

Article

Advanced Intelligent Approach for Solar PV Power Forecasting Using Meteorological Parameters for Qassim Region, Saudi Arabia

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Abstract: Solar photovoltaic (SPV) power penetration in dispersed generation systems is constantly rising. Due to the elevated SPV penetration causing a lot of problems to power system stability, sustainability, reliable electricity production, and power quality, it is critical to forecast SPV power using climatic parameters. The suggested model is built with meteorological conditions as input parameters, and the effects of such variables on predicted SPV power have been studied. The primary goal of this study is to examine the effectiveness of optimization-based SPV power forecasting models based on meteorological conditions using the novel salp swarm algorithm due to its excellent ability for exploration and exploitation. To forecast SPV power, a recently designed approach that is based on the salp swarm algorithm (SSA) is used. The performance of the suggested optimization model is estimated in terms of statistical parameters which include Root Mean Square Error (RMSE), Mean Square Error (MSE), and Training Time (TT). To test the reliability and validity, the proposed algorithm is compared to grey wolf optimization (GWO) and the Levenberg–Marquardt-based artificial neural network algorithm. The values of RMSE and MSE obtained using the proposed SSA algorithm come out as 1.45% and 2.12% which are lesser when compared with other algorithms. Likewise, the TT for SSA is 12.46 s which is less than that of GWO by 8.15 s. The proposed model outperforms other intelligent techniques in terms of performance and robustness. The suggested method is applicable for load management operations in a microgrid environment. Moreover, the proposed study may serve as a road map for the Saudi government's Vision 2030.

Keywords: regression analysis; renewable energy resources; solar photovoltaic forecasting; intelligent algorithms



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1. Introduction

The usage of electricity is rising exponentially due to the population increase, urban growth, and increased convenience [1]. Because of the emissions of greenhouse gases and depletion of conventional sources of energy, the deployment of clean energy sources such as solar, wind, and biomass has garnered attention. Solar photovoltaic (SPV) energy is becoming more popular among renewable sources of electricity due to a variety of benefits such as clean, quiet operation, affordability, and low operating costs. Moreover, the continued advancement of SPV systems introduces various problems in the operation and management of SPV-based energy systems [2]. Furthermore, increased SPV penetration may affect the stability of the grid, sustainability, and reliability problems in a smart grid. As a result, one of the main tools for this framework is SPV power forecasting, which plays a critical role in the efficient implementation of renewable power generation and the minimization of uncertainty in distributed systems. SPV power forecasting that is specific

and reliable greatly aids in the scheduling and monitoring of power for customers and distribution companies [3]. It improves the efficiency of the system and stabilizes the power due to the unpredictable nature of SPV power generation [4]. Furthermore, forecasting plays a vital role in power companies because it allows them to schedule production and distribution based on load profiles, as well as clarify power generation to behave as functioning reserve generators [5]. It is essential for establishing contemporary transactive energy systems in a grid-powered distributed generation [6]. SPV power forecasting decreases the number of units needed in hot standby while also lowering operating costs. Therefore, it is crucial to forecast SPV power for maintaining the stability of the grid, optimal unit commitment, sustainability, and cost-effective generation.

Numerous kinds of research have recently been conducted to achieve reliable predictions using alternative approaches including mathematical analysis, regression methods, and optimization-based methodologies. There are two primary methods used for the prediction of SPV power which is named direct and indirect [7]. The direct approach directly quantifies the SPV output. On the other hand, the indirect method first determines the amount of solar radiation and then estimates the SPV power generated using the SPV plants' conceptual framework. Cloud imagery and numerical weather prediction techniques are used to model the indirect method. The direct approach entails modeling with a machine-learning method.

There have been studies that have solely concentrated on predicting solar irradiation because it is the primary factor upon which the efficiency of the SPV plant is heavily dependent. The author in [8] gave a thorough examination of both indirect and direct methods, as well as the benefits and drawbacks of different kinds of forecasting models. Antonanzas et al. provided a thorough examination of SPV power prediction models, with a focus on recent advances and emerging developments. It is reported that the majority of forecasting horizons considered are one day ahead, and the quantitative technique is preferable in most cases [9]. The author in [10] also gave an overview of SPV forecasting based on time horizons such as intra-hour, intra-day, and day ahead. Figure 1 outlines the various forecasting horizons, time horizons, and their potential application. The time horizon is further divided into intra-hour, intra-day and day ahead time zones. Furthermore, the applications in different time zones are provided in Figure 1.

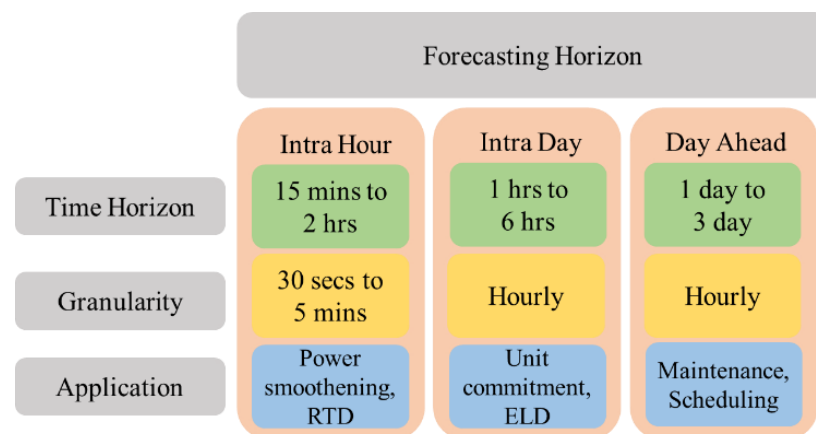


Figure 1. Overview of the forecasting horizon.

The time horizon of predicted SPV power output is critical in the control and management of SPV systems in various locations such as colleges, healthcare facilities, and so on. In [11], the authors investigated the viability of solar energy utilization in Nigerian tropical stations using the clearness index (KT) and diffuse ratio (DR). The researchers surveyed 11-year data of solar irradiance and temperature and equated it to varying KT and DR on monthly basis. Hence, the authors proposed that the SPV output should be evaluated in diverse circumstances, particularly considering spatiotemporal changes, requiring the need

for installers and stockholders to supervise grid-connected SPV plants. An SPV power prediction model focused on an artificial neural network (ANN) model for 5, 10, and 15 min time horizons based on three baseline models, auto-regressive moving average (ARMA), cloud tracking, and k-nearest neighbor (kNN), is postulated [12]. Ensemble methods such as random forest (RF) and extreme gradient boosting (XGBoost) improve stability and reduce variation and bias, making them ideal for solar radiation prediction [13]. Solar radiation data are needed for any photovoltaic system evaluation, although they are seldom accessible. Thus, artificial neural network (ANN) to estimate daily worldwide sun irradiation is required. Five models were evaluated in [14] using meteorological data from the Solar Energy and Environment Laboratory (LESE) to discover the best input variables for prediction. PV signal volatility makes planning and operation prediction and assessment challenging. The issue is overcome by an accurate prediction technique. The author in [15] uses EEMD, i.e., a novel feature selection technique, and a hybrid prediction engine that underpin the suggested strategy. The hybrid prediction engine uses improved support vector regression (ISVR) and optimization to fine-tune associated free parameters. PV power production might fluctuate owing to weather, making yield forecast difficult. Machine learning (ML) has improved PV power forecasting in recent years. Researchers have written extensively about this approach's potential. The author in [16] highlights prominent methods of machine learning family, i.e., ensemble, decision tree, Regression, and Fuzzy ANN and gaps in this field. The impact of aerosol particles over northern and eastern China finds a yearly reduction in irradiance of 1.5 kW/m^2 per day in comparison to polluted air surroundings [17]. The relationship between atmospheric aerosol and SPV power reduction will be investigated. As a result, a solar PV power forecasting model that accommodates this transition in the atmosphere is required. The authors of [18] suggested a convolution neural network strategy for various time horizons of 1 h, 1 day, and 1-week considering irradiance, wind velocity, and temperature as input variables. A grey-wolf optimizer-based model is introduced to investigate the effect of aerosol particles on SPV power forecasting in remarkably foggy surroundings [19]. To enhance the productivity of the support vector machine prediction model, an ensemble tree-based regression approach is used to maintain the root mean squared error (RMSE) in the range of 4.6% to 14.8% [20]. The authors suggested a 1.5-h time horizon long short-term memory-based SPV power prediction for Nicosia, Cyprus, and analyzed the efficiency using RMSE and the k-fold cross-validation method [21]. The authors of [22] used a particle swarm optimization method-based ANN model for predicting SPV power. The suggested approach is executed in Simulink on the MATLAB platform. The authors of Ref. [23] investigated the forecasting of global solar irradiance using humidity level, temperature, and a modified sunshine duration factor. The authors envisioned an ANN-based multilayer perceptron model to predict solar irradiance in two distinct regions. They emphasize the versatility of the anticipated ANN-based multilayer perceptron model by forecasting solar irradiance using unknown data [24]. In [25], the authors mentioned artificial-intelligence methods for sizing numerous SPV systems, SPV-wind hybrid systems, and modeling of a 24 h solar forecast system in Trieste, Italy. The implementation of ensemble trees approach-based machine learning approach for the forecasting of SPV power is performed, considering the meteorological parameters of the Qassim region, Saudi Arabia [26].

Oil prices collapsed dramatically in 2020 as a result of the global lockdown and pandemic, having a significant impact on economic systems that rely on oil, particularly in gulf countries. These nations are planning to broaden their supply of power and get back on track with robust and durable advancement. The solar potential of various parts of the world is represented in Figure 2. Countries located between 15° N and 45° N latitudes and 15° S and 45° S latitudes have enormous potential for solar energy utilization. Large-scale SPV systems are feasible in the Middle East, the Sahara Desert, and the Kalahari Desert of Africa. Saudi Arabia has recommended an ambitious program to get revolutionized and implement a circular economy energy transition pathway. Saudi Arabia has increased its SPV projects and plans to build 9.5 GW of solar power systems in collaboration with

Softbank by 2030 to promote renewable sources through gradual liberalization of gasoline industries.

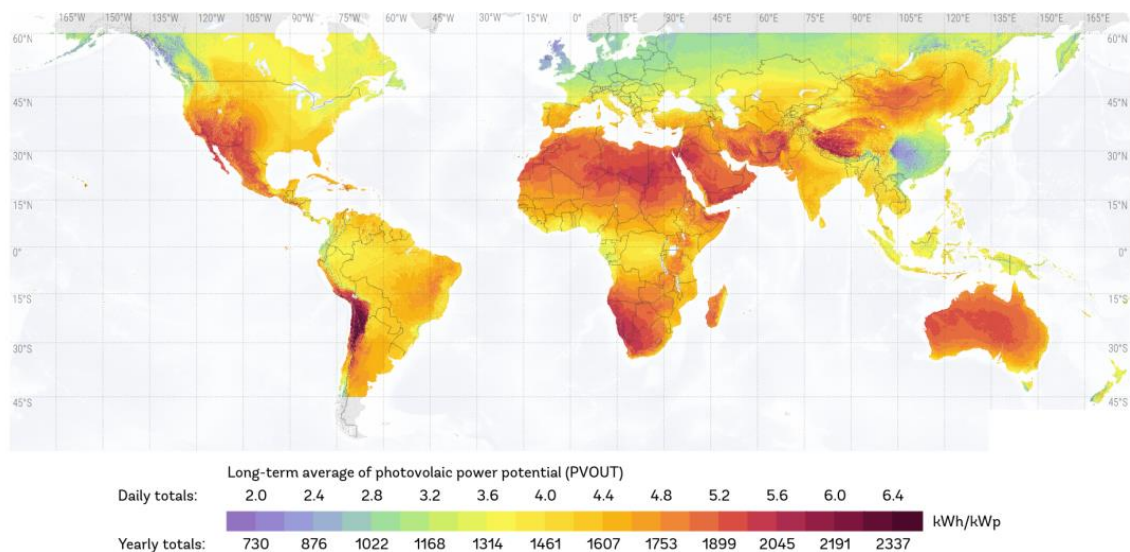


Figure 2. Solar potential in different parts of the world [27].

KSA's 2030 vision is to localize a large portion of the renewable (mostly solar) energy value chain for productivity expansion. As a result of this vision, the nation is concentrating on SPV system investigation and framework advancement. Moreover, it provides a significant scientific position for power technologists in the domain of SPV systems and performance estimation. The goal of this paper is to develop a new forecasting model by utilizing the advanced intelligent technique considering the meteorological parameters of the Qassim region, Saudi Arabia.

According to the available research, a new SPV forecasting framework with improved accuracy and reliability is required. The majority of published research emphasizes solar irradiance prediction, whereas just a few publications address SPV power prediction. While the ANN approaches used in the SPV power prediction model need a quantitative data set for training reasons, they are unable to make exact predictions in foggy and heavily polluted environments. In the literature, neural network-based prediction models with a short-term time horizon were rare.

The important contributions of this paper are summarized as follows:

- The paper proposes Salp Swarm Algorithm (SSA)-based intelligent model for forecasting SPV power generation.
- SSA is used to train the weights of the ANN model for mapping input variables and SPV power as output.
- For a deeper understanding of the input variables and their involvement in power prediction, a feasibility analysis of the inputs with SPV power is also performed.
- An investigation of the input factors and their correlation with SPV power is carried out, providing insight into the reliance of SPV power generation on each input considered.
- This paper offers a comparative performance assessment based on statistical indexes for the proposed model's training and testing phases.

This paper is structured as follows: the brief overview of the ANN technique and other optimization algorithms with their mathematical modeling is discussed in Section 2. Section 3 describes the location chosen for data collection and testing, as well as the data analysis. Section 4 contains the results and discussions of the intelligent model and its comparative study. Section 5 contains a conclusion followed by references.

2. Material and Methods

This paper proposes a short-term SPV power forecasting technique. Modern techniques for very short-term and short-term forecasting include metaheuristic techniques, machine learning algorithms, and deep learning models. When compared to traditional empirical techniques for SPV forecasting, intelligent optimization algorithms have recently produced superior results [28]. This section discusses various intelligent techniques for solar power forecasting.

2.1. Training Techniques

There is a variety of training algorithms employed for the modeling of neural networks. Some examples of these algorithms include gradient descent, newton's method, conjugate gradient, and Bayesian regularization. These training techniques aid in the development of a decision function for the weight updating of neural networks. These techniques have a few drawbacks, including the use of large amounts of memory, computation complexity, and slow convergence. These training algorithms create rules and indicate a particular function to modify the weight of the neuron after every iteration. Optimization algorithms can also be used to define the weights of the neural network by minimizing the cost function. Because the cost function is affected by numerous parameters, the optimization is both single and multi-dimensional. Optimization increases computational speed and improves convergence speed. In this paper, the LM technique is used as the foundation for developing an optimization algorithm-based training of ANN. In this paper, an advanced technique, i.e., SSA, is proposed for the training of ANN weights and compared to models created using the LM technique and an intelligent optimization technique—GWO.

2.1.1. Levenberg–Marquardt Technique

The damped least-square technique is another name for the LM algorithm. This technique is intended to improve training performance without the need to compute the Hessian matrix [29]. This method is especially useful for functions involving the sum of squared errors. This algorithm's main advantage is its training speed, but it requires a quantitative dataset for training purposes. It necessitates a large amount of computational memory. The cost function, i.e., $C(x)$, for LM is given in terms of sum of squares of error (e_i) as follows [29]:

$$C(x) = \sum_{i=1}^N e_i^2(x) \quad (1)$$

$$\nabla C(x) = J^T(x) e_i(x) \quad (2)$$

$$\nabla^2 C(x) = J^T(x) J(x) + S(x) \quad (3)$$

where $J(x)$ is a Jacobian matrix

$$J(x) = \begin{pmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \dots & \frac{\partial e_1(x)}{\partial x_n} \\ \frac{\partial e_2(x)}{\partial x_1} & \frac{\partial e_2(x)}{\partial x_2} & \dots & \frac{\partial e_2(x)}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial e_N(x)}{\partial x_1} & \frac{\partial e_N(x)}{\partial x_2} & \dots & \frac{\partial e_N(x)}{\partial x_n} \end{pmatrix} \quad (4)$$

$$S(x) = \sum_{i=1}^N e_i^2(x) \nabla^2 e_i^2(x) \quad (5)$$

Hessian matrix $H(x)$ can be approximated as [29]

$$H(x) = \nabla^2 C(x) = J^T(x) J(x) \quad (6)$$

Gradient (g) can be calculated as [29]

$$g = J^T(x)e_i(x) \quad (7)$$

where $H(x)$ represents the Hessian matrix, $e_i(x)$ represents the error vector, and $J(x)$ represents the Jacobian matrix containing the first-order derivative of the network error concerning the weights and biases. The computation of the Jacobian matrix is the most important step in this method. The following equation is used to approximate the Hessian matrix in this algorithm:

$$x_{i+1} = x_i - [J^T(x)J(x) + \mu I]^{-1} J^T(x)e_i(x) \quad (8)$$

when μ is zero, the equation is simply the Gauss–Newton method; when μ is large, the equation becomes gradient descent with a small step size. This training algorithm approximates the error while discarding second-order derivatives.

2.1.2. Grey Wolf Optimization

The mathematical modeling of grey wolf optimization is based on three phenomena, namely chasing, surrounding, and attacking the prey. The search agents are arranged based on fitness values. The superior ones are assigned as alphas (α); betas (β) come after alphas and are followed by delta (δ), and the remaining ones are designated as omega (ω). Figure 3 depicts the social hierarchy of the grey wolf pack. This group is known as a pack, and it is the dominant factor in guiding prey hunting [30]. GWO is quick and efficient, necessitates fewer parametric descriptions, and has a limited computation memory requirement. It emphasizes the exploration of a meta-heuristic technique instead of its exploitation. The expressions below depict grey wolf behavior such as hunting and attacking [31].

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_p(t) - \vec{X}(t) \right| \quad (9)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \quad (10)$$

where t stands for the number of iterations; $\vec{A}$ and $\vec{C}$ are the coefficient vectors; and the position vector of prey is $\vec{X}_p$, whereas the position vector of the wolf is $\vec{X}$.

$\vec{A}$ and $\vec{C}$ can be formulated as follows [31]:

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \quad (11)$$

$$\vec{C} = 2\vec{r}_2 \quad (12)$$

The value of $\vec{a}$ decreases in a linear fashion starting from 2 and ending at 0. $\vec{r}_1$ and $\vec{r}_2$ are the random values between 0 and 1.

The grey wolf's hunting characteristics are represented by the equation below [31]:

$$\vec{D}_\alpha = \left| \vec{C} \cdot \vec{X}_\alpha - \vec{X} \right|; \vec{D}_\beta = \left| \vec{C} \cdot \vec{X}_\beta - \vec{X} \right|; \vec{D}_\delta = \left| \vec{C} \cdot \vec{X}_\delta - \vec{X} \right| \quad (13)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha; \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta; \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad (14)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (15)$$

$\vec{X}_\alpha$, $\vec{X}_\beta$, and $\vec{X}_\delta$ are the position vectors of α , β , and δ wolf, respectively. Using a neural network MLP framework, the GWO algorithm is employed for the practical issue of SPV

power prediction. The termination condition for the proposed technique is as follows: (i) tolerance error; (ii) the maximum number of iterations.

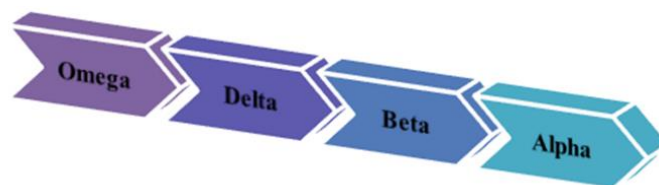


Figure 3. Social hierarchy of grey wolves.

2.1.3. Salp Swarm Algorithm

Mirjalili in 2017 introduced a population-oriented algorithm termed as salp swarm algorithm (SSA). This algorithm simulates the scavenging mechanism of salps in oceans [32]. The salp heading the chain will pave the path for other salps to follow.

Salp's position can be termed in m -dimensional space, where n represents the number of variables for a particular problem. Hence, the positions of all salps are kept in a two-dimensional matrix known as z . The governing equation for SSA is expressed as follows [33]:

$$z_n^i = \begin{cases} R_n + r_1(ub_n - lb_n)r_2 + lb_nr_3 \geq 0 \\ R_n + r_1(ub_n - lb_n)r_2 + lb_nr_3 \leq 0 \end{cases} \quad (16)$$

where z_n^i denotes the leader's position, and R_n is the position of food source. ub_n and lb_n denote the upper bound and lower bound in n th dimension of search space.

The coefficient r_1 is important in SSA as it keeps an appropriate balance between exploration and exploitation capability. It is shown in [33].

$$r_1 = 2 * \exp\left(-\left(\frac{4b}{B}\right)^2\right) \quad (17)$$

where b and B denote the current iteration and the maximum number of iterations, respectively.

The parameters r_2 and r_3 are uniformly generated arbitrary values between 0 and 1. They specify the step size as well as that the next point in the n th dimension must be directed towards positive or negative infinity.

Newton's Second Law of Motion is used to modify the locations of the follower salps which can be mathematically governed using Equation (18).

$$z_n^i = \frac{1}{2}at^2 + u_0t \quad (18)$$

where $i \geq 2$ and z_n^i depict the position of i th follower salp in n th dimension, u_0 denotes the initial velocity, and $a = \frac{u_{final}}{u_0}$, where $u = \frac{x-x_0}{t}$.

The number of iterations determines the computation time, and if the conflict between iterations is equal to 1, and $u_0 = 0$, this equation will appear to be as follows [33]:

$$z_n^i = \frac{1}{2}(z_n^i + z_n^{i-1}) \quad (19)$$

The mathematical modeling of salp chains can be done using Equations (16)–(19).

The exploration and exploitation mechanisms can be balanced by employing operator P using Equation (20) [33].

$$P(t) = P_{min} + \left(\frac{P_{max} - P_{min}}{P_{max}}\right) \times b \quad (20)$$

P_{max} and P_{min} are the upper and lower values of the operator P , respectively.

The parameters of ANN are tuned using the SSA-based optimization approach involving two phases: propagation and weight updating. Data are sent from the input layer to the output layer. The output of the output layer is compared to the goal values, and an error-based cost function is generated. The steps involved in the proposed salp swarm algorithm are shown in Figure 4.

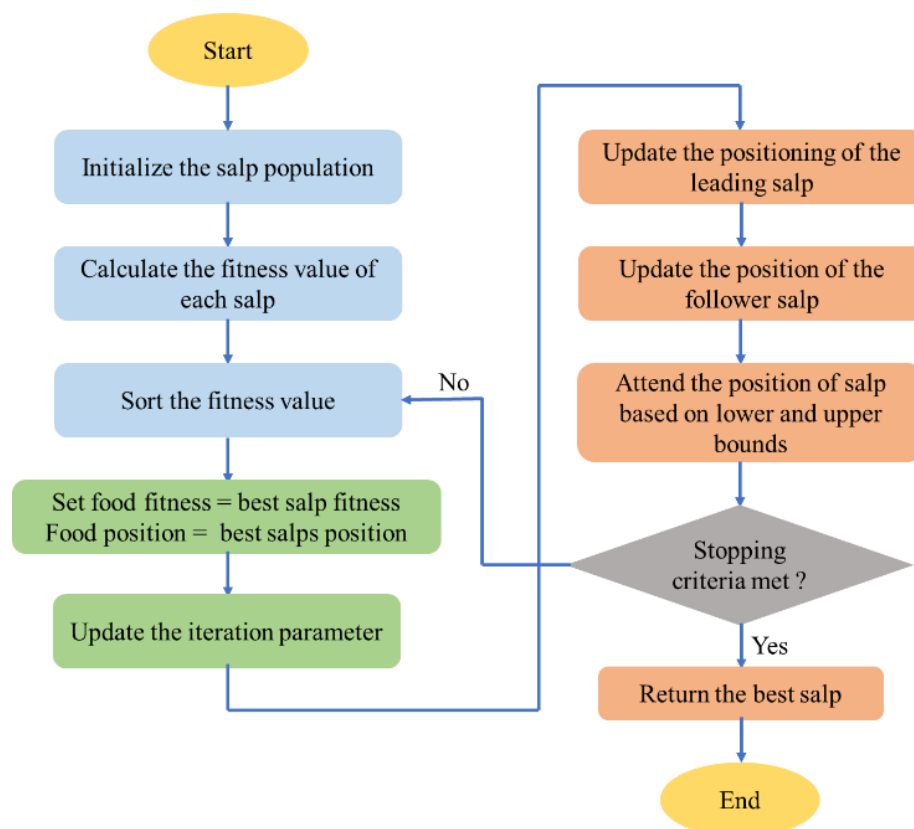


Figure 4. Flow chart of the proposed salp swarm algorithm.

3. Description of Chosen Site and Data Processing

This section examines the various types of inputs and data processing technologies used to develop the SPV power prediction models. The efficiency of the SPV system is determined by the choice of input parameters and location. Regardless of where the land is, the motion of clouds and the clearness index influence the power output of the SPV system. Variability in ambient temperature and solar irradiation all have an impact on SPV power. The use of appropriate types of input parameters results in an improved-performing prediction model. If the inputs chosen are superfluous, have a low correlation factor, or key parameters are missing, the estimated values will be complicated. Irradiance incident on the module and temperature of the SPV panel are the major input variables assumed for forecasting SPV power. The total power rating of the SPV system on the site is 6.30 kW, and power forecasting for this installed capacity is performed in the proposed work.

Based on 1-year historical data, a linear regression study was conducted to select the various inputs. The linear dependence of SPV power output to the input variables is determined using the Pearson product-moment correlation coefficient. Accordingly, 70% of the data are used for training purposes, 15% are used for testing, and 15% are used for validation. The above selections of 70%, 15%, and 15% for various stages were made through trial-and-error techniques. For the last ten years, the measurement values were cross-checked with data from the National Renewable Energy Laboratory (NREL) models. Table 1 represents the resolution and data range of different inputs considered as historical data for effective training of the prediction. The evaluated solar irradiance values

are within the range of the irradiance obtained from the selected sources. Table 2 shows the specifications of the PV system details utilized for the proposed work. In ANN and other data-mining techniques, the ranges of each input variable are in relation to the target values, so normalization is required to prevent ill-conditioning of the network.

Table 1. Details of data.

Data	Range	Time Resolution
Solar irradiation	0–1000 W/m ²	1 min
Temperature	5 °C–80 °C	1 min
Power	0–6300 W	1 min

Table 2. SPV system details used for the proposed work.

Parameters	Value
Coordinates	26.35° N, 43.76° E
Tilt Angle	25.7°
PV Modules	450 W _p
Cell Type	Monocrystalline
Cell Arrangement	144 [2 × (12 × 6)]
Dimensions	2108 × 1048 × 40 mm
Arrangement	7 (series) × 2 (parallel strings)
Peak Power	6300 W _p
Front Cover	3.2 mm tempered glass
Module Efficiency	20.37%
Exposure area of a module	1.640 m ²
Temperature Coefficients of PV module	
α_{pv}	+0.058%/°C
β_{pv}	−0.330%/°C
γ_{pv}	−0.430%/°C

Normalization also aids in having the same range of values for various inputs. To achieve a linear and robust relationship between nonlinear datasets, normalization is preferred. Equation (21) is used to normalize the inputs and target values [19].

$$X_N = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (21)$$

where $0 \leq X_N \leq 1$; X_i is the current value of data X ; and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the dataset X .

4. Simulations Results and Achievements

This subsection outlines the statistical indicators used to assess the effectiveness of the different prediction models. The implementation of various algorithms is performed to develop distinct forecasting models for SPV power output prediction. The various models are ANN-LM, GWO, and SSA-based forecasting models. The performance of the proposed model is evaluated in two stages: first, during the training phase and, then, during the testing phase. The results have been simulated in MATLAB 2023 software using PC with AMD Ryzen 7 5600H processor, 16 GB with 3200 MHz clock frequency, NVIDIA GeForce RTX 3050 Ti GPU, and 1 TB SSD storage.

4.1. Statistical Indicator

The effectiveness of the proposed advanced algorithm-based forecasting of SPV power output is assessed using well-known statistical indicators. These indicators include mean absolute percentage error (MAPE), mean squared error (MSE), root mean squared error

(RMSE), and training time (TT). These metrics are used to assess the prediction's accuracy. The mathematical expression for these statistical indicators is given as follows [26]:

$$\text{RMSE} = \sqrt{\frac{1}{K} \sum_{k=1}^K (m_k - P_k)^2} \quad (22)$$

$$\text{MSE} = \frac{1}{K} \sum_{k=1}^K (m_k - P_k)^2 \quad (23)$$

$$\text{MAPE} = \frac{1}{K} \sum_{k=1}^K \left| \frac{m_k - P_k}{m_k} \right| \quad (24)$$

K denotes the total number of observations, m_k denotes the actual SPV power output, and P_k denotes the predicted SPV power.

4.2. Performance of the SSA-Based Training of the ANN Model

The SSA algorithm is used to train the proposed neural network model, which considers two input parameters: solar irradiance and cell temperature. Figure 5 depicts the training and validation stages of the proposed SSA-based training of the ANN model for SPV power prediction. The SSA algorithm collects past information and aids in the effective modeling of an ANN network for forecasting SPV power. The SSA algorithm is used to assign optimal weights to the layers of an ANN by optimizing the cost function. The SSA-based training of the ANN model considers mean square error as the objective function to be optimized. The model consists of two input nodes, ten hidden layers, and one output. The impact of various input parameters such as solar irradiation and temperature is provided in Table 3.

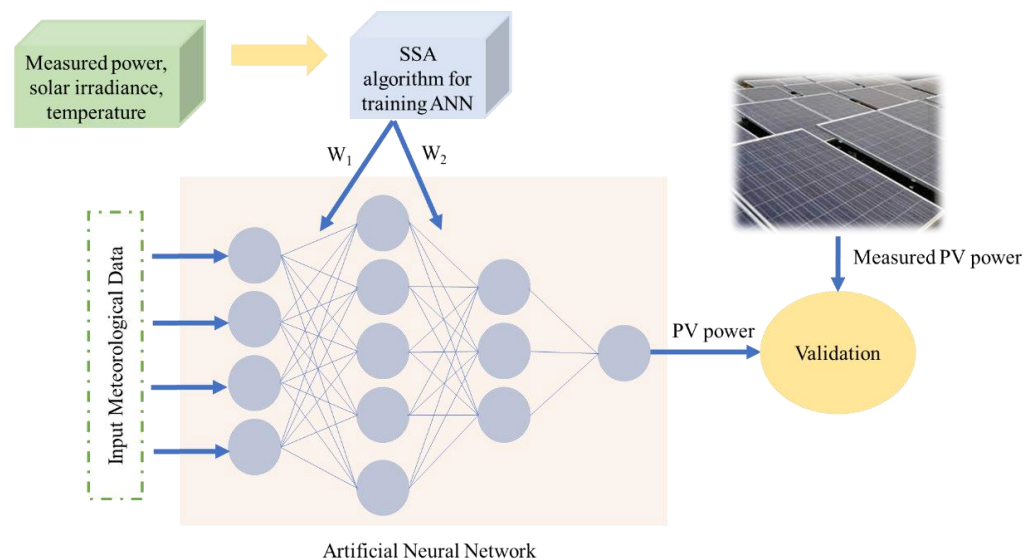


Figure 5. Typical layout of the proposed SSA model.

Table 3. Various input variables and their correlation coefficients.

Input Variables	Correlation Coefficient
Solar irradiation	0.995
Temperature	0.924

A comparison of the previously stated algorithms is performed using training time, iterations needed to achieve minimum error, and regression coefficient (R). The training error is defined as the error acquired when the training of the trained model is done for

predicted values. R expresses the model's connectivity with its input data. Figure 6 shows the performance of SSA based PV power forecasting for the proposed site.

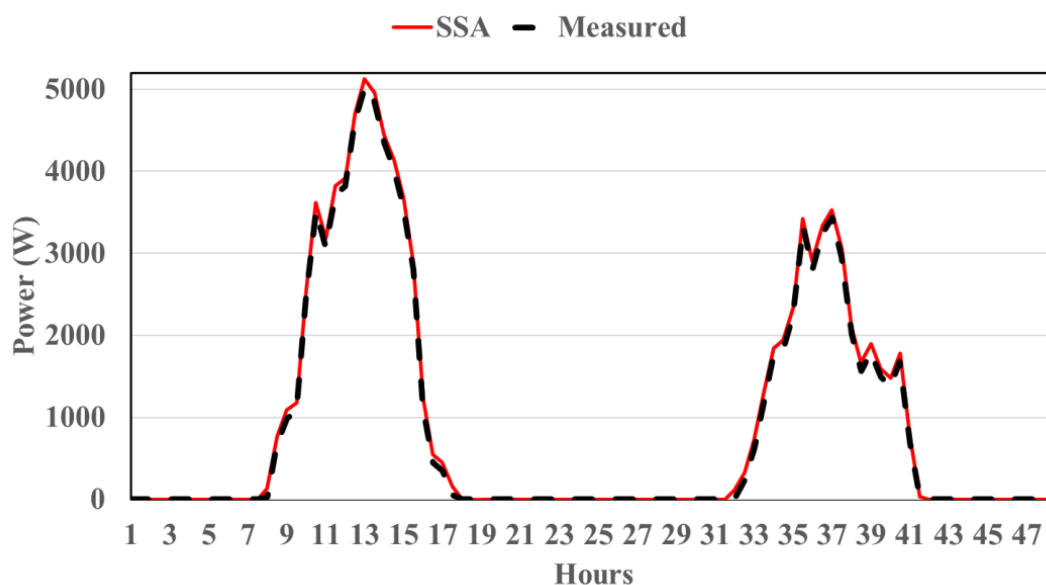


Figure 6. Comparison of forecasted value and measured value of SPV power using SSA-based training of ANN model.

It describes the fitness function's goodness. It is a way of measuring how well the variability in output is explained by the targets. The closer this coefficient is to 1, the better the input–output relationship. Table 4 compares the three training algorithms based on R and the number of iterations needed to achieve the minimum MSE.

Table 4. Comparison of different methods in terms of iteration numbers and regression coefficient.

Methods	Iteration	Regression Coefficients
SSA	5	0.993
GWO	17	0.985
ANN-LM	15	NA

The value of R using the SSA-based training of the ANN model is found to be 0.99312 with the fewest number of iterations, i.e., the training algorithm with the highest computational speed. According to these findings, the SSA-based model needs less computing time than other intelligent algorithms such as GWO. Furthermore, the suggested model has a lower training error value.

Based on Table 4, it is possible to conclude that the SSA training technique is superior to the other training methods. This technique has the lowest MSE, resulting in high associativity of inputs to outputs and a quicker computation time than ANN-LM and GWO techniques. Table 5 shows the training parameters for various algorithms.

Figure 7 depicts the performance of the SSA-based forecasting model of SPV at various stages, namely training, validation, and testing. The error for the testing stage is of the order of 10^{-4} , and the same error is for the validation stage.

In Figure 8, the forecasted SPV power output from ANN-LM, GWO, and SSA is compared to the measured data. During the daylight hours, the models forecast PV power every 15 min. It is clear from Figure 8 that SPV power production is lesser during the early hours of the morning, reaches its peak during the noon hours, and then decreases gradually during the night hours. However, the developed model's performance is found to be adequate during daylight hours.

Table 5. Tuned parameters of different algorithms for the training of model.

SSA				
Max iteration	Number of hidden layers	$P_{\min}$	$P_{\max}$	Tolerance error
100	10	0.35	0.80	10^{-4}
GWO				
Max iteration	Number of hidden layers	$\vec{a}$ decrease factor	$\vec{a}$ initial	Tolerance error
100	10	$2 - \frac{2 \cdot \text{iter}}{\text{maxiter}}$	2	10^{-4}
ANN-LM				
Number of delays	Max iteration	μ increase factor	μ decrease factor	Tolerance error
1	100	10	0.1	10^{-4}

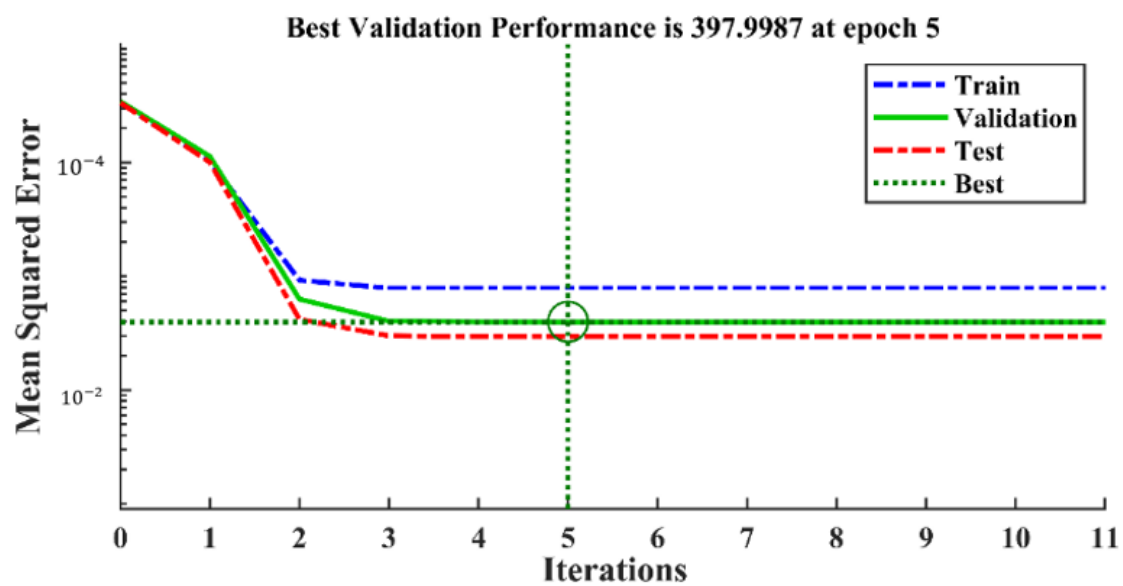
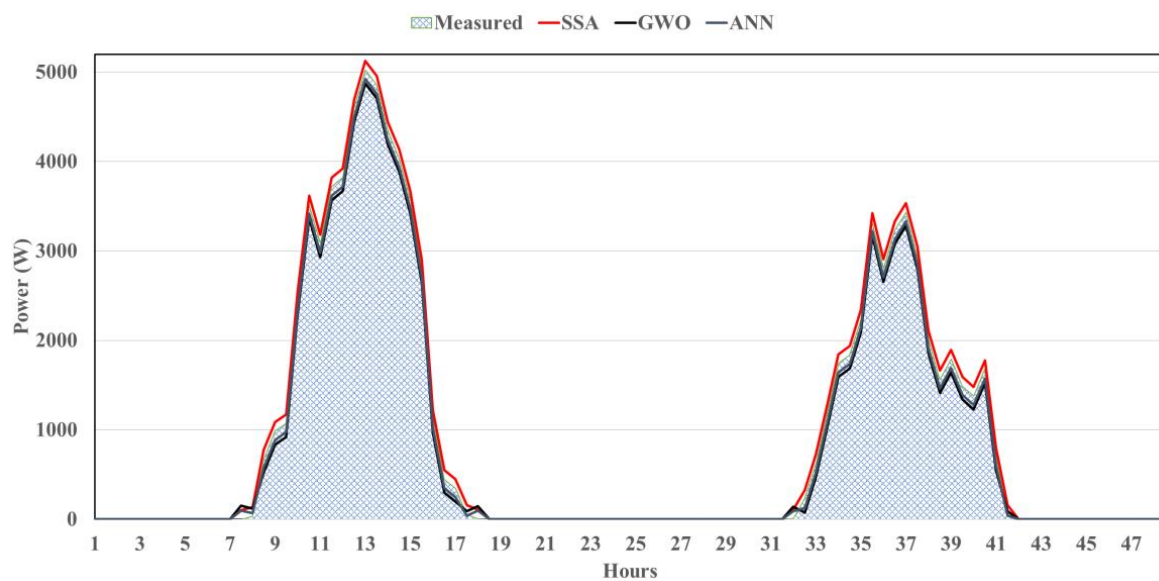
**Figure 7.** Mean squared error for different stages using SSA algorithm-based training model.**Figure 8.** Predicted solar power output for different training models.

Table 6 displays the performance measures such as MSE, RMSE, and TT for the multiple approaches. When contrasted with other intelligent strategies, the suggested SSA model has a higher value of statistical indicators.

Table 6. Performance indicators during the training phase using different algorithms.

Technique	RMSE (%)	MSE (%)	TT (s)
ANN	2.85	8.24	48.98
GWO	2.43	5.91	20.61
SSA	1.45	2.12	12.46

Based on Table 6, it can be deduced that the SSA-based approach outperforms the other intelligent techniques. Moreover, it is shown that the proposed SSA takes less time to train the network as compared to the GWO and ANN. The TT for SSA is 12.46 s which is less than that of GWO and ANN by 8.15 s and 36.52 s, respectively. The findings of the suggested model may be used for a variety of smart grid applications, including demand response, PV plant deployment, and monitoring. Figure 9 shows the regression coefficient plots for the SSA and GWO-based approaches, respectively.

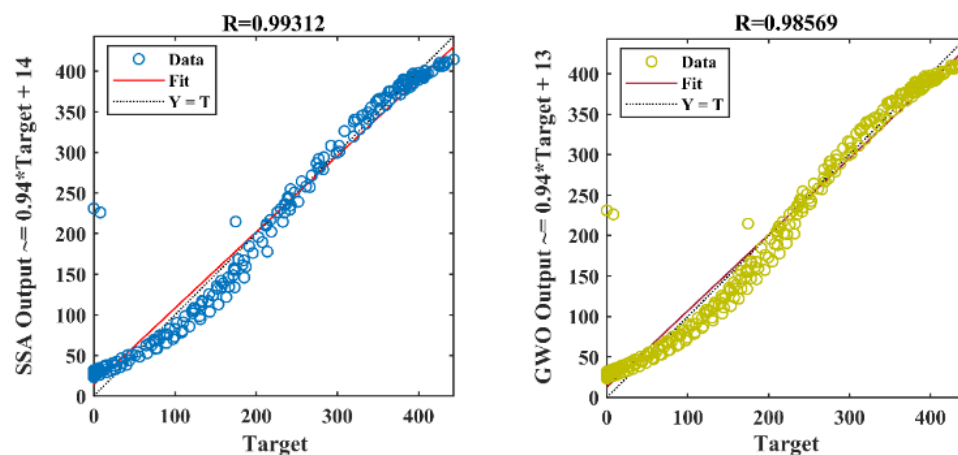


Figure 9. Regression plot in the training phase using SSA and GWO.

Figure 10 further illustrates the comparison of the proposed model with other models by showing the changes in mean absolute percentage error and of the forecast SPV power with the evaluated power.

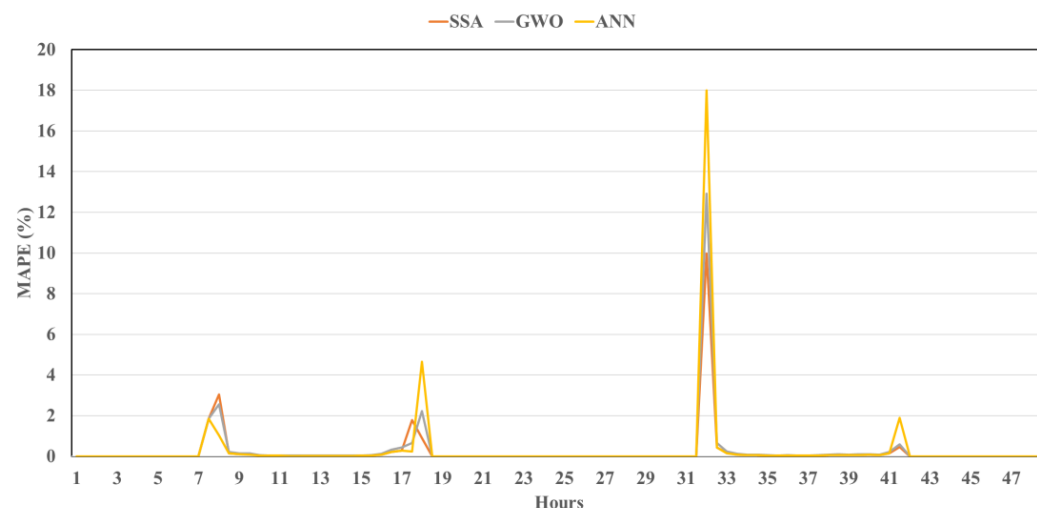


Figure 10. Error obtained using different training algorithms on an hourly basis.

5. Conclusions

A reliable and efficient model for predicting SPV electricity production is beneficial for both grid reliability and economic sustainability. A new model for SPV power forecasting based on the SSA approach has been designed and presented in the proposed work for the smart grid environment. To forecast SPV power output, the proposed model is built on meteorological parameters. The model's performance is assessed using statistical indicators and validated using meteorological data of the Qassim region, Kingdom of Saudi Arabia. SSA used incident irradiance and panel temperature as inputs. The correlation of each input with the output SPV power has been discussed to comprehend the input selection process. A comparison of the proposed SSA model with other intelligent techniques is also performed and found to be superior. The performance indicators MSE, RMSE, and TT are 2.12%, 1.45%, and 12.46 sec, indicating that the proposed advanced algorithm-based model is superior. The proposed model has fast computation and a lesser number of complications. The attained results could be applied in energy management systems in microgrid environments and demand-side management applications, resulting in more efficient, load smoothing, and cost-effective electricity generation for customers. The presented algorithm predicts solar power accurately and reduces the uncertainty of challenges faced by power operators such as load ramping, congestion, scheduling, unit commitment, maintenance, and economic dispatch, thus achieving the sustainable development goal of ensuring access to affordable, reliable, sustainable, and modern energy for all.

The limitations associated with the proposed approach are that the PV power prediction model require large amount of dataset for training but still are unable to predict accurately during hazy and high-pollution conditions. This research study can be extended by considering the impact of aerosol data on the power forecasting. In addition to this, the features and characteristics during the hazy and high pollution can be incorporated during forecasting to make the model more reliable and robust.

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Nomenclature and Abbreviations

SPV	Solar Photovoltaic
KT	Clearness Index
DR	Diffuse Ratio
ANN	Artificial Neural Network
ARMA	Auto-Regressive Moving Average
kNN	K-Nearest Neighbors

RMSE	Root Mean Squared Error
LM	Levenberg-Marquardt
GWO	Grey Wolf Optimization
SSA	Salp Swarm Algorithm
NREL	National Renewable Energy Laboratory
MSE	Mean Squared Error
TT	Training Time
$C(x)$	cost function
e_i	sum of squares of error
$J(x)$	Jacobian matrix
$H(x)$	Hessian matrix
g	Gradient
$e_i(x)$	error vector
$\vec{A}, \vec{C}$	coefficient vectors
$\vec{D}$	Encircling behavior of grey wolves
$\vec{X}_p$	position vector of prey
$\vec{X}$	position vector of the wolf
$\vec{r}_1, \vec{r}_2$	Random values
z_n^i	leader's position
R_n	position of food source
ub_n, lb_n	upper bound and lower bound
b	current iteration
B	maximum number
P	Adaptive operator
P_{max}	Upper values of the operator P
P_{min}	lower values of the operator P
u_o	Initial velocity
K	total number of observations
m_k	actual SPV power output
P_k	predicted SPV power.

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