Optimizing Renewable Energy Use with Advanced Predictive Models under Changing Weather Conditions

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Abstract- Optimizing the utilization and distribution of renewable resources has become necessary due to the rise in their use under various weather situations. One of the most important ways to boost productivity, lessen reliance on fossil fuels, and create energy management plans is to forecast the quantity of energy renewable sources will consume. Researchers are interested in using machine learning (ML) techniques since they are among the best instruments for precisely forecasting energy usage patterns. The forecast of energy consumption has been the subject of numerous studies up to this point, but less attention has been paid to thoroughly examining how climate affects machine learning models' effectiveness. The current research investigates the efficiency of two machine learning methods, including Adaptive Reinforcement Algorithm Regression (ADAR) and Stochastic Regression (SR), in predicting renewable energy consumption under variable weather conditions. Also, the Pelican Optimization (POA) and Crystal Structure (CSA) algorithms have been used to improve the performance of these models, and by combining them, SRPO, SRCS, ADPO, and ADCS hybrid models have been developed to increase the prediction accuracy. This study investigates the effect of climate change on the performance of the models and shows that the ADCS model provides the most accurate forecast. The findings of this research can help policymakers and energy analysts to make more optimal decisions for renewable energy management and pave the way for sustainable development by considering the weather conditions.

Keywords: Renewable energy, Adaptive reinforcement Algorithm, Regression, Stochastic Regression, Pelican Optimization Algorithm, Crystal Structure Algorithm

1. Introduction

The world now experiences a fast-moving transition toward renewable power sources because safety from climate change and decreased greenhouse gas output remain vital. Solar energy stands alongside water, wind, and biomass as the four main renewable sources that show different distinctive features alongside both their strengths and weaknesses [1]. The climate represents a crucial factor that affects the functionality and operability of renewable energy systems, among other manufacturing factors. Energy generation through solar and wind power depends entirely on weather conditions since they act as determinants for sustainable power creation [2].

Research into how climate elements impact renewable energy operations leads to methods that boost renewable resource usage and make the energy delivery system more dependable and efficient [3]. The ability of machine learning to assess and reduce renewable energy system exposure to climate change phenomena has proven to be an invaluable analytical asset. The use of ML algorithms combined with big data analysis improves the accuracy of energy forecasting, strengthens the defense of renewable energy infrastructure against environmental unpredictability, and increases the performance of energy management systems. For example, solar energy, as a function of sunlight absorbed through photovoltaic panels, is highly dependent on the weather conditions of an area. While clear skies and abundant sunlight result in maximum energy production, cloudy skies with rain and/or relatively weak sun angles during the day reduce efficiency [4].

ML models, like deep learning techniques and time series forecasting, can predict solar energy availability based on historical weather data, satellite imagery, and real-time meteorological inputs, enabling better grid integration and storage solutions [5, 6]. The quantity of energy that wind turbines can harvest depends directly on wind speed and overall stability conditions. The optimal conditions for producing electricity with wind turbines operate between 12 and 25 mph wind speed, but such conditions do not occur year-round [7, 8]. Wind operates in extensive patterns that show stability in coastal and highland regions, ideal locations for wind energy plants. The wind speeds measured over land possess unstable characteristics that lead to intermittent energy production periods. Reinforcement learning and neural networks combined with ML techniques enable turbine optimization through blade angle adjustments as well as strategic location prediction for peak energy output while protecting structures from severe weather threats [9]. Over land-based sites, wind power fluctuates frequently because wind velocities often change, thus affecting energy generation output. Machine learning methods, including reinforcement learning and neural networks, can optimize turbine performance by varying blade angles and anticipating the best positioning for maximum power output while preventing damage to the structure due to extreme weather conditions [10].

Hydropower, based on the generation of electricity from flowing water, is also a weather-dependent renewable energy resource sensitive to precipitation and temperature. Water in rivers and reservoirs is vital to generate hydropower. Drought leads to a shortage of water, decreasing the water level and, therefore, the hydropower plant efficiency, while snowmelt or heavy precipitation raises the water level and results in more energy being generated [11]. Seasonal fluctuations in precipitation and snowfall in mountainous regions also affect the functioning of hydropower plants. Predictive analytics based on ML can quantify hydrological behavior, forecast water resource availability, and plan reservoir control to optimize electricity generation versus nature conservation [12]. Biomass stands apart from other renewable energy sources since climatic conditions act on growth rates but do not impact energy generation directly [13]. The conversion of wood alongside agricultural waste and energy crops provides examples of biomass materials because energy output depends on raw material use [14]. Climate changes, including temperature, precipitation, and soil conditions, influence crops' energy-producing growth, which impacts biomass technologies [15]. ML techniques, such as regression models and spatial analyses, can optimize biomass supply chains, predict crop yields, and enhance decision-making for efficient resource allocation [16]. The variability of renewable energy supply due to meteorological fluctuations necessitates flexible energy systems, storage solutions, and advanced demand management techniques [17]. Machine learning finds substantial application in such industries by optimizing energy storage use, predicting the behavior of demand, and integrating diverse sources of energy to balance the grid [18]. Besides scaling up renewable energy sources, it will become critical to ensure energy security and sustainability by using machine learning to comprehend and counteract the impacts of climatic conditions on energy production and usage [19].

1.1. Literature Review

The energy demand is increasing in terms of production and consumption due to the increasing population density and the quick development of the industrial revolution [20]. Numerous studies acknowledge the significance of advancing the production of renewable energy [21]. The fuels that provide the world's power assets are coal, natural gas, and oil, which are collectively known as fossil fuels. Over the past 200 years, fossil fuels have been used extensively because of their effectiveness and proven production methods [22]. Due to the dramatic rise in natural gas and oil prices brought on by the 1973 oil crisis, some nations were forced to look into alternative energy sources to meet their energy demands [23]. Since it is still difficult to identify a suitable alternative, over 80% of national energy systems still rely heavily on fossil fuels for power generation, and the majority of electricity production today still comes from these sources [24]. To address possible issues [25], nations have adopted renewable energy policies in response to pollution, global warming, and energy sustainability. Many governments now have serious concerns about the production and consumption of renewable energy [26]. Fossil fuel use raises the risk of pollution, and an excessive reliance on fossil fuels may result in an increase in greenhouse gas emissions as human activity and energy demands rise [27]. While fossil fuel supplies are rapidly running out, the amount of fuel used has increased dramatically, roughly fivefold, since 1970 [25]. Renewable energy sources like solar, photovoltaic, hydro, geothermal, and tidal energy could be potential replacements for fossil fuels in the future, so the world needs to get ready for that. These energy sources, in contrast to fossil fuels, are affordable, renewable, and have the potential to have a positive environmental impact quickly. Due to its nearly zero carbon dioxide emissions, renewable energy can play a crucial role in achieving environmental sustainability [28]. Energy consumption encompasses all energy types used in various sectors, including transportation, industry, commercial, and residential. Fossil, renewable, and fission energy are examples of energy forms [29]. Weather has a significant and intricate impact on energy use, influencing forecasts of energy demand, operational effectiveness, and the viability of renewable energy [30]. Conversely, the disparity in energy consumption is a complicated relationship that links energy production and consumption. For instance, temperature, cloud cover, and solar irradiance are the primary determinants of solar power generation [31]. The efficiency of power generation may be impacted by extreme weather conditions and cloud cover, necessitating the use of additional energy storage devices to augment power generation, which would raise energy consumption [32]. Another common example is the impact of atmospheric stability, wind direction, and wind speed on wind power generation. While high wind speeds and turbulence can cause operational difficulties, power gap maintenance, and increased energy consumption, ideal wind conditions can optimize turbine performance [33]. Additionally, some researchers have discovered that weather variables like water flow and precipitation patterns can also have an impact on hydropower generation [34]. Climate change has the potential to alter the seasonality of energy consumption. For instance, Invidiata and Ghisi [35] investigated how Brazil's warming temperatures might affect the country's need for heating and electricity, leading to shifts in patterns of energy use. Planning and policymaking for sustainable energy depend on understanding these dynamics, as climate change increases weather pattern variability. Resources have grown scarce in recent decades due to rising demand. Energy demand management has become more crucial as renewable energy sources are increasingly integrated into the electrical grid [36]. For governments and private businesses to effectively manage the energy supply and demand, demand forecasting is essential. For power production and distribution systems, it is crucial to use statistical models to accurately forecast future trends in energy consumption. People have been predicting energy production and consumption using conventional forecasting models for the past few decades [37]. Mohamed et al. [38] forecasted Malaysia's load demand issue for a year using a bi-seasonal ARIMA model. The one-step-ahead forecasting approach was found to have minimal impact. However, conventional forecasting models have limitations because of the intricacy of the environment and the inherent unpredictability of climate forecasting. Because machine learning (ML) techniques, such as Deep Learning (DL), can quantify weather data and handle complex nonlinear relationships, they have been adopted by many researchers to predict energy consumption. This is because machine learning techniques are particularly effective for handling large datasets of renewable energy and the complex, multidimensional characteristics of weather. For instance, Ahmad et al. [39] predicted changes in electricity using artificial intelligence techniques like support vector and Artificial Neural Network (ANN) methods and discovered that hybrid approaches are better suited for forecasting energy consumption. Electricity consumption in cities like Agartala in Tripura, India, was predicted by Banik et al. [40] They discovered that a single random forest and XGBoost combination prediction could increase accuracy by 15–29%. When weather data is unpredictable, a single machine learning algorithm might not be sufficient to predict energy consumption with any degree of accuracy. Bogner et al. [41] for example, employed five distinct machine learning techniques, including Quantile Regression Forest (QRF) and Gradient Boosting Model (GBM), to forecast and assess energy production and consumption using hydrological and meteorological data collected in Switzerland every 15 minutes. It was discovered that, when depending on intricate and extremely unpredictable meteorological data, the application of ML techniques can increase the predictability of energy production and consumption, whereas DL techniques might be more practical. Nevertheless, because the decision-making process is opaque, many machine learning models, particularly intricate models like deep neural networks, function as "black boxes." It is challenging to comprehend the decision-making process because of this opacity. By combining the significance of various features and their influence to comprehend and aid in decision-making, Khan et al [42]. utilized the SHAP to determine the importance of each prediction function, offering a model-independent explanation. Wakjira et al. [43] developed a hybrid prediction model and used a unified SHAP method to explain the output of the top-performing model after conducting a thorough evaluation of several machine learning models. They also determined how various variables interacted with one another and incorporated the created model into a software program for real-world use. The following gaps in the body of literature are filled by this study: (1) traditional and single ML models' limited ability to accurately predict energy consumption under complex and unpredictable conditions; (2) ML models' lack of transparency, which makes decision-making difficult because they are "black boxes"; and (3) ML models' inadequate contextual adaptation and optimization for particular geographic and climatic conditions.

1.2. Study Objective and Novelty

With the advent of ever-growing global dependence on renewable energy, it is relevant to develop precise forecasting models that would help optimize energy consumption in different weather conditions. This paper presents an advanced machine learning framework that includes an Adaptive Boosting Algorithm (ADA) and Stochastic Regression (SR), and its optimization is done with the Pelican Optimization Algorithm (POA) and the Crystal Structure Algorithm (CSA). Hybrid models, such as SRPO, SRCS, ADPO, and ADCS, have also been developed to improve the accuracy of forecasts. The innovation of this study lies in its comprehensive approach to modeling renewable energy consumption, which integrates climate change, model optimization, and hybrid techniques to improve predictability. Unlike many previous studies using static models, this paper will present an adaptive framework incorporating climate data in a model that may increase forecast accuracy. This model increases the convergence speed and stability of the POA and CSA models due to greater accuracy in providing predictions. This research has applications in energy management, smart grids, and energy policy. Thus, accurately forecasting energy consumption will enable grid operators to optimize energy distribution and reduce reliance on fossil fuels for supply. Renewable energy industries can provide better operational strategies using these models. Also, the results of this research can help policymakers formulate energy policies compatible with climate change. This scientific work proves that new optimization algorithms can be successfully applied to enhance the accuracy of machine learning models in energy forecasting. It forms the basis for the next generation of research in intelligent energy systems that play an important role in developing sustainable infrastructure.

2. Study Methodology

2.1. Data Collection

This dataset is part of the solar and meteorological factors designed to underpin renewable energy forecasting in response to management and efficiency optimization under varying weather conditions that affect both the generation and utilization of energy. The dataset link is:

(https://www.kaggle.com/datasets/pythonafroz/renewable-power-generation-and-weather-conditions/data).

GHI (Global Horizontal Irradiance) [W/m²] is the total solar radiation received per unit area on a horizontal surface. This is a key factor in the production of solar energy. The parameter Temp (Temperature) [°C] indicates the ambient temperature in degrees Celsius. Temperature variations impact energy demand and renewable energy efficiency. Pressure [hPa], atmospheric pressure measured in hectopascals, influences wind patterns and energy production. Humidity [%] is the percentage of water vapour in the air that affects air density and the efficiency of wind and solar energy. Windspeed [m/s], the wind speed at a given location, is crucial for wind energy generation. Rain_1h [mm], the amount of rainfall in millimeters recorded in the past hour, may impact solar energy production. Snow_1h [mm], the amount of snowfall in millimeters recorded in the past hour, potentially affecting solar panel performance. Clouds_all [%], the percentage of cloud cover in the sky, affects solar energy generation by reducing sunlight exposure. Is_Sun (Binary: 1/0) indicates whether the sun is shining (1) or obscured by clouds (0). Sunlight Time [minutes] is the duration of direct sunlight exposure per hour. The Day Length [minutes] represents the total duration of daylight for the specified day. The Sunlight Time, Day Length [ratio] represents the fraction of sunlight time to total day length, which is a measure of solar availability. The weather type is categorical data that describes the weather condition (e.g., clear, cloudy, rainy, snowy, foggy, etc.). Hour [0–23], the hour of the day in 24-hour format, influences energy demand and solar intensity. The month [1–12], the month of the year, affects seasonal variations in renewable energy generation. Energy delta [Wh], the change in energy consumption (in watt-hours), represents the fluctuation in renewable energy production and usage.

Table 1 presents the dataset of key meteorological and time variables affecting renewable energy consumption and statistical summaries, including minimum, maximum, mean, standard deviation, and mode. GHI (horizontal global radiation), a fundamental factor in solar energy production, ranges from 0 to 229.20 W/m^2, and its mean is 65.93 W/m^2 with a standard deviation of 57.65. The temperature varies between -16 and 35.80 degrees Celsius, and its average is 12.71 degrees, while the pressure varies between 978 and 1046 hectopascals, and its average value is 1015.61 hectopascals. The percentage humidity varies between 22 and 100%, and its average is 73.16%. Wind speed, an important factor in wind energy production, varies between 0 and 13.60 m/s, and its average is 4.08 m/s. Precipitation-related factors, including rain and snow, have very low averages (0.07 mm and 0.00 mm), indicating their limited impact on energy production. Cloud cover varies between 0 and 100%, averaging 64.94%. The Is Sun variable, a binary value, confirms that the Sun was present in most cases. Sunshine time ranges from 15 to 1020 minutes, averaging 417.55 minutes per day, while day length varies from 450 to 1020 minutes. The ratio of radiation time to day length is 0.52, which shows the changes in solar energy availability. Time factors include the hour (between 2 and 19) and the month (between 1 and 12), which affect energy production and consumption. The output variable Energy delta indicates changes in energy consumption, which varies between 1 and 4640 watt-hours, and its average is 1173.87 watt-hours with a standard deviation of 1235.45 watt-hours, which indicates significant fluctuations in energy consumption based on weather conditions.

Table 1. Data sets of key meteorological and temporal variables

Variables	Indicators					
	Category	Min.	Max.	Ave.	St. Dev.	Mode
GHI	Input	0	229.20	65.93	57.65	5.30
temp		-16	35.80	12.71	8.15	15.80
pressure		978	1046	1015.61	8.86	1015
humidity		22	100	73.16	16.92	94
Wind _speed		0	13.60	4.08	1.82	3
rain_1h		0	7.31	0.07	0.30	0
snow_1h		0	2.82	0.00	0.06	0
Clouds _all		0	100	64.94	36.18	100
Is Sun		1	1	1	0	1
Sunlight Time		15	1020	417.55	247.13	285
Day Length		450	1020	804.83	182.47	1020
Sunlight Time/day length		0.01	1	0.52	0.28	0.57
Weather _type		1	5	3.20	1.29	4

hour		2	19	10.63	3.84	11
month		1	12	6.20	2.91	7
Energy delta [Wh]	Output	1	4640	1173.87	1235.45	2

Fig. 1 shows a correlation matrix that analyzes the relationships between variables related to renewable energy consumption under different climate conditions. In this graph, the intensity and size of the circles indicate the degree of correlation between the variables. Darker colors and larger circles indicate stronger correlation values, whether positive or negative. The color scale on the right ranges from 1 to -1, with 1 indicating a perfectly positive correlation, -1 a perfectly negative correlation, and 0 indicating no correlation between the two variables. The variables examined include the Solar Radiation Index (GHI), temperature, pressure, humidity, wind speed, rainfall and snowfall, cloud cover, duration of sunlight, day length, weather type, time of day, and month. Also, the variable "Energy delta [Wh]" indicates changes in energy consumption under different conditions. The correlation matrix analysis shows that variables, such as GHI, temperature, and day length, have a stronger correlation with energy changes, while factors such as precipitation and cloud cover have a weaker correlation.

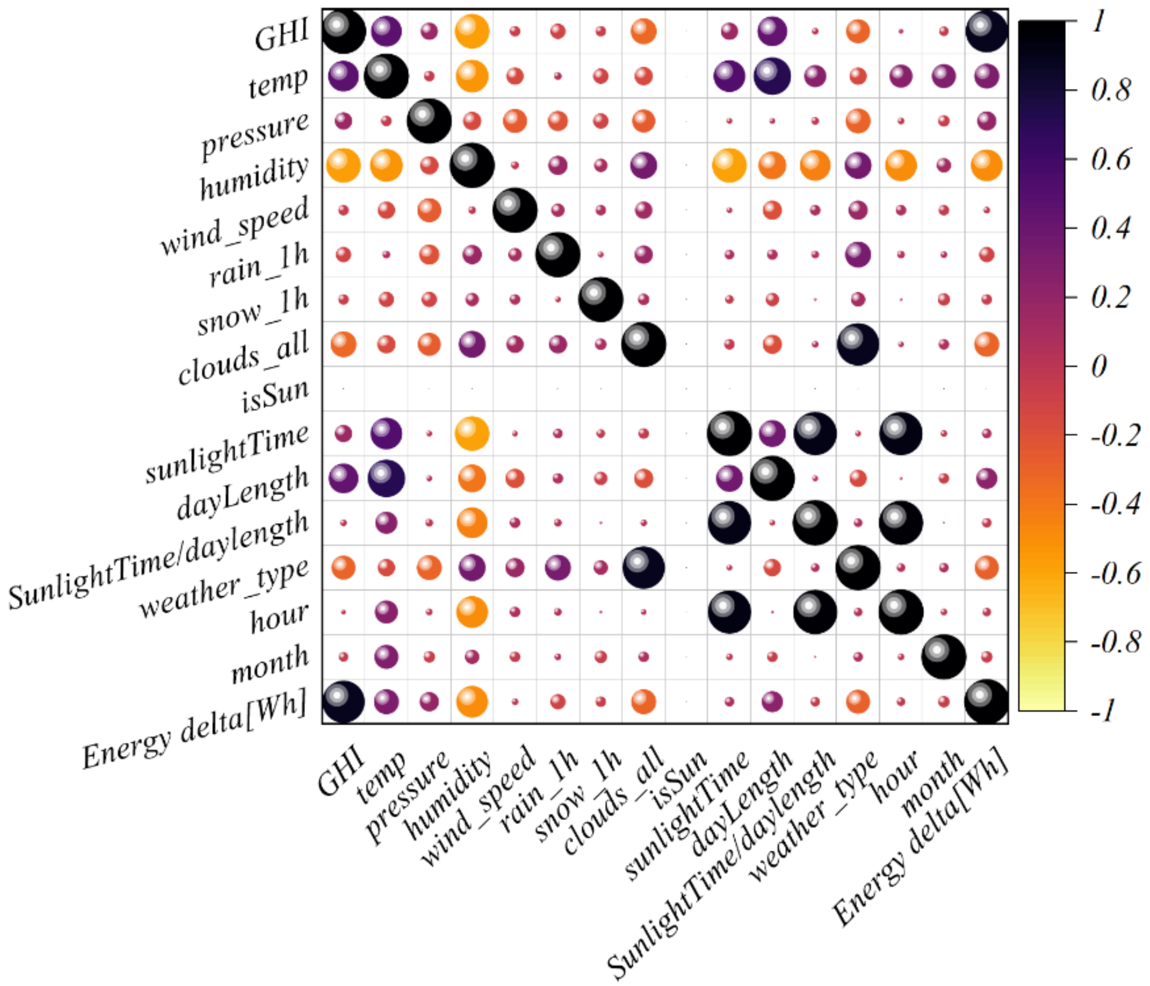


Fig. 1. The correlation between input and output variables.

2.2. Models

2.2.1. Adaptive boosting algorithm regression (ADAR)

Flexible lift learning, also known as AdaBoost, has been widely used in AI to build strong classifiers from a small number of ineffective sub-classifiers (like binary trees and SVM) [44]. Its effectiveness in avoiding overfitting issues has also been thoroughly shown. AdaBoost is presently the foundation of the preparation method, which is advancing significantly. Using a weighted irregular inspection approach, the sub-classifiers $\{h_n(.)|n = 1,2,\dots,N\}$ proceed with sequential preparation, selecting a subset of tests from the entire dataset for each $h_n(.)$ to be constructed.

$$X_n = \mathfrak{G}(X, W_n, Y), \tag{1}$$

The starting datasets, sample measurements, and sampling ratios are shown separately in X, W_n, and Y, whereas

𝔊 illustrates the testing procedure recommended by Pavlos et al. Each instance's weight W_n is calculated as follows:

$$W_n^i = \frac{1}{Z_n} W_{n-1}^i e^{\gamma_{n-1} \cdot \tau(y_i, \hat{y}_i)}, i = 1,2,\ldots,N. \quad (2)$$

The total weights are used to normalize the weights between $(0,1)$ and N, the total number of samples in the original collection, and Z_n represents the expected label of the previously learned classification $h_{n-1}(\cdot)$. A negative logit equation is used to calculate the constant γ_{n-1}:

$$\gamma_{n-1} = \frac{1}{2} \ln\left(\frac{1-\rho_{n-1}}{\rho_{n-1}}\right), \quad (3)$$

The weighted error rate of the classifier $h_{n-1}(\cdot)$ is represented by ρ_{n-1}, and:

$$\rho_{n-1} = \frac{\sum_{y_i \neq \hat{y}_i} W_{n-1}^i}{\sum_{i=1}^{N} W_{n-1}^i} \quad (4)$$

The factor γ_{n-1} is bigger than 0 if $\rho_{n-1} < 0.5$. As follows, the sign function denoted by $\tau(\cdot)$ is definite:

$$\tau(y_i, \hat{y}_i) = \begin{cases} 1 \; if \; y \neq \hat{y} \\ -1 \quad else \end{cases} \quad (5)$$

This is the scaling factor $e^{\gamma_{n-1}}$.If $y \neq \hat{y}$ and $\gamma_{n-1} > 0$, then $\tau(y_i, \hat{y}_i)$ in Eq. (2) is larger than 1. Gaining weight increases the likelihood that the example that was incorrectly detected by $h_{n-1}(.)$ will be selected for $h_n(.)$ Training [45].

2.2.2. Stochastic gradient boosting regression (SGBR)

Leo Breiman introduced randomness into function estimation processes and called the process "bagging." Early AdaBoost implementations used random sampling as well, but this was merely a kludge to avoid certain difficulties with deterministic weighting. In his later work, Breiman suggested adaptive bagging, which combined bagging and boosting in least-squares fitting by replacing the ordinary residuals in boosting with out-of-bag residuals. A modification to gradient boosting, based on Breiman's work, introduced some randomness by using a random subsample of the training data at each iteration instead of the full dataset. To balance computational efficiency with possible volatility in base learner estimates, the degree of randomness rises as the fraction of sampled data falls. In the following, randomization effects in Stochastic Gradient Boosting regression were investigated using the Huber M-TreeBoost from Friedman's best regressor. Experiments with Gaussian and "slash" error distributions were performed in terms of robustness. The Gaussian distribution has a 1:1 signal-to-noise ratio, while the slash distribution with extremely heavy tails tests the model's robustness under the worst conditions. AdaBoost generally stands out as one of the most used algorithms in machine learning and aims to convert weak classifiers, which could be decision trees or support vector machines, into strong classifiers [46]. It has been proven to reduce overfitting. AdaBoost selects subsets by weighted sampling and supports sequential training. Every sub-classifier is iteratively trained, updating the instance weights based on their classification accuracy. Those instances that get misclassified receive more weight, improving their chances of selection in subsequent iterations. Weight updating is done based on a negative logit function to achieve adaptiveness in learning. If the classifier's error rate is less than 0.5, the adaptive factor strengthens the model, and classification performance improves over time.

2.3. Optimizers

2.3.1. Pelican optimization algorithm (POA)

POA is a new metaheuristic-based optimization technique using nature, developed by Dehghani and Trojovský. POA takes inspiration from social living in pelicans and organized hunting methods, using techniques based on coordinated movement. This method models the behavioral patterns through two major phases: exploration and exploitation [47]. In the process of exploration, the positions generated through randomness govern the finding of prey by pelicans to enhance their capability in exploring the POA. Each pelican updates its position in the sight of prey to enhance the objective function value of candidate solutions using a stochastic update process. A new position will be accepted if it improves the optimization outcome; otherwise, the original position is kept. The exploitation phase imitates the behavior of pelicans gliding above the water and opening their wings to scoop fish into it. Refinement during this phase is achieved because the algorithm iteratively conducts pelicans to approach positions wherein optimal solution vectors lie. By defining some predefined parameters of this algorithm, updating is controlled, and the right balance between global and local search is ensured. A position would be accepted if an improved value of the objective function has been achieved. It thus systematically refines candidate solutions up to convergence by an iterative updating of the population with exploration and exploitation [48]. A proper balance between the two phases equips the algorithm with the capability not to get stuck in local optima but ensures efficient optimization. The structured mechanism for updating adaptively makes POA a strong algorithm in complex optimization problems. POA refines candidate solutions iteratively by updating the population through exploration and exploitation until convergence. This algorithm balances the two phases for efficient optimization without local optima. Adaptability is assured because of its structured updating mechanism, thus making POA a robust algorithm for complex optimization problems. In other words, POA implements the optimization of functions by imitating the hunting strategies of pelicans, including a stochastic global search and refinement guided by better accuracy. It effectively maintains diversity in solutions for convergence toward optimum or near-optimum solutions within a given solution space. Figure 2 shows the flowchart of the POA.

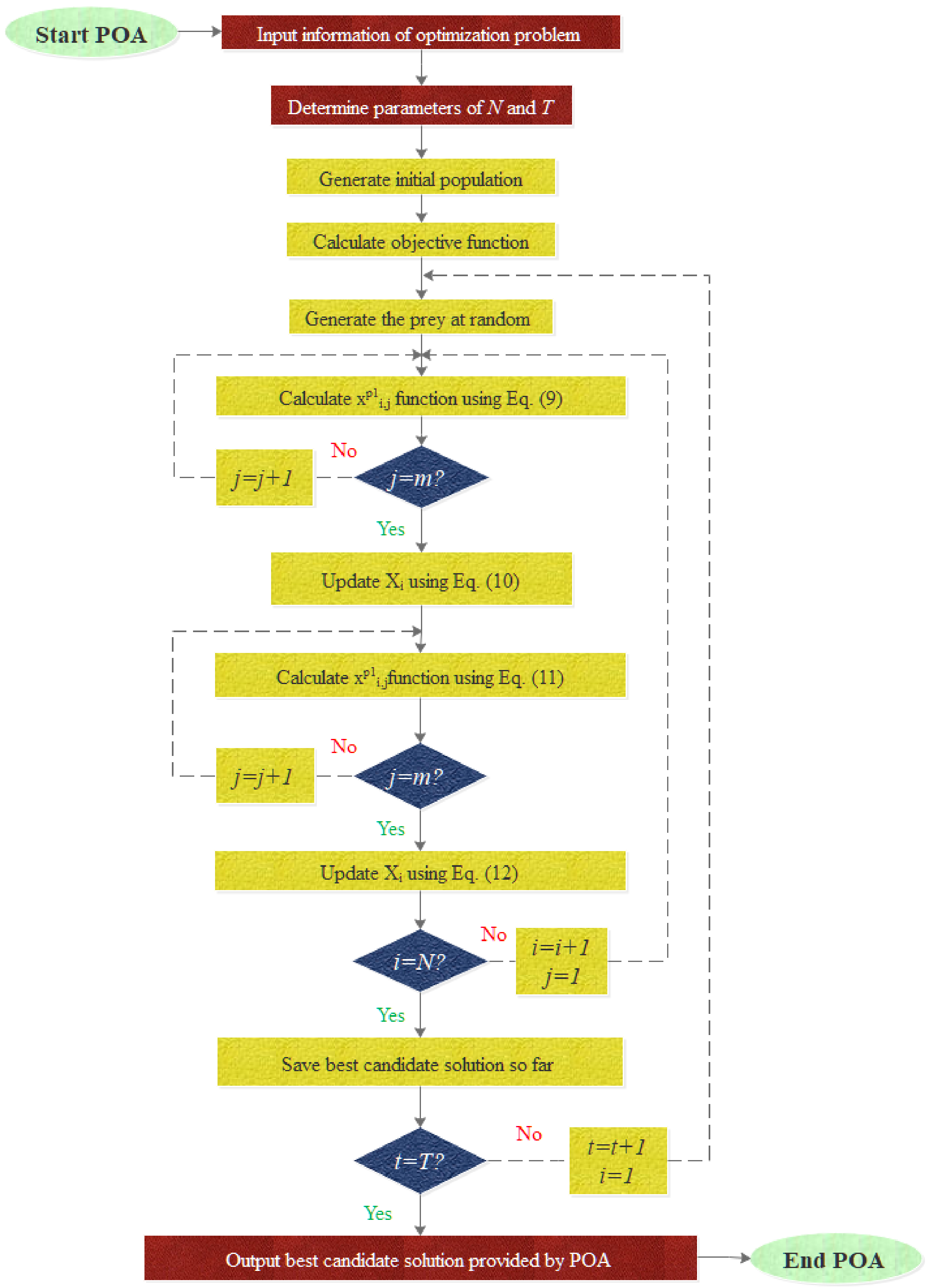


Fig. 2. The flowchart of the POA.

2.3.2. Crystal structure algorithm (CSA)

The crystals are formed by arranging atoms or molecules repetitively in either a simple or complex structure. "Crystal" comes from the Greek word "krustallos," meaning rock crystal or ice. Crystallography is the scientific study of the structure and properties of crystals. Examples of common crystals include salt, sugar, snowflakes, gemstones, quartz, and diamonds. Crystals have a characteristic three-dimensional shape with specific faces and angles and have been distinguished as divine with flat faces or as rock crystals without flat faces. The basic unit of a crystal is its lattice, the regular, periodic arrangement of points in space. Another fundamental unit, which, besides the lattice, forms the crystal, is the basis: it outlines the positions of atoms within the crystal. These units contribute to the overall structure of a crystal. Crystal structures are defined mathematically by lattices and vectors that define positions in space.

Crystal, on the other hand, is a newly developed metaheuristic optimization method that takes inspiration from the principles of crystallography. It imitates the formation and positioning of the crystals in the search space by considering crystallography's basic and advanced properties. The algorithm initializes candidate solutions as crystals and updates their positions through different crystal configurations. The best and mean crystal structure will affect the updating to ensure efficient optimization. CryStAl is a parameter-free algorithm and requires no internal tuning: CryStAl uses predefined limits on the number of iterations or function evaluations. It deals with the application of structural design optimization, where the minimization of the structure's weight should satisfy all the constraints on the design [49]. The optimization process includes structure elements, properties of materials, and limitations on stress. Feasible solution designs are made through constraint violation handled by the penalty function. Crystal can successfully solve difficult engineering problems using crystal-inspired optimization techniques. Figure 3 shows the flowchart of CSA.

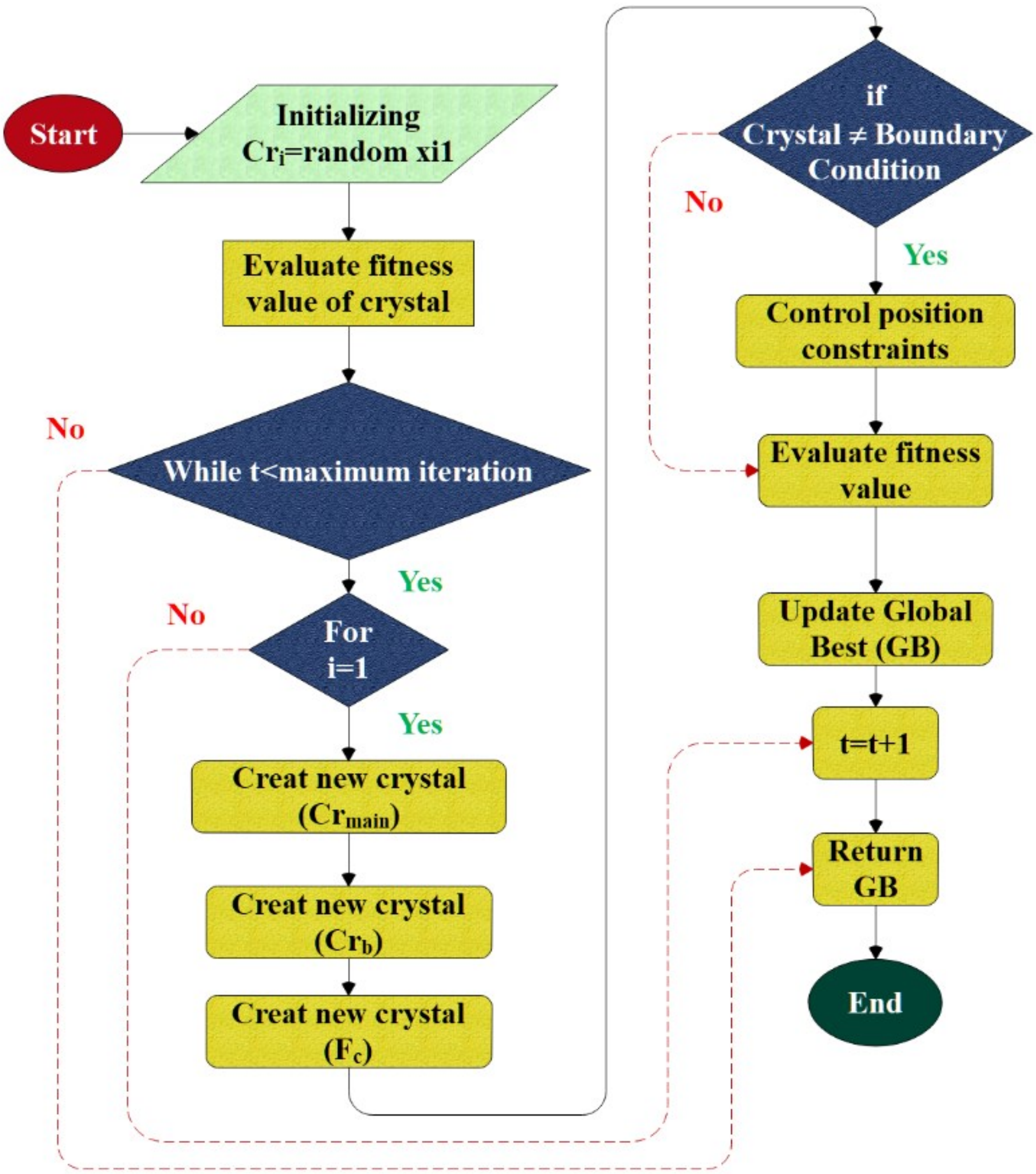


Fig. 3. The flowchart of the CSA.

2.4. Performance Evaluation Metrics

By calculating the average size of prediction mistakes, **RMSE** assigns greater weight to larger errors. A factor of two, or the square root of the average squared disparities between the two, separates predictions from actual outcomes.

R² indicates the proportion of the variance of the dependent variable that can be explained by the independent variables in a model. Values vary from 0 to 1, with higher values denoting a better fit between the model and the data.

The mean of the squared differences between the actual and anticipated values is calculated using **MSE**. Lower numbers imply greater model performance, while larger errors caused by the squaring procedure are highlighted.

WAPE is an acronym for a statistic used to assess the precision of model outputs, particularly those of regression issues. In percentage terms, it is the ratio of the total absolute inaccuracy to the total real values. It is resistant to scale changes in data because it is weighted based on the magnitude of the real values.

Often employed in hydrology, the **NSE** estimates the amount of residual variation with the variance in the observed data. It displays the degree of agreement between the observed data and the projected values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - b_i)^2} \tag{6}$$

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(b_i - \bar{b}\right)(m_i - \bar{m})}{\sqrt{\left[\sum_{i=1}^{n}\left(b_i - \bar{b}\right)^2\right]\left[\sum_{i=1}^{n}(m_i - \bar{m})^2\right]}}\right)^2 \tag{7}$$

$$\text{MSE} = \frac{1}{n}\sum_{j=1}^{n}(m_i - b_i)^2 \tag{8}$$

$$WAPE = \max\left[\frac{|b_i - m_i|}{b_i}\right] \tag{9}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(m_i - b_i)^2}{\sum_{i=1}^{n}(b_i - \bar{b})^2} \tag{10}$$

Where the measured and anticipated values are denoted by m_i and b_i, respectively. Furthermore, n denotes the sample number, $\bar{b}$ denotes the anticipated mean value, and $\bar{m}$ is the measured mean value.

3. Result and Discussion

In this study, the consumption of renewable energy in different weather conditions has been investigated, and a more accurate prediction has been provided using machine learning models and optimization algorithms. To evaluate the performance of the models, RMSE (Root Mean Square Error), R^2 (Coefficient of Determination), MSE (Mean Square Error), WAPE (Weighted Absolute Percentage Error), and NSE (Nash-Sutcliffe Efficiency) indicators have been used as the main accuracy measurement criteria. The studied models include the single Adaptive ADAR and SR models and the hybrid SRPO, SRCS, ADPO, and ADCS models combined using the POA and CSA optimization algorithms.

Fig. 4 shows how four models, including SRPO and SRCS, along with ADPO and ADCS, show their RMSE convergence over multiple iterations for forecasting tasks. The ADCS model exhibits the best predictive power because it reaches an RMSE of 164.96, while SRPO results in the highest RMSE at 273.46. ADPO performs better than SRCS during the assessment and produces inferior results compared to ADCS. Different models show how they handle weather condition changes through the prediction of renewable energy consumption, where ADCS delivers the best results, although SRPO faces high prediction errors.

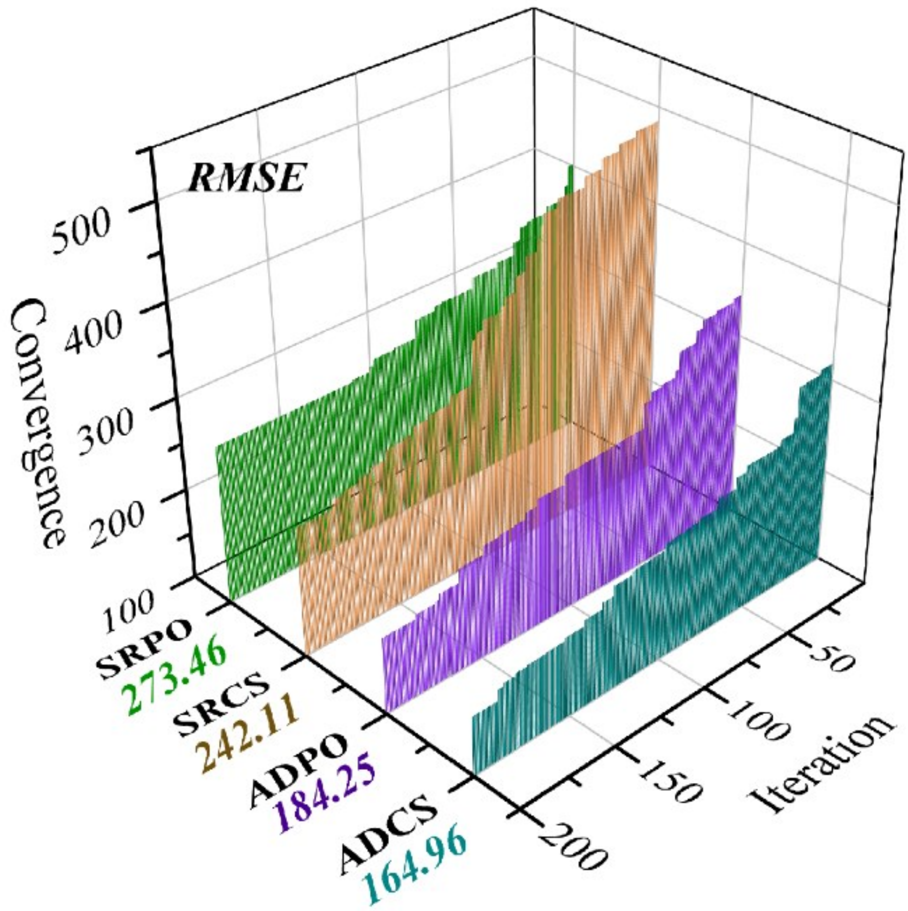
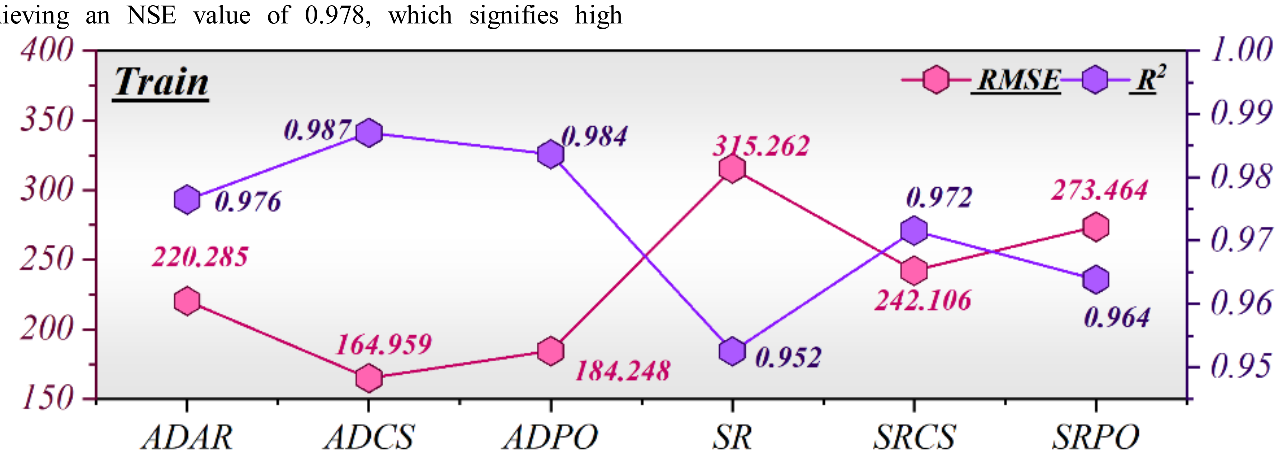
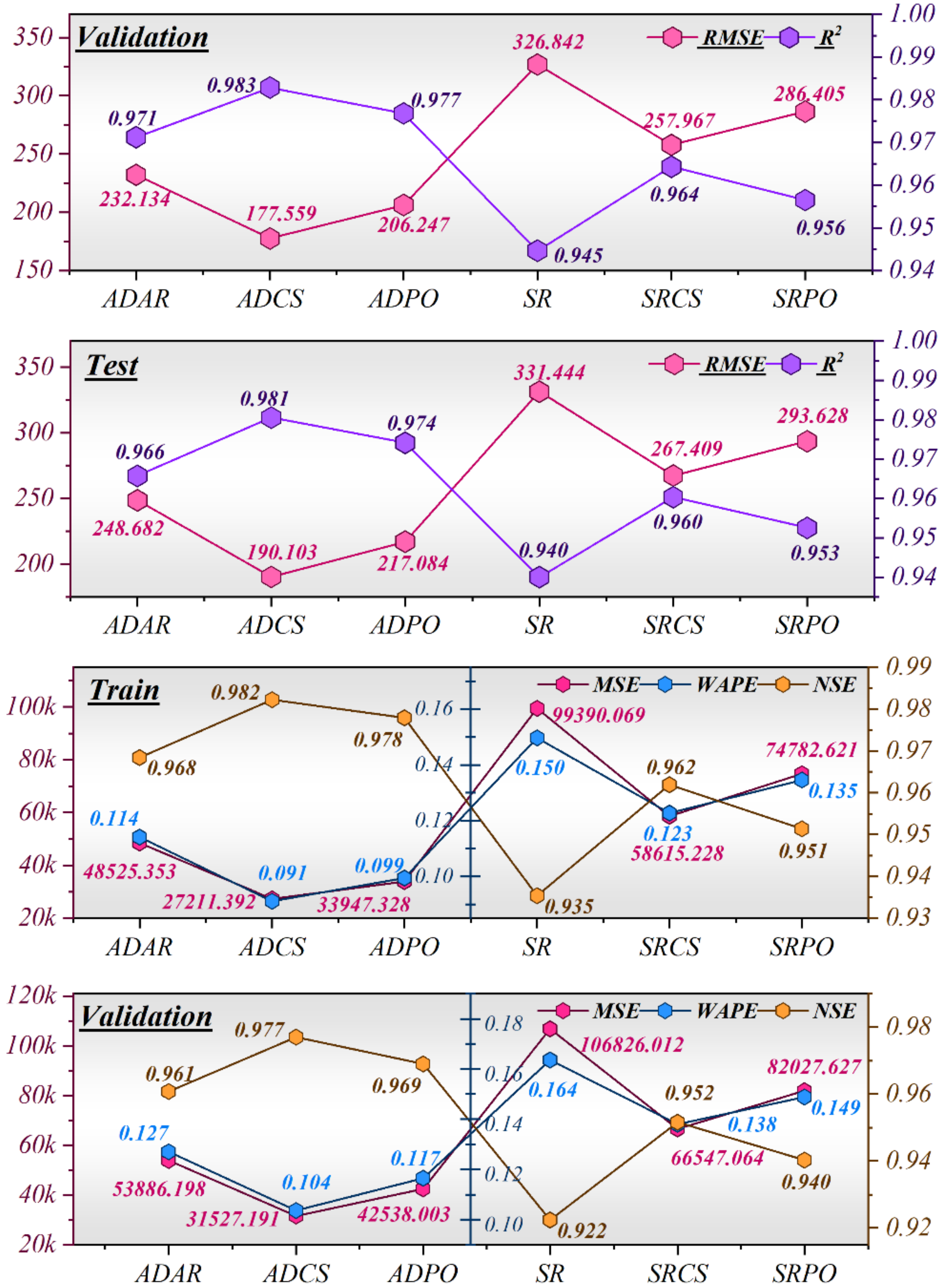


Fig. 4. The convergence curve of four hybrid models based on RMSE.

Fig. 5 examines six models, including ADAR, ADCS, ADPO, SR, SRCS, and SRPO, on three Training, Validation, and Testing datasets. Data prediction accuracy from ADCS peaked by achieving a minimal RMSE of 164.959 in Training data, while validating at 177.559 and testing at 190.103, alongside R^2 values of 0.987, 0.983, and 0.981, respectively. The SR model achieves the lowest performance indicators among all models, with high RMSE values at 315.262, 326.842, and 331.444, and corresponding R^2 values at 0.952, 0.945, and 0.940. The performance of ADPO surpasses ADCS according to MSE, WAPE, and NSE metrics because it displays low MSE (33947.328) and WAPE (0.099) while achieving an NSE value of 0.978, which signifies high reliability. The SR model demonstrates the lowest capabilities, displaying 99390.069 as its highest MSE in the Training period and achieving an NSE score of 0.935. Real-world forecasting of renewable energy consumption under changing weather conditions achieves better results through the ADCS model, which strengthens energy grid stability and improves error reduction. The poor results from SR Testing demonstrate that complex models need development to decrease forecast inaccuracy and maximize the efficiency of renewable power systems. The accuracy of forecasting helps decision-making processes achieve stable energy delivery and maintain a lower rate of energy system losses.




Validation
RMSE
R^2
ADAR
ADCS
ADPO
SR
SRCS
SRPO
232.134
177.559
206.247
326.842
257.967
286.405
0.971
0.983
0.977
0.945
0.964
0.956
Test
RMSE
R^2
ADAR
ADCS
ADPO
SR
SRCS
SRPO
248.682
190.103
217.084
331.444
267.409
293.628
0.966
0.981
0.974
0.940
0.960
0.953
Train
MSE
WAPE
NSE
ADAR
ADCS
ADPO
SR
SRCS
SRPO
48525.353
27211.392
33947.328
99390.069
58615.228
74782.621
0.114
0.091
0.099
0.150
0.123
0.135
0.968
0.982
0.978
0.935
0.962
0.951
Validation
MSE
WAPE
NSE
ADAR
ADCS
ADPO
SR
SRCS
SRPO
53886.198
31527.191
42538.003
106826.012
66547.064
82027.627
0.127
0.104
0.117
0.164
0.138
0.149
0.961
0.977
0.969
0.922
0.952
0.940

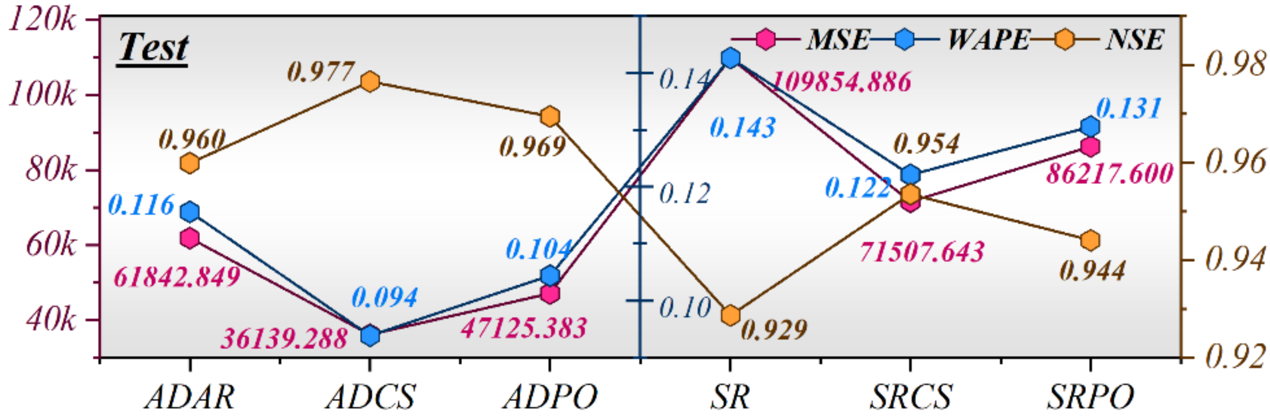
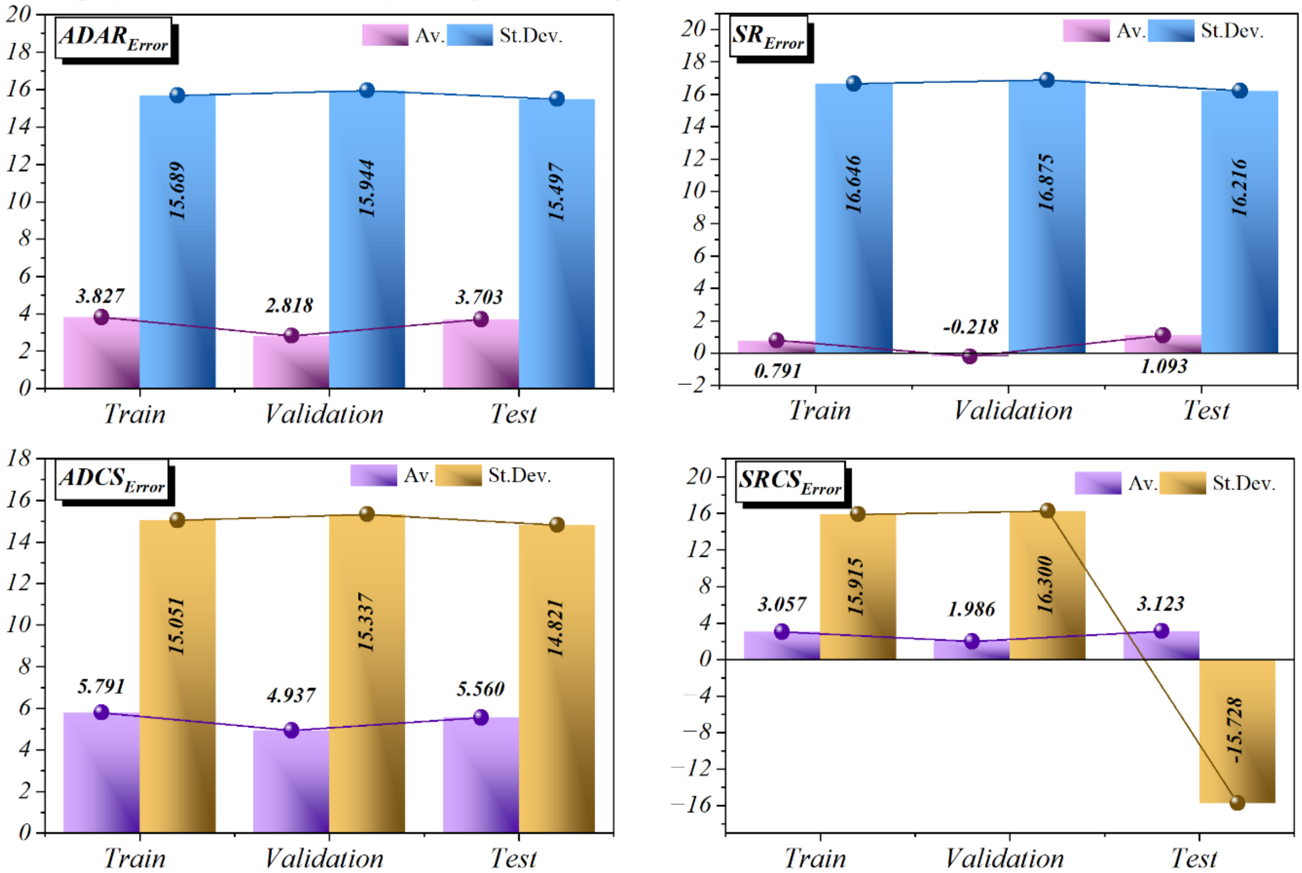


Fig. 5. Symbol-line plot for the evaluation metrics of the models.

In Fig. 6, the displayed graphs study the performance of the SR, SRCS, SRPO, ADAR, ADCS, and ADPO models by evaluating the mean error and standard deviation in the Training, Validation, and Test samples. During Validation, the SR_ model produces the best accuracy through its lowest average error (-0.218), yet SRCS displays the most unstable results during Testing with -15.728. SRPO delivers a more stable performance than SRCS due to its lower 0.976 Validation and 2.163 Testing values. Testing the performance of SR and SRPO yielded standard deviations close to 16, while SRCS displayed maximum variability during the Testing period. All stages of analysis show that ADAR achieves the minimum error levels, which results in high accuracy during validation (2.818). ADCS exhibits inferior performance through its elevated average error measurement, which reaches a value of 5.560 in Testing. ADPO shows superior results to ADCS, even though it performs worse than ADAR. The forecasting stability of SRPO stands out among the SR models, but ADAR delivers the most accurate predictions of renewable energy demand while demonstrating minimum error within all benchmark points.



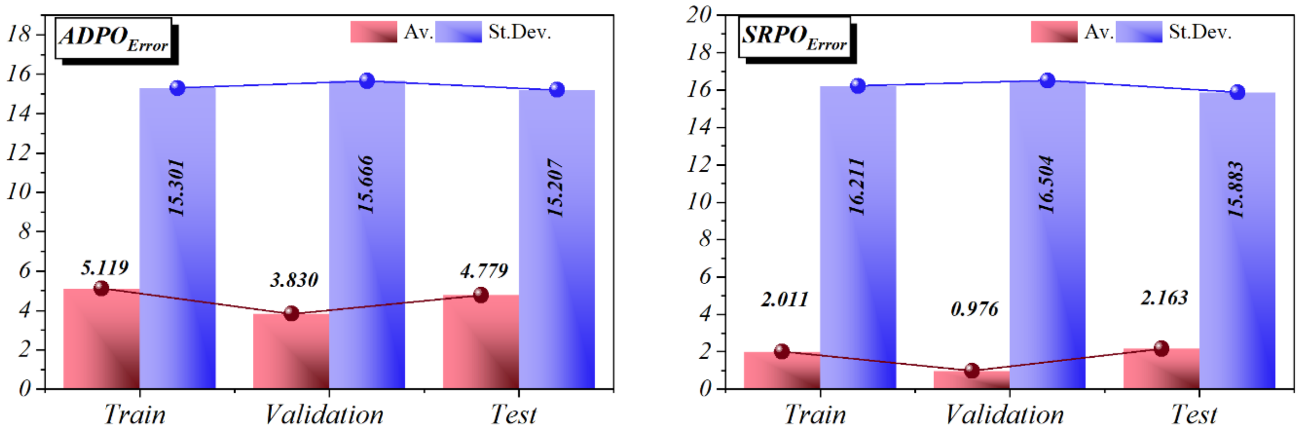


Fig. 6. The performance of the models through the evaluation of the mean error and standard deviation.

Fig. 7 shows the feature importance values for the two ADAR and SR models under different weather-related parameters, with S1 and ST representing different experimental settings. The ADAR model receives the most influence from the variable "snow_1h" with a significance value of 0.224 on ST, followed by "hour" with a value of 0.114, while "wind_speed" has the least influence with a value of 0.031. In contrast, the SR model also identifies "snow_1h" as the most influential feature with a value of 0.222 on ST, and "GHI" (with a value of 0.118) also plays an important role, while "Sunlight Time" has the least effect with a value of 0.034. The ADAR model shows stronger responses to environmental parameters, especially in features such as "snow_1h" and "hour". These findings have important real-world applications, especially for optimizing renewable energy consumption under changing climate conditions. By identifying the key environmental factors that affect solar radiation, these models help improve the efficiency of photovoltaic systems and ultimately contribute to the sustainability and management of the energy grid.

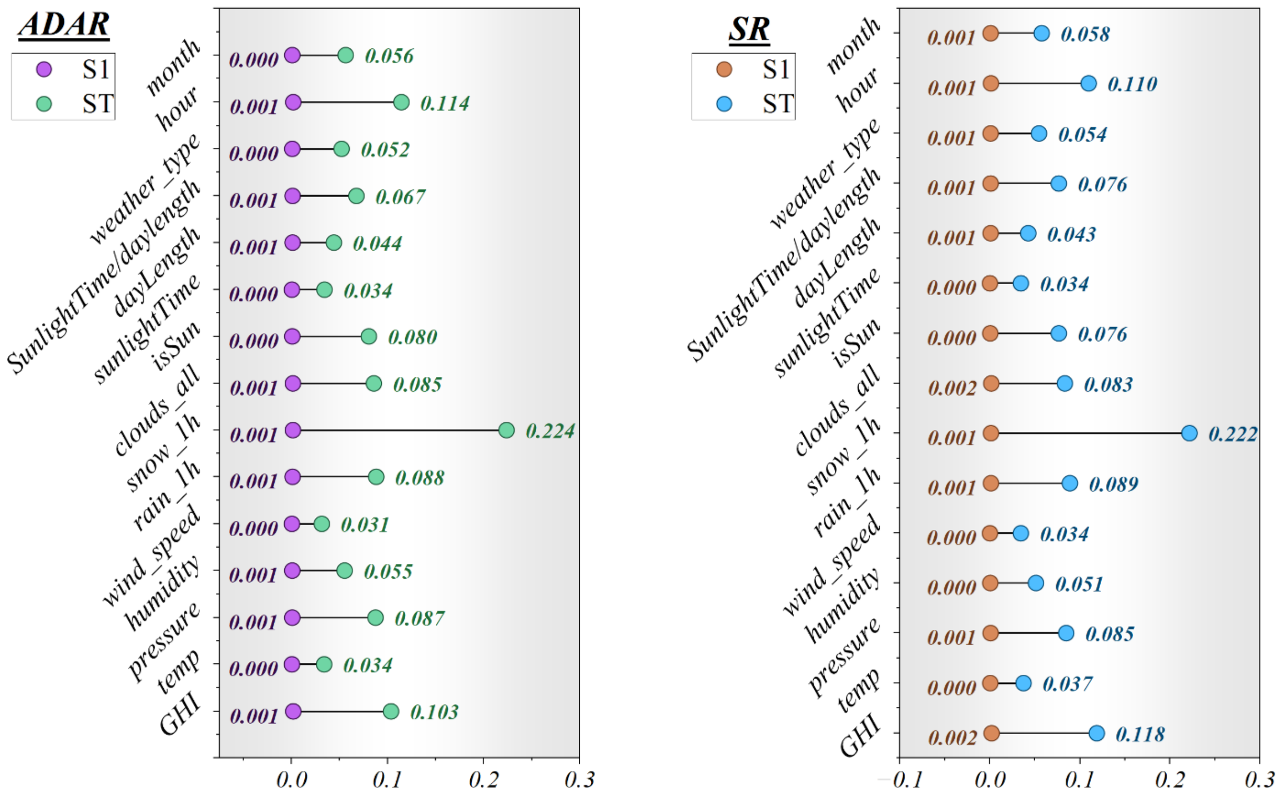


Fig. 7. Lollipop diagram for the impact of input variables on output.

3.1. Comparative Performance of Models and Practical Implications

The results demonstrate that the ADCS model outperforms other predictive models in terms of accuracy and stability across training, validation, and test datasets. This superior performance can be attributed to the synergistic combination of Adaptive Boosting (ADAR) and the Crystal Structure Algorithm (CSA). ADAR enhances model learning by sequentially focusing on difficult-to-predict data points, while CSA facilitates a global optimization strategy that avoids local minima and accelerates convergence. This combination allows ADCS to better capture the nonlinear and stochastic nature of energy consumption influenced by varying weather conditions. In contrast, models like SR and SRPO showed weaker performance, likely due to their limited capacity to handle complex, high-dimensional relationships between weather variables and energy consumption. The hybridization used in ADCS enables better generalization and robustness against outliers and noise within the dataset. From a practical standpoint, the ADCS model's predictive accuracy has significant implications for renewable energy systems. Accurate forecasting allows for improved energy grid management, particularly in balancing supply and demand in real time. For instance, grid operators can use the predictions to make informed decisions on load distribution, reducing reliance on fossil-fuel-based peaking plants. Additionally, the improved forecasts can guide the optimal scheduling of energy storage systems and integration of distributed energy resources (DERs). In the context of policy-making, such models offer tools to support long-term planning under climate uncertainty. Governments and energy agencies can use high-accuracy forecasts to develop more responsive energy policies that consider seasonal and daily variability, improve resource allocation, and invest in renewable infrastructure with higher confidence. As climate variability increases, such intelligent forecasting systems become essential for ensuring sustainability, energy security, and economic efficiency.

4. Conclusion

The utility of renewable energy depends on environmental conditions that cause periodic consumption changes through varying temperature rates, wind velocity, solar power availability, and environmental elements. Energy optimization, improved distribution, and reduced waste depend on accurate forecasting models. Forecasting renewable energy usage under different weather conditions, powered by machine learning algorithms and optimization systems, is an effective energy management approach. The organizers evaluated two algorithm models called Adaptive Boosting Algorithm Regression (ADAR) and Stochastic Regression (SR) using the Pelican Optimization Algorithm (POA) along with the Crystal Structure Algorithm (CSA). They combined them to increase the level of prediction accuracy, creating hybrid prediction models called SRPO, SRCS, ADPO, and ADCS. The results showed that the hybrid models performed better than the individual ones. The R^2 and RMSE indices showed that the ADCS model performed best with accuracy R^2=0.987,0.983,0.981 and RMSE=164.959, 177.559, 190.103 on the training, validation, and test data. The ADPO model also performed well with accuracy R^2=0.984,0.977,0.974 and RMSE=184.248, 206.247, 217.084, but performed slightly worse than ADCS. The SR model achieved the least effective results with R^2=0.952,0.945,0.940 and RMSE=315.262, 326.842, 331.444, showing that this model was unstable when predicting renewable energy consumption based on weather conditions. The results showed that hybrid models, especially ADCS and ADPO, performed better and provided higher accuracy in predicting renewable energy consumption than single models. These findings indicate the high efficiency of hybrid models in analyzing the impact of weather conditions on renewable energy consumption. The system optimizes energy network management, lowers resource wastage, and maximizes renewable energy generation and distribution. Furthermore, integrating hybrid models ensures a more stable and adaptive forecasting system that can consider diverse environmental conditions. 0Improved forecast accuracy will help policymakers and energy suppliers better plan sustainable energy strategies. The results also show that the use of hybrid models based on machine learning reduces forecast errors and increases energy reliability in the long term. Furthermore, optimizing renewable energy consumption based on real-time weather conditions can significantly improve energy efficiency and cost-effectiveness. Future research should explore integrating more environmental factors and advanced deep learning techniques to increase models' prediction accuracy and adaptability.

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Nomenclature

Abbreviation / Symbol	Definition
ADA / ADAR	Adaptive Boosting Algorithm Regression
ADCS	Adaptive Boosting + Crystal Structure Algorithm (Hybrid Model)
ADPO	Adaptive Boosting + Pelican Optimization Algorithm (Hybrid Model)
CSA	Crystal Structure Algorithm
DL	Deep Learning
GHI	Global Horizontal Irradiance (W/m²)

ML	Machine Learning
MSE	Mean Squared Error
NSE	Nash-Sutcliffe Efficiency
POA	Pelican Optimization Algorithm
RMSE	Root Mean Square Error
SR	Stochastic Regression
SRCS	Stochastic Regression + Crystal Structure Algorithm (Hybrid Model)
SRPO	Stochastic Regression + Pelican Optimization Algorithm (Hybrid Model)
SGBR	Stochastic Gradient Boosting Regression
WAPE	Weighted Absolute Percentage Error
$\hat{y}$	Predicted value
$\bar{y}$	Mean of predicted values
$\bar{y}_m$	Mean of measured values
n	Number of samples
y_m	Measured value
y_p	Predicted value

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