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Research Paper

Enhancing solar radiation predictions through COA optimized neural networks and PCA dimensionality reduction

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ABSTRACT

The inherent variability and uncertainty of solar radiation, influenced by factors such as seasons, weather, and cloud cover, pose significant challenges in accurately forecasting energy output from solar power systems. Robust forecasting models that can capture the dynamic behavior of solar radiation are crucial for optimizing energy generation, distribution, and storage processes. This study proposes an integrated approach that combines neural networks, metaheuristic optimization algorithms, and principal component analysis (PCA) for precise solar radiation forecasting. The methodology uses one year of solar radiation data from November 2022 to October 2023 from Vellore district, India. PCA is employed for dimensionality reduction, mitigating the curse of dimensionality. The reduced dataset is segregated into winter, summer, and monsoon subsets to capture distinct seasonal patterns. Neural networks are trained on these seasonal datasets, with their weights optimized by metaheuristic algorithms, including particle swarm optimization (PSO), gray wolf optimization (GWO), whale optimization algorithm (WOA), and coati optimization algorithm (COA). A comprehensive comparative study evaluated the performance of ANN-PSO, ANFIS-GWO, ANN-WOA, ANN-COA, and traditional ANN models. The ANN-COA model, integrating ANN with COA for weight optimization and PCA for dimensionality reduction, achieved the most accurate forecasts, outperforming other approaches. It attained optimal RMSE of 12.06 for winter, 6.72 for summer, and 9.49 for monsoon season, MAE of 6.66, 5.50, and 6.25, MAPE of 3.58 %, 1.68 %, and 2.31 %, and R^2 of 0.973, 0.982, and 0.985 for winter, summer, and monsoon seasons respectively, demonstrating its robustness and suitability for time-series solar radiation forecasting.

1. Introduction

With India's energy consumption expected to continue rising as the third largest global consumer, reaching 9.8 % of worldwide use by 2050, the country faces major challenges in meeting demands through clean sources (Roy, 2024). To reach its landmark goals of net zero emissions by 2070 and 50 % renewable electricity by 2030, India must transition its rapidly growing energy needs over the coming decades mostly to renewables. This energy transition is critical for India's contribution to global climate change efforts (Gupta and Guha, 2024). To help enable this shift while still meeting immediate hydrocarbon fuel demands, India is pursuing strategies such as attracting oil/gas production investments, improving refinery efficiency, expanding biofuels, developing gas grids and city gas networks, and diversifying supply. The aim is to provide the Indian public with clean, green energy access through a mix of solutions (Hassan et al., 2024).

Renewable energy is playing an increasingly important role in India's pursuit of energy security and self-sufficiency. Since the 1970s oil crises, when oil supply uncertainties and price spikes raised concerns, India has focused on growing its renewable sources. The renewable energy push aims to reduce dependence on imported oil and improve energy autonomy (Nguyen et al., 2024). With its large-scale investments in renewable power, India now ranks fourth globally for installed renewable energy capacity, including hydropower, wind power, and solar power installations. This renewable energy push aligns with India's COP26 commitment to achieve 500 gigawatts of non-fossil fuel energy capacity by 2030, representing an ambitious target for further growth. India is steadily establishing its position as a leader in renewable energy adoption (Chatterjee, 2024). Achieving India's ambitious renewable energy targets requires a robust, multi-faceted decision-making approach to analyze and select optimal sources. A recent study presents such an approach for India's sustainable energy planning, implementing multiple weighting and ranking methods to assess renewable options. The analysis ranked solar power as the top

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alternative for India, with wind and biomass interchangeably at second and third place. This multi-criteria decision analysis provides rigorous perspective into prioritizing renewable sources as India scales up adoption (Husain et al., 2024). To maximize utilization of fluctuating solar power generation, forecasts of expected production are crucial for electricity grid management and solar energy trading. Having accurate solar forecasting will greatly aid efficient use of variable solar resources as India expands its solar capacity. Reliable prediction of solar output will become increasingly important for smoothly integrating large amounts of solar power into the grid and electricity markets. Advanced solar forecasting capabilities will complement India's robust evaluations in strategically growing its renewable portfolio (Lorenz et al., 2009). Solar photovoltaic power generation depends critically on incoming solar irradiation, including direct beam irradiance (measured perpendicularly as Direct Normal Irradiance, DNI) and diffuse irradiance (measured horizontally as Diffuse Horizontal Irradiance, DHI). Accurate forecasting of DNI and DHI allows for better prediction of solar electricity output. Solar irradiance forecasting can utilize various approaches, from physical models like numerical weather prediction and sky/satellite imagery models, to data-driven machine learning techniques like regression, neural networks, support vector machines, and Kalman filtering. Hybrid methods combine multiple techniques for enhanced forecasts (Pereira et al., 2024).

Solar irradiance data takes the form of a complex time series where the mechanisms governing data generation may not be fully understood. Computational methods from artificial intelligence, including neural networks, fuzzy logic systems, and hybrid intelligent frameworks, have demonstrated promising performance on related time series forecasting tasks. The development of sophisticated yet interpretable solar irradiation models could lead to improved renewable energy system control and grid integration (Palit and Popovic, 2006). Neural networks, specifically Artificial Neural Networks (ANN), are computational models inspired by the human brain's neural structure, capable of learning from input data and discerning intricate patterns. They emulate the brain's ability to recognize complex information through training (Shanmuganathan, 2016). ANN proves to be swifter and more precise in resolving intricate and nonlinear problems when compared to conventional techniques (Ghritlahre and Prasad, 2018). Constructing an Artificial Neural Network (ANN) first requires identifying inputs, organizing the architecture, training the system, and then applying the developed ANN to predict desired outputs. For meteorological factors like temperature, humidity, wind velocity, and solar radiation, nonlinear prognostic models can be utilized over hourly, daily, or monthly intervals. While ANNs offer valuable learning and customization for particular tasks, their education presents difficulties, needing extensive computational resources. Despite these advantages in learning and adaptability, the process of training ANNs presents significant challenges in terms of the computational time required (Abdel-Nasser and Mahmoud, 2019).

In this study, we propose a hybrid approach that combines the power of artificial neural networks (ANNs) with metaheuristic optimization algorithms to forecast solar radiation accurately. ANNs, known for their ability to model nonlinear relationships and learn from data, have been widely employed in various forecasting applications (Abd Elaziz et al., 2021). However, their performance is heavily dependent on the selection of appropriate network architecture and weight initialization (Huang and Wang, 2018). Metaheuristic optimization algorithms, such as Coati Optimization Algorithm (COA) (Dehghani et al., 2023),Whale Optimization Algorithm (Kumar Chandar, 2021),Grey Wolf Optimization (GWO) (Kumar Chandar, 2021),Particle Swarm Optimization and Genetic Algorithm (Ali Ahmadi et al., 2013) have proven effective in optimizing the weights and hyperparameters of ANNs, leading to improved forecasting accuracy. The paper discusses controlling frequency and power deviations in a hybrid renewable energy system (HRES) with multiple sources like photovoltaic, biogas generator, and energy storage systems. To overcome frequency and power fluctuations under varying load conditions, a control strategy using FO-Fuzzy-PID controllers is proposed. The OWOA metaheuristic optimization algorithm is used to tune the parameters of these FO-Fuzzy-PID controllers (Agajie et al., 2023). This research develops integrated models combining adaptive neuro-fuzzy inference systems (ANFIS), ANN, and improved reptile search algorithm (IRSA) for enhanced groundwater level forecasting (Jithendra and Basha, 2023). This study proposes and validates an optimized adaptive neuro-fuzzy technique for modeling web service quality attributes, demonstrating the capabilities of AI-based hybrid approaches for enhancing forecasting (Jithendra et al., 2024). A new controller design for robot manipulators based on the butterfly optimization algorithm (BOA) was proposed, where BOA enhances global search by utilizing neighboring butterflies' cooperation and avoids local optima trapping, combined with a fitness function to improve trajectory tracking by minimizing steady-state error, settling time, and overshoot simultaneously (Elsisi et al., 2021). The use of the bat-inspired algorithm (BIA) for intelligent tuning of model predictive control (MPC) parameters for aircraft longitudinal flight control. The BIA, inspired by the echolocation behavior of bats, is employed to optimize the MPC horizon parameters by minimizing various time-domain objective functions, addressing the challenges of conventional tuning methods (Essa et al., 2022). A fast model predictive controller formulated using discrete-time Laguerre functions (DTLF-MPC) is proposed to overcome the high computational burden of traditional MPC. To improve the performance of the hybrid DTLF-MPC, the Dandelion Optimizer (DO) strategy is employed (Bergies et al., 2022). Furthermore, the study proposes two optimization methods for the energy management system (EMS) of seawater desalination plants - fuzzy logic (FL) and the Harris Hawks Optimization (HHO) algorithm. HHO, a recent nature-inspired metaheuristic, is employed to optimize the energy management strategy and coordinate energy flow between solar PV, utility grid, and battery storage to meet the plant's energy needs cost-effectively. Thus, HHO effectively optimized the cost-efficient operation of the solar-powered desalination system by optimally managing energy interchange among various sources (Mohamed et al., 2022).

The proposed approach utilizes one year of solar radiation data collected from the Vellore district in India. The dataset is preprocessed by calculating the average daily solar radiation and subsequently applying principal component analysis (PCA) for dimensionality reduction (Palit et al., 2022). The reduced dataset is then divided into three distinct seasons: summer, winter, and monsoon, to capture the seasonal variations in solar radiation patterns.

By integrating ANNs with metaheuristic optimization algorithms, this study aims to develop an accurate and robust forecasting model for solar radiation. The metaheuristic algorithm is employed to optimize the weights and hyperparameters of the ANN, enhancing its ability to capture the complex relationships and patterns present in the SR data (Kaveh and Mesgari, 2023). The proposed approach is expected to contribute to the efficient planning and management of solar energy systems, facilitating the transition towards a more sustainable energy future.

One such promising metaheuristic algorithm is the COA, which often exhibits superior mechanisms for balancing exploration (searching new regions of the solution space) and exploitation (refining promising solutions). By effectively managing this trade-off, COA can lead to more efficient and effective optimization of the ANN's parameters, avoiding premature convergence to local optima. This capability allows the algorithm to navigate the complex search space more effectively, ultimately enhancing the predictive performance and generalization ability of the solar radiation forecasting model.

1.1. Objective and motivation

Solar energy generation has the potential to play a key role in meeting increasing global energy demands while reducing our reliance on fossil fuels and minimizing environmental impacts. Accurate

Table 1
Various optimization techniques employed to enhance the performance of artificial intelligence models.

AI Model and MH Algorithm	Acquired Results	Ref.
Ant Colony Optimization (ACO) and Artificial Neural Network	Selecting Solar Radiation features based on ACO and ANN. The model achieved high testing accuracies and low MAPE.	(Iqbal et al., 2022)
machine learning enabled with Deer Hunting Optimization Algorithm (DHOA)	Feature Extraction, and Machine learning algorithms optimized by DHOA in MLP, CNN, and RNN are applied for solar irradiation prediction.	(Vaisakh and Jayabarathi, 2022)
Genetic Algorithm Optimization of wavelet neural network	Daily solar radiation prediction using Genetic Algorithm Optimization of WNN. Efficient method for nonlinear and non-stationary solar radiation forecasting.	(Wang et al., 2011)
Neural Network and PSO Approach for Global Solar Irradiance Prediction	Hybrid neural network with PSO for short-interval solar irradiance prediction. Outperformed standalone BPNN in predicting solar irradiance for short intervals. Hybrid BPNN based on PSO algorithm	(Aljanad et al., 2021)
General Regression Neural Network with Grey Wolf Optimization	grey wolf optimization-based general regression neural network for solar power forecasting.	(Tu et al., 2022)
Machine Learning Algorithms for Predicting Solar Power Generation	Artificial neural network (ANN) with a genetic algorithm (GA).	(Sangeetha et al., 2023)
Principal Component Analysis for Short Term Prediction of Solar Irradiance based on Weather Patterns	Artificial neural networks for short-term solar irradiance prediction, incorporating principal component analysis for data preprocessing to enhance accuracy.	(de Guia et al., 2020)
principal components analysis and the BP neural network	Solar power generation prediction using principal components analysis and BP network. BP neural network model with reduced input parameters for prediction.	(Xiu et al., 2014)

forecasting of solar radiation levels is essential to efficiently operating solar power systems and grid integration. In this research, we aimed to develop an effective predictive model for forecasting average daily solar radiation levels based on a dataset consisting of 8 features namely Outdoor Temperature, Feels Like, Dew Point, Wind Speed, Wind Gust, Wind Direction, Humidity, Ultra-Violet Radiation Index.

A challenge with using machine learning techniques on a dataset with multiple correlated variables is managing model complexity and avoiding overfitting. As such, we first utilized principal component analysis (PCA) to reduce the dimensionality of the data and derive three uncorrelated principal components capturing the greatest variance. Reducing dimensionality both improves generalization ability and reduces computational expense for downstream modeling.

As daily solar irradiation heavily depends on seasonality, the transformed PCA inputs were divided into three distinct training sets – summer, winter, and monsoon. Capturing unique weather attributes and seasonal differences through separate models, rather than attempting to fit one high-dimensional function, improves representation of underlying data patterns associated with each period.

For each seasonal dataset, a neural network approach was pursued for forecasting of average daily radiation. Compared to statistical methods applied historically, neural networks can better model intricate nonlinear relationships via multilayer processing and have shown prowess in solar forecasting applications. However, optimizing network architecture and weights remains challenging. Therefore, metaheuristic COA was used to efficiently search the complex solution space and derive near-optimal weights for each seasonal neural predictor.

- The core motivation behind this research was to develop a sophisticated solar forecasting approach through leveraging data dimensionality reduction, neural network prediction, and metaheuristic optimization techniques.
- This research aimed to demonstrate a systematic data-driven methodology for harnessing the abundance of solar irradiance datasets to build robust forecasting models.
- To develop enhanced solar irradiance forecasting, integration of PCA, ANN, and COA was pursued.
- The suggested hybrid methodology couple's dimensionality reduction via PCA for input preprocessing, ANN modeling to capture nonlinear data relationships, and COA metaheuristic optimization for network weight determination.
- Constructing this predictive framework by synergistically linking multiple techniques provides the capacity to produce more accurate one-day-ahead projections of mean daily solar radiation versus employing any individual method alone.

2. Related work

Dimension reduction techniques have become increasingly important for improving the efficiency and performance of neural network models, especially for high-dimensional data. Recent research has explored various methods for reducing dimensions before feeding data into neural networks.

A common approach is using linear methods like principal component analysis (PCA) to extract key features (Surono et al., 2023). Sugiyarto Surono et al. (2023), demonstrated the enhancement of recurrent neural network (RNN) model accuracy by over 10 % for air quality prediction using PCA dimension reduction alongside k-means clustering. However, PCA cannot capture nonlinear relationships. Consequently, researchers have focused on nonlinear techniques like autoencoders (Zang et al., 2022). The EVNet model uses explainable nonlinear encoding and decoding to reduce dimensions while retaining significant information. Advanced models like copula matrices have also been employed. Ayyub Sheikhi et al. (2022) introduced a copula-based approach improving prediction error by over 50 % across various datasets (Sheikhi et al., 2022). By comparison, stochastic neural networks leverage probability and statistics for sufficient dimension reduction (Liang et al., 2022).

An alternative direction is embedding reduction directly within the neural architecture. Harbir Antil (2023) put forth a DNN-EIM methodology applying the empirical interpolation technique to curtail training data dimensions in deep networks. The DNN-EIM method attained over 75 % shorter training time with no accuracy decline (Antil et al., 2023). Dimensionality reduction is commonly used to deal with complex high-dimensional data. A shallow neural network model for non-negative matrix factorization has been proposed by Dutta and Das (2022) for low rank approximation and meaningful representations. The model uses hierarchical learning, modified weight initialization, a regularized objective function, and an adjusted ReLU activation to generate sparse part-based representations while avoiding overfitting (Dutta and De, 2022).

Principal component analysis (PCA) is a technique used to reduce the dimensionality of data and simplify the structure of neural network-based solar radiation forecasting models. It can be applied to improve the efficiency and accuracy of models that predict solar radiation across different timescales, from intra-hour forecasts to longer term projections (Li et al., 2020). Along with other domains like image classification, chemical process modeling, and medical datasets analysis. In image classification, a model based on PCA initialization of convolutional neural networks (CNNs) has been proposed to address the gradient diffusion problem and improve training efficiency (Ren et al., 2016). In chemical process modeling, PCA is used to preprocess data and simplify

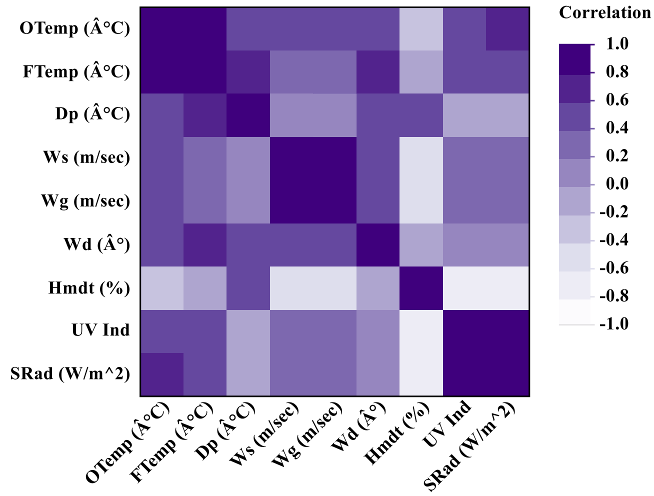


Fig. 1. The Pearson correlation was calculated for the input including meteorological parameters and the solar radiation output.

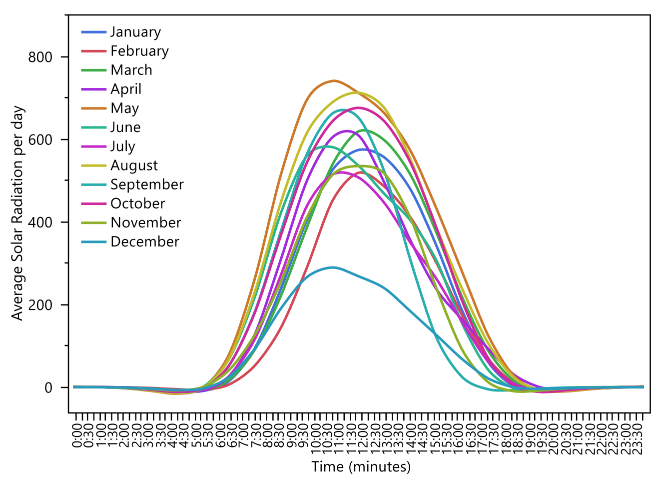


Fig. 2. Monthly averaged, daily insolation data for a horizontal surface in W/m^2.

the structure of neural network models, resulting in improved prediction accuracy (Habibi-Yangjeh et al., 2009). PCA has become a valuable tool for developing optimized solar radiation forecasting systems.

Models for predicting photovoltaic (PV) power output fall into four main categories: physical, statistical, artificial intelligence (AI), and hybrid models. AI models predominantly employ neural networks like backpropagation neural networks (BPNNs) (Yadav et al., 2020) radial basis function neural networks (RBFNs) (Yang et al., 2020), and recurrent neural networks (RNNs) (Pang et al., 2020) to estimate PV generation. Statistical approaches include regression models, transfer function models, autoregressive integrated moving average (ARIMA) models (Louzazni et al., 2021), Markov chain models (Cui et al., 2022), as well as gray models (Tu et al., 2022). Hybrid models combine elements from the physical, statistical, and AI categories. Each modeling technique has its own strengths and weaknesses based on factors like solar irradiance forecasting, adaptability to new data, and computational complexity. Continued research aims to leverage the advantages of the different modeling philosophies to develop more accurate and robust PV forecasting. Typical artificial intelligence prediction models employ artificial neural networks (ANNs) or combine neural networks with fuzzy systems (Jithendra et al., 2024). However, training ANNs can be challenging due to issues like local minima and overfitting. Researchers have explored using metaheuristic optimization algorithms to improve the training of ANNs.

Metaheuristic algorithms like genetic algorithms, particle swarm optimization, and ant colony optimization have been used to optimize the weights and architecture of ANNs. These algorithms are useful for avoiding local minima and accelerating training convergence (Luan et al., 2019).

Other recent work has combined ANNs with ant colony optimization (Mavrovouniotis and Yang, 2015), particle swarm optimization (Mohandes, 2012), and multiple hybrid algorithms (Huang et al., 2021) for tasks like classification, forecasting, and control. The metaheuristic components help avoid overfitting and speed up training.

In this paper we have integrated neural network with the COA optimization algorithm and applying PCA then seasonally segmented data, this study aims to develop a robust and precise forecasting framework for solar radiation. The synergistic combination of these techniques leverages the strengths of neural networks in modeling nonlinear relationships, the efficiency of COA in optimizing network parameters, and the dimension reduction capabilities of PCA. This integrated approach is expected to yield accurate solar radiation forecasts, which can contribute to the effective planning and management of solar energy systems.

3. Methodology

3.1. Data collection

The meteorological data used to develop the proposed empirical models were obtained from School of Mechanical Engineering, VIT University in Vellore, Tamil Nadu, India. Solar radiation measurements, recorded in watts per square meter (W/m2), were collected at the Vellore campus using the instrument Pyron meter. The time stamps on the solar radiation data follow the International Organization for Standardization (ISO) standard time.

Data were collected at 5-minute time resolution, but only data between 6:00 AM to 6:00 PM were November 2022 to October 2023.The study site has three classic seasons, summer season from March to June, monsoon from July to September and winter from October to February. The Weather parameters Outdoor Temperature, OTemp $(\widehat{A}^{\circ}C)$, Feels Like, FTemp $(\widehat{A}^{\circ}C)$, Dew Point, Dp $(\widehat{A}^{\circ}C)$, Wind speed, Ws (m/sec), Wind Gust, Wg (m/sec),Wind Direction, Wd$(\widehat{A}^{\circ}C)$,Humidity, Hmdt (%), Ultra-Violet Radiation Index, UV Ind, Solar Radiation, SRad (W/m2). When selecting variables for a predictive model, it is important to consider which ones have available data that is highly correlated with the target variable. To do this, the correlation between each potential weather predictor and solar radiation was statistically analyzed using the full dataset, as shown in Fig. 1. This figure presents the correlation coefficients for all eight weather parameters with respect to SRad (the output or target variable). The full dataset was used to calculate these correlations. The Fig. 2 shows the monthly averaged, daily insolation data for a horizontal surface in W/m2.

An inverse relationship was found between temperature and humidity, as indicated by the negative correlation coefficient.

For this study, the full one-year dataset was split into seasonal subsets - winter from November 1, 2022 to February 28, 2023, summer from March 1, 2023 to June 30, 2023, and the rainy season from July 1, 2023 to October 31, 2023. By dividing the data this way, seasons with distinct weather patterns were analyzed separately. This seasonal segmentation of the data allowed for a more detailed examination of how predictive models perform during different times of the year.

3.2. PCA

Principal Component Analysis (PCA) is a flexible statistical technique used to condense a dataset containing cases and variables into its fundamental elements, referred to as principal components. These

Table 2
Parameter Specifications.

Parameter	Value
Population size	60
Maximum no. of generations	100
Number of hidden neurons	10
Activation function	Sigmoid

components are optimal linear combinations of the original variables, effectively capturing the maximum variance across all variables. Through this process, PCA offers an approximation of the initial data table by emphasizing only a handful of significant components (Greenacre et al., 2022).

The initial stage involves standardizing variables using Eq. (1), which is a crucial step in the PCA process

$$z = \frac{x - \mu}{\sigma} \tag{1}$$

Where z is the z-score, x is the original value of the variable, μ is the mean of the variable and σ is the standard deviation of the variable.

Calculate the correlation matrix (C) for meteorological data.

$$C = \frac{1}{n-1} Z\prime.Z \tag{2}$$

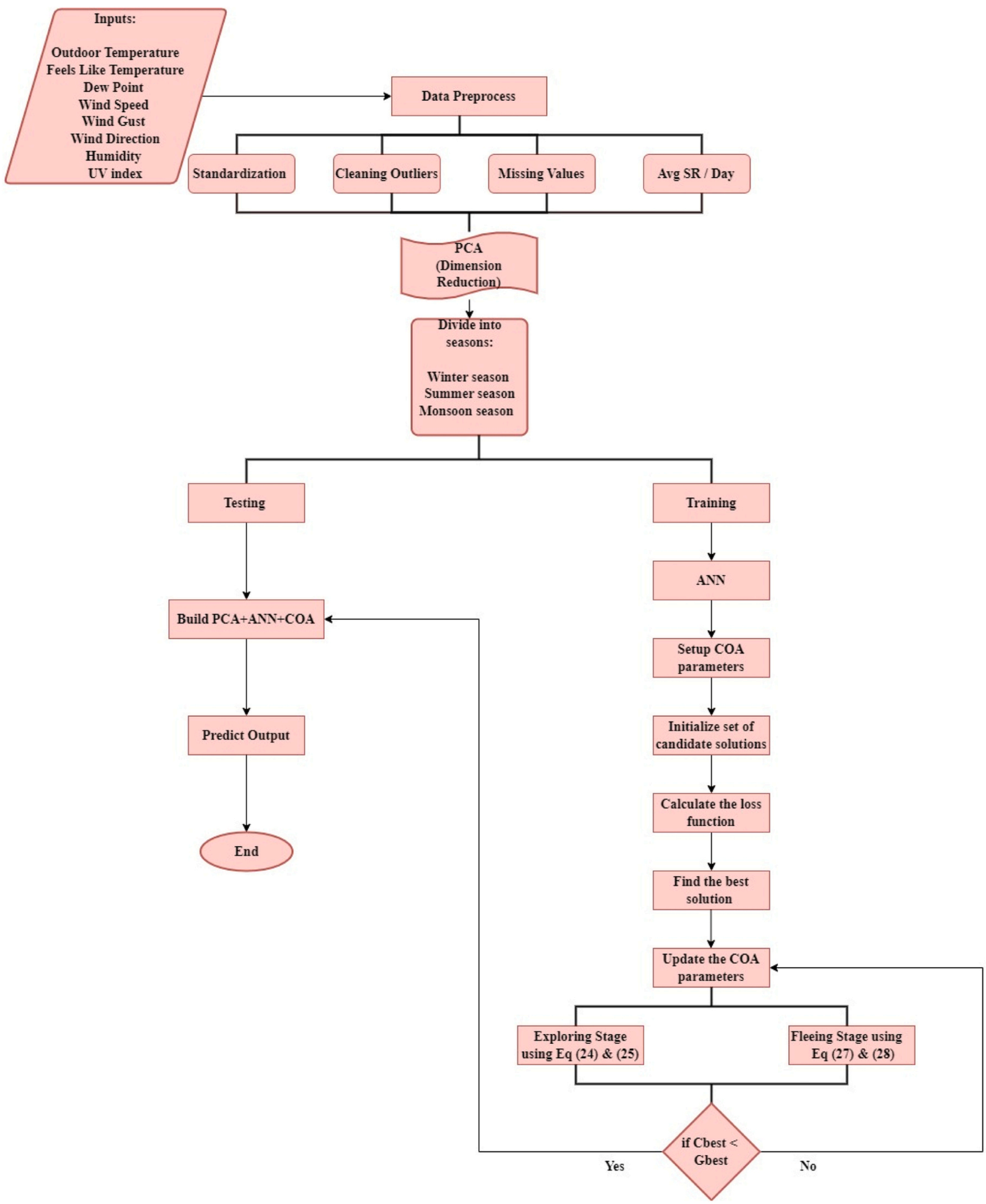


Fig. 3. A taxonomy of PCA-ANN-COA.

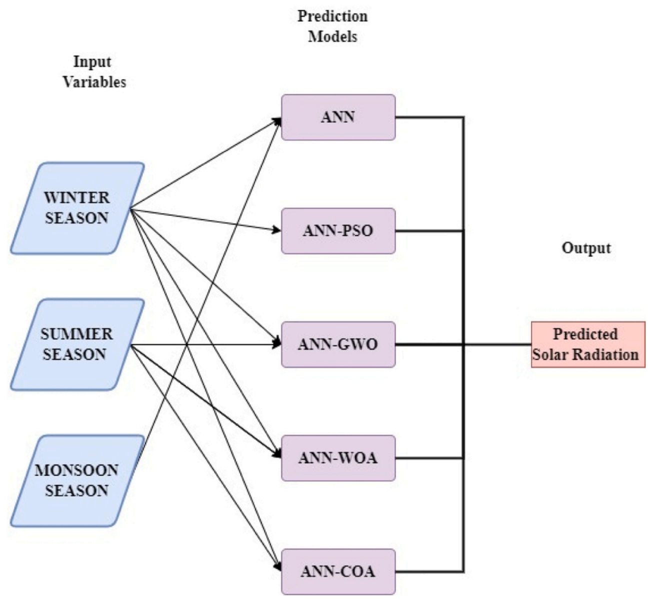


Fig. 4. Model design that was developed.

Where Z is standardized meteorological data and *Z′* is transpose.

Find the eigenvalues and eigenvectors for the meteorological matrix.

$$C.V = \lambda.V \tag{3}$$

Here, λ is referred to as an eigenvalue, and V represents an eigenvector of the correlation matrix C.

Arrange the eigenvectors in descending order based on their corresponding eigenvalues.

Choose the top eigenvectors, and construct a dataset using this new representation.

After constructing the dataset with the selected eigenvectors, the concluding step in PCA involves utilizing this transformed data for further analysis. With this new representation, it becomes easier to identify interrelated meteorological parameters for forecasting.

3.3. ANN

Artificial neural networks (ANNs) are computing systems inspired by the biological neural networks in animal brains (Siami-Namini et al., 2018). ANNs consist of interconnected nodes called artificial neurons that transmit signals between each other. The connections have numeric weights that are tuned based on experience, making neural nets adaptive to inputs and capable of learning. ANNs typically have an input layer to receive data, an output layer to produce a prediction or decision, and one or more hidden layers in between that derive the signal transformations. During training, the network learns relationships between inputs and outputs by adjusting the weights through backpropagation of errors made on training data. Once trained, ANNs can be used to make predictions on new unseen data. The topology or structure of an ANN depends on the task and is often determined empirically by testing different architectures. ANNs have been applied extensively to time series forecasting across many domains due to their ability to model complex nonlinear relationships.

Artificial Neural Networks (ANNs) typically rely on an optimization technique known as gradient descent to iteratively update the connection weights and node biases using the backpropagation algorithm. This process aims to minimize the Mean Squared Error (MSE) between the network's predicted outputs and the observed data (Kara et al., 2011). The activation function used for all nodes in the network is the sigmoid

Table 4
Principal Components (Pcs) for weather variables.

Pcs	Eigenvalue	Percent	Cum Percent
Pcs1	4.013038	50.163	50.163
Pcs2	2.135929	26.699	76.862
Pcs3	1.208964	15.112	91.974

Table 5
Outcomes of PCA.

Variance	Pc1	Pc2	Pc3
OTemp (Â°C)	**0.43704**	0.1691	-0.29504
FTemp (Â°C)	**0.42157**	0.29534	-0.25828
Dp (Â°C)	0.18665	**0.62071**	-0.01504
Ws (m/sec)	**0.39516**	-0.23573	**0.42796**
Wg (m/sec)	**0.38491**	-0.23234	**0.44197**
Wd (Â°)	**0.36283**	0.20452	**0.36032**
Hmdt (%)	-0.23732	**0.53708**	0.25869
UV Ind	0.32273	-0.24302	*-0.52036*

The variables in bold and italic have high correlations and are the components included in the PCs.

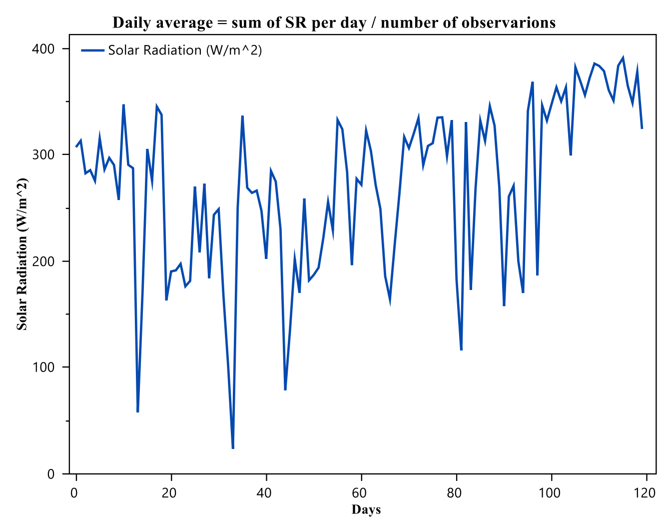


Fig. 5. The average daily solar radiation (W/m2) during winter in Vellore, Tamil Nadu.

Table 3
Correlation matrix of weather variable.

	OTemp	FTemp	Dp	Ws	Wg	Wd	Hmdt	UVInd
OTemp	1	**0.9443**	**0.5343**	0.4532	0.4368	0.553	-0.3322	**0.5959**
FTemp		1	**0.7141**	0.3887	0.3659	**0.6131**	-0.1676	**0.5193**
Dp			1	0.0022	0.0059	0.47	**0.5574**	-0.042
Ws				1	**0.9844**	**0.5853**	-0.4829	0.3794
Wg					1	0.5532	-0.4522	0.3609
Wd						1	-0.0601	0.1452
Hmdt							1	*-0.6713*
UV Ind								1

Bold and italics highlight pairs of weather factors strongly linked (both positively and negatively) in the correlation table.

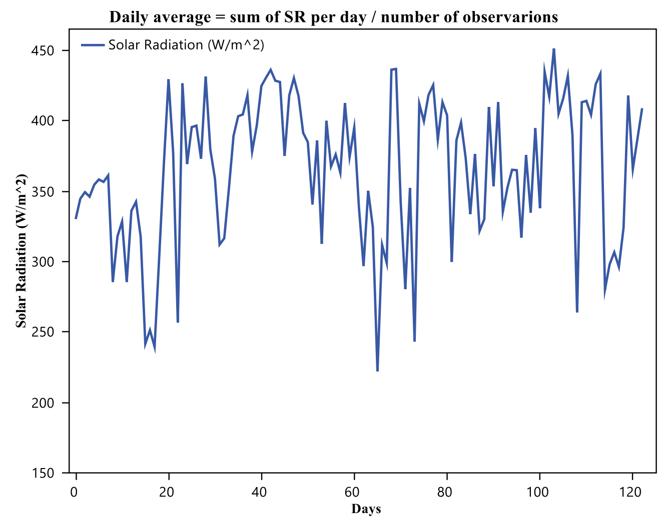


Fig. 6. The average daily solar radiation (W/m2) during summer in Vellore, Tamil Nadu.

function (Pratiwi et al., 2020), as shown in Eq. (4)

$$f(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

Where z represents the weighted sum of the inputs to the node.

To assess the training process, the Mean Squared Error (MSE) is commonly used as an error metric (Manry et al., 1996).

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(R_j - F_j\right)^2 \tag{5}$$

Where N is the total number of observations, R_j and F_j represent the real and forecasted values.

4. Optimization methods inspired by the principles of nature

4.1. Particle swarm optimization

Particle swarm optimization is categorized within the realm of swarm intelligence, which is a subset of evolutionary computing approaches. Within the framework of PSO, particles are analogous to birds, positions and velocities represent signals, and solutions correspond to

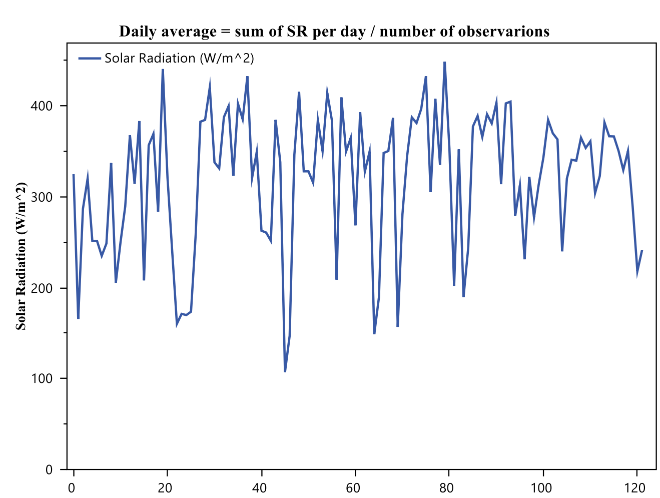


Fig. 7. The average daily solar radiation (W/m2) during monsoon in Vellore, Tamil Nadu.

foods. The positions and velocities serve as indicators of the coordinates of solutions and the speed at which particles should iteratively approach these solutions (Rini et al., 2011).

The iterative update of particle positions (x(n)) and velocities (v (n+1)) is achieved through Eqs. (6) and (7) as follows:

$$v(n+1) = w * v(n) + c1 * r1(p(n) - x(n)) + c2 * r2(g(n) - x(n)) \tag{6}$$

$$x(n+1) = x(n) + v(n+1) \tag{7}$$

Here, the current velocities and positions are denoted by v(n) and x (n), respectively. The parameters include the inertia weight (w), local weight (c1), random variables (r1 and r2), and global weight (c2). Additionally, p(n) represents the best position for each particle, while g (n) signifies the best position achieved by any particle thus far (Hajimirsadeghi and Lucas, 2009).

In this study, PSO is employed to optimize the weights of feedforward networks specifically for addressing the forecasting challenge of seasonal solar radiation.

4.2. Grey wolf optimization

GWO is a swarm intelligence algorithm inspired by the hierarchical leadership and hunting behavior of grey wolves. It mathematically models their social structure, with a population divided into four groups: α, β, δ and ω.Alphas lead the group and make hunting decisions, while betas assist them. Omegas, submissive to α, $\beta$and δ wolves, have the lowest hierarchy (Mirjalili, 2015).

4.2.1. Surrounding the target

During the hunting process, gray wolves surround their prey. To mathematically represent this encircling behavior, the following equations are employed:

$$\widetilde{X}(t+1) = \widetilde{X}_p(t) - A.\left|C.\widetilde{X}_p(t) - \widetilde{X}(t)\right| \tag{8}$$

$$A = 2.a.r_1 - a \tag{9}$$

$$C = 2.r_2 \tag{10}$$

$$a = 2 - 2\frac{t}{Max\_Iter} \tag{11}$$

Here, $\widetilde{X}$ represents the position vector of the gray wolf, $\widetilde{X}_p$ denotes the position vectors of the prey, t signifies the current iteration in Eq.(8), and A and C are coefficient vectors in Eq.(9) &(10). Additionally, r1 and r2 represent random vectors within the range [0,1]. In the Eq. (11) The parameter 'a' controls the distance, with its value decreasing linearly from 2 to 0 throughout the iterations. 'Max_Iter' represents the maximum number of iterations.

4.2.2. Assaulting the target

Gray wolves locate prey with α,β and δ wolves' guidance. In each iteration, the top three wolves (α,β,δ) are retained. Other wolves update positions using:

$$\widetilde{D}_\alpha = \left|C_1\widetilde{X}_\alpha - \widetilde{X}(t), \widetilde{D}_\beta = \left|C_2\widetilde{X}_\beta - \widetilde{X}(t)\right|, \widetilde{D}_\delta = \left|C_1\widetilde{X}_\delta - \widetilde{X}(t)\right|\right| \tag{12}$$

$$\widetilde{X}_1 = \widetilde{X}_\alpha - A_1D_\alpha, \widetilde{X}_2 = \widetilde{X}_\beta - A_2D_\beta, \widetilde{X}_3 = \widetilde{X}_\delta - A_3D_\delta \tag{13}$$

$$\widetilde{X}\left(t+1\right) = \frac{\widetilde{X}_1 + \widetilde{X}_2 + \widetilde{X}_3}{3} \tag{14}$$

This results in the final position within a circle defined by alpha, beta, and delta in the search space. In essence, alpha, beta, and delta estimate the prey's position, guiding other wolves to update their positions randomly around the prey.

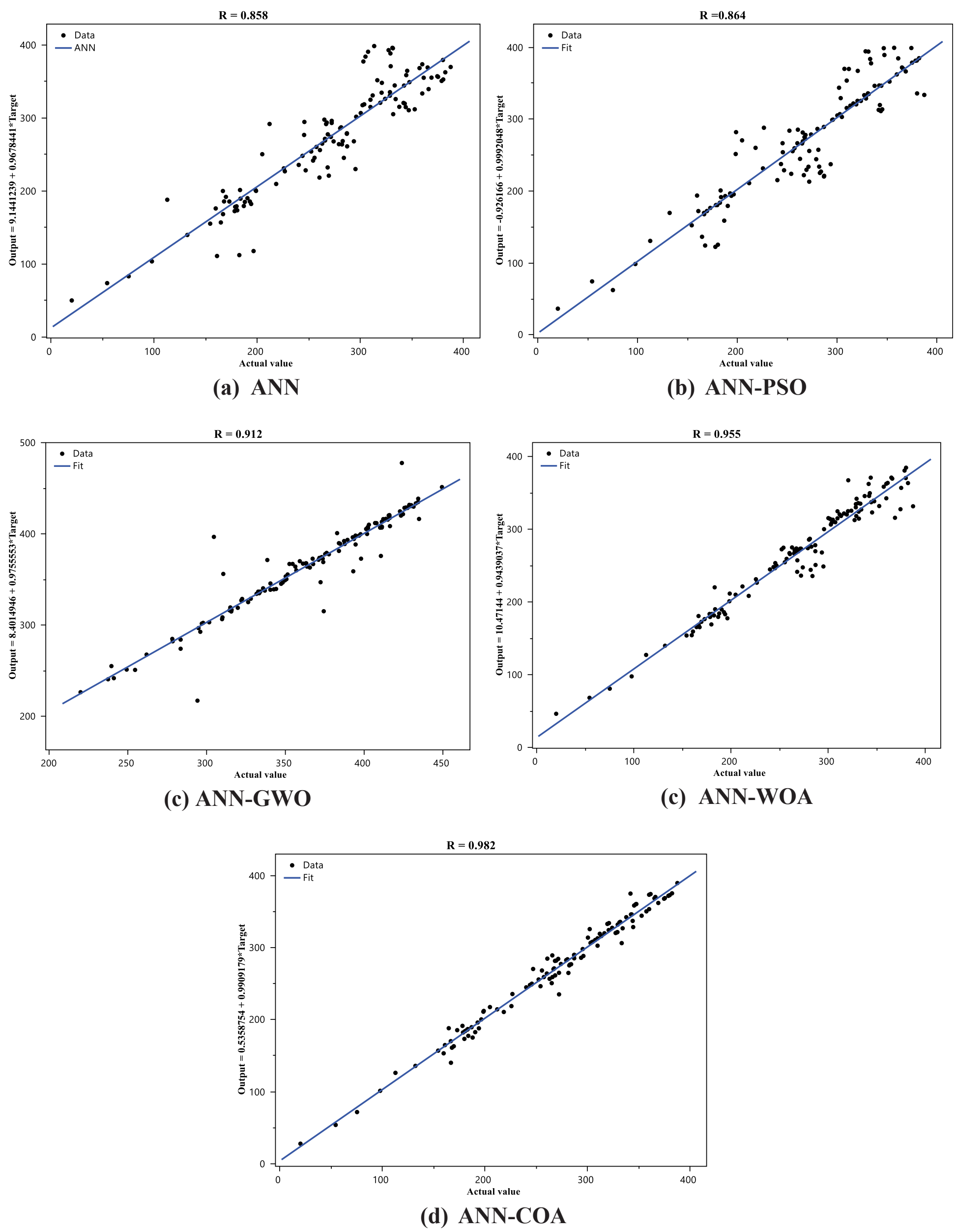


Fig. 9. A regression study of observed and expected Solar Radiation (W/m^2) using proposed models for the Winter season.

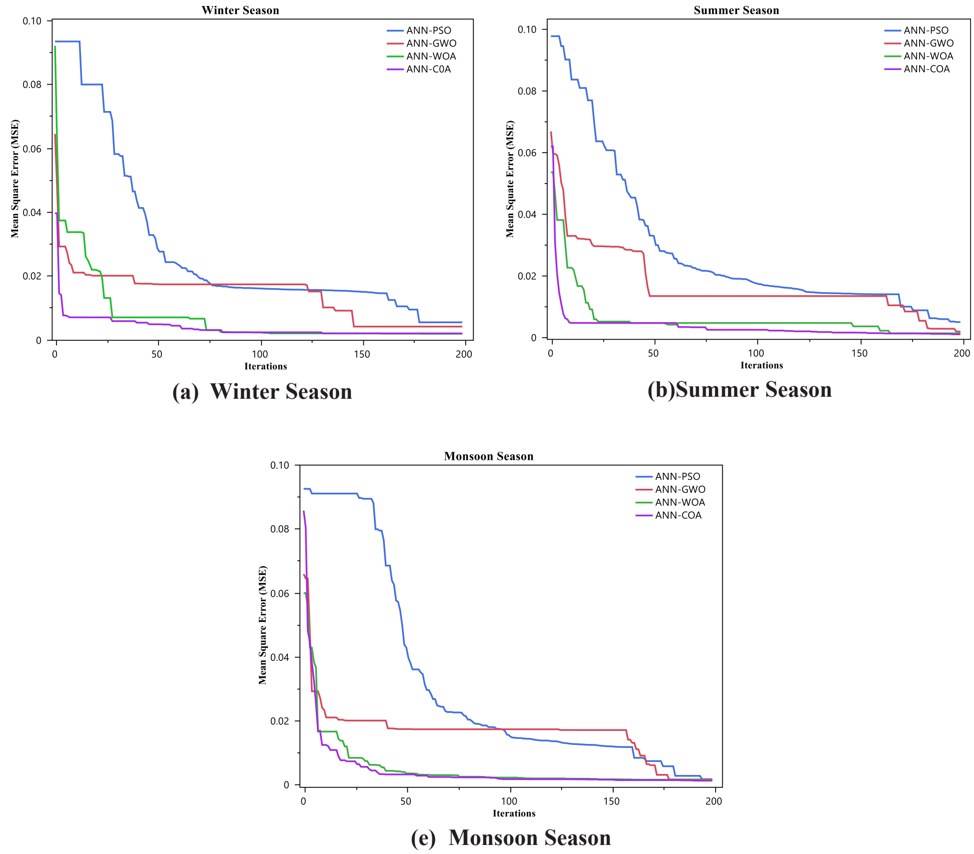


Fig. 10. Convergence rate of suggested models across three seasons during training.

4.3. *Whale optimization algorithm*

The whale optimization algorithm (WOA) developed by Mirjalili and Lewis (Mirjalili and Lewis, 2016) in 2016 has three main components that drive the search process: encircling prey, bubble-net attacking, and searching for prey. The encircling prey component involves the algorithm spiraling in towards a promising solution. Bubble-net attacking is inspired by humpback whales creating bubbles to herd prey. This component helps diversify the search. Finally, the algorithm conducts a wider search for prey, exploring new potential solutions. Together these three mechanisms allow WOA to balance exploitation of good solutions and exploration of the search space.

4.3.1. *Surrounding quarry*

Once the algorithm identifies the current best potential solution, the other candidate solutions will start moving towards that prominent individual. This movement is guided by the Eq. (15).

$$D = |C.W_{best}(t) - W(t)| \tag{15}$$

$$W(t+1) = W_{best}(t) - A.D \tag{16}$$

In the equation, W(t) represents an individual solution in the current iteration and $W_{best}(t)$is the best individual solution found so far. The parameters A and D are control variables that are calculated using Eqs. (17) and (18), respectively. These control parameters A and D are important for defining how much movement towards the current best solution will occur during the encircling mechanism.

$$A = 2.r_1.a - 1.a \tag{17}$$

$$C = 2r_2 \tag{18}$$

Where the coefficients r1 and r2 are random vectors ranging from 0 to 1. The parameter 'a' is a decreasing coefficient calculated between 2 and 0.

4.3.2. *Bubble-net attacking*

The bubble-net attacking technique used by whales is modeled in the WOA algorithm in Eq. (19).

$$W(t+1) = |W_{best}(t) - W(t)|.e^{bl}.\cos(2\pi l) + W_{best}(t) \tag{19}$$

The bubble-net attack uses a random number l between −1 and 1, and a shape parameter b set to 1. A selection probability controls the balance between encircling prey and bubble-net attacking, which often occur together.

$$W\left(t+1\right) = \begin{cases} W_{best}(t) - A.D, if \rho \le 0.5 \\ W_{best}(t) - W(t).e^{bl}.\cos(2\pi l) + W_{best}(t), if \rho > 0.5 \end{cases} \tag{20}$$

where ρ indicates a random number in [0,1].

Search for prey

If $|A| > 1$,the algorithm enhances exploration by conducting a more random search.

$$D = |C.W_{rand} - W| \tag{21}$$

$$W(t+1) = W_{rand} - A.D \tag{22}$$

In the Eqs. (21) and (22), W_{rand}represents a candidate solution randomly selected from the current population of solutions being evaluated.

4.4. *Coati optimizer*

Invented by Mohammad Dehghani in 2023, the COA is a novel population-based optimization method inspired by the collective hunting and evasion behaviors of coatis, omnivorous mammals in the Americas (Dehghani et al., 2023). The COA introduces a mathematical model for its various steps, where coatis, diurnal mammals found in the Americas, inspire the algorithm. Their behaviors, including hunting and escaping from predators, are mathematically modeled, and the algorithm initializes coatis' positions in the search space randomly using a specific equation. As a population-based metaheuristic, COA represents coatis as

Algorithm 1. Pseudocode of the COA metaheuristic

```
Begin COA
Input optimization problem specifications
Set number of iterations T and population of coatis N
Generate initial position of each coati using Eq. 23 and evaluate objective function for starting
population
for i = 1 to T:
Update iguana position based on optimal population member's location
Exploring Stage:
    for i = 1 to N/2:
          Calculate new coati location using Eq. 24
          Update coati location using Eq. 29
    End for
    for i = N/2+1 to N:
           Compute random iguana location using Eq. 26
          Determine new coati position using Eq. 25
           Update coati position using Eq. 29
    End for
Fleeing Stage:
    Assess local parameter bounds using Eq. 27
    for i = 1 to N:
        Compute new coati position using Eq. 28
        Improve coati location using Eq. 29
    End for
   Retain best candidate solution
End for
Output optimal solution found by COA
End COA optimization
```

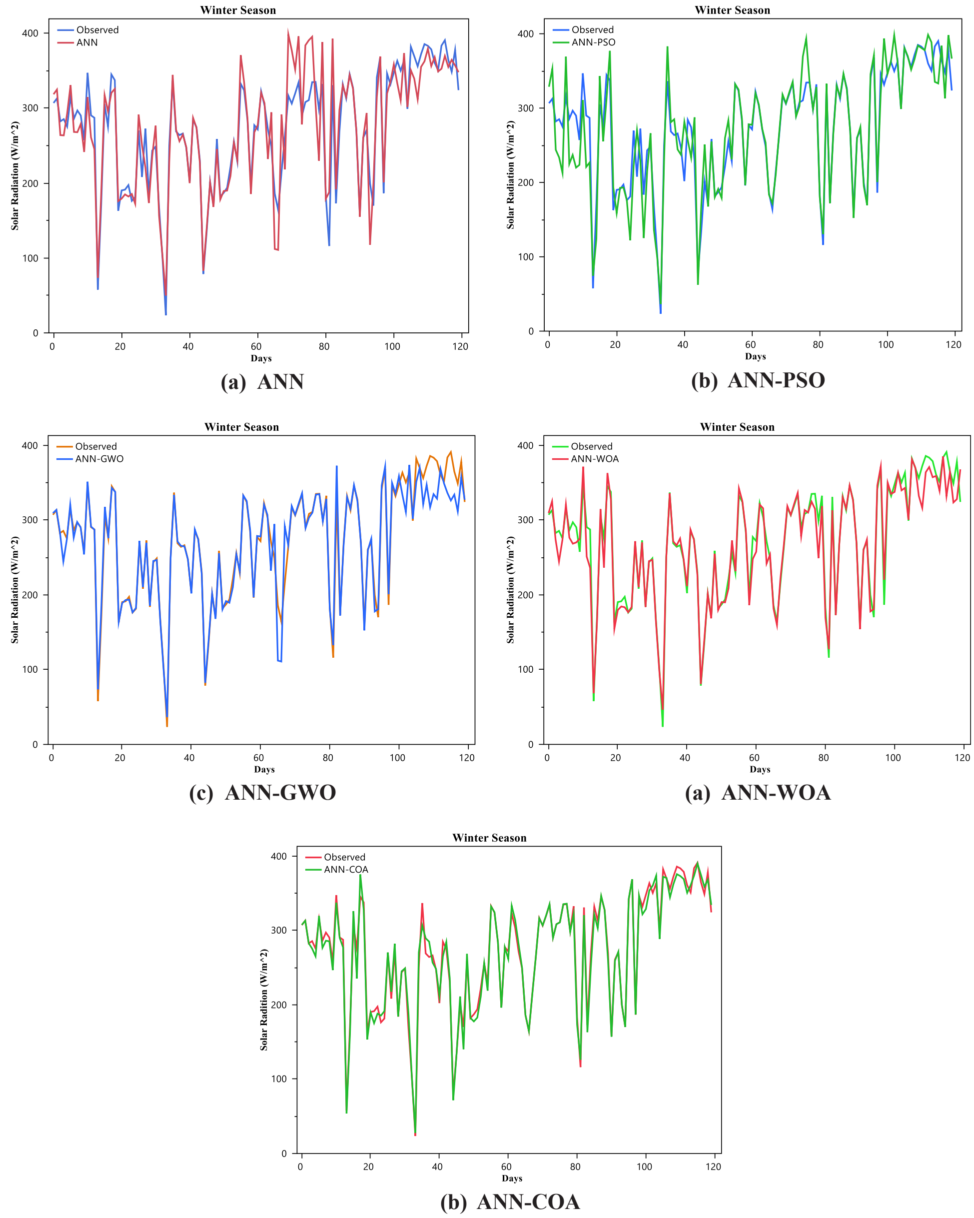


Fig. 8. The Winter Season's observed and anticipated average solar radiation per day using the suggested model.

algorithm members, and their positions determine candidate solutions. The algorithm's mathematical model comprises the population matrix and objective function values. COA updates coatis' positions based on their natural behaviors, such as attacking iguanas for exploration and escaping predators for exploitation, simulated in two phases to enhance both global and local search capabilities.

In COA implementation, coatis' positions in the search space are randomly initialized.

$$C_{(i,j)} = rand \times \left(UB_j - LB_j\right) + c_{(i,j)}\ j = 1, 2, \ldots.n \tag{23}$$

In the optimization algorithm, an appropriate fitness function $f(C_i)$ is selected to evaluate the quality of potential solutions. The fitness value of each candidate solution is calculated.

4.4.1. Stage 1: Exploring stage

The COA algorithm divides its population into two groups to simulate how coatis search for food. One group represents coatis resting in trees, guided towards optimal solutions. The other group models' coatis prowling the ground for new solutions to explore. This two-pronged approach balances exploration and exploitation to prevent getting stuck in local optima. Further refinements to the algorithm aim to improve convergence rates.

$$\widetilde{X}_i^{t+1} = \widetilde{X}_i^t + r.\left(\widetilde{X}_{best}^t - I.\widetilde{X}_i^t\right) \tag{24}$$

Where $\widetilde{X}_i^{t+1}$ represents the location data of the i-th coati in the population being modeled. I is defined as a randomly selected integer within the range [1,2], t signifies the current iteration number in the ongoing process.

For coatis that are waiting on the ground in search of prey, their locations can be modeled mathematically in the following way:

$$\widetilde{X}_i^{t+1} = \begin{cases} \widetilde{X}_i^t + r.\left(IG^t - I.\widetilde{X}_i^t\right), ifff\left(IG^t\right) < f\left(\widetilde{X}_i^t\right) \\ \widetilde{X}_i^t + r.\left(\widetilde{X}_i^t - IG^t\right), else \end{cases} \tag{25}$$

$$IG^t = LB + r.(UB - LB) \tag{26}$$

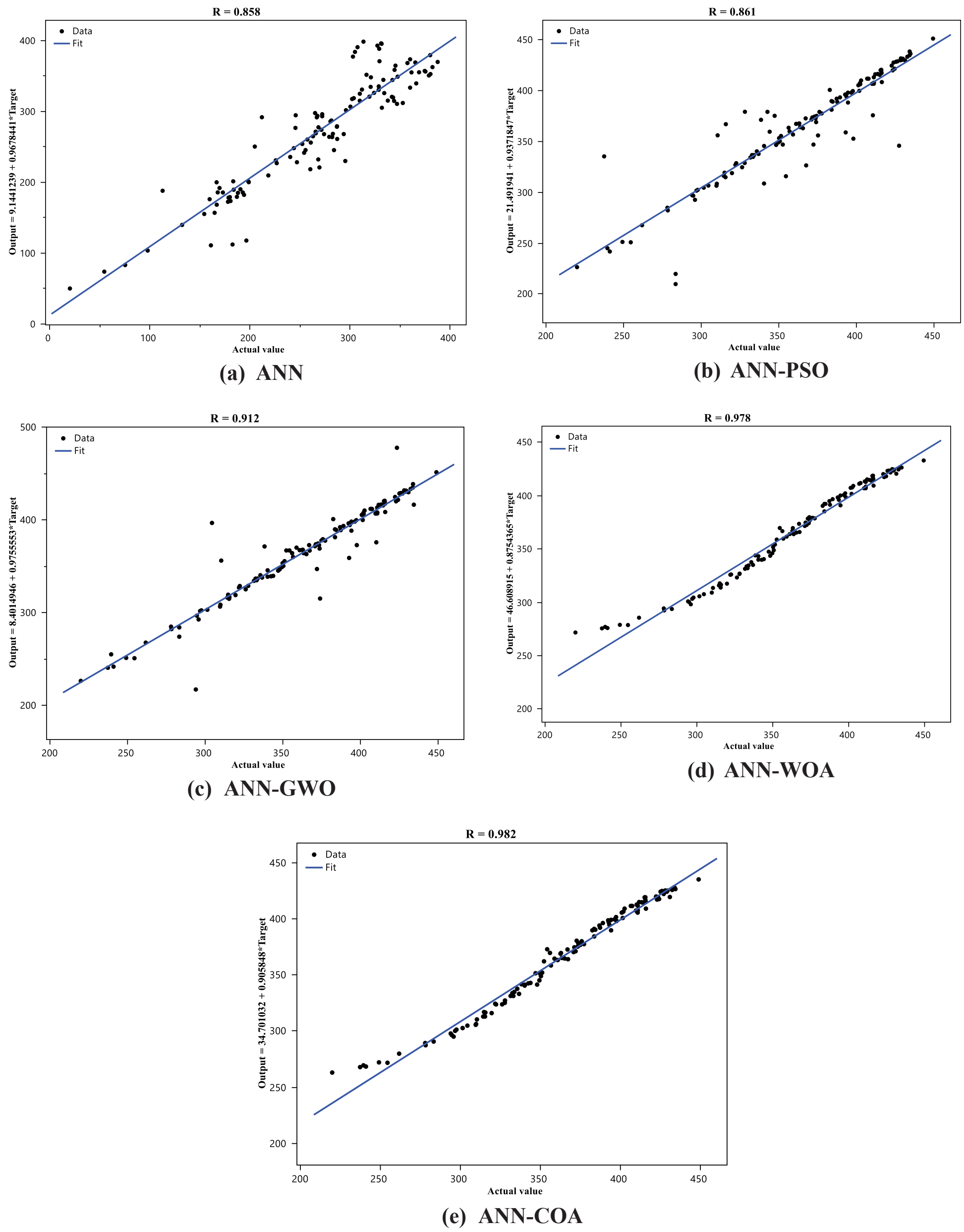


Fig. 11. A regression study of observed and expected Solar Radiation (W/m^2) using proposed models for the summer season.

4.4.2. Stage 2: Fleeing stage

The fleeing model depicts the coati's behavior when escaping predators through mathematical representations. It simulates a scenario in which predators are hunting each individual coati within the population.

$$LB^{local} = \frac{LB}{t}, UB^{local} = \frac{UB}{t} \tag{27}$$

$$\widetilde{X}_i^{t+1} = \widetilde{X}_i^t + (1-2r).\left(LB^{local} + r.\left(UB^{local} - LB^{local}\right)\right) \tag{28}$$

As the final step, a greedy selection algorithm is applied to the coati population to determine the overall optimal solution. This top solution is then stored and displayed as output. The greedy selection process follows the mathematical expression as per Eq. (29).

$$\widetilde{X}_i^{t+1} = \begin{cases} \widetilde{X}_i^{t+1}, iff\left(\widetilde{X}_i^{t+1}\right) < f\left(\widetilde{X}_i^t\right) \\ \widetilde{X}_i^t, else \end{cases} \tag{29}$$

5. Hybridization of ANN and COA

In this study, the raw solar radiation data was first aggregated to daily average values. This condensed the high-frequency intraday measurements into a simplified daily time series. PCA was then applied on the daily average solar radiation data for dimensionality reduction. The first 3 principal components which captured maximum variance in the data were retained as shown in Table 4. The reduced 3-dimensional PCA-transformed dataset was divided into winter, summer and monsoon subsets to capture seasonal patterns. The PCA features for each season were used as inputs to train separate artificial neural network ANN shown in Fig. 4. The weights and biases of the ANNs were optimized using the COA. COA conducted a global search to find optimal network parameters minimizing the prediction error.

For training and testing, the PCA-ANN-COA models were developed on 75 % training data and evaluated on 25 % test data for each season. Using 3 PCA features improved model generalization compared to using raw high-dimensional data.

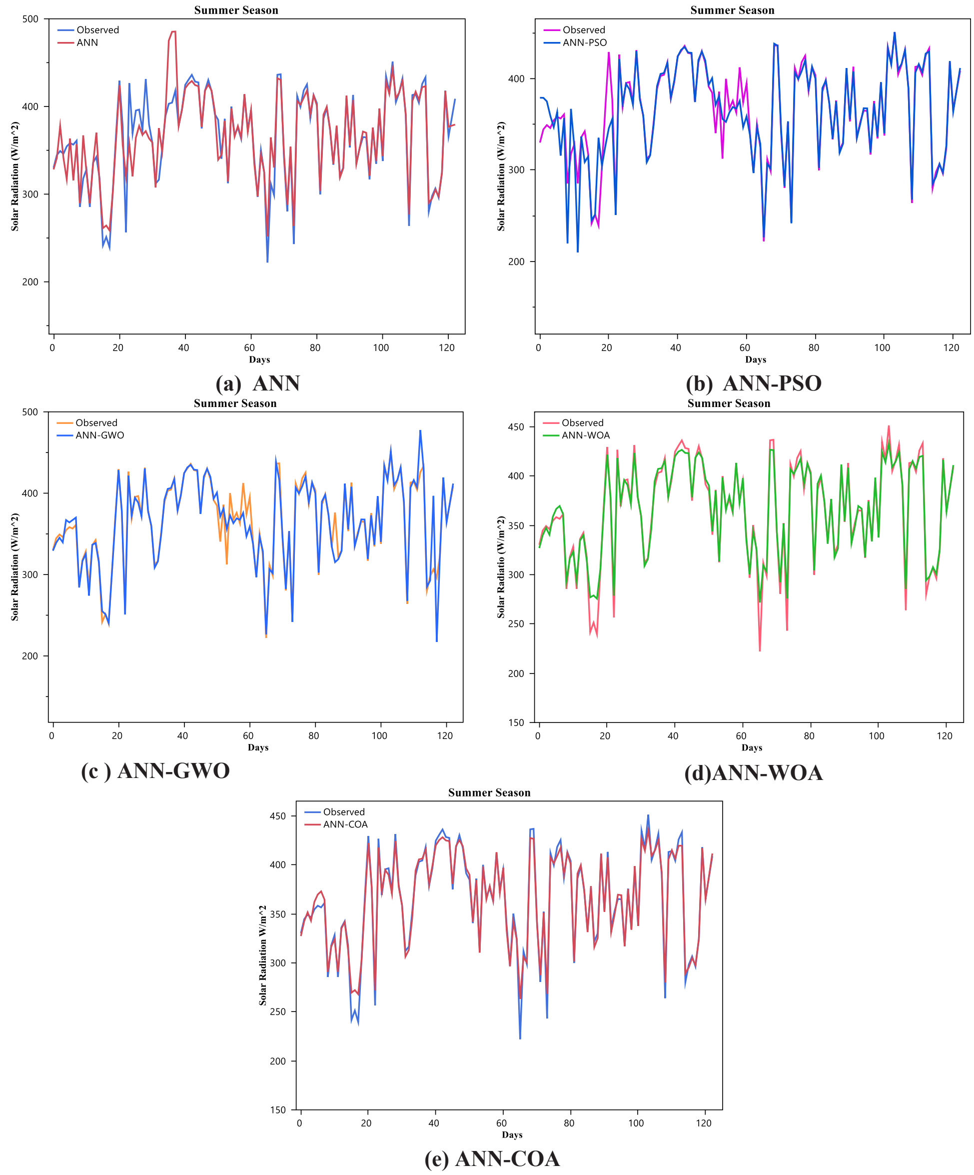


Fig. 12. The summer season's observed and anticipated average solar radiation per day using the suggested models.

During training, the COA algorithm evaluated the fitness of each candidate ANN solution in its population using mean squared error (MSE) as the loss function. MSE, calculated as shown in Eq. (5), quantifies the deviation between the ANN's predicted outputs and the true target values. COA iteratively optimized the ANN weights and biases to minimize the MSE. The ideal optimized parameter settings obtained after COA training are presented in Table 2. The workflow for developing the integrated PCA-ANN-COA model is depicted in Fig. 3. The key steps were - applying PCA for feature extraction from the average solar radiation per day data, using the PCA features to train the ANN, and leveraging COA to optimize the ANN parameters by minimizing the (MSE) loss function. Through this training approach, COA was able to fine-tune the ANN model parameters for maximizing forecasting accuracy on the seasonal datasets. The MSE metric provided a quantitative approach for COA to compare and select optimal ANN weights that best fit the training data.

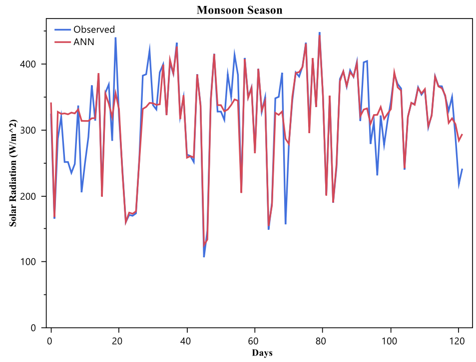
6. Results and discussions

One year of observations recorded every 5 minutes documenting the relationship between meteorological parameters and global solar radiation in Vellore from 2022 to 2023 were analyzed on a daily basis. The raw data was preprocessed and converted to daily averages for each parameter. Factors like Outdoor Temperature, Feels like Temperature, Dew Point, Wind speed, Wind Gust, Wind Direction, Humidity and Ultra- Violet Radiation Index were examined to determine how they impacted average daily solar radiation exposure in Vellore. A forecasting model was developed using hybrid neural networks for seasonal data incorporating multidimensional principal component analysis and metaheuristic optimization methods. This model was implemented in the MATLAB (Matrix Laboratory) computing environment.

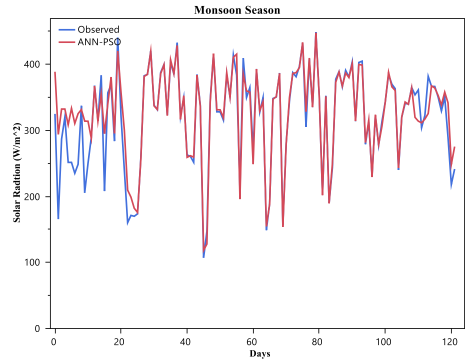
6.1. Data compression

Analyzing the correlations between the original variables and extracted principal components is key to interpreting PCA models. Variables highly correlated with certain components strongly influence those components, revealing their relative importance in shaping the PCA representation of the data. This correlation analysis uncovers what drove the lower-dimensional rendering of the dataset.

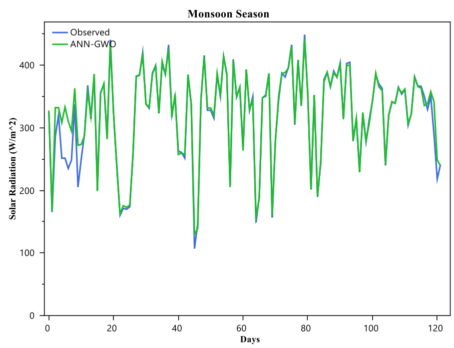
Table 1 demonstrates a significant positive link between the following variables:



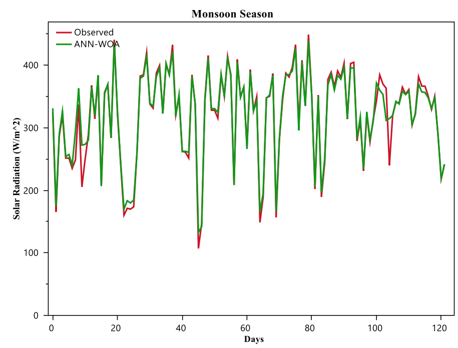
(a) ANN



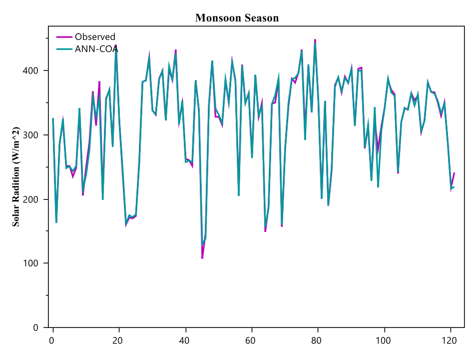
(b) ANN-PSO



(c) ANN-GWO



(d) ANN-WOA



(e) ANN-COA

Fig. 13. The Monsoon Season's observed and anticipated average solar radiation per day using the suggested model.

Table 6
An analysis comparing improved prediction models using statistical methods on training and testing data.

Season	Model	Training				Testing			
		RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
Winter	ANN	32.6747	23.1322857	0.09876192	0.83477	22.7918	17.781327	0.06842582	0.86784
	ANN-PSO	23.8643	17.781327	0.06842582	0.87441	32.6747	23.1322857	0.09876192	0.83477
	ANN-GWO	21.1196	9.74609366	0.04679668	0.91582	20.7108	17.9691048	0.05815765	0.86859
	ANN-WOA	14.3132	7.16015567	0.04068379	0.95785	18.7669	13.0598336	0.0429953	0.89995
	ANN-COA	12.0567	6.6598956	0.03584126	0.97258	8.35067	7.1895908	0.02168631	0.93304
Summer	ANN	23.6971	14.4190845	0.04012097	0.7845	23.1494	10.7021809	0.02983931	0.73872
	ANN-PSO	23.424	12.2565866	0.03791189	0.81313	17.9876	8.51120212	0.02331527	0.81735
	ANN-GWO	10.1826	6.15927499	0.018881	0.9619	17.6334	7.91425008	0.02312358	0.89514
	ANN-WOA	7.3191	5.64475578	0.01587101	0.97533	5.31528	4.43032708	0.01222408	0.97691
	ANN-COA	6.72008	5.50313369	0.01676161	0.98158	5.06201	4.15049743	0.0113606	0.98072
Monsoon	ANN	30.5844	19.3403389	0.06225341	0.82638	19.303	13.2961303	0.04229587	0.83206
	ANN-PSO	26.6019	15.8851616	0.05361626	0.87783	16.2262	9.39046688	0.02987347	0.88526
	ANN-GWO	16.5318	7.83994865	0.02764656	0.95753	15.1026	8.80876683	0.02615169	0.90014
	ANN-WOA	13.4505	6.75946362	0.02492657	0.97384	11.0721	4.8421759	0.01785192	0.94564
	ANN-COA	9.4906	6.25059862	0.02311407	0.98533	9.99082	4.31182135	0.01516422	0.95855

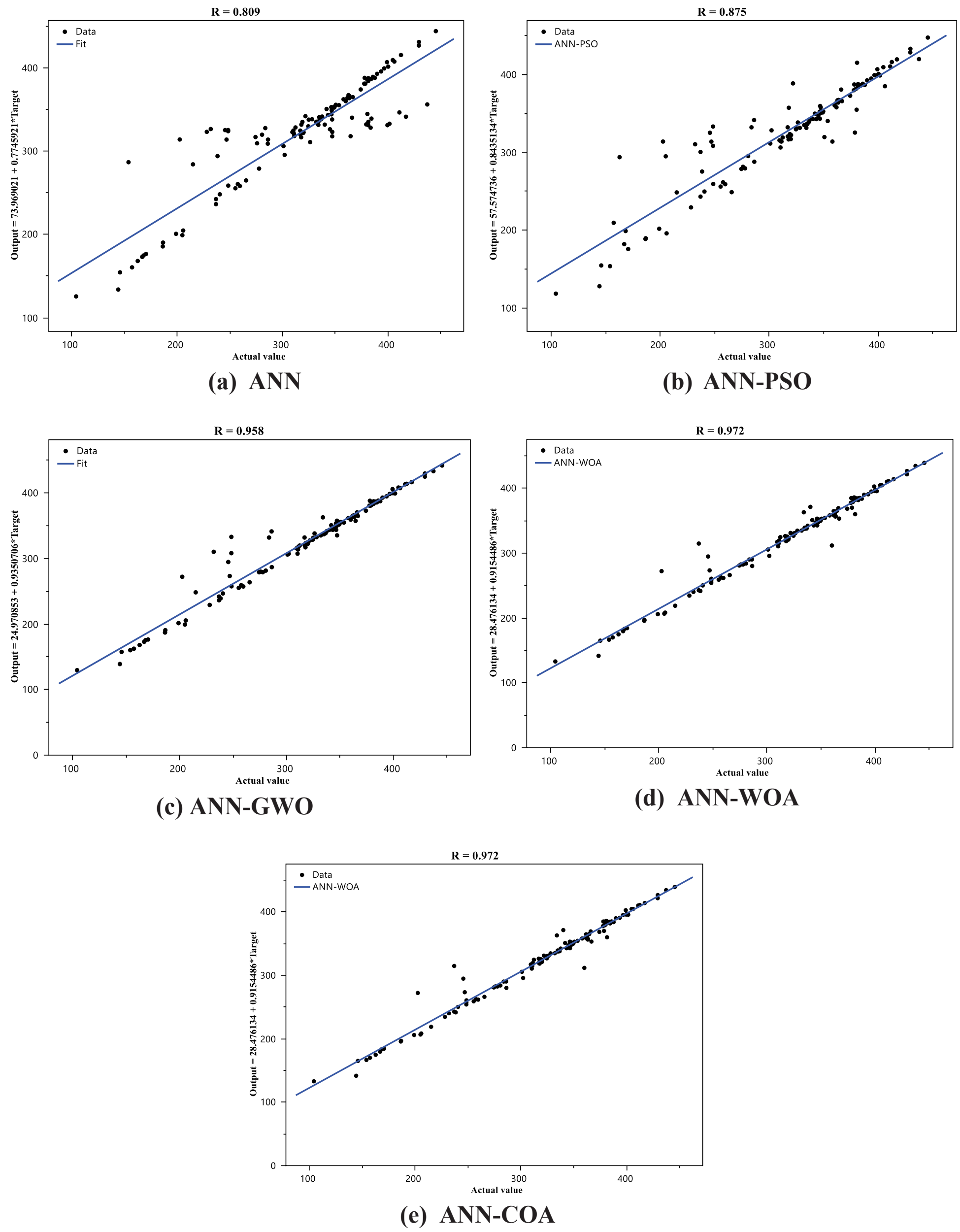


Fig. 14. A regression study of observed and expected Solar Radiation (W/m^2) using proposed models for the Monsoon season.

- Dewpoint and humidity;
- Wind speed and wind guest;

There was a significant inverse relationship found between the amount of Humidity and Ultra-Violet Radiation Index.

Varimax rotated PCA extracted three principal components with eigenvalues above 1.00, significantly simplifying the data's complexity while retaining its core patterns based on which variables loaded onto each component. These three components add up to an overall cumulative variance of 91.974 %. Table 4 displays the magnitude of these variables' eigenvalues, which establish the order of importance.

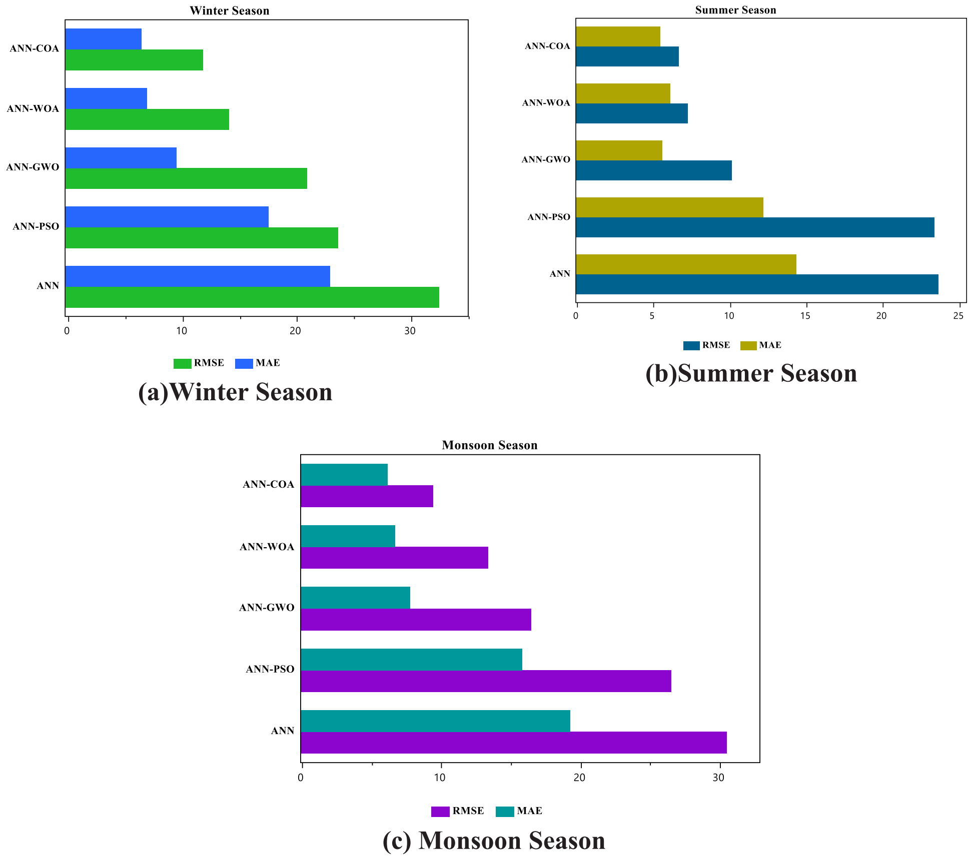
The raw weather dataset consisted of 8 features capturing different meteorological measurements: Outdoor Temperature (Â°C), Feels Like Temperature (Â°C), Dew Point Temperature (Â°C), Wind Speed (m/sec), Wind Gust Speed (m/sec), Wind Direction (Â°), Humidity (%), and Ultra-Violet Radiation Index. To reduce dimensionality in this multivariate data while retaining the core information, principal component analysis (PCA) was utilized. The first 3 principal components explained over 91.97 % of variance in the data, and corresponded to interpretable latent features related to temperature, wind, and humidity shown in Table 5. These 3 components were therefore selected as inputs into a feedforward artificial neural network for building a predictive model.

The neural network architecture consisted of the 3 PCA features fed into an input layer, a single hidden layer of 15 sigmoidal activation nodes, and an output layer predicting the SR. This structure balancing model complexity and predictive performance. By first reducing the weather data dimensions with PCA and extracting 3 key features, the subsequent neural network was able to train effectively and generalize accurately for predictions.

6.2. *Evaluation of the trained SRF model with COA-ANN*

6.2.1. *RMSE*

One often used statistic to assess prediction accuracy is the root mean square error, or RMSE. The square root of the mean of the squared deviations is the mathematical formula for RMSE. An overall measurement



(a)Winter Season (b)Summer Season

(c) Monsoon Season

Fig. 15. Comparing the effectiveness of different proposed models based on their RMSE and MAE values.

of the usual deviation between the expected and actual values is given. Greater accuracy and dependability are indicated by a lower RMSE (Uno et al., 2005). Which is represented by Eq. (30).

$$RMSE = \sqrt{\frac{\sum_{j=1}^{N} \left(R_j - F_j\right)^2}{N}} \tag{30}$$

6.2.2. MAE

The mean absolute error (MAE) measures the average magnitude of differences between predicted and actual values. It calculates the absolute errors on a per-item basis across the dataset, then takes the arithmetic mean (Reich et al., 2016). Lower MAE indicates better predictive capability. Which is represented in Eq. (31)

$$MAE = \frac{1}{N}\sum_{j=1}^{N} \left|R_j - F_j\right| \tag{31}$$

6.2.3. MAPE

The mean absolute percentage error (MAPE) is a commonly used metric to evaluate forecasting precision in time series analysis (Chen et al., 2017). It indicates accuracy as a percentage of the absolute errors across all observations over the actual values. Which is represented in Eq. (32).

$$MAPE = \frac{1}{N}\sum_{j=1}^{N} \frac{\left|R_j - F_j\right|}{F_j} \tag{32}$$

6.2.4. R^2

The coefficient of determination (R^2) evaluates the reliability of predictions, with values spanning 0–1. When R^2 approaches 1, it denotes greater predictive accuracy (Chicco et al., 2021). Mathematically, R^2 represents the proportion of variance in the response that is predictable from the explanatory variables. Which is represented in Eq. (33).

$$R^2 = 1 - \frac{\sum_{j=1}^{N} \left(R_j - F_j\right)^2}{\sum_{j=1}^{N} \left(R_j - \overline{R}_j\right)^2} \tag{33}$$

where R_j and F_j represent the real and forecasted values. $\overline{R}_j$ indicates the mean of real values.

N is the total number of iterations.

7. Experimental results

This study investigates the fluctuations in average solar radiation levels across different seasons in Tamil Nadu, India from 2022 to 2023. To analyze the solar radiation patterns, three seasonal time-series datasets representing winter, summer, and monsoon, as shown in Figs. 5, 6, and 7, were retrieved from the SMEC of VIT University. The prediction models utilized data from the preceding year as input to forecast solar radiation for the subsequent year. This approach was employed to assess the impact of input data on the output predictions.

Several techniques, including Artificial Neural Network (ANN), ANN coupled with Particle Swarm Optimization (ANN-PSO), ANN with Grey Wolf Optimizer (ANN-GWO), ANN with Whale Optimization Algorithm (ANN-WOA), and Adaptive ANN with Coati Optimization Algorithm (ANN-COA), were employed to predict solar radiation in Tamil Nadu. Historical data from the previous winter, summer, and monsoon seasons were used as inputs to forecast future solar radiation, as depicted in Fig. 4. Concurrently, the predicted solar radiation values were utilized to estimate the subsequent solar radiation values, illustrated in Fig. 5.

Fig. 10 shows that the ANN-COA model converged faster to the ideal solution compared to other models, when observed and predicted summer training and testing outputs were compared. Figs. 8,12 & 13

examines the forecasted and observed solar radiation values for the different models, including ANN, ANN-PSO, ANN-GWO, ANN-WOA, and ANFIS-COA.

7.1. Comparison of forecasting techniques for SR

Accurate solar radiation forecasting is crucial for efficient energy management and planning. The ability of artificial intelligence (AI) and machine learning (ML) models to associate inputs and outputs promptly makes them suitable for prediction tasks. However, these models can be susceptible to errors (Singla et al., 2022). Consequently, hybrid predictors combining multiple techniques are essential for improving forecast accuracy. A reliable prediction model should incorporate an effective feature selection strategy, often involving optimization methods to identify the optimal predictors (Al-Hajj et al., 2021). Hybrid ML models offer advantages over traditional approaches, such as efficient refinement mechanisms based on metaheuristic optimizations to optimize training parameters (Sansine et al., 2022). The effectiveness of machine learning approaches, such as artificial neural networks (ANNs), depends on the adaptability and versatility of the system. The accuracy of these algorithms is influenced by their architecture and the values of their parameters (Ağbulut et al., 2021). Based on the examination of previous studies, the proposed methodologies in this research achieved accurate solar radiation prediction while requiring less computational time and demonstrating superior performance.

The performance of the proposed ANN-based solar radiation forecasting models optimized using various metaheuristic algorithms is analyzed across the winter, summer, and monsoon seasons. Figs. 8, 11, and 12 present a comparison of the observed and predicted average daily solar radiation obtained from the different models for the winter, summer and monsoon periods respectively.

It can be clearly observed that the ANN-COA model integrating ANN with the Coati optimization algorithm demonstrates the closest conformance to the actual solar radiation across all seasons, while the standalone ANN exhibits the largest deviations. As shown in Fig. 10, ANN-COA a display faster and stabler error minimization during training compared to PSO, GWO, and WOA techniques.

Based on the quantitative performance benchmarks, the integrated ANN-COA model exhibited superior solar radiation prediction accuracy over the ANN variants optimized with WOA, GWO, and PSO algorithms during both the training and testing phases, as evidenced across the evaluation metrics compiled in Table 6. The proposed ANN-COA methodology achieved the lowest error and highest correlation relative to the actual solar radiation data among all techniques explored across the two critical validation stages.

The comparative assessment depicted in Fig. 15 concisely delineates the superior generalization performance of the proposed ANN-COA model relative to other approaches, as quantified via RMSE and MAE metrics evaluated on previously unseen test data across all three seasons. The ANN-COA model demonstrates significant improvements over all competitive baselines, underscored by substantially lower error rates that speak to its efficacy in accurate extrapolation to new data. The consistency of outperformance verifies the robustness of the integrated methodology to seasonal variations as well as one-step-ahead forecasting challenges that underpin real-world applicability.

This study highlights the capabilities of ANN-COA for solar radiation prediction. COA overcomes ANN's limitations like local convergence while leveraging its nonlinear modeling strength. The proposed approach advances solar power planning applications which require accurate forecasts from limited data.

8. Conclusion

This study demonstrated a novel solar radiation forecasting approach combining neural networks, coati optimization algorithms, and principal component analysis. The core methodology involved developing specialized models for distinct seasons that capture unique solar radiation patterns in summer, winter, and monsoon periods. By optimizing neural network weights using modern nature-inspired algorithms like COA, WOA, GWO, and PSO the models can learn complex relationships in weather data including Outdoor Temperature, Feels Like Temperature, Dew Point, Wind speed, Wind Gust, Wind Direction, Humidity, Ultra- Violet Radiation Index to make accurate predictions. The use of PCA enabled managing the dimensionality of the dataset to further improve model accuracy. Comparative testing showed the ANN-COA integrated model outperforming traditional methods and combinations using other optimization algorithms. The proposed model achieved remarkable performance, with RMSE of 12.06 for the winter season, 6.72 for summer, and 9.49 for the monsoon season. Furthermore, it attained a MAE of 6.66, 5.50, and 6.25, a MAPE of 3.58 %, 1.68 %, and 2.31 %, and an R^2 value of 0.973, 0.982, and 0.985 for winter, summer, and monsoon seasons, respectively. The proposed technique achieved optimal error metrics and correlation coefficient values across all seasons, highlighting its consistency.

By processing the high-frequency measurements into consolidated daily averages, the researchers could effectively analyze broader relationships and seasonal patterns affecting solar energy potential in the region. This study provides useful insights for informing the effective use of solar power in Vellore based on a detailed understanding of how local weather conditions impact solar radiation.

Overall, this integrated approach combines the strengths of neural networks, metaheuristic optimization, and principal component analysis to enable accurate and robust solar radiation forecasting. The methodology's innovations in leveraging computational techniques for dimension reduction, specialized seasonal modeling, and model optimization collectively contributed to its effectiveness.

Accurate forecasting of solar radiation is crucial for the efficient planning, operation, and management of solar energy systems. The proposed techniques can maximize the utilization of solar resources by facilitating integration with grids, load balancing, and optimizing generation, distribution, and storage within solar power systems.

For future work, researchers could explore the application of this approach to other geographical regions with different climatic conditions to assess its generalizability. Additionally, the integration of other relevant meteorological variables, such as cloud cover, humidity, and wind speed, could potentially further improve the accuracy of the solar radiation forecasting models. Furthermore, investigating the use of ensemble techniques or hybrid models that combine different optimization algorithms and neural network architectures could be an interesting direction for future research. Finally, the proposed methodology could be extended to forecast other renewable energy sources, such as wind and hydropower, to support the efficient management and integration of diverse energy sources in smart grids.

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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

Data Availability

Data will be made available on request.

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