Day-ahead Photovoltaic Power Production Forecasting Using a Hybrid Artificial Neural Network Model Integrated with Metaheuristic Algorithms

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Abstract-The escalating global energy demands and the environmental repercussions of fossil fuel utilization have given rise to a marked increase in the level of interest in renewable energy sources. Solar energy, in particular, is distinguished by its abundance and minimal environmental impact. This study sets out to compare three distinct hybrid models that are designed to enhance the forecasting accuracy of daily photovoltaic power prediction: JAYA-ANN, GA-ANN and PSO-ANN. The models were developed and tested using historical data on PV power output, including air temperature, PM10 levels, and solar irradiance. The study's findings indicated that the JAYA-ANN hybrid model exhibited superior performance, with a Mean Absolute Percentage Error (MAPE) of 7.38% and a Root Mean Squared Error (RMSE) of 681.71 kW for the test subset. The JAYA-ANN model demonstrated superior performance in comparison to both GA-ANN and PSO-ANN models. On the basis of the entire dataset, the JAYA-ANN model exhibited the highest level of prediction accuracy, with an MAPE of 11.59% and an RMSE of 413.91 kW. The study confirms that the JAYA-ANN hybrid model serves as an effective tool for photovoltaic power estimation. Beyond this, it offers noteworthy opportunities to advance the integration of solar resources into the energy sector while maintaining grid stability through enhanced forecasting accuracy.

Keywords: Forecast, photovoltaic power, jaya optimization algorithm, particle swarm optimization, genetic algorithm, artificial neural networks.

1. Introduction

Today, the development of various technologies to improve the quality of life in human societies and the resulting increase in global warming have prioritized environmental factors to reduce major industrial pollutants, including carbon dioxide (CO_2) [1]. Laws against CO_2 and greenhouse gas emissions, and the heavy fines imposed for these emissions, have driven energy system designers to design systems with maximum efficiency and minimum pollution (renewable energy) [2]. In addition to these, the rapid increase in electricity demand and the environmental impacts of fossil fuels have also accelerated the global transition to renewable energy sources. Photovoltaic (PV) systems are one of the cornerstones of this transition, but their strong dependence on meteorological conditions creates variability that complicates grid stability and operational planning. Therefore, artificial intelligence technologies, encompassing applications such as demand forecasting, anomaly detection, and predictive maintenance, provide powerful tools for optimizing energy distribution and aligning technical efficiency with social justice goals [3]. Artificial intelligence technologies are widely used, especially in predicting the electrical power obtained from renewable energy sources.

When similar studies in the literature are examined, the artificial neural network model was used in the daily photovoltaic power estimation and the particle matter input increased the estimation accuracy [4]. A combination of random forest, principal component analysis and feature selection was used for the photovoltaic power prediction. As the number of data used in the model increased, the accuracy of the model also increased [5]. Global horizontal radiation, diffuse horizontal radiation, temperature and humidity inputs were used for the daily photovoltaic power estimation [6]. In the experimental design approach, ANN model was designed for the medium-term photovoltaic power forecasting and the MAPE value was realized as 4.7% [7]. Monthly photovoltaic power estimation was made using the long short-term memory recurrent neural network model. As the installed power of the facility to be predicted increased, the performance of the prediction model also increased [8]. In the support vector machine estimation model, RMSE and MABE values were obtained as 0.7082 W and 0.6238 W, respectively [9]. In the convolutional neural network and variational mode decomposition hybrid model, active power, temperature, humidity, global radiation, diffuse radiation were used as input data and the model was found more successful for the summer season [10].

ANN and JAYA-ANN hybrid forecasting models were compared for the daily photovoltaic power forecasting. The JAYA-ANN hybrid model showed much superior performance than the ANN model, and its MAPE and RMSE values were realized as 4.39% and 207.15 kW, respectively [11]. Gate recurrent network-based model showed better performance compared to traditional prediction models, long short-term memory, deep neural network and artificial neural network models [12]. Photovoltaic power data was used in a bidirectional long-short-term memory model developed with a genetic algorithm, and the accuracy of the model decreased as the prediction period increased [13]. Convolutional neural network-based long short-term memory and convolution-based long short-term memory hybrid models were found more successful than the long short-term memory prediction model [14]. Cloud rate, humidity, precipitation, pressure, temperature and wind speed data were used and the random forest prediction model provided the most accurate results [15]. Genetic algorithm and particle swarm optimization-based adaptive neuro fuzzy inference system model was successful and RMSE, MAE, nMAE values were realized as 5.09, 3.47 and 4.43, respectively [16].

In many previous studies, machine learning and hybrid metaheuristic approaches have been applied for PV forecasting. However, these studies often compare different algorithms on different datasets (making direct comparison difficult) and neglect specific meteorological inputs like particulate matter (PM10). These shortcomings limit reproducibility and the interpretation of comparative performance.

This study proposes a transparent and reproducible comparison of three hybrid metaheuristic-ANN approaches (JAYA-ANN, PSO-ANN, and GA-ANN) on the same dataset. The dataset consists of daily averages from the fall of 2021 from a 52.80 MW PV plant located in the Marmara Region of Turkey. Input data includes PV power output, air temperature, PM10 concentration, and solar irradiance; a second dataset also includes wind speed and relative humidity.

The aims and contributions of the study can be listed as follows:

- We propose a JAYA-ANN hybrid model for PV power prediction one day in advance and compare its performance with PSO-ANN and GA-ANN using the same dataset.
- We systematically evaluate the impact of adding two common meteorological variables (wind speed and relative humidity) to the basic feature set (PV output power, temperature, PM10, and solar irradiance).
- To increase reproducibility, we present the ANN architecture and evaluation metrics for a detailed and transparent methodology.
- We analyze why the Jaya-based optimization method provides superior prediction performance, and suggest practical strategies to improve accuracy in future studies.

Additionally, when evaluating the study in terms of its strengths and limitations, the direct comparison on a single dataset and the inclusion of PM10 as a relevant predictor variable are considered strengths, while the data obtained from a single location, within a daily average time resolution, and from a single season (fall 2021) may limit the analysis of short-term variability.

2. Artificial Neural Networks

A neural network consists of small interconnected processing units, just like the nervous system in biology. Information is transmitted through these units along interconnections, and the output is a function of the value collected. ANNs are not programmed to perform the specific tasks. However, they are trained on datasets until they learn the patterns used as input. In this way, they can understand new relationships and patterns [17].

In the ANN structure, the number of inputs is usually more than one. Neurons with more than one input are called multi-input neuron. Figure 1 shows the structure of a multi-input neuron. In Figure 1, the weight matrix is represented by w values, while the input vector is represented by x values. The weight matrix w is created by multiplying the weighted inputs ($x_1, x_2,..., x_m$) by the associated weights ($w_{1,1}, w_{1,2},..., w_{1,m}$). The weight w has two indices; the signal source corresponding to the feeding neuron is displayed in the second index, and the next neuron for that weight is displayed in the first index. To form the network input *n*, the neuron furthermore has a bias (*b*) that is added to the weighted inputs ($w_{i,j}$) and it is defined by Equation (1) [18].

In this study, we implement a feedforward multilayer perceptron (MLP) that maps historical PV power and meteorological inputs to the PV power output of the following day. The ANN used in the study consists of a multi-input layer, a single hidden layer with 10 neurons, and an output neuron. Network weights and biases were optimized using three different metaheuristic optimizers (JAYA, PSO, and GA) in separate experiments. Mean absolute percentage error and root mean squared error were used as evaluation metrics.

$$a = f\ \sum_{i=0}^{m}\left(x_i w_{i,j} + b\right) \tag{1}$$

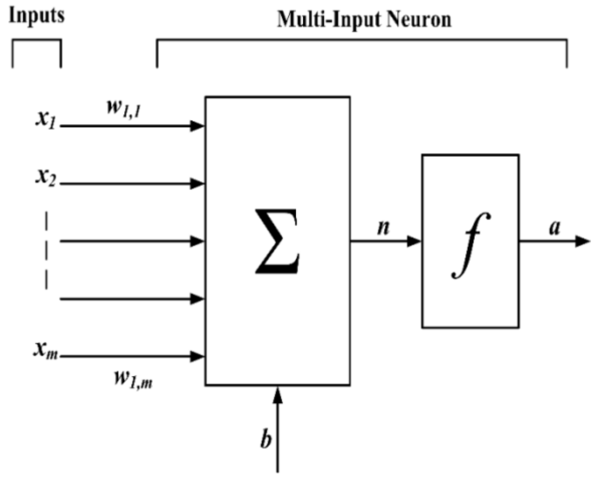


Fig. 1. Multi-input neuron.

3. JAYA Optimization Algorithm

Population-based optimization algorithms usually have common control parameters such as population size and maximum number of iterations. However, it seems that each algorithm needs its own specific control parameters. For instance, genetic algorithm needs the special control parameters such as selection operator, crossover rate, and mutation rate. Similarly, the Soft Actor-Critic algorithm uses its own specific control parameters, such as scout bees, worker bees, and observer bees. Other algorithms, such as particle swarm optimization and bee colony algorithm, also include their own control parameters [19].

The correct choice of control parameters can directly affect the performance of the algorithm. As the number of control parameters increases, the optimization process becomes more complex, and it may take longer. For this reason, the Jaya algorithm, which is one of the algorithms that only contains the common control parameters, is more advantageous compared to other algorithms that contain the special control parameters.

In Jaya, adjusting the location increases the problem's likelihood of advancing toward the optimal solution while avoiding the worst solution and without being trapped in the local maximum or local minimum solution. As a result, during the location update, it applies both the solution with the lowest fitness value and the solution with the highest fitness value in the population. Thus, it is possible to conduct a considerably larger search in the solution space [20]. Equation (2) specifies the equation for location updates. Figure 2 also includes a flow diagram for the Jaya algorithm.

$$X'_{k,j} = X_{k,j} + r_1 \times \left(Best_j - \left|X_{k,j}\right|\right) - r_2 \times \left(Worst_j - \left|X_{k,j}\right|\right) \tag{2}$$

In Equation (2), *k=1,2,…,N* given is the index of the candidate solution, *j=1,2,…,D* represents the relevant dimension of the problem, *Best* represents the best solution in the population, *Worst* represents the worst solution in the population. r_1 and r_2 represent the decimal values created between [0,1].

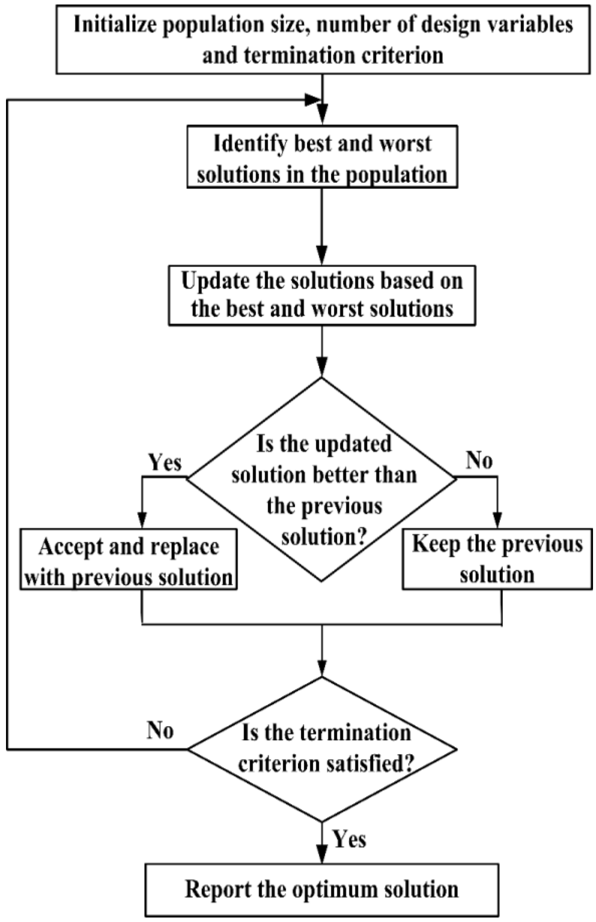


Fig. 2. The flow diagram of the Jaya algorithm.

4. Genetic Algorithm

Genetic algorithms (GA) are computer approaches that use Darwin's idea of natural selection to solve a variety of problems. This approach works by encoding solutions into a chromosomal-like data structure and preserving crucial information with recombination operators. GA begins with a population of randomly created chromosomes, assesses their performance, and provides chances for proliferation depending on fitness. The fittest chromosomes have a better probability of replicating, similar to natural selection. GA is based on natural forces that promote the survival of the fittest and the spread of superior features. Individuals with stronger survival traits survive longer in natural environments and have more possibilities to pass along their genes. During this process, the genes of better people in the group become dominant, causing the extinction of less suited individuals [21].

The process steps of genetic algorithms, which can be applied in many areas, are given below, and the flow diagram of GA is presented in Figure 3 [22].

- All possible solutions in the search space are encoded strings.
- Usually a set of solutions is randomly selected and considered as the initial population.
- A fitness value is calculated for each sequence, and the fitness values found indicate the solution quality of the sequences.
- A group of sequences is randomly selected and propagated according to a certain probability value.
- The fitness values of new individuals are calculated and they are subjected to crossover and mutation processes.
- The above processes continue for a predetermined number of iterations.
- The iteration is terminated when the specified number of generations is reached.
- The most appropriate sequence is selected according to the objective function.

5. Particle Swarm Optimization

Particle swarm optimization (PSO), a mathematical optimization technique developed by James Kennedy and Russell Eberhart in 1995, draws inspiration from the notion of swarm intelligence. It is based on the behavior of groups of fish and birds, and has been widely used for nonlinear optimization problems in a variety of industries.

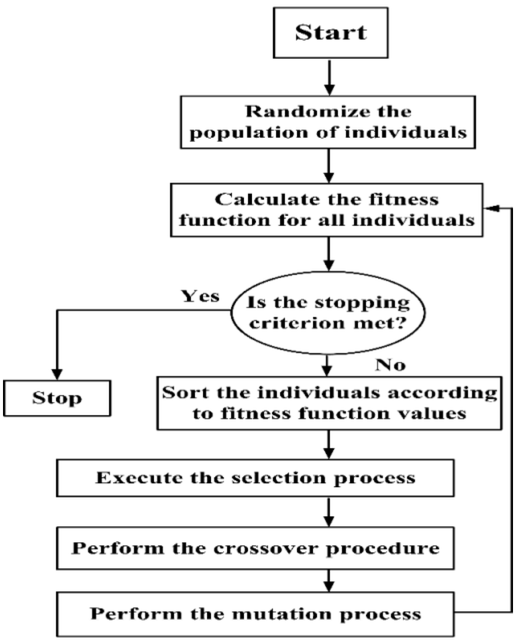


Fig. 3. The flow diagram of GA.

In contrast to evolutionary algorithms, which may remove individuals with inferior fitness, PSO fosters collaboration among individuals throughout the search process. PSO focuses on the junction places where agents fly while keeping the greatest distance from one another within a specific region, and has the ability to achieve global optimality [23]. In addition to being simple to comprehend and implement, the PSO method is resilient to noise and uncertainty in the objective function. The particle population in PSO acts as a sort of distributed sampling, allowing the algorithm to handle noisy and complicated target landscapes. This is important in practical circumstances when real-world systems are unpredictable or variable. Furthermore, PSO converges faster than other optimization methods, enabling the optimal solution to be reached in a shorter period of time while lowering computing burden [24].

In multidimensional search space, let the position of the particle i be denoted by $X_i(t)$ and its speed by $V_i(t)$. The PSO algorithm updates the velocities of the particles according to Equation (3).

$$V_i(t+1) = w(t).V_i(t) + c_1 r_1 \big(X_L(t) - X_i(t)\big) + c_2 r_2 \big(X_G(t) - X_i(t)\big) \quad (3)$$

In response to this new speed of the particle, the new position of the particle is given in Equation (4).

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (4)$$

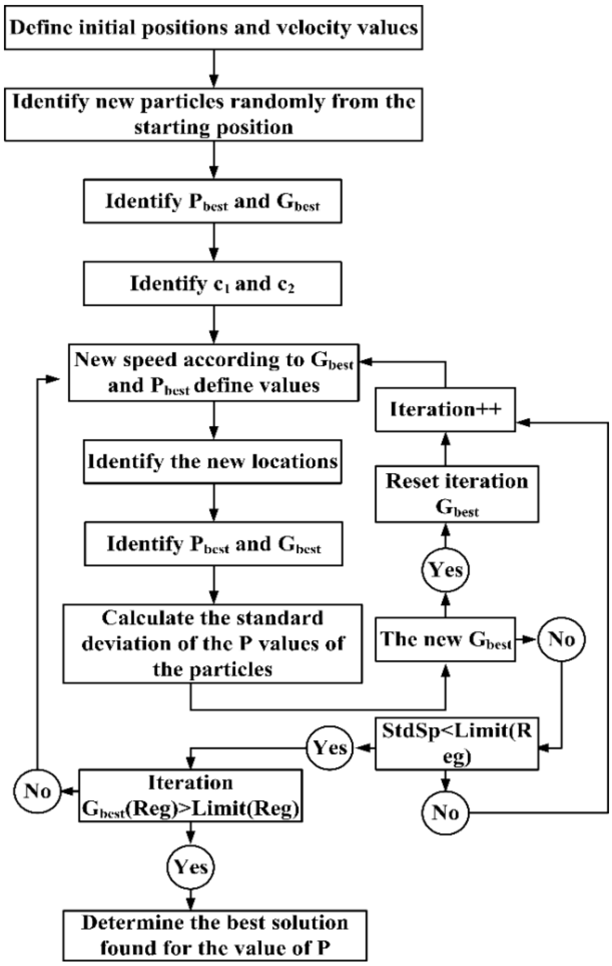


Fig. 4. The flow diagram of the PSO.

In this case, an n-dimensional vector represents the position and velocity of each particle in an n-dimensional search space. The global best solution in Equation (3) is represented as $X_G(t)$, whereas the local best solution is represented as $X_L(t)$. The degree of orientation towards the local best is determined by the coefficient c_1, which represents the local learning coefficient, and the degree of orientation towards the global best is determined by the coefficient c_2, which represents the global learning coefficient [25].

Furthermore, the particle movements are given a random degree of freedom by the random integers r_1 and r_2. Each iteration of the algorithm finds a different solution though this random degree of freedom. The flow diagram of PSO is shown in Figure 4.

6. Prediction Results of Hybrid Models for Photovoltaic Power Production

This research uses a PV power plant in Turkey's Marmara Region. The associated dataset was created using historical photovoltaic power output, air temperature, PM10, and solar radiation factors from the 2021 fall season. The data were presented as daily averages, and a day-ahead prediction was performed. In the predictions, the suggested JAYA-ANN hybrid model was compared to GA-ANN and PSO-ANN hybrid models. The complete dataset and the test dataset were compared in terms of their correctness. In addition, the hybrid prediction models' findings were compared to those of the persistence model. The input and output parameters for hybrid prediction models are shown in Table 1.

Table 1. The input and output parameters used in hybrid prediction models

Inputs	Outputs
Photovoltaic power production	Photovoltaic power production
Air temperature	
PM10	
Solar radiation	

RMSE and MAPE functions, which are widely preferred in the literature, were used to evaluate the errors in the hybrid prediction models [26, 27]. The model was trained with the 80% of the total dataset, validated with the 10% of the total dataset, and tested with the 10% of the total dataset. RMSE was calculated by using Equation (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{j}\sum_{i=1}^{j}\left(X_{m_i} - X_{e_i}\right)^2} \quad (5)$$

In Equation (5), X_{e_i} is the predicted value, X_{m_i} is the actual value, and j is the number of data points. MAPE was calculated by using Equation (6).

$$\mathrm{MAPE} = \frac{1}{j}\sum_{i=1}^{j}\left(\frac{X_{m_i} - X_{e_i}}{X_{m_i}}\right) \times 100 \quad (6)$$

The JAYA-ANN hybrid prediction model was run using historical photovoltaic power output, solar irradiance, temperature, and PM10 data, and the MAPE and RMSE values for the test subset were 7.38% and 681.71 kW, respectively. Figure 5 shows the JAYA-ANN prediction and the actual power output for the test subset. After that, the PSO-ANN hybrid prediction model was run, and the test subset's MAPE and RMSE values were 12.83% and 1155.2 kW, respectively. Figure 6 shows both the PSO-ANN forecast and the actual power generation for the test subset. Finally, the GA-ANN hybrid prediction model was run, and MAPE and RMSE values for the test subset were obtained as 14.98% and 1428.0 kW, respectively. Figure 7 shows the GA-ANN prediction and the actual power production for the test subset.

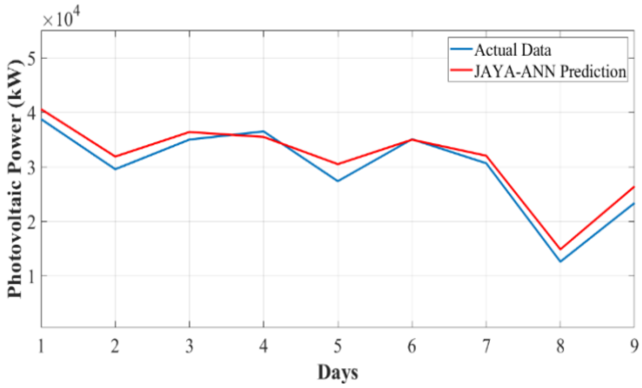


Fig. 5. JAYA-ANN prediction and actual power production for the test subset.

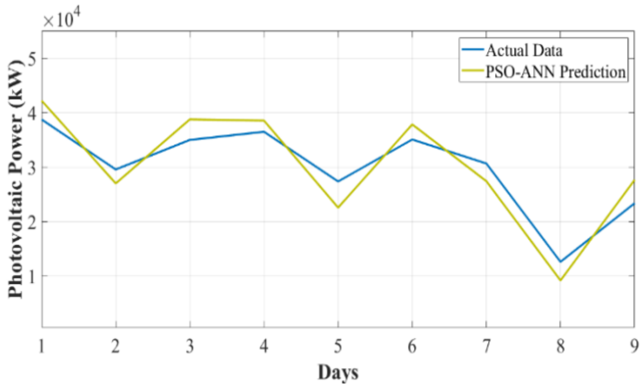


Fig. 6. PSO-ANN prediction and actual power production for the test subset.

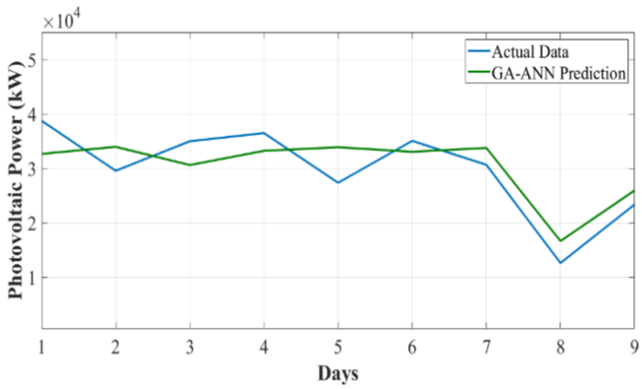


Fig. 7. GA-ANN prediction and actual power production for the test subset.

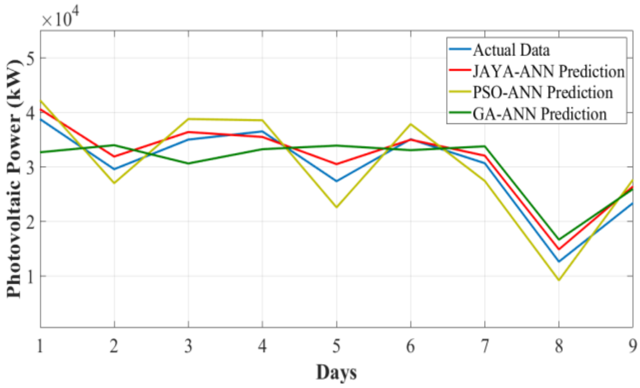
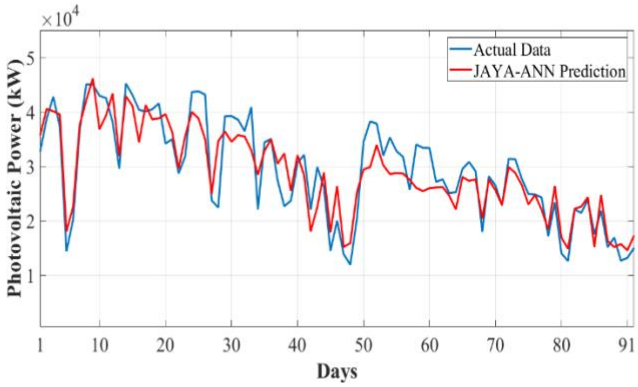


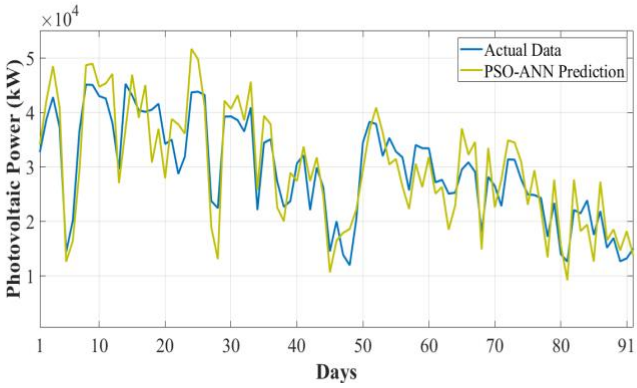
Fig. 8. JAYA-ANN, PSO-ANN, GA-ANN prediction results for the test subset.

For the test subset, the prediction results of all hybrid models implemented are shown in Figure 8. Among three different hybrid models, the proposed JAYA-ANN hybrid model showed the best prediction performance with MAPE = 7.38% and RMSE = 681.71 kW.

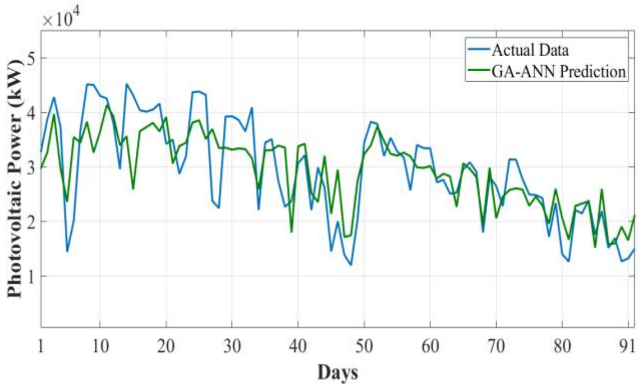
In the rest of the study, the prediction results of Jaya-artificial neural network, particle swarm optimization-artificial neural network and genetic algorithm-artificial neural network models are compared using the entire dataset. For JAYA-ANN, PSO-ANN and GA-ANN prediction models, MAPE and RMSE values were obtained as 11.59%, 14.84%, 17.14%, and 413.91 kW, 467.65 kW, 583.31 kW, respectively. Figure 9 shows the prediction results of three hybrid models for the entire dataset.



(a)



(b)



(c)

Fig. 9. Prediction results for the entire dataset (a) JAYA-ANN, (b) PSO-ANN, (c) GA-ANN hybrid models.

For the whole dataset, the prediction results of all hybrid models implemented are shown in Figure 10. Among three different hybrid models, the proposed JAYA-ANN hybrid model showed the best prediction performance with MAPE = 11.59% and RMSE = 413.91 kW.

In addition, the prediction outcomes of the JAYA-ANN, PSO-ANN, and GA-ANN hybrid models were compared to the persistent model. The JAYA-ANN hybrid model improved MAPE and RMSE values by 44.79% and 45.95%, respectively. The PSO-ANN hybrid model improved MAPE and RMSE values by 29.3% and 38.94%, respectively. The GA-ANN hybrid model improved MAPE and RMSE values by 18.35% and 23.83%, respectively.

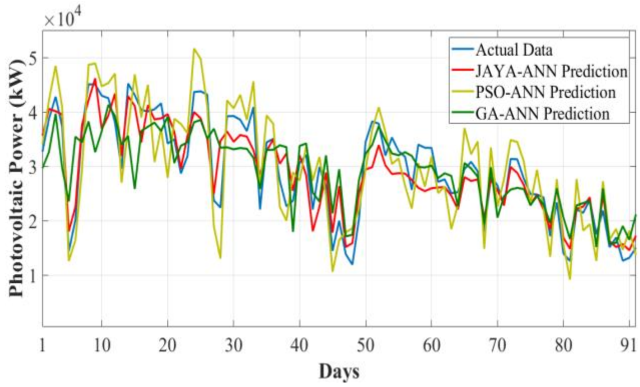


Fig. 10. JAYA-ANN, PSO-ANN and GA-ANN prediction results for the whole dataset.

Table 2. MAPE and RMSE results

	MAPE (%)	RMSE (kW)
JAYA-ANN (test)	7.38	681.71
JAYA-ANN (all)	11.59	413.91
PSO-ANN (test)	12.83	1155.2
PSO-ANN (all)	14.84	467.65
GA-ANN (test)	14.98	1428
GA-ANN (all)	17.14	583.31

As a consequence, the suggested JAYA-ANN hybrid model performed better in terms of MAPE, RMSE, and improvement rates. Thus, the JAYA-ANN hybrid model appears to be an excellent choice for predicting daily solar power generation. Table 2 shows the MAPE and RMSE results for the whole dataset and the test subset.

It is evident that the JAYA-ANN hybrid model outperformed the PSO-ANN and GA-ANN hybrid models and the persistence model. To improve prediction accuracy, wind speed and relative humidity parameters were added to the existing dataset. As a result, two different datasets, Dataset-1 and Dataset-2, were created from the complete dataset to estimate solar power generation. In other words, Dataset-1 had photovoltaic power production, air temperature, PM10, and solar radiation, whereas Dataset-2 included photovoltaic power production, air temperature, PM10, solar radiation, wind speed, and relative humidity.

For the test subset of Dataset-1, the MAPE result was obtained to be 7.38%, and the RMSE result was calculated to be 681.71 kW. For the test subset of Dataset-2, the MAPE result was obtained to be 5.09%, and the RMSE result was calculated to be 466.82 kW. Figure 11 shows the prediction results of photovoltaic power production for the test subset of Dataset-2. Furthermore, for the entire Dataset-1, MAPE and RMSE were determined to be 11.59% and 413.91 kW, respectively, while the ones were determined to be 8.51% and 313.29 kW for the entire Dataset-2, respectively. Figure 12 shows the prediction results photovoltaic power production for the whole Dataset-2. Additionally, Figure 13 shows the prediction results of JAYA-ANN hybrid model for both datasets.

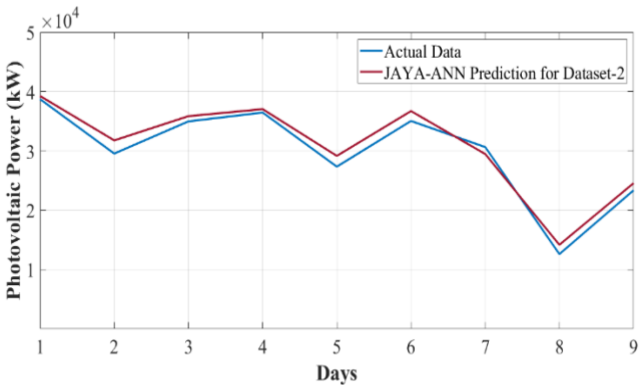


Fig. 11. The prediction results for test subset of Dataset-2.

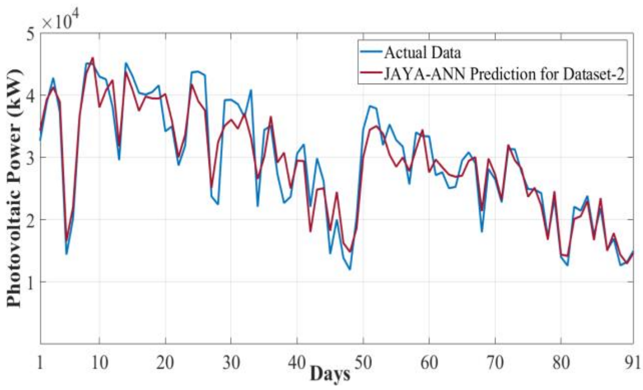


Fig. 12. The prediction results for the whole Dataset-2.

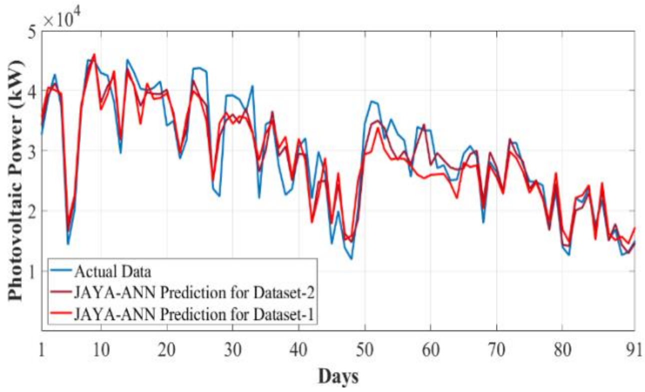


Fig. 13. The prediction results of JAYA-ANN hybrid model for both datasets.

7. Conclusion

This study presents a comparative evaluation of three metaheuristic-ANN hybrid approaches for PV power forecasting from the previous day, using the same dataset and simulation protocol. The proposed JAYA-ANN hybrid model consistently outperformed the PSO-ANN and GA-ANN models in terms of MAPE and RMSE under our simulation settings (improvement rates for MAPE values were 42.48% and 50.74%, respectively, and for RMSE values were 40.99% and 52.27%, respectively). The main reasons for JAYA's superior performance are its parameter-light design (no algorithm-specific parameters except for population and iterations) and its ability to improve global search behavior by pulling the best solution and pushing away the worst.

Ultimately, improved day-ahead PV forecasts can reduce reserve requirements, simplify unit commitment planning, and lower operating costs for system operators. The improvement observed when wind speed and relative humidity are added suggests that including a broader meteorological context could significantly improve daily PV forecasts.

Future studies should test the presented methods on multi-seasonal, multi-regional datasets and at higher temporal resolutions (hourly or minute-by-minute). Among the best improvements are the inclusion of sky images or numerical weather prediction (NWP) features.

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