$v_{ij}(t+1) = wv_{ij}(t) + c_1(j) r_1 \big(p_{lj} - x_{ij}(t)\big) + c_2(j) r_2 \big(p_{gj} - x_{ij}(t)\big) \tag{12}$$

In the modified velocity function, the acceleration function c_1 and c_2 are refined as sharing a single acceleration coefficient to fine tune the extensive range hyperparameters will slow down the search process. Thus, the acceleration coefficients are modified in the proposed work which improves the parameter optimization process. Due to the optimal parameters, the final prediction model will provide better prediction performances in energy consumption analysis.

4 Results and Discussion

The experiments of the proposed energy prediction model using Optimized convolutional Neural Network – Bidirectional Long Short Memory (OCNN-BiLSTM) are performed in python tool and the benchmark household energy consumption dataset from UCI data repository [28] is used for evaluation. The benchmark data has different data features to describe household energy consumption. The entire dataset has 2075259 records and the number of attributes in the dataset is 9. Specifically, three different attributes in the dataset describes the energy consumption features such as minute average voltage, current value, and power values. The dataset has few missing values and by imputation method utilizes mean values to fill the empty field. Further the data is normalized using min-max normalization. The entire dataset is divided 80:20 for training and testing and the parameters like Root Mean Square Error (RMSE), Absolute Error (MAE), R^2 score is used for performance evaluation. The simulation parameters used in the proposed model experimentation is listed in Table 2.

Table 2. Simulation Hyperparameters

S.No	Parameter	Value/Range
1	Kernel Size	(3×3)
2	Number of Filters	64,128
3	Activation Function	ReLU
4	Pooling type	Max pooling
5	Optimizer	Adam
6	No of units in BiLSTM	200
7	Batch size	64
8	Number of epochs	50
9	Dropout Rate	0.2
10	Number of Particles	30
11	Inertia Weight (w)	0.729
12	Coefficient c_1 and c_2	1.494

Mathematical formulation for the performance metrics is given as

$$RMSE = \sqrt{\frac{1}{2}\sum_{j=1}^{n}\big(A_j - p_j\big)^2} \tag{13}$$

$$MAPE = \frac{100}{n}\sum_{j=1}^{n}\left|\frac{A_j - p_j}{A_j}\right| \tag{14}$$

$$MAE = \frac{\sum_{j=1}^{n}|A_j - p_j|}{n} \tag{15}$$

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\big(A_j - p_j\big)^2}{\sum_{j=1}^{n}\big(A_j - mean(A)\big)^2} \tag{16}$$

The prediction performance of the proposed model is presented in figure 2 and it can be observed that the predicted values of the proposed model is close to the ground truth values of energy consumption. This closeness defines that the proposed model has high prediction accuracy and low error. Due to the optimal parameter selection of hybrid CNN-BiLSTM model using CPSO, the proposed model exhibited maximum prediction performances. The other parameters like RMSE, MAPE, MAE and R^2 score obtained by the proposed model is presented in table 3.

Table 3. Performance metrics of the proposed OCNN-BiLSTM model

Metrics	Training	Testing
RMSE	26.5422	26.2154
MAPE	3.1041	2.9652
MAE	18.9822	18.6456
R^2-Score	0.9999	0.9989

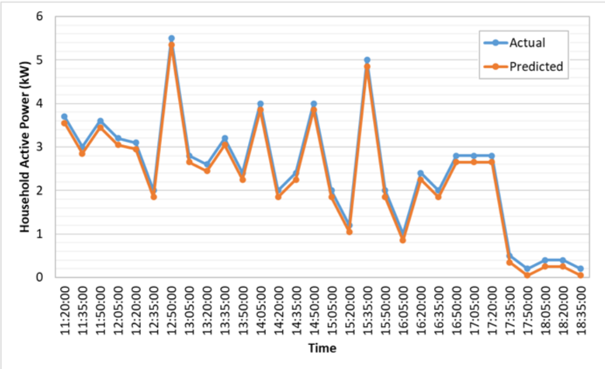

Fig. 2. Actual vs predicted values of global active power using proposed hybrid Optimized CNN-BiLSTM

The proposed OCNN-BiLSTM model performance is comparatively analyzed with existing ML methods like Linear Regression (LR), Extreme Learning Machine (ELM), Neural Network (NN), LSTM, Stacked LSTM (SLSTM), ConvLSTM (CLSTM), BiLSTM, and SLSTM-BiLSTM models.Figure 3 depicts the comparative analysis of RMSE obtained for all the methods. Results show that the proposed OCNN-BiLSTM better performances through minimum RMSE. Due to hyperparameter tuning the optimal parameters are selected for the prediction model which reduces the error in the prediction process.

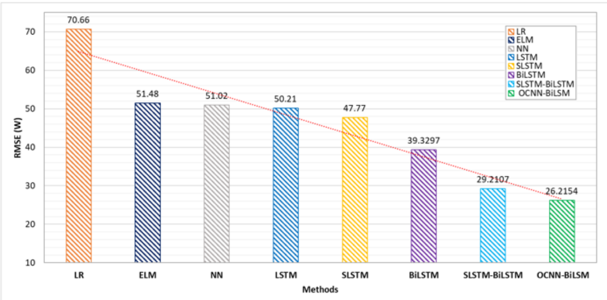

Fig. 3. RMSE Comparative Analysis

The comparative analysis of MAPE metrics for the proposed and existing methodologies are presented in figure 4. The MAPE obtained by the proposed is minimum compared to existing methods. The obtained 2.965% is 1.2% lesser than SLTM-BiLSTM model, 2.3% lesser than BiLSTM model, 2.5% lesser than SLSTM model, 3.1% lesser than LSTM model, 4% lesser than NN and 5.5% lesser than ELM and 7.3% lesser than LR model.

The MAE metric comparative analysis for the proposed and existing methodologies are presented in figure 5. The MAE obtained by the proposed is minimum compared to existing methods. The obtained 18.65W is 4W lesser than SLTM-BiLSTM model, 7W lesser than BiLSTM model, 9W lesser than SLSTM model, 18W lesser than LSTM model, 14W lesser than NN and 20W lesser than ELM and 44W lesser than LR model.

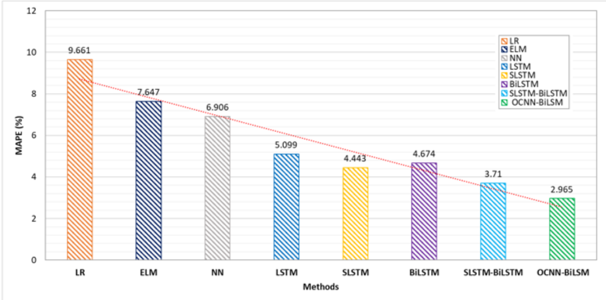

Fig. 4. MAPE Comparative Analysis

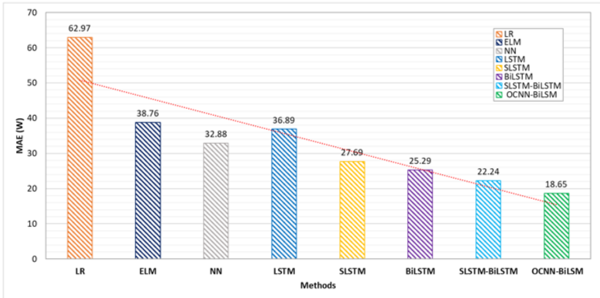

Fig. 5. MAE Comparative Analysis

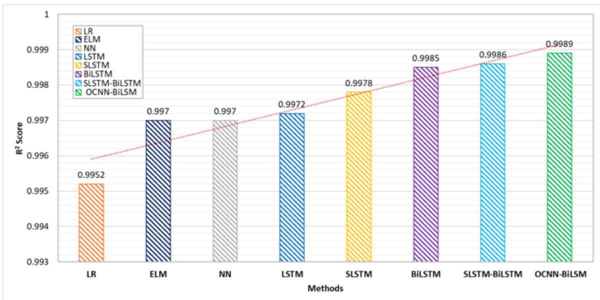

Fig. 6. R^2-Score Comparative Analysis

The comparative analysis of R^2 score presented in figure 6 depicts the better performance of proposed model. The proposed model maximum score of 99.89% is higher than the existing LSTM and BiLSTM model. When compared to ML and basic neural network models the proposed model exhibits better performances for R^2 scores.

Table 4. Overall Comparative Analysis

S. No	Methods	MAPE (%)	R^2 Score	RMSE (W)	MAE (W)
1	Linear Regression (LR)	9.661	0.9952	70.66	62.97
2	Extreme Learning Machine (ELM)	7.647	0.997	51.48	38.76
3	Neural Network (NN)	6.906	0.997	51.02	32.88
4	Long short-Term Memory (LSTM)	5.099	0.9972	50.21	36.89
5	Stacked LSTM (SLSTM)	4.443	0.9978	47.77	27.69
6	Bidirectional LSTM (BiLSTM)	4.674	0.9985	39.3297	25.29
7	SLSTM-BiLSTM	3.71	0.9986	29.2107	22.24
8	**OCNN-BiLSM (Proposed)**	**2.965**	**0.9989**	**26.2154**	**18.65**

Table 4 presents the numerical values of metrics obtained for the proposed model and existing prediction models. The proposed model can provide significant practical implications for real-world smart home environments, especially concerning energy management systems. The proposed model superior predictive accuracy, demonstrated by an RMSE of 26.2154W and an R2 score of 0.9989, ensures that energy consumption predictions are highly precise. This precision allows for more efficient resource allocation, minimizing energy wastage and subsequently reducing energy costs for consumers. In practical terms, such predictive accuracy simplifies the optimization of appliance usage. For example, an energy-intensive device can be scheduled to operate during off-peak hours when energy rates are lower. This not only reduces the energy demand during peak hours but also provides significant cost savings on household energy charges. Additionally, the accurate prediction of energy consumption enables services to implement dynamic load management strategies effectively. Real-time energy consumption predictions also allow for immediate adjustments in energy distribution, enhancing the reliability of energy supply and preventing potential disruptions. Overall, the proposed model represents a significant advancement in smart home energy management and provides practical solutions to meet the increasing energy demands while promoting sustainability and efficiency.

5. Conclusion

An optimized convolutional neural network – Bidirectional Long short-term memory (OCNN-BiLSTM) is presented in this research work for energy consumption prediction in smart home applications. The presented research work extracts the optimal features from the energy consumption data and analyzes the features to predict the energy consumption. To attain improved prediction performance and to tine the prediction model, canonical particle swarm optimization is incorporated in the proposed work. Experimental analysis using the benchmark energy consumption dataset validate the better performance of proposed prediction model in terms of minimum RMSE, MAPE, MAE and maximum R2-score compared to existing ML and DL methods. The future scope of the research work can be made by incorporating hybrid optimization algorithms for better performances.

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