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Pre-Feasibility Analysis of an Improved Sand Piper Optimization Convolution Neural Network (ISO-CNN) based Hybrid Solar and Biomass Energy System

Arpita Johri [1], Dr. Mainak Basu [2], Dr. Varnita Verma [3]

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Abstract: The economic benefit and remarkable energy security can be achieved through the sustainable development of renewable energy and energy-efficient technology, which leads to the deduction in capital investment for the energy system. Renewable Energy System (RES) is a highly emerging attention-seeking area in the current economic condition because of an inexhaustible source. The accuracy of solar prediction is lagged due to the volatility and intermittency in solar forecasts. The installed power of biomass is below its potential even though highly available biomass source. So pre, feasible analysis is required to predict both solar and biomass energy for the future based on the prior data collection. For that, the deep learning method of convolutional neural network (CNN) is introduced, which is optimized by an improved sandpiper optimization (ISO) for forecasting both photovoltaic (PV) and biomass energy. Based on the successive four-month data collection, the MATLAB platform is used to simulate the output power of the proposed system. The proposed output is compared with conventional optimization-based predictions and results in high predictive accuracy due to climatic conditions.

Keywords: *achieved, compared, biomass, intermittency, prediction*

1. Introduction

Owing to the environmental hazards and depleting resources of conventional energy resources, the world has adopted renewable energy systems (RES) as an alternative energy mechanism to reduce greenhouse gas emissions. RES like solar, biomass, geothermal, and wind are pollution-free, abundant, naturally accessible sources [1]. Solar energy is very crucial in a solar power system to design and has inborn characteristics. However, due to the varying weather condition, there is difficulty in the stability of solar irradiance to perform better outcomes [2]. So, researchers have found short-term prediction techniques in renewable energy sources to conquer these uncertainties [3]. Biomass energy is another RES produced from organic materials such as plants and animals. It produces fewer pollutants in the air than fossil fuels and improves the environment and energy security [4]. However, bulk storage and transportation arrangements are required to overcome feedstock uncertainty's effects, leading to high investment prices in large-scale biomass plants [5]. Thus, hybrid renewable energy sources (HRES) are adopted to suppress their drawbacks. The decrease in biomass usage is due to hybridization with solar energy. Hence, the investment cost has been reduced [6]. The hybridization of solar and biomass energy sources has resulted in more reliable pre-feasibility analysis and high efficiency in energy conversion [7].

Photovoltaic (PV) and biomass power are predicted by using various methods, namely machine learning (ML) methods [8] and deep learning (DL) methods [9]. Both learning methods are types of artificial intelligence. Even when the ML model is easier to build, it takes more human interaction, whereas DL models are also the subfield of ML and are challenging to synthesize and simulate. DL Models have a multilayered neural network that can learn by itself [10]. This paper utilizes the DL method for implementation.

In recent years, support vector machines (SVM) [11] and artificial neural networks (ANN) [12] were used to predict power in solar PV and biomass under unexpected changes due to climatic conditions. However, SVM does not perform well under large data sets, so a convolutional neural network (CNN) is adopted to predict the power without human supervision [13]. The CNN structure incorporates five layers, of which convolution and pooling layers are assembled alternately [14]. Some of the algorithms are proposed in recent papers to optimize weight parameters in the network, like wildebeest herd optimization (WHO) (15), artificial bee colony algorithm (ABC) [16], bat algorithm (BA), and particle swarm optimization (PSO) [17], etc. The algorithms mentioned above have tried to optimize best weight parameters by collecting decentralized solar and biomass data, but due to the sudden changes in the weather conditions, hyperparameter optimization for forecasting

[1]*Ph.D. Scholar, School of Engineering & Sciences, G.D. Goenka University, Gurgaon (Haryana), India & Assistant Professor in the Department of Electronics & Communication Engineering, ABES Engineering College, Ghaziabad (Uttar Pradesh), India; arpitajohri@gmail.com*

[2]*Assistant Professor, School of Engineering & Sciences, G.D. Goenka University, Gurgaon (Haryana), India; mainak.basu@gdgu.org*

[3] *Post-Doctoral Fellow in the School of Interdisciplinary Research Engineering at IIT Delhi; varnitaverma2@gmail.com*

solar and biomass by the above algorithms has performed with a lesser convergence rate [18].

Rather to ANN, CNN has three characteristics: weight sharing, local connection mode, and spatial pooling. The local connection mode reduces the count of parameters in the network, making it less difficult to train the network [19]. CNN also minimizes the prediction error and performs better prediction than other neural networks [20]. An improved sandpiper optimization (ISO) is applied with CNN to enhance the weight parameters of the layers in CNN. An ISO-based CNN (ISO-CNN) model is adopted in this paper for the pre-feasible analysis of HRES with solar and biomass in terms of necessary solar irradiance, climatic conditions, and biomass. The principal motive of the work is to forecast solar and biomass.

The major contributions of the work are mentioned below:

- In addition, monthly average data sets of solar irradiance and biomass recourse have been collected for September, October, November, and December.
- CNN-based ISO is utilized to evaluate the optimum weight parameter in the network to forecast HRES.
- Under varying times, the power from solar and biomass is predicted and compared with conventional techniques.

The organization of this paper is as follows:

Section 2 discusses the various algorithm-based CNN to solar and biomass forecasts. Section 3 explains the proposed model constituting a convolution neural network and improved sandpiper optimization. Section - 4 discusses the predicted output power of solar and biomass. Finally, section 5 concludes the paper.

2. Related Works

The introduction of much redundant information and the necessity of strict variables restricted the forecast-based hybrid long short-term memory (LSTM) and CNN applications. To overcome that obstacle, Jiaqi Qu et al. [21] proposed day-ahead hourly power prediction of PV. As LSTM could lengthen the temporal features whereas the attention mechanism avoided flaws of distraction and so attention based long-term and short-term temporal neural network prediction model (ALSM) was designed in the paper. The paper includes two temporal modules such as short-term (ST) and long-term (LT) temporal modules based on CNN and LSTM. In addition, the attention module was also incorporated to form the ALSM model. The work adopted the relevant and target variable prediction pattern (MRTPP), which accepts relevant datasets as input and predicts the target variable using the CNN model. The ST and LT temporal changes in time series were captured simultaneously to perform the pre-feasible analysis in solar energy forecasting for a day.

Beneficial to mitigate the training difficulty of CNN and to make it converge smoothly, Haxixiang Zang et al. [22] proposed a hybrid model-based deep CNN for short-term solar forecasting. Variational mode decomposition (VMD) was introduced with multiple input factors like time series PV power and other climatic variables like temperature irradiance. Among them, time-based solar irradiance disintegrated into numerous components via VMD. Each element should be in the form of 2D correlated with daily and hourly time scales and fed to CNN. The time series features of power could be learned by convolution kernels and lead to an advanced prediction by reducing the data size.

Ultraviolet (UV) radiation from solar was an important factor in improving the human body's immune system, so the UV index (UVI) prediction was significant. Abdul Abrar Masrur Ahmed et al. [23] proposed an optimization algorithm-based deep learning method to develop UVI forecasting. Initially, historical data on UV irradiance was collected, and a hybrid deep learning model was introduced as CNN-LSTM. When the data flowed to the network, the Hybrid CNN-LSTM model was optimized by four optimization methods. After comparing the four algorithms, the genetic algorithm (GA) provides better efficient prediction with lower error than the other three methods.

Chiou-Jye Huang and Ping-Huan Kuo [24] proposed collective input high precision deep neural network models termed PVPNet for short-term PV forecasting. CNN model was applied with PVPNET and included two-dimensional operations; moreover, the input of PVPNet was solar heat, PV irradiance, and output from the panel for the previous five days. The work performed in the next 24 hours means a full day of probabilistic solar energy forecasting. The accuracy of the forecasting process was found by mean absolute error (MAE), and root mean square error (RMSE) value. Then this presentation was compared with various machine learning methods based on error values and resulted in efficient forecasting by the PVPNET model.

The uncertainties in PV output power would reduce the actual time control performance and cause economic troubles. To rectify that, accurate forecasting of solar power was needed. Deniz Korkmaz et al. [25] designed deep CNN and input signal decomposition algorithms named empirical mode decomposition (EMD) to perform short-term solar forecasting. AlexNet architecture was utilized in CNN to forecast 1 hour to 5 hours ahead of PV power. The historical data of solar irradiance, temperature, wind, and electrical power was given as input then EMD converted the actual data into sub-sectors. The input parameters were reconstructed as 2D feature maps fed into CNN. The stochastic gradient descent (SGD) method was applied in the AlexNet model to extract the convolution kernel during the backpropagation process. Furthermore, higher weather-based data and geographical attributes were introduced to perform better predictions.

Prediction of biomass was essential, which notified how small the amount and timing of fertilizer, water, and pesticides needed to improve harvest production. Liyuan Pan et al. [26] proposed a non-destructive method for biomass prediction using light detection and ranging (LiDAR). The biomass prediction network was based on plant height, the density of the point cloud, and plant structure. First, three modules, namely the completion module, were used to predict missing points due to sunshade obstruction. Next, the regularization module regulated the neural representation of the whole plot. Then finally, the projection module adopts CNN to extract the salient features of the point cloud from the bird's viewpoint. After introducing several sensors to the system, the prediction accuracy was improved.

The energy produced by RES was higher than the user's demand during the off-peak hour, which caused damage to the motors and generators. To conquer that, Kurusheed Aurangzeb et al. [27] proposed energy forecasting of renewable energy by using multiheaded CNN with the energy storage system. The energy storage system was incorporated with RES like solar and wind to forecast the energy and balance the energy management in residential areas. Nearly 80 homes were considered in this paper to show the balance of energy consumption by predicting the power. Moreover, electricity cost was reduced without compromising the user's energy consumption by considering a small grid model. Furthermore, the forecasting model in another energy sector, like the industrial area, will be implemented in future work.

Vishnu Suresh et al. [28] proposed the pre-feasible PV prediction analysis using CNN with a sliding window algorithm (SWA). The paper was implemented for CNN-based methods like standard CNN, multiheaded CNN, and CNN-LSTM using sliding window approaches and data pre-processing. Accuracy and benchmarking metrics were calculated for an hour, day, and week under both summer and winter seasons. Root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE) were also calculated. Results from autoregressive moving averages and multiple linear regression models were compared with these evaluation metrics to improve short-term and medium-term predictions.

Xiang Zhang and Zhuoqun Wei [29] proposed bat algorithm (BA) optimized hybrid extreme learning machine (ELM) based wavelet transform (WT) and principle component analysis (PCA) to forecast solar radiation. The paper revealed that the historical data of solar was decomposed into two time-series data by WT. PCA minimized the dimension of meteorological factors and historical data after determining the lag phase of historical radiation through partial autocorrelation function (PACF). In such a way, the reduction in dimension by PCA avoids the problems in multiple regressions of pre-selected variables during prediction. ELM was adopted to forecast the PV irradiance, which BA optimized. ELM depended on the function of the feed-forward network with a single hidden layer.

Mohamed E. Zayed et al. [30] proposed a solar dish stirling power plant prediction using a chimp optimization-based random vector functional link (RVFL) neural network. The paper predicts not only the instantaneous output power but also the power production every month of the solar power plant by including RVFL. First, the optimum value of the RVFL neural network was estimated by adopting the chimp optimization algorithm. Then, based on the four functions of the chimpanzee's colony, the scheme determined the best value. Then obtained result was compared with four conventional optimization based RVFL networks and suggested as an effective prediction made by this model.

As the higher demand for RES due to pollution free, the fuel cell plays an essential part in the world, Dr. Suresh. G et al. [31] implemented the power flow prediction of a small grid using HRES like PV, wind, and fuel cells. The hybrid algorithm of turbulent flow water-based optimization (TFWO) and battle royale optimization (BRO) was introduced in the paper to manage the power flow of the grid. TFWO predicted the load requirement, whereas BRO processed that expected load to predict the power demand. PV, wind, micro turbine, fuel cell, and energy storage systems were incorporated in the paper. Based on the hybrid input, the load demand and power needed for the load were predicted, and the power flow to the load in the smart grid with less computing time.

3. Proposed Methodology

Forecasting of HRES involves more than one renewable energy source, which eliminates power intermittency. In our proposed work, solar and biomass energy sources are predicted using the ISO-optimized CNN shown in Fig. 1.

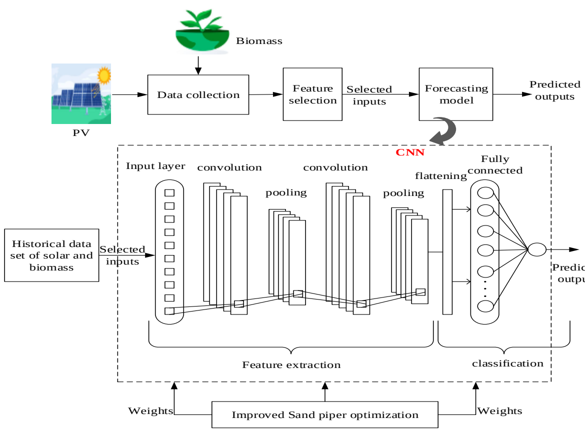

Fig. 1. Diagram of ISO-based CNN for hybrid renewable energy prediction

Based on the solar irradiance, temperature, biomass, PV and biomass generation, etc., are mentioned in the dataset. However, the input is in a large set. Therefore, feature selection feeds only the selected inputs into the forecasting model. The proposed forecasting model is ISO-based CNN, in which the selected input data to train and validate the CNN is given to the input layer of CNN. Convolution kernels do feature extraction using shared weights in the convolution layer. An algorithm of ISO is adopted to evaluate the optimal weight in the layer. The CNN model is validated and trained as the target variable, and finally, the output is predicted by a dense layer through the flattening process based on test data.

3.1. Data set collection for photovoltaic energy

As a renewable energy source, solar energy generated from PV is a green energy source because of its non-generation of carbon. Solar energy is a sustainable energy source that directly uses the sun's radiation and temperature and does not cause greenhouse gas like other fuel-based sources. The non-linear output power from PV causes the system's effectiveness and reliability such that the solar energy prediction is applicable to mitigate the uncertainties. The monthly average of historical data set for solar energy is collected based on meteorological conditions like temperature, humidity, irradiance, etc. A deep learning algorithm of CNN is proposed in the paper to forecast global irradiance every month [32].

3.2. Data set collection for biomass energy

Biomass is another renewable energy source directed from biological sources. Biomass is based on the carbon cycle from the atmosphere to the soil through biological plants. Biomass is mainly produced in agricultural fields and forests. Biomass prediction depends on plant structure. The image-based biomass prediction shows specific difficulties by using a linear regression method. A historical data set of biomass energy is collected for four months, and a deep learning method is adopted in the paper for energy prediction [33].

3.3. Cost analysis of proposed system components

The proposed hybrid system includes solar and biomass energy for predicting power. In PV panels, the solar modules are connected in series and parallel, in which the sunlight strikes in terms of solar irradiance and temperature to generate DC power. The lifetime of a PV array is twenty years, and the generated solar power data is pre-collected for four months. In the case of a 1 KW solar energy system, installation, and replacement cost approximately 5000$ and 4000$, respectively. The installation and replacement cost of 4 KW PV is computed as,

$$C_{i\,PV} = 2 \times C_{ai} \tag{1}$$

$$C_{r\,PV} = 2 \times C_{ar} \tag{2}$$

where, $C_{i\,PV}$ is the installation or capital cost of PV, C_{ai} is the considerable value of installation cost for 1 KW, $C_{r\,PV}$ is the replacement cost of PV, and C_{ar} is the cost of replacement that is taken as considered value. Both installation and replacement cost of solar is doubled by the particular considerable price of capital and replacement for each power system capacity.

Similarly, the capital and replacement cost of biomass is approximately for 1KW 3500$ and 3000$, respectively. The cost analysis for 4 KW biomass systems is determined as follows,

$$C_{i\,B} = 2 \times C_{ai\,B} \tag{3}$$

$$C_{r\,B} = 2 \times C_{ar\,B} \tag{4}$$

where, $C_{i\,B}$ is the installation cost of biomass, C_{aiB} is the considered value for installation cost of biomass, $C_{r\,B}$ is the cost of replacement for biomass, and C_{arB} is the considerable value of biomass replacement cost for 1 KW [34].

3.4. CNN for feature extraction

CNN has a weight sharing capability to minimize the model parameters and increase the training efficiency. In addition, CNN can carry prior information on historical data sets for the future power prediction of HRES. The monthly average data set for solar and biomass power is selected as input features of CNN to predict the power of HRES. It includes three layers other than the input and output layers, as shown in the basic structure of CNN in Fig. 2. Two parts divide the five layers, namely feature extraction, and classification. The input, convolution, and pooling layers deal with the feature extraction category. At the same time, the classification part includes both fully connected and output layers.

Input layer: The input data sets of solar and biomass are specified by an input layer and fed into the multiple learned kernels using shared weights in the next layer. It accepts 2D input data, and the entire convolution and pooling layer is in a 2D structure.

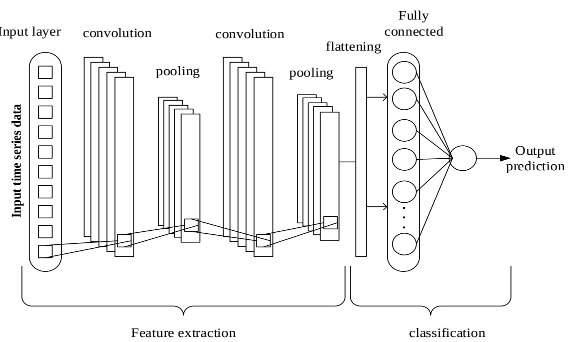

Fig. 2. Basic Architecture of CNN

Convolution layer: The convolution layer is a core layer of CNN that extracts local features from input data sets using convolution kernels. It also includes two crucial functions: local connection and weight sharing. Both parts operate at the same time through convolution kernels. It functions under different input channels without changing its weight, and the weights in this layer are also called a filter. In feature extraction, there are many numbers of convolution and pooling layer in CNN design then each convolution layer provide the output, which is computed as

$$X_j = f(\sum_{i=1}^{D_i} g_i * h_j + C_j \text{ where } j = 1, 2, ,..., D_o \tag{5}$$

where g_i denotes input data of i^{th} the channel, h_j is the weight of the layer, C_j is bias of the layer connected to j^{th} data, f is the transfer function, and $*$ indicates a convolutional process.

Pooling layer: Usually**,** this layer performs the down-sampling process and is placed between two convolution layers. The data from one channel means solar data is considered for a few convolution layers. The down sampling or pooling process for that data is done in the application with feature extraction. The pooling process contains two operations: mean pooling and max pooling. The average mean pooling for the entire data is,

$$X_j = \sum_{i=1}^{nd} \frac{1}{n_d} g_i \text{ where } j = 1, 2, ,..., D_i \tag{6}$$

where n_d indicates several data in a pool and j is the number of input data.

Max polling is another down-sampling process that maintains the local features. It minimizes the input data dimension concerning the target prediction data. Then feature extracted data is provided towards the fully connected layer.

Fully connected layer: This layer is placed in the upper position of CNN and combines all the feature-extracted data through flattening. Flattening is nothing but the conversion of multi-dimensional data into a single output data. Finally, this layer predicts the future value based on prior and input data.

Output layer: The predicted data from the fully connected layer is provided as output based on the target variable through the output layer.

The classification part also includes many full connection layers, and the CNN model has the input-output pattern as follows,

$$IL \Rightarrow [CL \to PL] * P \Rightarrow [FL] * Q \Rightarrow OL \tag{7}$$

where, IL, CL, PL, FL, OL represents activities of input, convolution, pooling, fully connected, and output layer, respectively. P *and* Q is the count of convolution and fully connected layers [35, 36].

3.5. ISO-based CNN to evaluate the maximum weight

To enhance prediction accuracy using CNN, ISO is required to estimate the best weight parameters in the layer. An ISO optimization is adopted with CNN in the proposed model to enhance the optimal weight of the layer. Sandpipers are omnivorous sea birds that eat insects, fish, earthworms, etc. They are talented birds that create a sound like rain by using their feet for hunting earthworms and breadcrumbs for hunting fish. In our proposed model, the inputs like historical data of solar and biomass power are fed into ISO-based CNN to optimize the maximum weight. The fitness value of the weight parameters is evaluated based on the fundamental behavior of sandpipers, namely migration and attack. A group of sandpipers migrates from one place to another towards the best fittest weight of the layer. The best fittest value is set as the maximum value of weight in the layer. So high-cost functions, less accuracy, and high computational complexity occur due to the collision during migration. Therefore, to avoid collision between them, the collision avoidance agent is introduced, and the position of the search agent $\vec{A}_{ps}$ is expressed as the following equation,

$$\vec{A}_{ps} = A_s \times \vec{R}_{ps}(z) \tag{8}$$

where A_s is the collision avoidance $\vec{R}_{ps}$, the current searching position of the weight, and z denotes the current iteration in searching areas (weight of layers).

After avoiding the collision, the search agent converges towards the best weight of the layers, and it is expressed below equation,

$$\vec{L}_{ps} = A_b \times (\vec{R}_{bf}(z) - \vec{R}_{ps}(z)$$

(9)

where $\vec{L}_{ps}$ is the location of searching weight, A_b is the collision avoidance for better exploration, $\vec{R}_{ps}$ towards the best fittest value of weight $\vec{R}_{bf}$.

The optimum value of weight parameters of layers in CNN is expressed by,

$$\vec{G}_{ps} = \vec{L}_{ps} + \vec{A}_{ps} \tag{10}$$

where $\vec{G}_{ps}$ is the gap between the search agent and the best fittest search agent (weight of the layer). The speed of the sandpiper is changed during migration and then catches the accurate position to evaluate the weight of the layers. The weight of the layer is attacked by creating the spiral behavior of the sandpiper, which is mentioned three-dimensionally.

$$H' = S_{rad} \times \sin(u) \tag{11}$$

$$J' = S_{rad} \times \cos(u) \tag{12}$$

$$K' = S_{rad} \times u \tag{13}$$

$$s = c \times e^{t\,d} \tag{14}$$

where S_{rad} is the spin radius, u is the variable $[0 \le u \le 2\pi]$, c and d represents constant of round shape, e represents natural algorithm base. Hence, the layer's optimum weight is easily evaluated using the above four equations. Then the updated position is given by,

$$\vec{R}ps(z) = (\vec{G}ps \times (H' + J' + K')) \times \vec{R}bf(z) \tag{15}$$

Where $\vec{R}ps(z)$ updates the position of weight parameters in the layer and provides optimal solution [37].

ISO optimizes the weight sharing in the convolution layer, and Fig. 3 represents the workflow diagram of weight optimization.

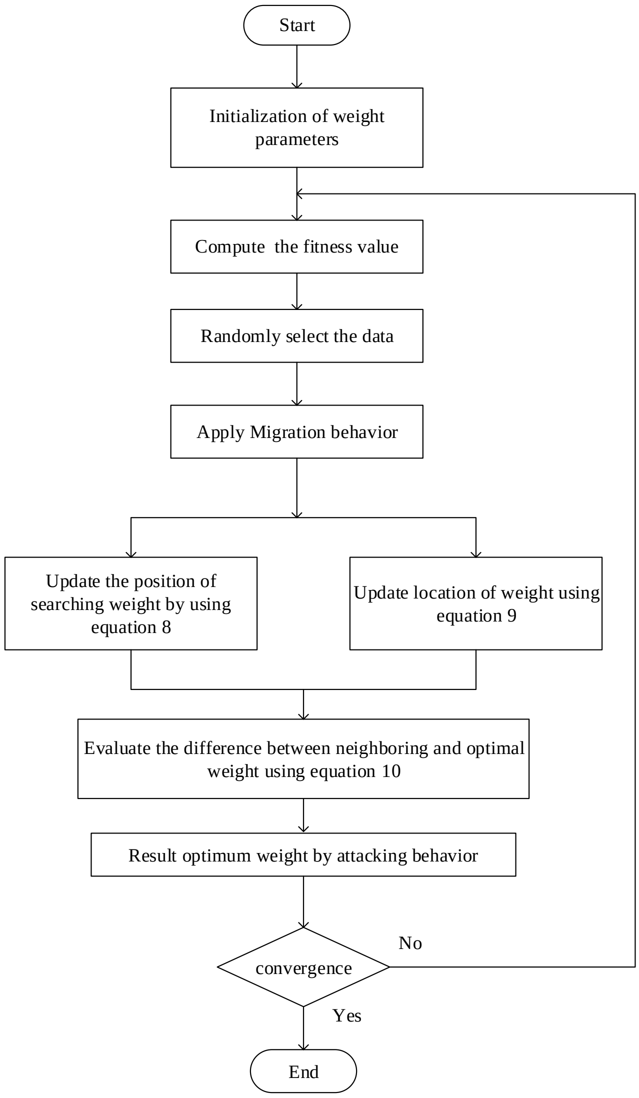

Fig. 3. Flowchart of ISO for weight optimization in CNN

4. Result and Discussion

The results of output predicted data for hybrid solar and biomass renewable energy are elaborated in this section by implementing the proposed forecasting model in MATLAB tool. First, the data from both energy sources is collected based on climatic conditions. Then, the forecasting of energy is done based on the selected input data by using the forecasting model of a deep learning algorithm. ISO optimizes the CNN to estimate the optimal weight sharing in the convolution layer. CNN is trained to predict solar and biomass energy by optimizing the better weight in layers. Moreover, the simulation result of the cost analysis curve for both non-conventional energy sources is elaborated in this section.

4.1. Data set collection for both solar and biomass

The metrological parameters, such as solar irradiance, temperature, biomass, solar generation, etc., in terms of hour, day, and month form historical data sets for energy efficient forecasting. Moreover, the preceding monthly data set of solar and biomass is utilized to forecast future power.

The data set for both solar and biomass is collected from the Hawaii space exploration analog and simulation (Hi-SEAS) weather station [38 and 39].

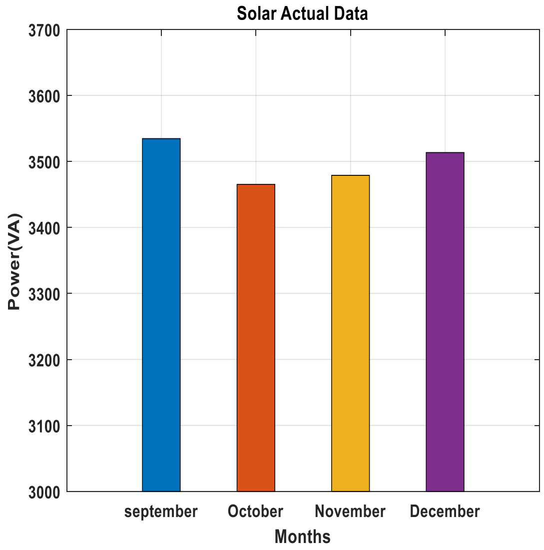

Fig. 4. Actual data of solar taken from the dataset

Fig. 4 represents the bar graph for the actual data collection of solar energy from the dataset. Using PV panels, the data is collected from the sunlight, and the graph reveals the PV power for successive four months of September, October, November, and December. From the December month's graph, a large amount of power is collected that is above 3600VA compared to the other three months. Based on the varying climatic condition, the data collection of PV is changed every month.

Fig. 5 reveals the actual data collection of biomass for four continuous months, which is mentioned in Fig. 5. Biomass power is collected based on biological organisms like plants, animal wastes, forests, etc. Therefore, the biomass power data in November is higher than the other three months, which is greater than 2900VA. This input data set is fed into the forecasting model of CNN, which ISO optimizes.

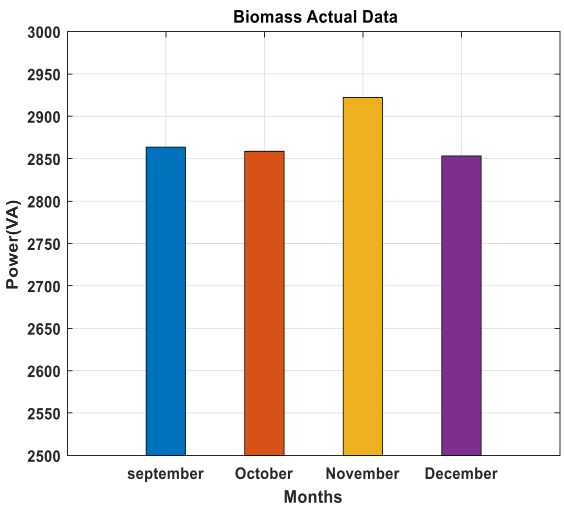

Fig. 5. Actual data of biomass taken from the dataset

4.2. Economic analysis of hybrid energy system

The cost analysis of RES is an important clarification because energy from non-conventional energy sources is cheaper than power from fossil fuels. The factors like increased customer demand, less emission, and marketing competition result in cheaper costs of solar and biomass. Due to the replacement of fossil fuel with biomass, a ton of carbon-dioxide cost is saved. Both solar and biomass are the best alternative to energy production by fossil fuels due to their cheaper cost. To explain that renewable energy sources follow some learning curves. It explains that when the accumulative installed capacity doubles, the cost decreases in the same fraction.

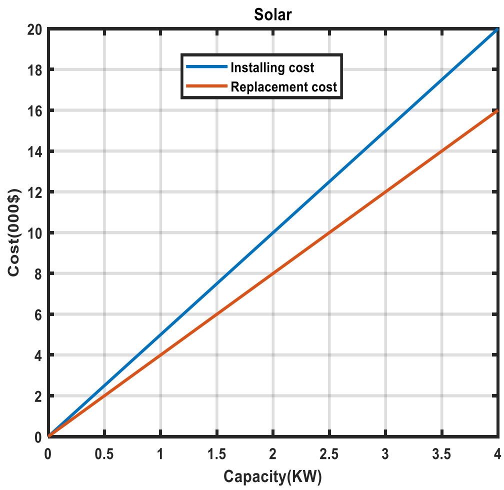

Fig. 6. Cost analysis of solar

Fig. 6 shows the economic analysis curve of solar, which includes both PV installation and replacement costs. The installation cost is nothing but the capital purchasing cost, while the replacement cost is the price of replacing the PV system at the end of a lifetime. The graph indicates that the replacement cost is less than the capital cost of PV. The graph is plotted for a capacity of 4KW. The capital and replacement costs rise with an increase in the size of the PV plant, as mentioned in Table 1.

Table 1: Cost analysis of PV with varying capacity

Capacity (KW)	Installation cost ($)	Replacement cost ($)
1	5000	4000
2	10000	8000
4	20000	16000

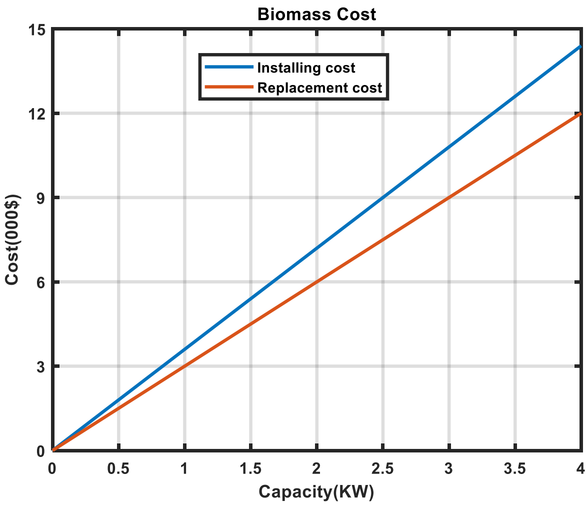

Fig. 7: Cost analysis of biomass

Fig. 7 shows the cost analysis graph for biomass for varying capacities, revealing that the installation cost is higher than the replacement cost. Also, both costs of biomass increased concerning the size of the biomass plant. However, due to the cheaper cost of biomass, profitable energy production is done. Like solar, the details of both capital and replacement cost are mentioned in Table 2.

Table 2: Cost analysis of biomass with varying capacity

Capacity (KW)	Installation cost ($)	Replacement cost ($)
1	3500	3000
2	7000	6000
4	14000	12000

4.3. Output prediction by ISO-CNN

Due to the discontinuity of solar power, unreliable power generation occurs; therefore, forecasting is essential to meet our demands. The deep learning algorithm CNN is implemented to predict hybrid solar and biomass power for varying months from September to December. First, the optimum weight of the convolution layer is estimated using ISO. Next, CNN forecasts solar and biomass energy based on the input variables. Then the predicted data of both solar and biomass is compared with conventional optimization-based predictions.

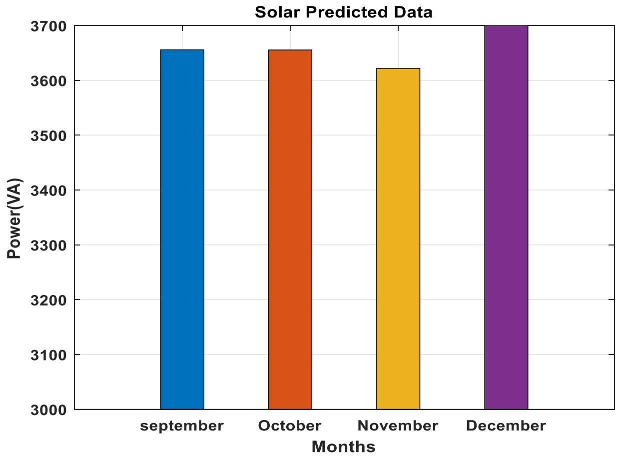

Fig. 8: Data predicted by the proposed method

Fig. 8 shows the output predicted data for solar by the proposed CNN model, which intimates that the CNN model accepts the monthly average of prior data and forecasts the energy for the varying month from September to December. The predicted solar output for December is greater than the other three months, which is nearly 3700VA. So, the predicted output data is slightly near to the actual data.

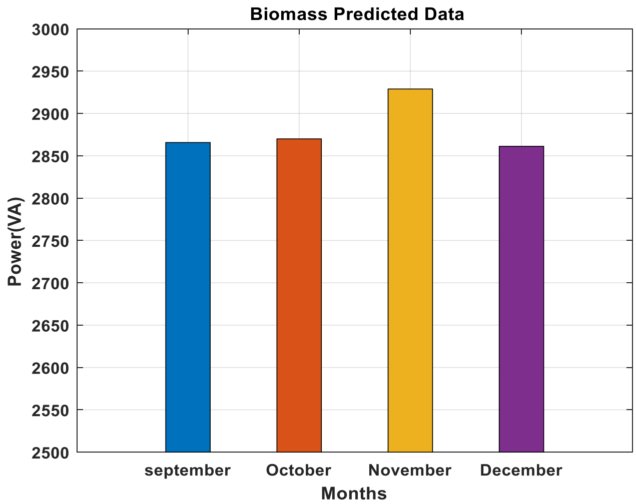

Fig. 9: Data predicted for biomass

The predicted data output for biomass is mentioned in Fig. 9, which indicates that the proposed CNN model forecasted the biomass output based on the preceding data collection for September to December. In biomass prediction, the output data is high for November, like the actual data. So, depending on the prior data collection, the CNN model forecasts the energy prediction.

A hybrid solar-biomass system analysis depends on the meteorological parameters, including biomass and solar power generation. Based on that, the data of solar and biomass for successive four months in a year is included in the proposed work. The pre-feasible analysis of hybrid energy systems can forecast the energy prediction for the same four months next year.

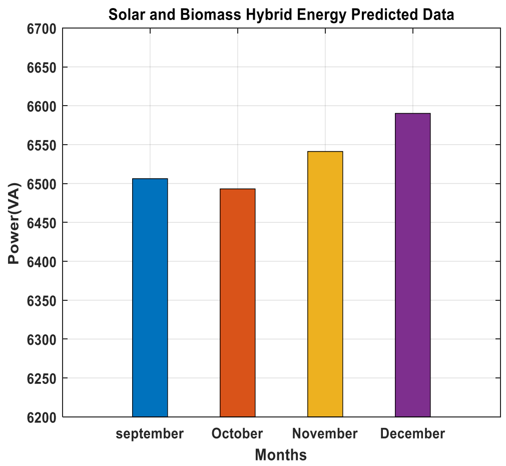

Fig. 10: Data predicted for hybrid solar-biomass system

The predicted output for hybrid solar biomass is shown in Fig. 10. From the graph, the monthly average power for December is higher than the other three months, which is 6550VA.

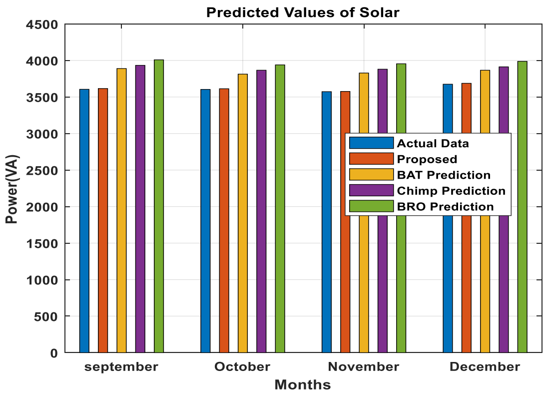

Fig. 11. Comparative analysis of prediction methods for solar

The predicted solar data by the proposed ISO-CNN model is compared with actual data and other optimization-based predictions and is shown in Fig. 11. In this bar graph, the forecasted output is differentiated from various optimization-based predictions such as BAT algorithm, chimp optimization, and battle royale optimization (BRO) predictions. The output prediction from the proposed model is closer to the actual data collection for each month. From the comparative analysis, prediction-based conventional optimization is higher than the actual data. So, the prediction by the proposed model is providing effective and accurate output than others.

Fig. 12 shows the proposed model's comparative analysis of biomass prediction with actual data. Similar to the solar prediction method, this graph also reveals that the forecasted biomass power from the ISO-CNN model is matched up with conventional prediction using various optimizations. However, by implementing the proposed model, solar and biomass energy prediction are closer to the actual data set than conventional techniques.

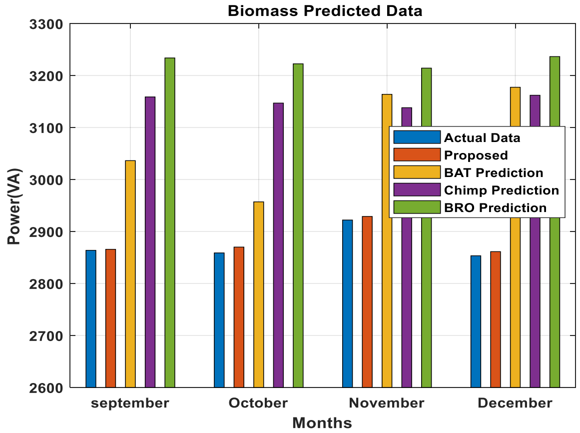

Fig. 12: Comparative analysis of prediction methods for biomass

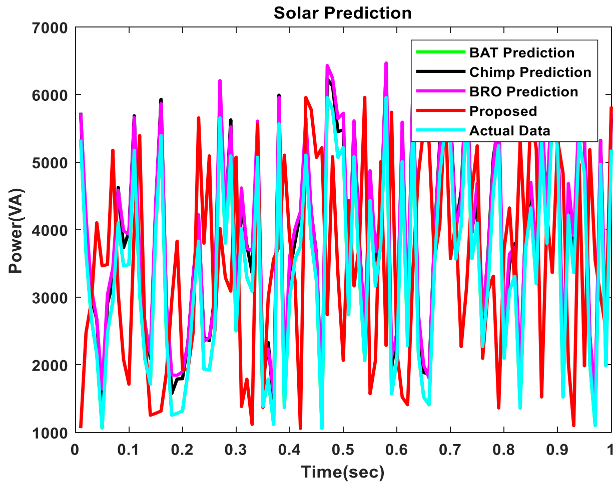

Fig. 13: Prediction of power for varying times (solar)

Fig. 13 shows the solar energy prediction for varying times compared with conventional techniques. The predicted power graph for solar is close to the collected data set, showing that energy forecasting by the proposed model performs with higher accuracy than conventional methods. However, solar power forecasting varies from 0 to 1 sec.

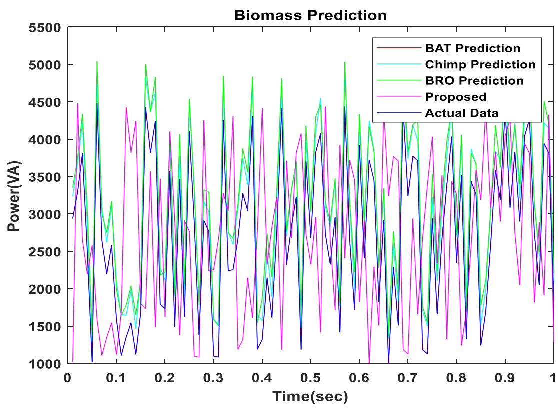

Fig. 14: Prediction of power for varying time (biomass)

Biomass power forecasting by the proposed model for varying times is structured in Fig. 14 and compared with conventional methods and actual data. Similarly, the proposed biomass prediction produces effective and accurate forecasting. The proposed model's output power and actual data are close to each other when compared with existing techniques. From the graph, biomass energy is forecasted for different periods of 0 to 1 sec.

5. Conclusion

This paper forecasted hybrid PV-biomass powered by introducing ISO-CNN based on the previous year's data. ISO is adopted for optimizing the weight parameters in the convolution layer in CNN. The results of the proposed work are performed in MATLAB tool and compared with actual data and some conventional techniques such as forecasting-based BAT algorithm, chimp optimization, and BRO algorithm. Moreover, the economic analysis of both PV and biomass results in capital and replacement costs for varying capacities of power, which leads to the replacement cost being less than the capital cost. The power prediction of HRES is implemented for not only continuous four months of September, October, November, and December but also varying times. Overall, the proposed model predicts accurate hybrid solar biomass power, and the performance analysis of the proposed model is compared with other solutions. Moreover, accurate information about the expected changes in energy to be generated is provided by this forecasting technique.

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