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Original article

Boosting energy harvesting via deep learning-based renewable power generation prediction

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ABSTRACT

The high-level variation of different energy generation resources makes the reliable power supply significantly challenging to end-users. These variations occur due to the intermittent nature of energy output and time-varying weather conditions. The recent literature focuses on the improvements in power generation and consumption forecasting, which is a demand of the current smart grids' smooth operations with a balanced amount of energy generation and consumption for the connected customers. Inspired by the applications of load forecasting, therefore, in this work, we develop an efficient and effective hybrid model for power generation and consumption forecasting, thereby contributing to energy harvesting by providing valuable prediction data to the concerned renewable energy analysts. Herein, we integrate a convolutional neural network with an echo state network for robust renewable energy generation and consumption forecasting. The convolutional network is used to extract meaningful patterns from the historical data which is then forwarded to the echo state network for temporal features learning. The output spatiotemporal feature vector is then fed to fully connected layers for final forecasting. The proposed hybrid model is derived after extensive experiments over machine and deep learning models, where the results indicate that the proposed model substantially decreases the forecasting errors using RMSE, MSE, NRMSE, and MAE metrics, when compared to state-of-the-art models and acts as a paradigm towards energy equilibrium between production resources and consumers.

1. Introduction

Conventional electric power systems depend on non-renewable energy resources such as oil, gas, and coal which results in greenhouse gases and energy losses during electricity generation and transmission, respectively (Ma and Ma, 2018). Furthermore, large-scale electricity transmission brings a huge risk when electrical or mechanical faults occur in a centralized grid station. To overcome these challenges, the concept of Distributed Energy Resources (DER) is developed which strengthens a stable and reliable power transmission to the end-users and lowers environmental impacts. To utilize energy storage units' above limits penetation, employ DER sensors and devices effectively, and ensure proper integration of local power generation to the electricity grids, the concept of Micro Grid (MG) is developed to combine these contributors with utility systems via point of cloud coupling (Doe, 2011). The MG systems overcome many challenges occurring in conventional grids systems, but several new challenges are encountered when managing electricity using the new MG-based settings. For instance, these systems are purely based on energy harvesting resources, especially, renewable power resources such as solar and wind, where these sources are highly unstable and uncontrollable to provide consistent supply (Ma et al., 2013). Furthermore, electricity consumption is also affected by different consumers behavior and weather conditions. For this purpose, many advanced strategies are developed in the literature to forecast electricity consumption and supply, balance the dispatch, and provide a consistent power supply (Ma and Ma, 2018).

The current literature focuses to improve the prediction results of electricity supply from renewable energy generation resources and consumption. For power generation and consumption

Abbreviations: CNN-ESN, convoluational neural network-echo state network; LSTMs, Long-short term memory; GRUs, Gated recurrent unit; CNN-LSTM, Convolutional-LSTM; CNN-GRU, Convolutioanl-GRU.

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Nomenclature

RMSE	Root Mean Square Error
MSE	Mean Square Error
RRMSE	Normalized Root Mean Square Error
MAE	Mean Absolute Error
DER	Distributed Energy Resources
MG	Micro grid
CNN	Convolutional Neural Network
ESN	Echo State Network
CNNESN	Convolutional Neural Network Echo State Network
RPGP	Renewable Power Generation Prediction
ECP	Electricity Consumption Prediction
AI	Artificial Intelligence
SVM	Support Vector Machine
DL	Deep Learning
RNN	Recurrent Neural Network
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Unit
CLSTM	Convolutional LSTM
AVG	Average
STD	Standard Deviation
DKASC	Desert Knowledge Australia Solar Centre
IHEPC	Individual Household Electric Power Consumption
DT	Decision Tree
RL	Linear Regression
MLP	Multilayer Perceptron
GPU	Graphics Processing Unit
CPU	Central Processing Unit
RPI	Raspberry Pi

predictions, deep learning-based strategies, especially hybrid models achieved state-of-the-art accuracies. However, different predictive modeling techniques are developed to perform these tasks and the current literature lacks a generalized model to perform both tasks at a time. The researchers are focusing to improve the forecasting results without considering the computational complexity of a model. Furthermore, error rates reduction in predictive modeling has a great impact on electricity losses and costs. A survey of 19 utility companies concluded that a one percent reduction in error rates can save 10,000 MW of electricity which means an accurate predictive model can save up to 1.6 million dollars in a year. Considering these motivations and limitations of the existing works, therefore, in this work, we developed a hybrid Convolutional Neural Network (CNN) and Echo State Network (ESN) model for reliable electricity generation and consumption prediction. The prediction results of the proposed model are higher and its computational complexity is lower than state-of-the-art models. The main contributions of the proposed model are as follows:

- A generalized hybrid model is developed for Renewable Power Generation Prediction (RPGP) and Electricity Consumption Prediction (ECP) to adjust the demand and supply in MGs and smart grids.
- The proposed model combines CNN with ESN to efficiently predict future electricity generation and consumption. The CNN module is incorporated to learn the meaningful patterns from the historical data and ESN is used to extract sequential information which is then inputted to fully connected layers for the final prediction.
- The CNNESN model is finalized after extensive experiments over machine and deep learning-based models. The experimental results indicate that the proposed model is computationally inexpensive with better generalization abilities and precisely predicts future electricity generation and consumption.
- The performance of the proposed CNNESN model is evaluated on benchmarks renewable power generation and electricity consumption datasets and concluded that the proposed model achieved better prediction results as compared to state-of-the-art models.

The rest of the paper is structured as Section 2 recent literature about renewable power generation and electricity consumption prediction, Section 3 explains the internal architecture of the proposed CNNESN model, Section 4 has experimental results, and the conclusive remarks are given in Section 5.

2. RPGP and ECP literature

In the literature, various methodologies are developed to predict renewable power generation and electricity consumption (Rafique and Jianhua, 2018). For different purposes of electricity management, various horizons are considered such as long-, medium-, and short-term, where long-and medium-term predictions are mainly focusing on load dispatch, price settlement, and maintenance scheduling (Ma and Ma, 2018). Short-term prediction is responsible for energy flow scheduling, storage units, and loads. Data-driven approaches such as data mining gained much attention to predict renewable power generation and electricity consumption in smart grids (Amasyali and El-Gohary, 2018). These approaches are based on historical energy generation/consumption and weather data. Data driven approaches are mainly divided into statistical and Artificial Intelligence (AI) techniques (van der Meer et al., 2018). The statistical models are based on a mathematical relationship between input and model's output data. Several statistical techniques are proposed for RPGP and ECP. Statistical techniques developed for RPGP and ECP include power Bayesian (Wang et al., 2019; Tang et al., 2019), autoregressive (Mahmud and Sahoo, 2019; Guefano et al., 2021), moving average (Aasim et al., 2019; Pappas et al., 2008), Markov (Wang et al., 2015; Meidani and Ghanem, 2013), gray theory (Wu et al., 2018; Ding et al., 2018), Kalman filter (Yang, 2019; Zheng et al., 2019), Hammerstein (Ait Maatallah et al., 2015; Lu et al., 1989) and multiple kernel model (Reikard, 2009; Wu et al., 2019). The statistical techniques can learn linear data effectively, however, their prediction accuracy is hugely affected for non-linear data (Afrasiabi et al., 2020). The AI model has strong abilities to learn non-linear complex data compared to statistical techniques. Some popular AI models developed for RPGP and ECP included Support Vector Machine (SVM) (Tan et al., 2020; Li et al., 2020), artificial neural network (Wang et al., 2019; Kuo and Huang, 2018), extreme learning machine (Ali and Prasad, 2019; Rafiei et al., 2018), fuzzy neural network (Ali and Prasad, 2019; Sideratos et al., 2020), decision tree (Gupta et al., 2021; Xie et al., 2019), generative adversarial networks (Wang et al., 2019; Bendaoud et al., 2021). Compared to statistical techniques, AI models achieved better prediction accuracies for EPGP and ECP. However, these models are based on a shallow architecture that requires handcrafted feature engineering and pose limited generalization abilities, resulting network instability and parameters non-convergence due to sufficient data of EPGP and ECP. Hence, these challenges in conventional AI models encourage the researchers to reconsider RPGP and ECP based on Deep Learning (DL) (Wang et al., 2017).

DL based models achieved considerable attention in several domains such as image classification, video recognition, signal processing, language processing, and time series tasks. These models have the potentials to learn the features unsupportively with strong generalization capabilities compared to statistical and AI-based models. Similarly, for RPGP and ECP several predictive models are developed based on DL such CNN (Khan et al., 2019; Korkmaz, 2021), Recurrent Neural Network (RNN) (Rahman et al., 2018; Li et al., 2019), Long Short-Term Memory (LSTM) (Zhou et al., 2019; Wang et al., 2019), ESN (Yao et al., 2019; Trierweiler Ribeiro et al., 2020) and Gated Recurrent Unit (GRU) (Wang et al., 2018; Wang et al., 2018). These models have better convergence capabilities compared to other models in several domains. However, for effective deep learning modeling, first, we need to know the nature of renewable power generation and electricity consumption data, that are time-series in nature, including spatial and temporal information, where CNN models can only extract spatial information while RNN, LSTM, ESN, etc., can model temporal information very well. Therefore, predictive models based on these strategies are not applicable for accurate RPGP and ECP (Tascikaraoglu and Uzunoglu, 2014; Hussain et al., 2021).

To this end, hybrid models have sufficient potentials to extract spatiotemporal features from historical renewable power generation and electricity consumption data. For RPGP and ECP, several hybrid combinations of models are developed in the literature, including CNN-GRU (Sajjad et al., 2020), CNN-RNN (Kim et al., 2019), CNN-LSTM (Qu et al., 2021; Kim and Cho, 2019), and LSTM-CNN (Wang et al., 2019; Farsi et al., 2021), Convolutional LSTM (CLSTM) (Wang et al., 2018; Woo et al., 2018), and autoencoder with bidirectional LSTM (Khan et al., 2021). These models have the ability to accurately predict renewable power generation and electricity consumption patterns. However, the results of these models further needs be improved for reliable power prediction. Furthermore, hybrid models are computationally expensive compared to solo models. Therefore, in this work, we develop a novel CNNESN based model for efficient and effective RPGP and ECP.

3. The proposed model

RPGP and ECP are very important to provide sufficient energy to end-users with balanced electricity generation and consumption. Accurate consumption and generation prediction is a challenging task due to the variable consumption of the customer, noisy arrangement of the data, and unpredictable weather conditions. For this purpose, several techniques are developed to predict electricity generation and consumption, as mentioned in Section 2. However, the prediction results further need to be improved and the computational complexity of the model should be accurate enough to be be deployed in real-time for a trustworthy MG system. Therefore, this work develops a novel lightweight CNNESN based model for RPGP and ECP, as shown in Fig. 1. The proposed CNNESN model includes two main architectures, CNN and ESN, which are further described in the following subsections.

3.1. Convolutional neural network

Nowadays, researchers from computer vision and pattern recognition domains are inspired by the performance of deep learning, specifically CNN, which is the subfield of artificial intelligence, primarily inspired by the visual cortex of human beings (Xu and Vaziri-Pashkam, 2021). Due to weights sharing and local connection strategy, CNN architecture achieved remarkable accuracy in different tasks such as energy prediction, load forecasting, and many others. Generally, CNN comprises three types of layers, for example, convolutional, pooling, and fully connected layers. The convolutional layer extracts discriminative features from the input data, where a filter or kernel convolve over the extracted feature map from the previous layer to produce the output feature vector i. The initial layers are responsible to extract the local features while the intermediate layers extract the global features. The convolutional layer can be represented by a mathematical equation as follows:

$$O_i^{(l)} = \left(\sum_{j \in c_i}^{t_j^{l-1}} * W_{j,i}^{(l)} \right) + b_i^{(l)} \tag{1}$$

$$F_i^l = f\left(y_i^l\right) \tag{2}$$

Here in, F_i^l is the extracted feature vector by the convolutional layer l, while the c_i is a set of features vector. The output of the convolution is represented by $O_i^{(l)}$, their bias term is represented by $b_i^{(l)}$, the convolutional kernel is shown as $W_{j,i}^{(l)}$ and f represents activation function. In this paper, we used RelU as an activation function, their mathematical representation is given in Eq. (3).

$$f(x) = max(0, x) \tag{3}$$

To reduce the spatial resolution of the input data, usually pooling layers are used and there are different types of pooling layers such as average pooling, min pooling, and max pooling, where, we used max-pooling layers to select the most prominent features.

3.2. Echo state network

In the past few years, substantial attention is achieved by deep neural networks containing multiple layers architecture in the field of neural networks (Goodfellow et al., 2016). Additionally, the hierarchic standardized RNN has also played a crucial part in different convoluted tasks including deep learning. In (Gallicchio et al., 2017), Gallicchio et al. initially fused ESN with deep learning frameworks, that is computationally intelligent with respect to other RNN variants, as ESN is also a novel and special form of RNN. RNN is modeled by jaeger et al. (Jaeger, 2001), which provides an essential architecture and a supervised learning approach to RNN, and the hidden layers of ESN are developed by a reservoir. The ESN architecture mainly consists of a reservoir '*R*', input '*I*' and an output '*O*', where '*I*' indicates the input unit, accredit to the input layer, '*R*' as internal units for the reservoir, and '*O*' as output units. The input, internal, and output units are given in Eqs. (4)–(6) with their corresponding operations. Also, the updated (unit updates) equations for internal and output units are also given in Eqs. (7) and (8).

$$u(i) = [u_1(i), u_2(i) \cdots .u_I(i)]^T \tag{4}$$

$$x(i) = [x_1(i), x_2(i) \cdots .x_R(i)]^T \tag{5}$$

$$y(i) = [y_1(i), y_2(i) \cdots .y_O(i)]^T \tag{6}$$

$$x(i+1) = f(W_{in} * u(i+1) + W * x(i) + W_{back} * y(i)) \tag{7}$$

$$y(i+1) = g(W_{out} * u(i+1)) \tag{8}$$

$$W_{out} = \left(M^{-1} * T\right)^T \tag{9}$$

In Eq. (7), 8, '*f*' and '*g*' indicatea activation function for both output and reservoir units, whereas the total weight metrics consist of "$W_{in}(R*I)$", "$W(R*R)$", "$W_{back}(R*O)$", and "$W_{out}(O*R)$" as input, reservoir, output backward, and readout metrics, respectively. The weight matrix "W_{out}" is randomly selected and remains unchanged, whereas for reservoir it updates in the learning process

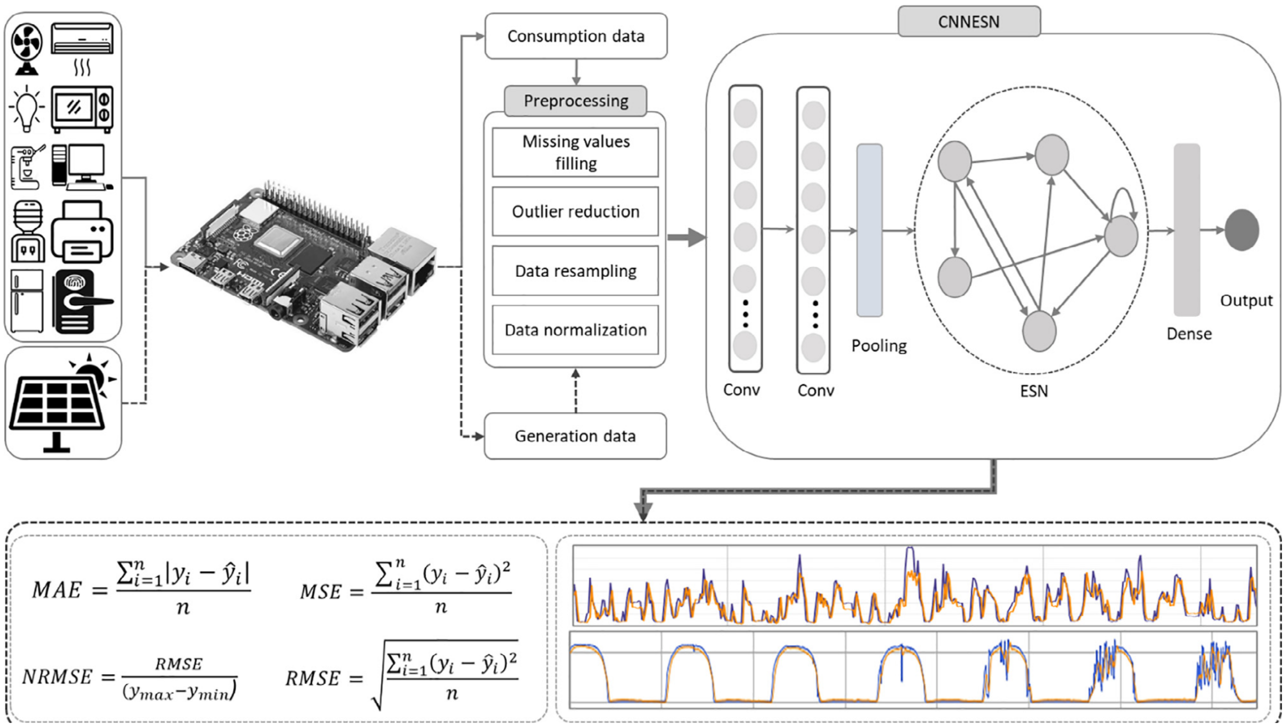


Fig. 1. The proposed CNNESN model for RPGP and ECP. The historical data of electricity generation and consumption are first preprocessed for refinement and then inputted into the CNNESN model. Finally, the CNNESN model is evaluated on different evaluation metrics.

(Chouikhi et al., 2017; Ma et al., 2016). The target outputs "$T((S - S_o + 1) * O)$" and reservoir state vectors "$I((S - S_o + 1) * R)$" are selected to calculate the readout weights. Here, 'S' indicates the training step whereas 'S_o' indicates the wash-out time step. Eq. (9) calculates the readout as the time step is equal or bigger than 'V_o'. The major role in ESN is mainly played by these reservoirs as they influence the overall performance of the network through its three major parameters. After that, the number of reservoir neurons 'N' has also shown a massive impact on the performance of ESN, due to its internal structure related to the hidden state's information (Chouikhi et al., 2017). It also depends on the training size of data and the intricacy of targeted tasks that need to be attained. Correspondingly, the ESN performance is also affected by the rate of connectivity 'α', absolute eigenvalue by the weight matrix 'W', and the special radius 'ρ', where 'ρ' is indicated between 0 and 1 intervals. Concluding, ESN is better and faster than RNN's (Chen et al., 2018) with respect to learning and approximation.

3.3. CNNESN architecture

The historical data of electricity generation and consumption are first preprocessed to remove the abnormal data such as outlier, missing, and redundant values. These values are recorded due to sensor fault, unconditional weather conditions, and short circuits, etc. (Genes et al., 2017). To remove the outlier values, in this work, we used sigma-rules (Chandola et al., 2009) where the mathematics behind these rules are given in Eq. (10).

$$f(d_i) = \begin{cases} avg(D) + 2std(D), if d_i > avg(D) + std(D) \\ d_i, otherwise \end{cases}, \tag{10}$$

where D represents the data, $avg(\mathrm{D})$ is the average, and $std(\mathrm{D})$ is the standard deviation of the data. To recover missing values, we used NAN interpolation technique, where the mathematics behind this technique is given in Eq. (11).

$$f(d_i) = \begin{cases} \frac{d_{i-1}+d_{i+1}}{2}, d_i \in NAN, d_{i-1}, d_{i+1} \notin NAN \\ 0, a_i \in NAN, a_{i-1} or a_{i+1} \in NAN \\ a_i, a_i \notin NAN \end{cases}, \tag{11}$$

where d_i represents electricity generation, consumption, or weather variable values. If these values are null, we replace them with NAN. Furthermore, we utilized the data normalization technique to transform huge, variated data into a specific range. The normalization technique is applied due to different ranges of electricity generation, weather information, and consumption. In this work, we used deafult (0~MinMax data normalization techniques.

The preprocessed data are then used for the training, validation, and testing purpose of the model. The preprocessed historical are divided into training 70%, validation 10%, and testing 20% purposes. In the training phase, the refined data has used an input to CNN layer which is responsible to extract meaningful patterns followed by ESN architecture to learn sequence information between those patterns. The output of the ESN architecture is then forwarded to fully connected layers for final electricity generation and consumption prediction. In the proposed CNNESN architecture we used two CNN layers with a filter size of 32 and 64, kernel size of one is used in each convolution with activation function ReLU, while the ESN includes a single reservoir with 16 units and using *tanh* as an activation function. The internal architecture of the proposed CNNESN mode is given in Table 1**,** and the block diagram is shown in Fig. 2. The proposed model is available at "https://github.com/zulfiqarahmadkhan/CNNESN".

4. Results

The experimental results are discussed in this section for renewable power generation and electricity consumption prediction. In this section, we discussed the datasets used in this paper, define the evaluation metrics, a brief discussion about experimental results of our ablation study, and comparison of the proposed

Table 1
The architecture of the proposed CNNESN model, layer type, kernel, filter, and parameters.

Type of layer	Size of kernel	Size of filter	Params
CNN layer 1	1	32	352
CNN layer 2	1	64	2112
Max pooling	–	–	–
Flatten	–	–	–
ESN (16)	–	–	1542
Dense (32)	–	–	3104
Dense (12)			396
Total params	–	–	7506

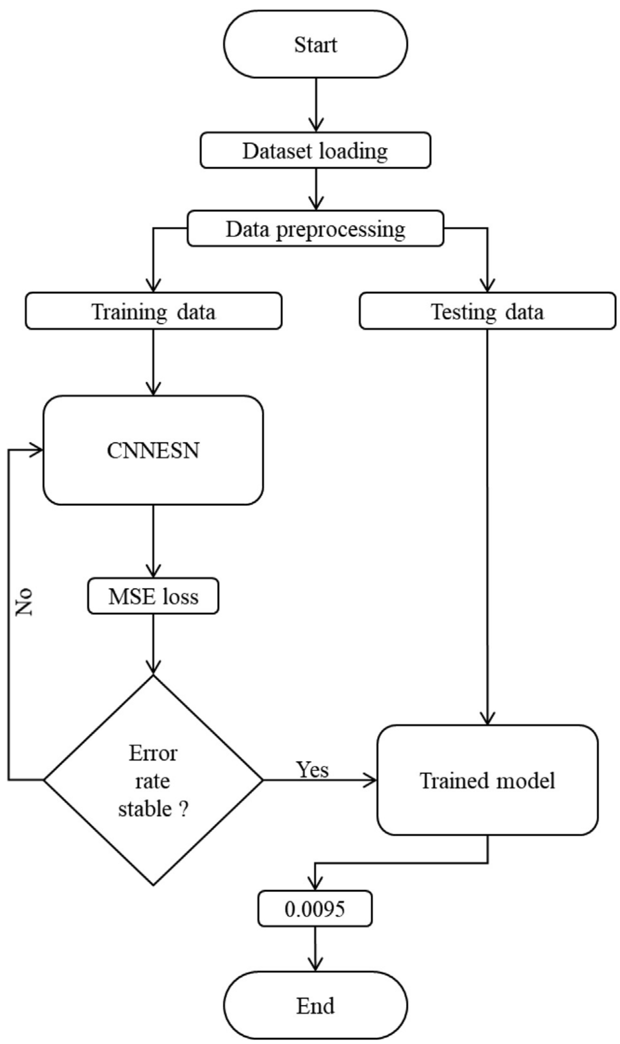


Fig. 2. A block diagram of the proposed CNNESN model.

model with other state-of-the-art models in terms of prediction performance and time complexity.

4.1. Electricity generation and consumption datasets

For RPGP, we utilized Desert Knowledge Australia Solar Centre (DKASC), Alice Springs, Australia datasets (DKASC, Alice Springs). DKASC includes multiple active solar power plants recording the daily data in a five-minute resolution from the date of installation. In this paper, we used three datasets collected from DKASC such as Trina 10.5 kW mono-si sual 2009 (Tarina 10.5 kW), Trina 23.4 kW mono-si sual 2009 (Tarina 23.4 kW), and Eco-Kinetics 26.5 kW mono-Si dual 2010 (Eco-Kinetics 26.5 kW). These datasets include renewable power generation and weather information data such as humidity, rainfall, temperature, etc. Some technical specifications of these datasets are given in Table 2, while statistical information of each dataset is given in Table 3. As given in Table 3, some values are negative, for example, the minimum value of Tarina 23.4 kW is −0.0341 which is considered as zero in this work and removed in the preprocessing step. The total generation capacity of the Eco-Kinetics 26.5 kW dataset is 26.5 kW, while the maximum value is 52.982, as reported in Table 3 which can be analyzed from Fig. 3, where the generation capacity of the plant is reduced after some time of the installation.

For electricity consumption prediction, we used the Individual Household Electric Power Consumption (IHEPC) dataset (Individual household electric power consumption Data Set). This dataset is recorded in one-minute resolution in the period of 2006–2010, including time-date information, active and reactive power, intensity, voltage, and submetering information. A short description of each attribute in IHEPC and DKASC datasets is given in Table 4**.**

4.2. Evaluation metrics

Renewable power generation and electricity consumption are time-series data problems, and the performance of a prediction model is evaluated on error metrics such Root Mean Square Error (RMSE), Mean Square Error (MSE), Normalized Root Mean Square Error (RMSE), and Mean Absolute Error (MAE), where the details can be deeply studied from a recent survey (Hussain et al., 2021). These metrics define the average difference between actual and predicted values of the model. The mathematical representation of these metrics is given in Eqs. (12)–(15).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m}(a_i - p_i)^2}{N}} \tag{12}$$

$$MSE = \frac{\sum_{i=1}^{n}(a_i - p_i)^2}{N} \tag{13}$$

$$NRMSE = RMSE/(a_{max} - a_{min} \tag{14}$$

$$MAE = \frac{\sum_{i=1}^{n}|a_i - p_i|}{N} \tag{15}$$

In these equations, a and p represent the actual and predicted values by the model, where N is the total number of records.

4.3. Ablation study

To substantiate the robustness of the proposed CNNESN model, we conducted experiments on several predictive modeling techniques, including traditional regression methods such as SVR, Decision Tree (DT), and Linear Regression (RL) and deep learning-based models such as Multilayer Perceptron (MLP), LSTM, CNN, GRU, ESN, CNN-GRU, CNN-LSTM, and optimally introduced the proposed CNNESN model. The detailed results of each predictive technique are given in Figs. 5-7 for RPGP and Fig. 8 for ECP, respectively. The results indicate that the traditional regression models performed worst as compared to deep learning-based models. For in-depth analysis, the prediction performance of solo deep learning-based models is compared with hybrid models. This is because renewable power generation and electricity consumption are time-series data including both spatial and temporal information with non-linear relationships. The proposed CNNESN model achieved the lowest error rates when compared to other solo and

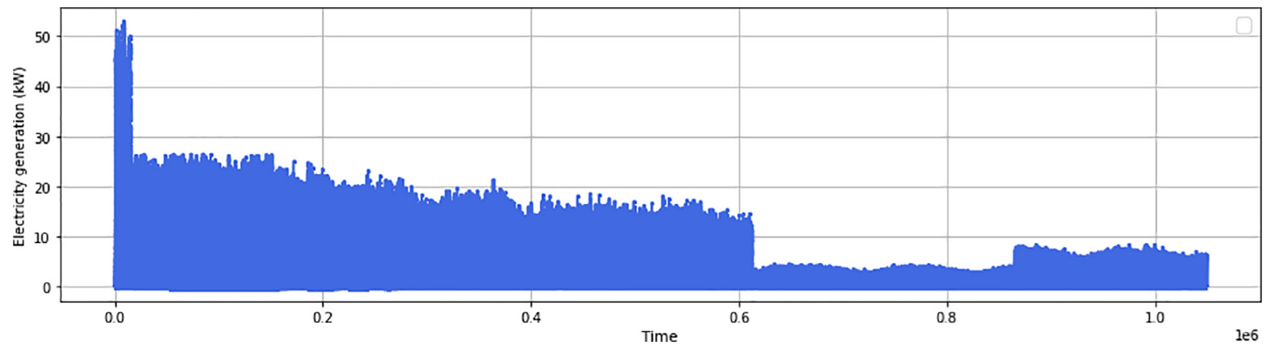


Fig. 3. Historical electricity generation data recorded in Eco-Kinetics 26.5 kW.

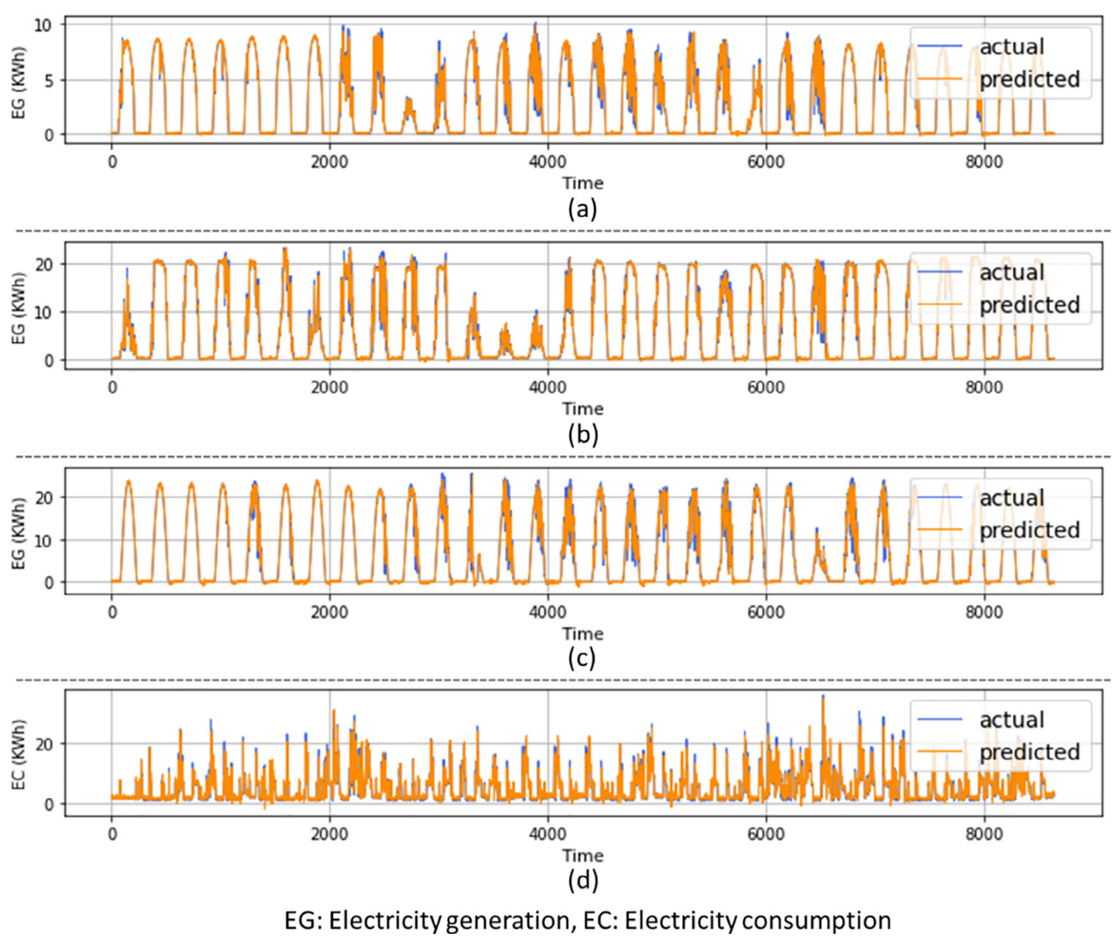


Fig. 4. Actual and predicted values by the proposed model a) Tarina 10.5 kW, b) Tarina 23.4 kW, c) Eco-Kinetics 26.5 kW, and d) IHEPC datasets.

hybrid combinations models. For instance, the proposed CNNESN model achieved 0.1366, 0.0187, 0.2396, and 0.059 RMSE, MSE, NRMSE, and MAE, respectively over Tarina 10.5 kW dataset. For Tarina 23.4 kW dataset, the proposed CNNESN model achieved 0.0913 RMSE, 0.0083 MSE, 0.3023 NRMSE, and 0.053 MAE while these values are 0.0406, 0.0016, 0.2393, and 0.0228, respectively over Eco-Kinetics 26.5 kW dataset. Compared to other models, CNNESN model also achieved the lowest error rates over IHEPC dataset, such as 0.0472 RMSE, 0.0022 MSE, 0.2341 NRMSE, and 0.0266 MAE. All the experiments are performed for one-hour ahead prediction and the proposed model achieved the lowest error rates compared to other predictive models. The predicted values by the proposed CNNESN model and actual values of the test

Table 2
Technical specifications of DKASC datasets.

Dataset	Specification	Value
Tarina 10.5 kW	Generation capacity (kW)	10.5
	No. of Panels	2 × 30
	Single panel generation capacity (W)	175
	Date of installation	08/01/2009
Tarina 23.4 kW	Generation capacity (kW)	23.4
	No. of Panels	4 × 30
	Single panel generation capacity (W)	195
	Date of installation	08/01/2009
Eco-Kinetics 26.5 kW	Generation capacity (kW)	26.52
	No. of Panels	156
	Single panel generation capacity (W)	170
	Date of installation	23/08/2010

Table 3
Statistical information of renewable power generation and electricity consumption datasets.

Features	Tarina 10.5 kW	Tarina 23.4 kW	Eco-Kinetics 26.5 kW	IHEPC
Minimum value	−0.0341	−0.0615	−0.140	0.076
Maximum value	11.331	23.426	52.982	11.122
Standard deviation	2.832	6.369	5.998	1.055
Average	2.188	4.616	3.515	1.089

Table 4
Datasets attributes and their description.

Dataset	Variables	Description
IHEPC	Time/Date	Time and date attribute
	Global active power	Minutely Avg global active power
	Global reactive power	Minutely Avg global reactive power
	Voltage	Minutely Avg voltage
	Intensity	Minutely Avg current intensity
	Sub-metering 1, 2, and 3	Electricity consumption in kitchen, laundry room, and heating/cooling systems
DKASC	Timestamp	Time and date attribute
	Active Energy	Total generated energy in 5-minute interval
	Weather attributes	Weather attributes in DKASC dataset including windspeed, temperature, humidity, global horizontal radiation, diffuse horizontal radiation, wind direction, rainfall, radiation global tilted, and radiation diffuse tilted.

set are shown in Fig. 4, indicating a narrow gap between them and ensuring the applicability of the proposed model for RPGP and ECP.

4.4. Comparative analysis of CNNESN with state-of-the-art models

In this section, we compared the performance of the proposed CNNESN model with other state-of-the-art models for RPGP and ECP tasks. In the literature, several researchers investigated DKASC datasets and evaluated their predictive modeling techniques with different data resolution and prediction horizons. However, for RPGP, in this work, we performed a general comparison with other models such (Zang et al., 2020; Chen et al., 2020; Li et al., 2019; Zhou et al., 2020; Cheng et al., 2021; Li et al., 2020; Korkmaz, 2021; Wang et al., 2019; Wang et al., 2019). The detailed performance of these models is given in Table 5, where the proposed model achieved the lowest error rates.

The performance of the proposed CNNESN model is also compared with other state-of-the-art models over the IHEPC dataset. For instance, the performance is compared with Kim and Cho (2019), Khan et al. (2020), Ullah et al. (2019), Kim and Cho (2019), Le et al. (2019), Sajjad et al. (2020), Khan et al. (2020), Haq et al. (2021), Ullah et al. (2021), Khan et al. (2021). In comparison to these state-of-the-art models, the proposed model also achieved the lowest error rates among them, as indicated in Table 6.

The reduced error rates of our method are observed due to several reasons. Firstly, we ignored the traditional CNN and RNNs variants because these architectures are specifically designed for visual analysis domains such as activity recognition (Ullah et al., 2021) and video data prioritization (Hussain et al., 2020). RNNs with CNNs perform better for these tasks but in terms of energy prediction tasks, authors have used several invariants and stacked multi-

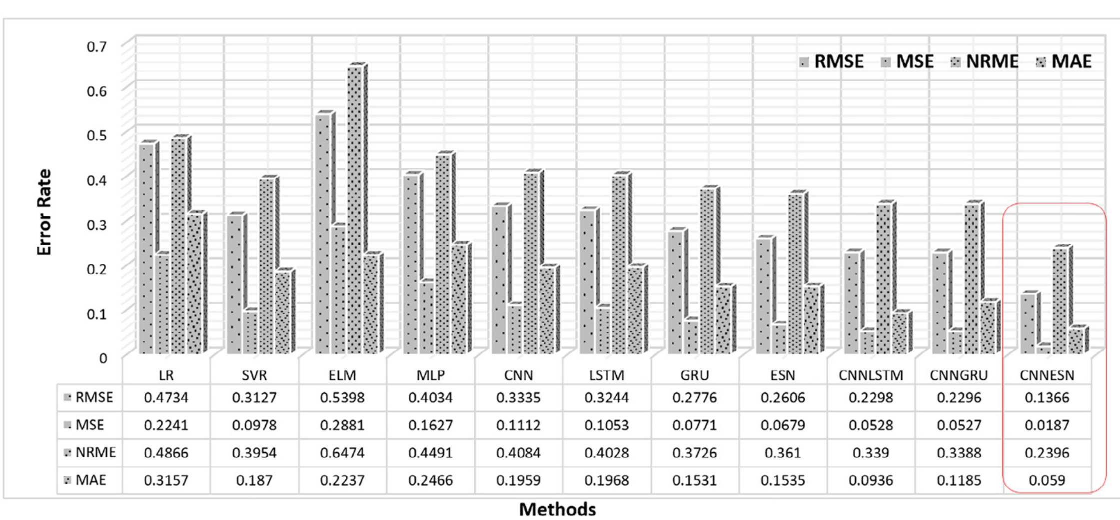
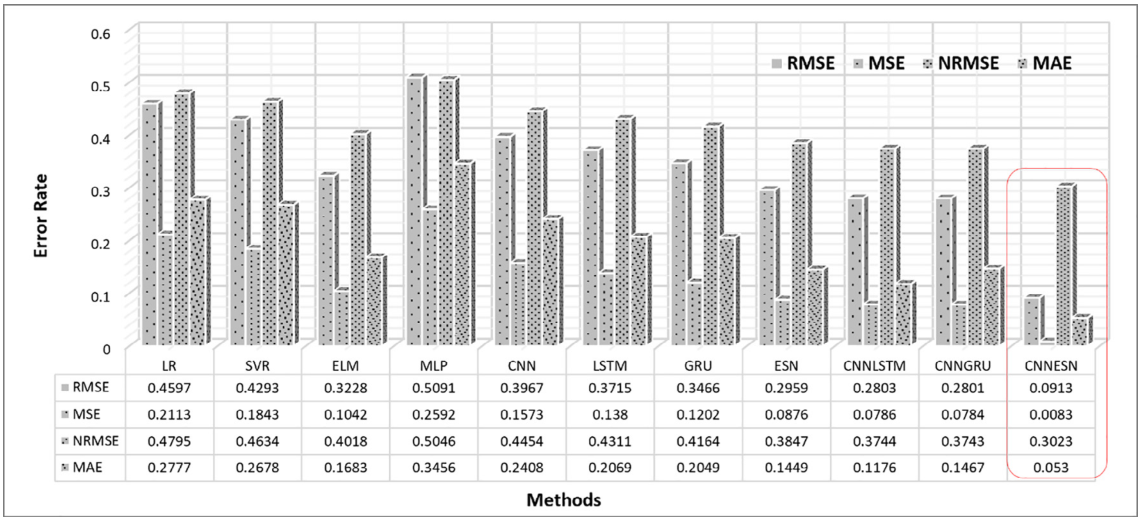
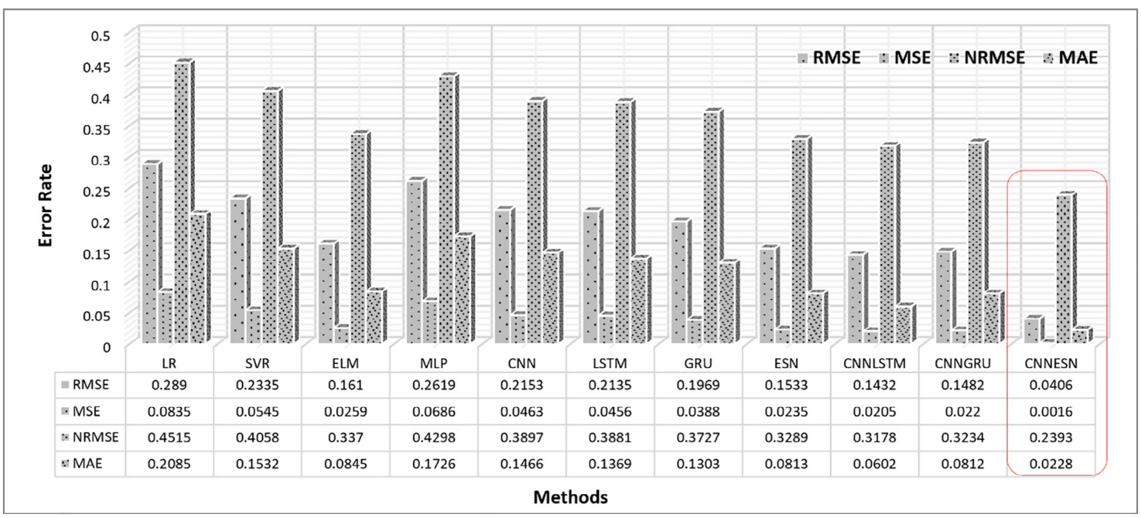


Fig. 5. Comparison of several models over Tarina 10.5 kW dataset.



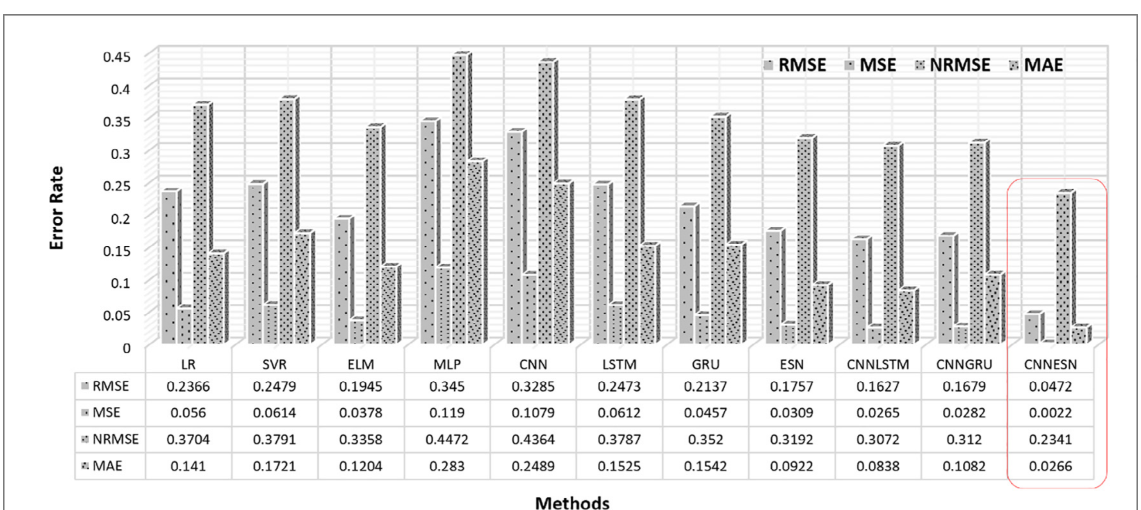
	LR	SVR	ELM	MLP	CNN	LSTM	GRU	ESN	CNNLSTM	CNNGRU	CNNESN
RMSE	0.4597	0.4293	0.3228	0.5091	0.3967	0.3715	0.3466	0.2959	0.2803	0.2801	0.0913
MSE	0.2113	0.1843	0.1042	0.2592	0.1573	0.138	0.1202	0.0876	0.0786	0.0784	0.0083
NRMSE	0.4795	0.4634	0.4018	0.5046	0.4454	0.4311	0.4164	0.3847	0.3744	0.3743	0.3023
MAE	0.2777	0.2678	0.1683	0.3456	0.2408	0.2069	0.2049	0.1449	0.1176	0.1467	0.053

Fig. 6. Comparison of several models over Tarina 23.4 kW dataset.



	LR	SVR	ELM	MLP	CNN	LSTM	GRU	ESN	CNNLSTM	CNNGRU	CNNESN
RMSE	0.289	0.2335	0.161	0.2619	0.2153	0.2135	0.1969	0.1533	0.1432	0.1482	0.0406
MSE	0.0835	0.0545	0.0259	0.0686	0.0463	0.0456	0.0388	0.0235	0.0205	0.022	0.0016
NRMSE	0.4515	0.4058	0.337	0.4298	0.3897	0.3881	0.3727	0.3289	0.3178	0.3234	0.2393
MAE	0.2085	0.1532	0.0845	0.1726	0.1466	0.1369	0.1303	0.0813	0.0602	0.0812	0.0228

Fig. 7. Comparison of several models over Eco-Kinetics 26.5 kW dataset.



	LR	SVR	ELM	MLP	CNN	LSTM	GRU	ESN	CNNLSTM	CNNGRU	CNNESN
RMSE	0.2366	0.2479	0.1945	0.345	0.3285	0.2473	0.2137	0.1757	0.1627	0.1679	0.0472
MSE	0.056	0.0614	0.0378	0.119	0.1079	0.0612	0.0457	0.0309	0.0265	0.0282	0.0022
NRMSE	0.3704	0.3791	0.3358	0.4472	0.4364	0.3787	0.352	0.3192	0.3072	0.312	0.2341
MAE	0.141	0.1721	0.1204	0.283	0.2489	0.1525	0.1542	0.0922	0.0838	0.1082	0.0266

Fig. 8. Comparison of several models over IHEPC dataset.

Table 5
Comparison of the proposed CNNESN model with state-of-the-art models over DKASC datasets.

Dataset	Paper	Method	Data Resolution	RMSE	MSE	NRMSE	MAE
DKASC, Yulara, 3A	Chen et al. (2020)	RCC-LSTM	5 min	0.94	–	–	0.587
DKASC-ASA	Zang et al. (2020)	DenseNet	1 h	–	0.081	–	0.152
	Li et al. (2019)	HIMVO-SVM	30 min	–	–	–	0.2805
	Zhou et al. (2020)	SDA-GA-ELM	5 min	–	–	21.07	0.2367
	Cheng et al. (2021)	GCN	5 min	0.336	–	–	0.177
	Li et al. (2020)	WPD-LSTM	5 min	0.2357	–	–	–
	Korkmaz (2021)	SolarNet	5 min	0.309	–	–	0.175
	Wang et al. (2019)	CNN-LSTM	5 min	0.343	–	–	0.126
	Wang et al. (2019)	LSTM-CNN	5 min	0.621	–	–	0.221
	Proposed	**CNNESN (Average)**	**5 min**	**0.0895**	**0.0095**	**0.2604**	**0.0449**

Table 6
Comparison of the proposed CNNESN model with state-of-the-art models over IHEPC datasets.

Paper	RMSE	MSE	MAE
Rajabi and Estebsari (2019)	0.79	–	0.59
Khan et al. (2020)	0.42	0.18	0.29
Haq et al. (2021)	0.32	0.10	0.31
Ullah et al. (2020)	0.5650	0.3193	0.3469
Kim and Cho (2019)	0.5957	0.3549	0.3317
Mocanu et al. (2016)	0.6663	–	–
Tao Han et al. (2020)	0.22	0.17	0.19
Khan et al. (2020)	0.47	0.19	0.31
Kim and Cho (2019)	–	0.3840	0.3953
Proposed	**0.0472**	**0.0022**	**0.0266**

Table 7
Different settings for model complexity analysis.

Setting	Memory	Model
GPU	8 GB	GeForce RTX 2070
CPU	64 GB	Intel Core i5-6600
RPI	4 GB	RPI 4B+

ple layers to achieve better prediction performance. The better performance comes at the cost of higher computational complexity and limited generalization towards unseen real-world data. In contrast, the ESNs, are introduced for textual prediction data due to their better modeling abilities of complex and dynamic patterns. Furthermore, ESNs are truly designed for high-level non-linear data with key benefit of short-term memory capacity which ensures to recall satisfying extent of the previous input to the current state.

4.5. Time complexity analysis

Alongside error rate reduction in the time-series domain, real-time implementation of predictive models demands to be lightweight so that they can be implemented on edge devices to reduce the computational cost in MG systems. The computationally expensive models may cause system instability and delay in response time which leads to power losses. Considering the application of the lightweight modeling techniques, the researchers are focusing to improve the forecasting results and reduce the computational cost of the model. In this work, we conducted experiments to find the computational complexity of the proposed model with the three available settings, as given in Table 7 and compared it with the state-of-the-art model developed for RPGP and ECP. The detailed time complexity analysis of the proposed model and other state-of-the-art models is given in Table 8**.** As shown in Table 8, the computational complexity of the proposed models is lower than other state-of-the-art models over CPU, GPU, and Raspberry Pi (RPI) which ensures the implementation of the proposed model in real time.

The lower computational complexity of the proposed model is due to the lightweight nature of ESN, where we only train the output weights of the network, speeding up the training and testing time of the network and provide better predictions accuracy for time series data. This is the main reason behind lower computational complexity of the proposed CNNESN model. Compared to other RNNs, ESN is fast, easy to implement, and does not suffer from bifurcations. In several domains, ESNs achieved better performance compared to other methods for non-linear dynamical modeling.

5. Conclusion

Balancing electricity generation and consumption is among the several main objectives of the smart grid. For effective electricity generation and consumption managament, predictive modeling techniques provide a significant role by matching the consumption and generation to ensure sufficient energy transmission towards end-users. Several predictive modeling techniques are already available to predict future electricity generation and consumption with questionable accuracy and higher computational complexity, that hinder their applicability in real-world scenarios. For this purpose, in this work, we developed an efficient and effective hybrid model for electricity generation and consumption prediction by integrating CNN and ESN architecture, achieving high prediction accuracy and demanding lowered running time. The proposed CNNESN model is finalized after an extensive ablation study of

Table 8
Comparative analysis of the proposed model with state-of-the-art in terms of running time.

Method	GPU	CPU	RPI	Remarks
Chen et al. (2020)	–	6.387	–	Intel Core i5 with 8 GB RAM
Cheng et al. (2021)	3.5		–	GTX 1080 GPU
Wang et al. (2019)	–	0.6217 h	–	Intel Core i5 with 8 GB RAM
Wang et al. (2019)	–	7.196	–	Intel Core i5 with 8 GB RAM
Haq et al. (2021)	0.72	1.44	–	GeForce RTX 2070
Tao Han et al. (2020)	–	6.38	20.36	Intel Core i7 with 16 GB RAM, RPI ARM Cortex A53 processor
Proposed	**0.544**	**0.874**	**1.014**	Refer to details in Table 7

machine learning, deep learning, and a hybrid combination of these models. The results aprove that the proposed model achieved higher prediction accuracy and demand significantly reduced running time when compared to state-of-the-art prediction models. The results reveal a high margin of reduction in the error rates over DKASC dataset (i.e., RMSE (21.95%), MSE (7.15%), and MSE (8.11%)) and IHEPC dataset (i.e., RMSE (17.28%), MSE (9.78%), and MAE (16.34 %)) as compared to state-of-the-art models. The dominant derived results indicate that our proposed model can also be effectively used in other time-series prediction domains such as traffic, weather, and stock price prediction. In the future, we aim to investigate emerging technologies such explainable artificial intelligence, reinforcement learning, lifelong learning, and active learning technique for power generation and consumption prediction.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Aasim, Singh, S.N., Mohapatra, A., 2019. Repeated wavelet transform based ARIMA model for very short-term wind speed forecasting. Renewable Energy 136, 758–768.

Afrasiabi, M., Mohammadi, M., Rastegar, M., Stankovic, L., Afrasiabi, S., Khazaei, M., 2020. Deep-based conditional probability density function forecasting of residential loads. IEEE Trans. Smart Grid 11 (4), 3646–3657.

Ait Maatallah, O., Achuthan, A., Janoyan, K., Marzocca, P., 2015. Recursive wind speed forecasting based on Hammerstein Auto-Regressive model. Appl. Energy 145, 191–197.

Ali, M., Prasad, R., 2019. Significant wave height forecasting via an extreme learning machine model integrated with improved complete ensemble empirical mode decomposition. Renew. Sustain. Energy Rev. 104, 281–295.

Amasyali, K., El-Gohary, N.M., 2018. A review of data-driven building energy consumption prediction studies. Renew. Sustain. Energy Rev. 81, 1192–1205.

Bendaoud, N.M.M., Farah, N., Ahmed, S.B., 2021. Comparing Generative Adversarial Networks architectures for electricity demand forecasting. Energy Build. 247, 111152.

Chandola, V., Banerjee, A., Kumar, V., 2009. Anomaly detection: A survey. ACM Computing Surveys (CSUR) 41 (3), 1–58.

Chen, B., Lin, P., Lai, Y., Cheng, S., Chen, Z., Wu, L., 2020. Very-short-term power prediction for PV power plants using a simple and effective RCC-LSTM model based on short term multivariate historical datasets. Electronics 9 (2), 289.

Chen, Q., Shi, L., Na, J., Ren, X., Nan, Y., 2018. Adaptive echo state network control for a class of pure-feedback systems with input and output constraints. Neurocomputing 275, 1370–1382.

Cheng, L., Zang, H., Ding, T., Wei, Z., Sun, G., 2021. Multi-meteorological-factor-based Graph Modeling for Photovoltaic Power Forecasting. IEEE Trans. Sustainable Energy 12 (3), 1593–1603.

Chouikhi, N., Ammar, B., Rokbani, N., Alimi, A.M., 2017. PSO-based analysis of Echo State Network parameters for time series forecasting. Appl. Soft Comput. 55, 211–225.

Ding, S., Hipel, K.W., Dang, Y.-g., 2018. Forecasting China's electricity consumption using a new grey prediction model. Energy 149, 314–328.

DKASC, Alice Springs, http://dkasolarcentre.com.au/download?location=alice-springs.

Doe, U.S., 2011. DOE Microgrid Workshop Report. Office of Elect. Del. and Energy Rel, San Diego, CA, USA.

Farsi, B., Amayri, M., Bouguila, N., Eicker, U., 2021. On short-term load forecasting using machine learning techniques and a novel parallel deep LSTM-CNN approach. IEEE Access 9, 31191–31212.

Gallicchio, C., Micheli, A., Pedrelli, L., 2017. Deep reservoir computing: A critical experimental analysis. Neurocomputing 268, 87–99.

Genes C., Esnaola I., Perlaza S.M., Ochoa L.F., Coca D., 2017. Recovering missing data via matrix completion in electricity distribution systems. 1-6.

Goodfellow I., Bengio Y., Courville A., Bengio Y., *Deep Learning*: MIT Press; Cambridge, 2016.

Guefano, S., Tamba, J.G., Azong, T.E.W., Monkam, L., 2021. Forecast of electricity consumption in the Cameroonian residential sector by Grey and vector autoregressive models. Energy 214, 118791.

Gupta A., Bansal A., Roy K., 2021. Solar energy prediction using decision tree regressor. pp. 489-495.

Haq, I.U., Ullah, A., Khan, S.U., Khan, N., Lee, M.Y., Rho, S., Baik, S.W., 2021. Sequential learning-based energy consumption prediction model for residential and commercial sectors. Mathematics 9 (6), 605.

Hussain, T., Muhammad, K., Ullah, A., Cao, Z., Baik, S.W., de Albuquerque, V.H.C., 2020. Cloud-assisted multiview video summarization using CNN and bidirectional LSTM. IEEE Trans. Ind. Inf. 16 (1), 77–86.

Hussain, T., Min Ullah, F.U., Muhammad, K., Rho, S., Ullah, A., Hwang, E., Moon, J., Baik, S.W., 2021. Smart and intelligent energy monitoring systems: A comprehensive literature survey and future research guidelines. Int. J. Energy Res. 45 (3), 3590–3614.

Individual household electric power consumption Data Set, https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption.

Jaeger H., 2001. The "echo state" approach to analysing and training recurrent neural networks-with an erratum note. *Bonn, Germany: German National Research Center for Information Technology GMD Technical Report*, 2001, vol. 148, no. 34, pp. 13.

Khan S., Javaid N., Chand A., Khan A.B.M., Rashid F., Afridi I.U., 2019. Electricity load forecasting for each day of week using deep CNN. 1107-1119.

Khan, N., Ullah, F.U.M., Haq, I.U., Khan, S.U., Lee, M.Y., Baik, S.W., 2021. AB-Net: A novel deep learning assisted framework for renewable energy generation forecasting. Mathematics 9 (19), 2456.

Khan, N., Haq, I.U., Khan, S.U., Rho, S., Lee, M.Y., Baik, S.W., 2021. DB-Net: A novel dilated CNN based multi-step forecasting model for power consumption in integrated local energy systems. Int. J. Electr. Power Energy Syst. 133, 107023.

Khan, Z.A., Ullah, A., Ullah, W., Rho, S., Lee, M., Baik, S.W., 2020. Electrical energy prediction in residential buildings for short-term horizons using hybrid deep learning strategy. Applied Sciences 10 (23), 8634.

Khan, Z.A., Hussain, T., Ullah, A., Rho, S., Lee, M., Baik, S.W., 2020. Towards efficient electricity forecasting in residential and commercial buildings: A novel hybrid CNN with a LSTM-AE based framework. Sensors 20 (5), 1399.

Kim, J.-Y., Cho, S.-B., 2019. Electric energy consumption prediction by deep learning with state explainable autoencoder. Energies 12 (4), 739.

Kim, T.-Y., Cho, S.-B., 2019. Predicting residential energy consumption using CNN-LSTM neural networks. Energy 182, 72–81.

Kim, J., Moon, J., Hwang, E., Kang, P., 2019. Recurrent inception convolution neural network for multi short-term load forecasting. Energy Build. 194, 328–341.

Korkmaz, D., 2021. SolarNet: A hybrid reliable model based on convolutional neural network and variational mode decomposition for hourly photovoltaic power forecasting. Appl. Energy 300, 117410.

Kuo, P.-H., Huang, C.-J., 2018. A high precision artificial neural networks model for short-term energy load forecasting. Energies 11 (1), 213.

Le, T., Vo, M.T., Vo, B., Hwang, E., Rho, S., Baik, S.W., 2019. Improving electric energy consumption prediction using CNN and Bi-LSTM. Appl. Sci. 9 (20), 4237.

Li, G., Wang, H., Zhang, S., Xin, J., Liu, H., 2019. Recurrent neural networks based photovoltaic power forecasting approach. Energies 12 (13), 2538.

Li, L.-L., Wen, S.-Y., Tseng, M.-L., Wang, C.-S., 2019. Renewable energy prediction: A novel short-term prediction model of photovoltaic output power. J. Cleaner Prod. 228, 359–375.

Li, L.-L., Zhao, X., Tseng, M.-L., Tan, R.R., 2020. Short-term wind power forecasting based on support vector machine with improved dragonfly algorithm. J. Cleaner Prod. 242, 118447.

Li, P., Zhou, K., Lu, X., Yang, S., 2020. A hybrid deep learning model for short-term PV power forecasting. Appl. Energy 259, 114216.

Lu, Q.C., Grady, W.M., Crawford, M.M., Anderson, G.M., 1989. An adaptive nonlinear predictor with orthogonal escalator structure for short-term load forecasting. IEEE Trans. Power Syst. 4 (1), 158–164.

Ma, J., Ma, X., 2018. A review of forecasting algorithms and energy management strategies for microgrids. Syst. Sci. Control Eng. 6 (1), 237–248.

Ma, Q., Shen, L., Chen, W., Wang, J., Wei, J., Yu, Z., 2016. Functional echo state network for time series classification. Inf. Sci. 373, 1–20.

Ma, X., Wang, Y., Qin, J., 2013. Generic model of a community-based microgrid integrating wind turbines, photovoltaics and CHP generations. Appl. Energy 112, 1475–1482.

Mahmud, K., Sahoo, A., 2019. Multistage energy management system using autoregressive moving average and artificial neural network for day-ahead peak shaving. Electron. Lett. 55 (15), 853–855.

Meidani, H., Ghanem, R., 2013. Multiscale Markov models with random transitions for energy demand management. Energy Build. 61, 267–274.

Mocanu, E., Nguyen, P.H., Gibescu, M., Kling, W.L., 2016. Deep learning for estimating building energy consumption. Sustain. Energy Grids Netw. 6, 91–99.

Pappas, S.S., Ekonomou, L., Karamousantas, D.C., Chatzarakis, G.E., Katsikas, S.K., Liatsis, P., 2008. Electricity demand loads modeling using AutoRegressive Moving Average (ARMA) models. Energy 33 (9), 1353–1360.

Qu, J., Qian, Z., Pei, Y., 2021. Day-ahead hourly photovoltaic power forecasting using attention-based CNN-LSTM neural network embedded with multiple relevant and target variables prediction pattern. Energy 232, 120996.
Rafiei, M., Niknam, T., Aghaei, J., Shafie-Khah, M., Catalão, J.P.S., 2018. Probabilistic load forecasting using an improved wavelet neural network trained by generalized extreme learning machine. IEEE Trans. Smart Grid 9 (6), 6961–6971.
Rafique, S.F., Jianhua, Z., 2018. Energy management system, generation and demand predictors: a review. IET Gener. Transm. Distrib. 12 (3), 519–530.
Rahman, A., Srikumar, V., Smith, A.D., 2018. Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks. Appl. Energy 212, 372–385.
Rajabi R., Estebsari A., 2019. Deep learning based forecasting of individual residential loads using recurrence plots. 1-5.
Reikard, G., 2009. Forecasting ocean wave energy: Tests of time-series models. Ocean Eng. 36 (5), 348–356.
Sajjad, M., Khan, Z.A., Ullah, A., Hussain, T., Ullah, W., Lee, M.Y., Baik, S.W., 2020. A novel CNN-GRU-based hybrid approach for short-term residential load forecasting. IEEE Access 8, 143759–143768.
Sideratos, G., Ikonomopoulos, A., Hatziargyriou, N.D., 2020. A novel fuzzy-based ensemble model for load forecasting using hybrid deep neural networks. Electr. Power Syst. Res. 178, 106025.
Tan, Z., De, G., Li, M., Lin, H., Yang, S., Huang, L., Tan, Q., 2020. Combined electricity-heat-cooling-gas load forecasting model for integrated energy system based on multi-task learning and least square support vector machine. J. Cleaner Prod. 248, 119252.
Tang, L., Wang, X., Wang, X., Shao, C., Liu, S., Tian, S., 2019. Long-term electricity consumption forecasting based on expert prediction and fuzzy Bayesian theory. Energy 167, 1144–1154.
Tao Han K.M., Tanveer Hussain, Jaime Lloret, Sung Wook Baik, 2020. An efficient deep learning framework for intelligent energy management in dependable IoT, *IEEE Internet Things J.*
Tascikaraoglu, A., Uzunoglu, M., 2014. A review of combined approaches for prediction of short-term wind speed and power. Renew. Sustain. Energy Rev. 34, 243–254.
Trierweiler Ribeiro, G., Guilherme Sauer, J., Fraccanabbia, N., Cocco Mariani, V., dos Santos Coelho, L., 2020. Bayesian optimized echo state network applied to short-term load forecasting. Energies 13 (9), 2390.
Ullah, F.U.M., Ullah, A., Haq, I.U., Rho, S., Baik, S.W., 2019. Short-term prediction of residential power energy consumption via CNN and multi-layer bi-directional LSTM networks. IEEE Access 8, 123369–123380.
Ullah, F.U.M., Ullah, A., Haq, I.U., Rho, S., Baik, S.W., 2020. Short-term prediction of residential power energy consumption via CNN and multilayer Bi-directional LSTM networks. IEEE Access 8, 123369–123380.
Ullah, F.U.M., Khan, N., Hussain, T., Lee, M.Y., Baik, S.W., 2021. Diving deep into short-term electricity load forecasting: comparative analysis and a novel framework. Mathematics 9 (6), 611.
Ullah, A., Muhammad, K., Hussain, T., Baik, S.W., 2021. Conflux LSTMs network: A novel approach for multi-view action recognition. Neurocomputing 435, 321–329.
van der Meer, D., Chandra Mouli, G.R., Morales-Espana Mouli, G., Elizondo, L.R., Bauer, P., 2018. Energy management system with PV power forecast to optimally charge EVs at the workplace. IEEE Trans. Ind. Inf. 14 (1), 311–320.
Wang, H.-z., Li, G.-q., Wang, G.-b., Peng, J.-c., Jiang, H., Liu, Y.-t., 2017. Deep learning based ensemble approach for probabilistic wind power forecasting. Appl. Energy 188, 56–70.
Wang, Y., Liu, M., Bao, Z., Zhang, S., 2018. Short-term load forecasting with multi-source data using gated recurrent unit neural networks. Energies 11 (5), 1138.
Wang, Y., Liao, W., Chang, Y., 2018. Gated recurrent unit network-based short-term photovoltaic forecasting. Energies 11 (8), 2163.
Wang, K., Qi, X., Liu, H., 2019. A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network. Appl. Energy 251, 113315.
Wang, K., Qi, X., Liu, H., 2019. Photovoltaic power forecasting based LSTM-Convolutional Network. Energy 189, 116225.
Wang, Y., Wang, J., Wei, X., 2015. A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: A case study of wind farms in northwest China. Energy 91, 556–572.
Wang, S., Wang, X., Wang, S., Wang, D., 2019. Bi-directional long short-term memory method based on attention mechanism and rolling update for short-term load forecasting. Int. J. Electr. Power Energy Syst. 109, 470–479.
Wang, Y., Wang, H., Srinivasan, D., Hu, Q., 2019. Robust functional regression for wind speed forecasting based on Sparse Bayesian learning. Renewable Energy 132, 43–60.
Wang, F., Yu, Y., Zhang, Z., Li, J., Zhen, Z., Li, K., 2018. Wavelet decomposition and convolutional LSTM networks based improved deep learning model for solar irradiance forecasting. Appl. Sci. 8 (8), 1286.
Wang, F., Zhang, Z., Liu, C., Yu, Y., Pang, S., Duić, N., Shafie-khah, M., Catalão, J.P.S., 2019. Generative adversarial networks and convolutional neural networks based weather classification model for day ahead short-term photovoltaic power forecasting. Energy Convers. Manage. 181, 443–462.
Wang, J., Zhang, N., Lu, H., 2019. A novel system based on neural networks with linear combination framework for wind speed forecasting. Energy Convers. Manage. 181, 425–442.
Woo S., Park J., Park J., 2018. Predicting wind turbine power and load outputs by multi-task convolutional LSTM model. 1-5.
Wu, L., Gao, X., Xiao, Y., Yang, Y., Chen, X., 2018. Using a novel multi-variable grey model to forecast the electricity consumption of Shandong Province in China. Energy 157, 327–335.
Wu, D., Wang, B., Precup, D., Boulet, B., 2019. Multiple kernel learning-based transfer regression for electric load forecasting. IEEE Trans. Smart Grid 11 (2), 1183–1192.
Xie Z., Wang R., Wu Z., Liu T., 2019. Short-term power load forecasting model based on fuzzy neural network using improved decision tree. 482-486.
Xu, Y., Vaziri-Pashkam, M., 2021. Limits to visual representational correspondence between convolutional neural networks and the human brain. Nat. Commun. 12 (1), 1–16.
Yang, D., 2019. On post-processing day-ahead NWP forecasts using Kalman filtering. Sol. Energy 182, 179–181.
Yao, X., Wang, Z., Zhang, H., 2019. A novel photovoltaic power forecasting model based on echo state network. Neurocomputing 325, 182–189.
Zang, H., Cheng, L., Ding, T., Cheung, K.W., Wei, Z., Sun, G., 2020. Day-ahead photovoltaic power forecasting approach based on deep convolutional neural networks and meta learning. Int. J. Electr. Power Energy Syst. 118, 105790.
Zheng, Z., Chen, H., Luo, X., 2019. A Kalman filter-based bottom-up approach for household short-term load forecast. Appl. Energy 250, 882–894.
Zhou, H., Zhang, Y., Yang, L., Liu, Q., Yan, K., Du, Y., 2019. Short-term photovoltaic power forecasting based on long short term memory neural network and attention mechanism. IEEE Access 7, 78063–78074.
Zhou, Y., Zhou, N., Gong, L., Jiang, M., 2020. Prediction of photovoltaic power output based on similar day analysis, genetic algorithm and extreme learning machine. Energy 204, 117894.