



# Optimization Techniques for Solar Photovoltaic Forecasting in IoT-Driven Smart Energy Management: A Review

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**Abstract** The presented paper conducts a comprehensive analysis of several Demand Response (DR) programs, advanced devices, and load planning algorithms, offering a detailed assessment based on insights derived from previous studies on Energy Management Systems (EMS). Over the past decade, there has been a noteworthy increase in the generation of electric power from renewable sources, with solar energy experiencing remarkable development in electricity production within the broader landscape of available renewable energy options. Given the pivotal role of solar photovoltaic (PV) energy in ensuring the stability and security of the grid, especially in the context of expansionary monetary policies, the paper underscores the essential nature of reliable PV power generation forecasting. The study references a substantial number of research endeavors that have evaluated PV electricity production from various perspectives. The growing utilization of renewable power is positioned

as a strategy to mitigate the adverse environmental impacts of greenhouse gas emissions. Different modeling processes have been explored and adopted in an effort to enhance the predictive accuracy of sustainable energy. The research highlights the increasing demand for renewable energy forecasts in facilitating transmission system supply and demand predictions. Natural events are discussed to elucidate their impact on the performance of PV systems. The paper systematically evaluates photovoltaic power production forecasts, emphasizing the importance of associating incoming data and modeling it before analysis. Various power generation modeling techniques, categorized across multiple classifications, are scrutinized for their effectiveness. The research critically reviews empirical investigations, encompassing quantitative and machine-learning models based on statistical methodologies.

**Keywords** IoT · Smart energy management · Smart plug · Cloud computing · Optimization techniques

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## Abbreviations

|        |                               |
|--------|-------------------------------|
| DR     | Demand response               |
| EMS    | Energy management systems     |
| PV     | Photo voltaic                 |
| GPR    | Gaussian process regression   |
| ARMA   | Autoregressive moving average |
| AR     | Auto regressive               |
| MA     | Moving average                |
| MATLAB | Matrix laboratory             |
| MSE    | Mean-squared error            |
| RMSE   | Root mean-squared error       |
| MAE    | Mean absolute error           |
| MAPE   | Mean absolute percent error   |
| SVM    | Support vector machine        |
| ANN    | Artificial neural network     |

|         |                                                   |
|---------|---------------------------------------------------|
| LSTM    | Long short-term memory                            |
| RNN     | Recurrent neural network                          |
| ARIMA   | Autoregressive integrated moving average          |
| SARIMA  | Seasonal autoregressive integrated moving average |
| DL      | Deep learning                                     |
| XAI     | Explainable artificial intelligence               |
| CNN     | Convolutional neural network                      |
| DNN     | Deep neural network                               |
| PSO     | Particle swarm optimization                       |
| GA      | Genetic algorithm                                 |
| ACO     | Ant colony optimization                           |
| NRMSE   | Normalised root mean square error                 |
| MLP     | Multi-layer perception                            |
| AGI     | Artificial general intelligence                   |
| AI      | Artificial intelligence                           |
| AM      | Activation maximization                           |
| AMT     | Automatic music transcription                     |
| ARNN    | Anticipation recurrent neural network             |
| BDT     | Boosted decision tree                             |
| BiFPN   | Bidirectional feature pyramid network             |
| BPMF    | Bayesian probabilistic matrix factorization       |
| CART    | Classification and regression tree                |
| ConvNet | Convolutional neural network                      |
| HMM     | Hidden Markov model                               |
| MART    | Multiple additive regression tree                 |

## Introduction

The current state of global warming and the energy crisis, exacerbated by the misuse of fossil fuels in previous decades, has significant implications for inclusive economic strategies, environmental concerns, and energy security. In response to these challenges, clean and sustainable energy sources have gained prominence as alternatives to conventional power sources [1]. Photovoltaic (PV) energy, as a renewable source, has witnessed increasing popularity due to its environmental friendliness and absence of pollution emissions [2]. To ensure stability in power generation, power prediction algorithms play a crucial role, especially in hybrid power plants, allowing for seamless switching between various energy sources [3]. Solar power prediction techniques are broadly categorized as either statistical or physical. Forecasting solar irradiation involves utilizing statistically derived factors and training data through deterministic methods, employing PV device models obtained from software programs like PVSyst and System Advisor Model [4].

## PV Power Generation Forecasting Classification

Researchers have attempted to categorize PV power generation predictions based on various parameters. Although there

are no universally established criteria for such categorization, common divisions include those based on forecasting horizon, historical solar irradiance fluctuations, and meteorological data patterns [5].

### Classification Based on Prediction Horizon

Prediction horizons define the timeframes over which PV power outputs are extended, such as 20, 40, 60, and 180 s. Forecasting model systems have demonstrated forecast errors ranging from 3.20 to 15.50 percent for prediction periods between 20 and 180 s [6]. Specific research findings suggest three categories for PV power output predictions based on time horizon, as illustrated in Fig. 3 [7]. The proposed method in this study covers forecast timeframes from 15 to 95 min, providing flexibility in prediction horizons (Fig. 1).

### Historical Data-Based Categorization of PV Power Forecasting Methods

The classification of PV power generation predictive methods can be based on historical information related to PV power output and associated climatic traits. Figure 7 illustrates a categorization into four main groups with subgroups, encompassing various modeling approaches: persistence, statistical, machine learning, and hybrid methodologies [9].

**Persistence Models** These models rely on the assumption that past PV power output patterns will persist into the future. Subgroups may include simple persistence models and advanced persistence models that consider additional factors [10].

**Statistical Models** This category involves methods that utilize statistical analyses of historical data to make predictions. Subgroups may include time-series analysis, regression models, and probabilistic forecasting.

**Machine Learning Models** Employing advanced algorithms, machine learning models analyze historical data to identify patterns and make predictions. Subgroups may include support vector machines, neural networks, and decision trees [11].

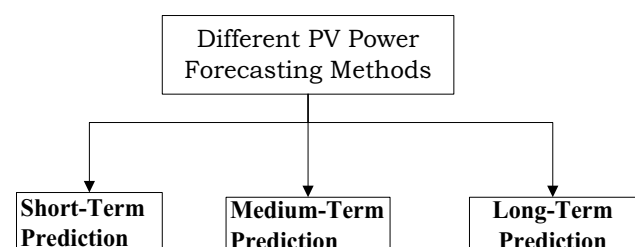


**Fig. 1** Forecasting of PV electricity classified according to time horizon [8]

**Hybrid Methodologies** Combining elements from multiple modeling approaches, hybrid methodologies aim to leverage the strengths of different methods. Subgroups may include statistical-machine learning hybrids or persistence-machine learning hybrids [12].

This categorization based on historical data provides a framework for understanding the diverse approaches utilized in PV power forecasting. Subsequent sections will delve into each category, exploring the methodologies, advantages, and challenges associated with persistence, statistical, machine learning, and hybrid models in the context of predicting PV power generation [13] (Fig. 2).

## Data Collection and Preparation

The process of forecasting PV power generation involves meticulous data collection and preparation to ensure the reliability and accuracy of the developed models [15]. The key steps in this phase are summarized in Fig. 1, and the methodology includes four crucial steps:

**Gather Data from the Solar PV System** The initial step involves collecting relevant data from the solar PV system, encompassing various contribution variables. This data is essential for understanding the characteristics and patterns associated with PV power generation.

**Remove Outliers & Impute Missing Values** To enhance the quality of the dataset, outliers are identified and removed, and missing values are imputed. This pre-processing step is vital for ensuring that the data is clean and free from anomalies that could potentially skew the forecasting model.

**Normalize the Original Data** Normalization is performed to transform the raw data into a usable format. This step ensures that the data is standardized, making it suitable for training various machine learning methods, including the neural network model.

**Develop, Test, and Validate the Model** The dataset, now refined and normalized, is used to train various machine learning methods, with a focus on the neural network model. This training phase involves using output responses with known values to refine the model system. The model is then tested and validated to assess its accuracy and effectiveness. The accuracy of the constructed model is evaluated using a variety of statistical measures. This thorough assessment ensures that the developed forecasting model meets the required standards for reliability and precision. Finally, with a validated model in place, it can be effectively utilized to forecast power generation from the solar PV system. This data collection and preparation phase forms the foundation for subsequent modeling and forecasting steps, emphasizing the importance of a robust and well-prepared dataset for accurate predictions [16] (Fig. 3).

Various studies using data from environmental sensors and integration of customer comfort to create extra advanced energy management systems have been developed recently [18].

The utilization of real-time environmental data, such as actual room temperature, customer preferences, and schedules, ensures enhanced consumer comfort and optimizes energy consumption [20]. Additionally, an intelligent system, relying on rule sets and practiced knowledge, has been developed to generate a reliable power profile. This profile

**Fig. 2** Classification of forecasting techniques using past data [14]

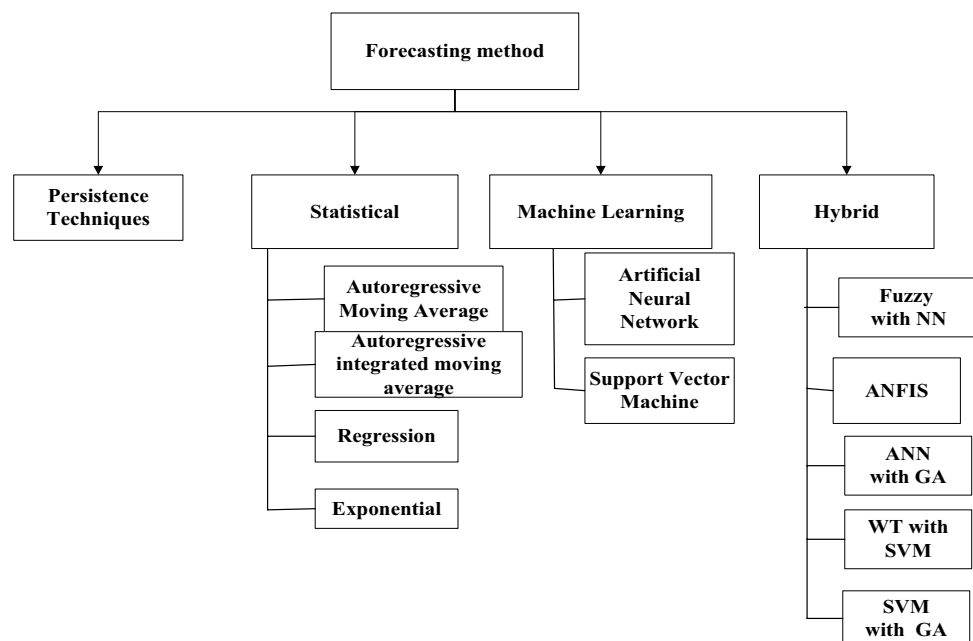


**Fig. 3** Diagram of proposed model [17]

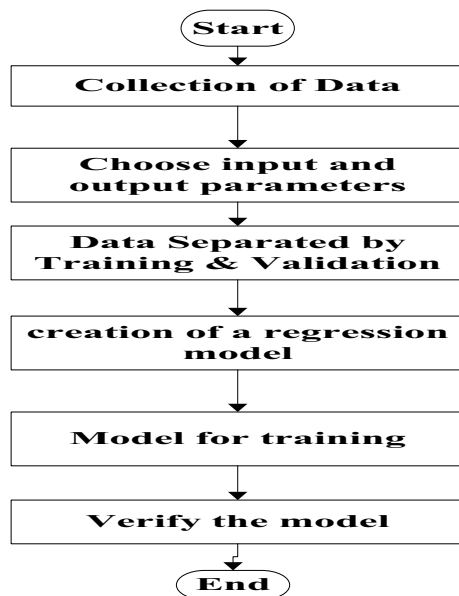
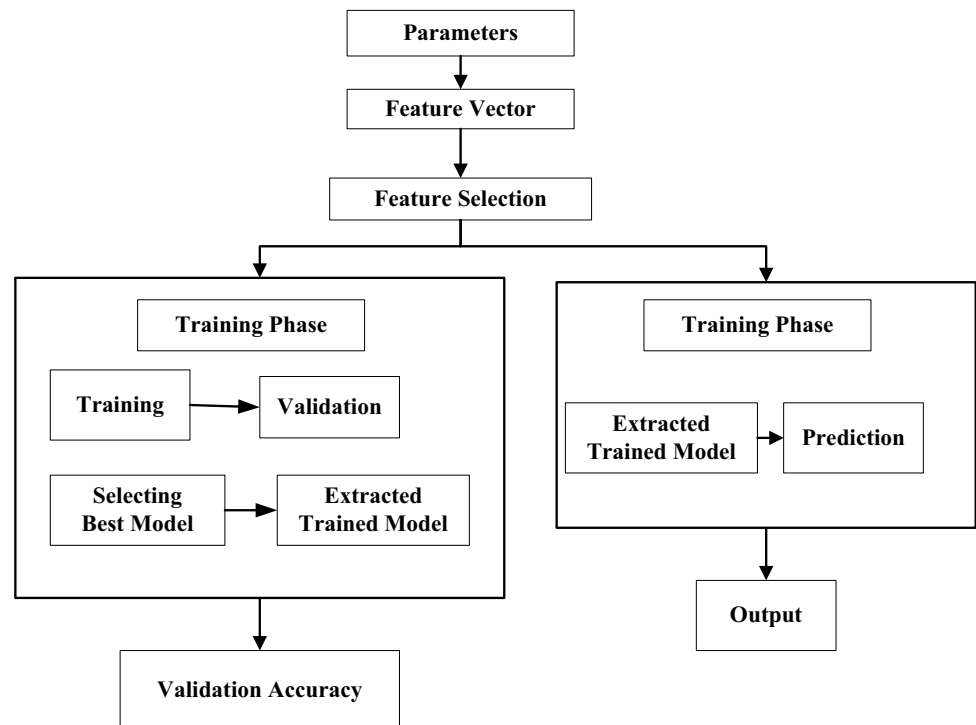


**Fig. 4** A basic prediction model flowchart [19]

effectively controls power activities, balancing consumer comfort and minimizing power costs.

### Data and Framework

This section outlines the data collection approach employed to assess machine learning algorithms [21]. Figure 4 visually

represents the evaluation framework, encompassing phases like data collection, pre-processing, cross-validation, and ten-fold cross-validation. The data-gathering process draws information from four distinct sources.

### Pre-processing of Model Input Data

To address the dynamic weather conditions affecting photovoltaic (PV) power generation, previous PV power output and meteorological data serve as input in forecasting systems. Efficient chronological pattern recognition during input data pre-processing substantially reduces computation rates and training complexity [22].

Optimizing forecasting model performance involves pre-processing incoming data due to shocks and the lack of consistency in the information they introduce. Various pre-processing techniques have been applied to forecast models, including static adjustments, historical lag identification, normalization, wavelet transform, and self-organizing maps [23]. Normalization, for instance, constrains data within a 0–1 range, reducing regression errors, enhancing accuracy, and preserving dataset correlation [24].

Numerous studies propose ideal energy models for consumer dependence on demand response (DR) techniques through optimization approaches [25]. These models focus on managing energy systems optimally to reduce operational costs, incorporating load shedding and scheduling on the demand side. DR estimation methods for both residential and commercial customers utilize regression models based

on usage time and temperature set points [26]. The approach presented demonstrates DR potential and adaptability for predicting peak load drops in a smart home energy management system [27]. Moreover, this technology links renewable energy sources to smart grid control (Fig. 5).

## Forecasting Models

The fundamental model system proposed for power forecasting in this work encompasses regression and prediction

methodologies. This model integrates linear regression, regression trees, and the Gaussian process [29].

In the linear regression model, a linear relationship is established between the system's input and output parameters. The GPR algorithm, based on a Gaussian process, utilizes a training dataset to determine values for unknown parameters [30]. The subsequent steps involved in developing the forecasting model are elucidated.

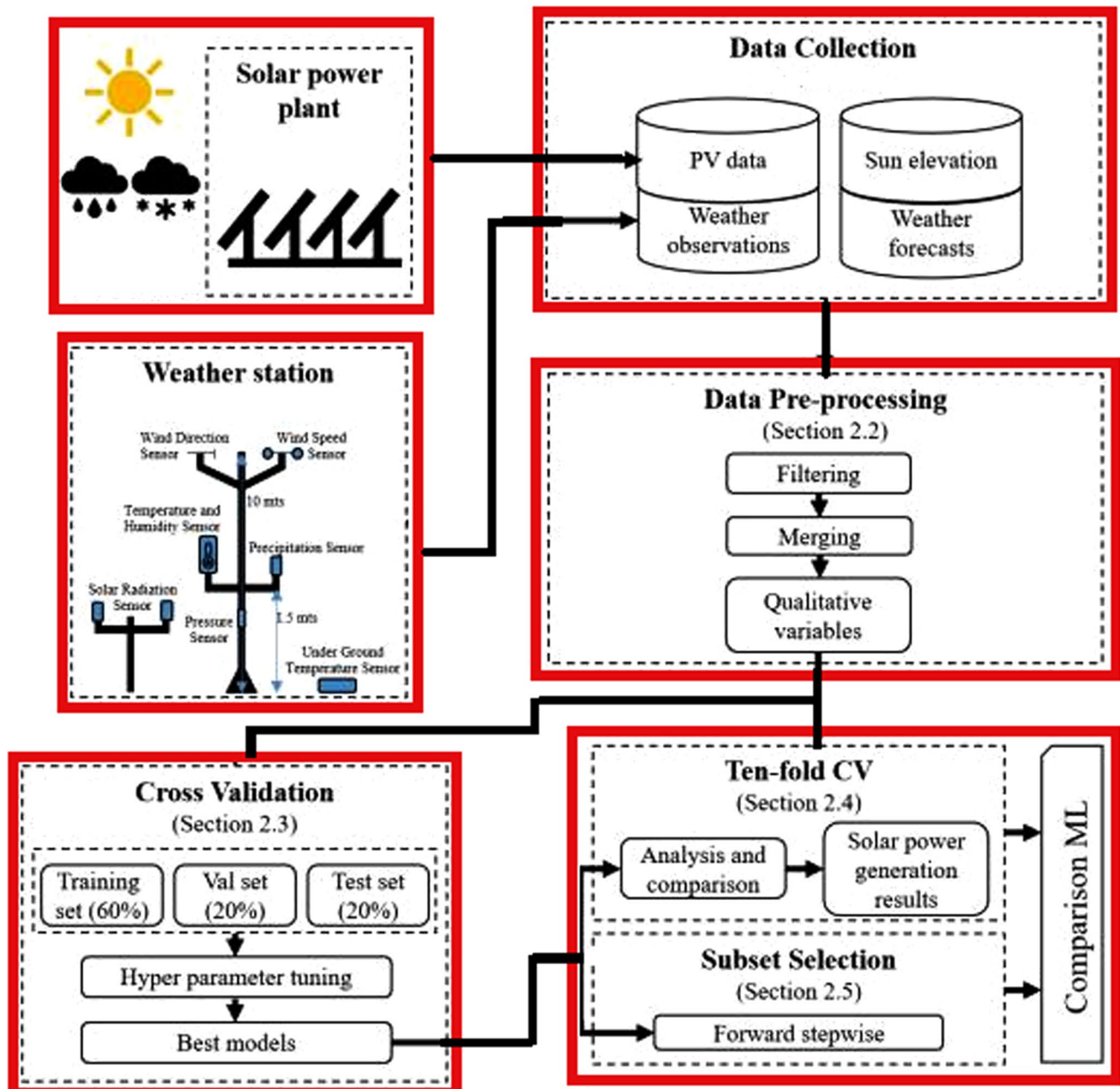


**Fig. 5** Comparison of machine learning methods for predicting solar power [28]

## Persistence Model

When devising PV power prediction models, performance evaluation against a reference model is crucial. This ensures that the prediction model surpasses relevant reference models. Only when a sophisticated forecasting technology significantly outperforms simple models is its development and use justified [31]. Persistence models, assuming constant power production over time, serve as common reference models. Among these, the simplest, referred to as simple or naïve persistence, assumes constant power output [32].

## Statistical Approaches Forecasting Models

A highly accurate power forecasting system model is imperative to sustain grid operation and promote PV system adoption. Various factors, particularly machine learning algorithms, influence forecasting model efficacy. Therefore, the development of a more accurate power forecasting model becomes necessary to enhance grid functionality and encourage PV system usage [33].

### Regression Technique

To predict PV power generation, two separate regression models employing both simple and advanced linear regressions are utilized [34]. The regression model demonstrates superior performance when utilizing both solar irradiance

and temperature as inputs compared to using only one of them. However, this technique requires the creation of a forecasting method based on regression, involving the use of a mathematical model and multiple explanatory factors [35].

### Autoregressive

Autoregressive models measure the correlations between dependent and independent factors. The categorization depends on how time series are handled, whether they are stationary or non-linear. Time series that oscillate around a fixed mean are termed stationary time series [36] (Fig. 6).

### Autoregressive Moving Average Model

Autoregressive moving average (ARMA) models play a crucial role in modeling time series, especially due to the simplification of linear prediction in ARMA processes [38]. An ARMA process combines both autoregressive (AR) and moving average (MA) models. When compared to pure AR and MA models, ARMA models can represent unknown processes with the fewest parameters, making them the most efficient linear models for stationary time series [39] (Fig. 7, Table 1).

**Fig. 6** ARMA-based predictions [37]

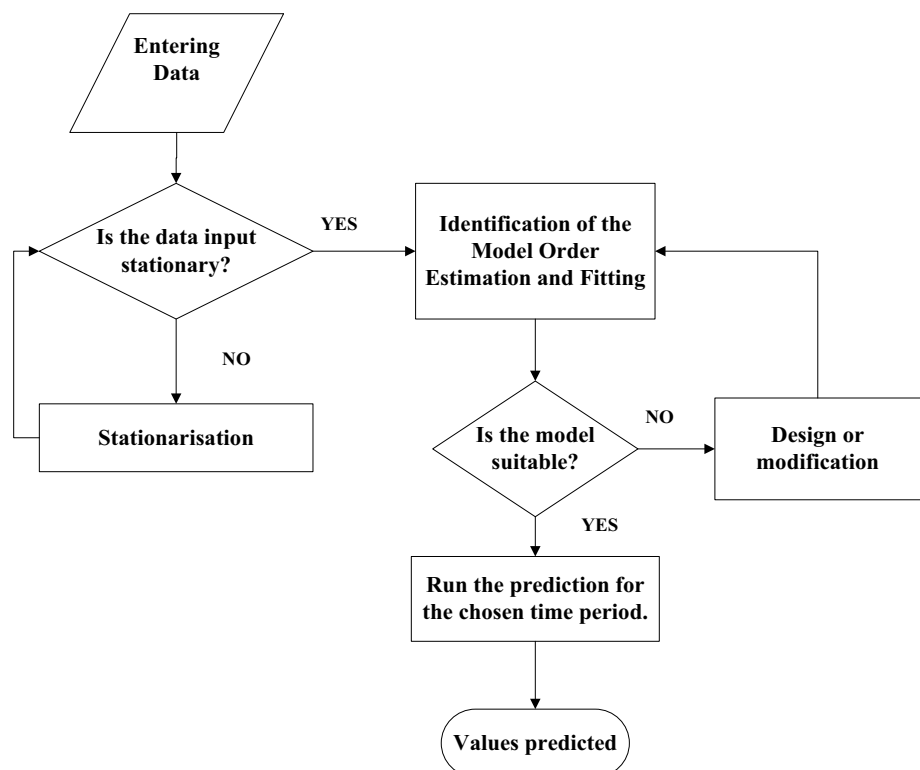
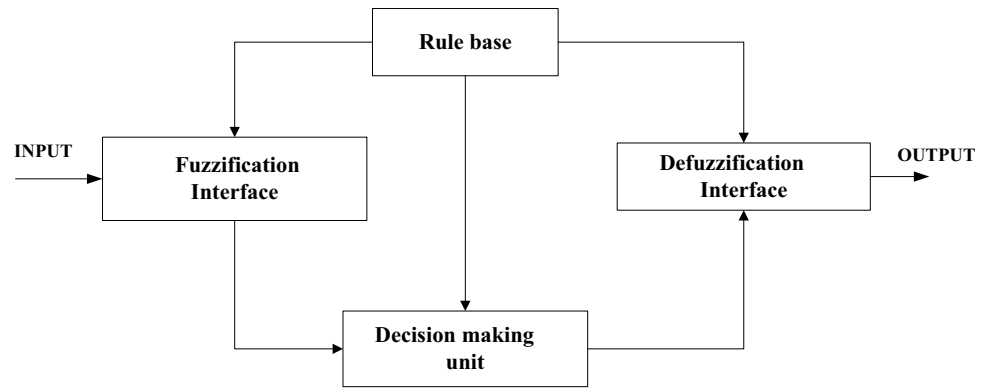


**Fig. 7** Basic block of fuzzy logic system [40]

### Exponential Smoothing Method

The fundamental exponential smoothing strategy, now known as the exponential smoothing method, was introduced by Brown in his original publication [46]. Holt later enhanced the method, giving rise to Holt's approach, and winter further refined it. In the exponential smoothing method, historical data receives uneven weights rather than equal weights [47]. These weights progressively decrease between the closest and farthest data points. Basic exponential smoothing, also known as exponentially weighted moving average, is a straightforward technique [48].

### Machine Learning Approaches Forecasting Models

#### Support Vector Machine (SVM)

The foundation of supervised machine learning lies in the concept of structural risk reduction, or SVM, which lowers the upper bound on anticipated risk [49]. This enables SVM to reduce training data accuracy, and Vapnik introduced SVM to address classification issues [50]. On the other hand, SVM is a relatively recent development in the realm of regression problems, and the application of SVM to time series regression is referred to as support vector regression (Fig. 8).

#### Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) refer to machine intelligence systems that emulate the functioning of the human brain. These modeling tools are adept at handling challenges associated with nonlinear data, pattern recognition, simulation, and optimization [52]. The accuracy of an ANN model's forecast is influenced by input parameters, training approach, and structural setup [53] (Fig. 9 and 10).

ANN proves effective in addressing practical issues characterized by non-linear and complex data, without making assumptions about the nature of relationships [54, 55]. The

training phase holds paramount importance in the implementation of ANN. The fundamental configuration of an ANN is depicted in Fig. 7 (Table 2).

### Physical Method

Physical models are constructed based on variables specific to PV power stations, such as location, weather conditions, and historical orientation data. These models can vary in complexity, from simple to more intricate designs [63, 64]. However, the predictability of these models is heavily reliant on weather forecasts and requires adjustments tailored to specific plants and regions, especially when unexpected changes in meteorological parameters can significantly impact performance predictions [65].

### Hybrid Model

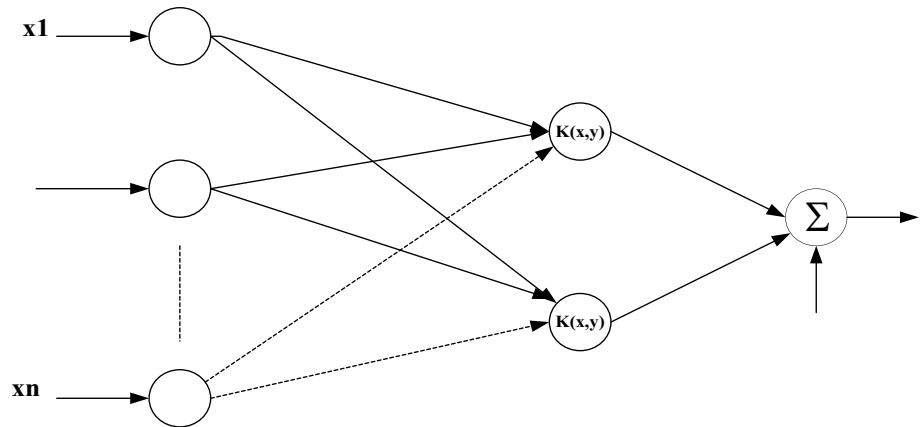
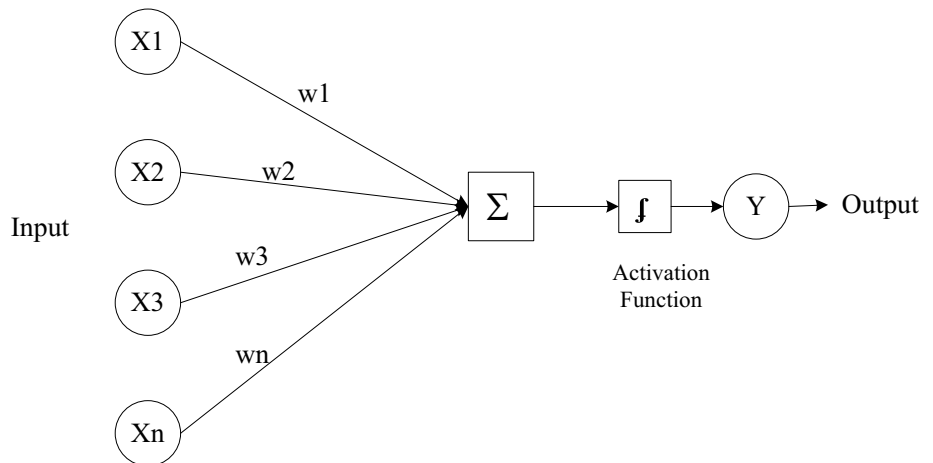
In situations where estimating solar power output using a single prediction model proves less accurate, a hybrid model incorporating two or more approaches can be employed [66]. Such models have demonstrated improved prediction accuracy across various applications. A primary objective of these hybrid models is to explore how different approaches can be combined to enhance forecast accuracy [67]. For instance, a hybrid fuzzy-GA forecasting model, integrating fuzzy inference models with genetic algorithms, has shown promise in solar energy predictions [68].

### Deep Learning

Deep Learning (DL) involves the use of a multi-layer perceptron network trained with an ADAM optimizer for optimal classification accuracy. The architecture comprises multiple hidden layers, with the number of layers depending on the specific classifier [69]. Explainable AI (XAI) techniques are then employed to extract classification rules used by the deep learner [70]. These rules, presented in disjunctive normal form, result from various combinations of input neurons

**Table 1** Overview and evaluation of ENN-based prediction methods

| References | Approach                                         | Workflow/strategy                                                                                                                    | Datasets                                         | Implementation | Predicted parameters            | Error metrics | Results or remarks                                                                            |
|------------|--------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------|----------------|---------------------------------|---------------|-----------------------------------------------------------------------------------------------|
| [41]       | Neural Network with Black Hole Optimization      | Neural network utilizes Black Hole method on pre-processed training data                                                             | Web servers in Calgary, Saskatchewan, and NASA   | MATLAB         | Number of queries per second    | MAP           | Inaccuracy up to 134 times lower than BP                                                      |
| [42]       | ANN-SaDE                                         | Feed-forward neural network trained using self-adaptive differential evolutionary method                                             | NASA and Saskatchewan                            | MATLAB         | Number of queries per second    | MAP           | 168 times more accurate with a 0.001 reduction in error compared to BP                        |
| [43]       | ANN-BaDE                                         | Optimization of ANN using DE method with three mutation procedures and three crossover strategies                                    | NASA, Saskatchewan, Google Cluster traces        | Python         | Request volume, CPU, memory use | MSE           | Accuracy increased over SaDE and BP by up to 91% and 97%, respectively                        |
| [44]       | ANN-TaDE                                         | ANN optimization with DE approach employing three mutation techniques, three crossover strategies, and control parameter adjustments | NASA and Saskatchewan                            | Python         | Number of queries per second    | RMSE          | Accuracy increased over BP and SaDE by 97.4% and 94.8%, respectively                          |
| [17]       | Self-directed workload forecasting method (SDWF) | Utilizes forecasting error trends to enhance accuracy by computing variance from prior forecasts                                     | NASA, Saskatchewan (HTTP traces), Google Cluster | MATLAB         | Request volume, CPU, memory use | MSE           | Error over comparable techniques reduced by up to 99.99%                                      |
| [45]       | FLGAPSONN: FLNN + GA + PSO                       | FLNN optimization using hybrid GAPSO method on pre-processed training data                                                           | Google Cluster traces                            | Python         | CPU, memory, disk usage         | MAE           | Increased accuracy over FLPSONN, FLGANN, and FLNN by 21.87%, 13.75%, and 30.55%, respectively |

**Fig. 8** SVM architecture [51]**Fig. 9** An ANN structure [5]

with co-occurring activations. While binary classifiers are utilized in this method, continuous classifiers may require sample division into quintiles to develop rules [71].

The training process involves feeding the four data clusters into a model, training four forecasting models using a time series approach. Each category's training data is represented as  $[y_1, y_2, \dots, y_n]$ , where 'y' denotes AC2 data, and the quantity of AC2 data in each category is specified [72]. The time step 't' is set for the new training set  $[y_1, y_2, \dots, y_t]$ , with the goal value established. The model parameters are adjusted during training to ensure the projected output consistently falls within a certain range [73]. After reaching the goal value, model training is completed, resulting in the obtained forecasting model [74] (Fig. 11).

#### Prediction Model Architecture

For prediction purposes, the Long Short-Term Memory (LSTM) layer receives the feature vector generated from the second layer of the Convolutional Neural Network (CNN). Each of the 32 units in the LSTM layer corresponds to an element of the feature vector [76]. The attention mechanism

assigns more weight to feature values significantly connected to the current output. Subsequently, an Fully Connected (FC) layer employs the unfolding technique to handle the output vector of the attention mechanism. The final output is the anticipated value of AC2 at the next instant [77].

LSTM proves to be highly beneficial in predicting time series data, and combining it with CNN has demonstrated outstanding predictive performance in various applications [78, 79]. The collaboration between CNN and LSTM enhances the extraction of meaningful features from experimental data. The attention mechanism introduces a weighting procedure, allowing more precise weightage values to be applied to the LSTM output vector, thereby augmenting the model's predictive capacity [80, 81].

The predictive power is determined by the inverse normalization equation:

$$Prp = Priac2 \times (Pmax - Pmin) + Pmin$$

Here, PRP represents the predicted value of power, Priac2 is the predicted value of AC2, Pmax is the maximum power value, and Pmin is the minimum power value (Table 3).

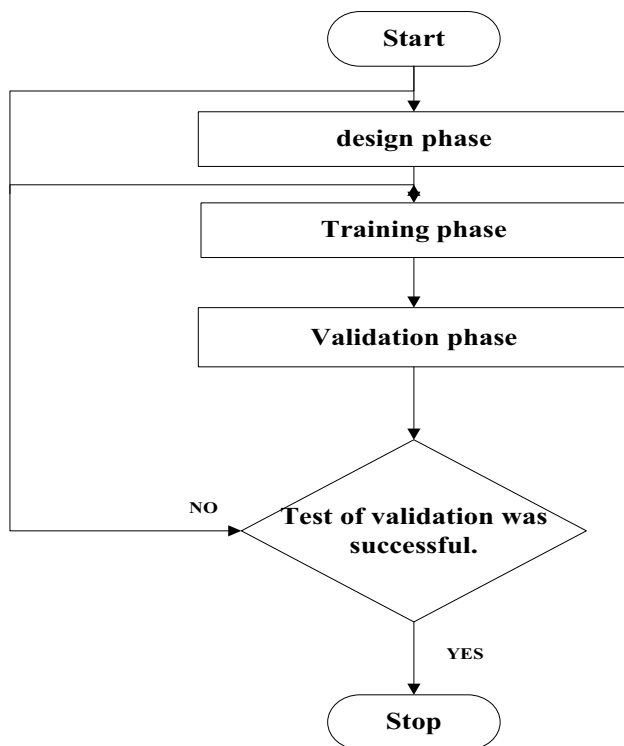


**Fig. 10** Flow chart of an ANN [56]

## Other Forecasting Models

### Particle Swarm Optimization

An uncomplicated yet effective metaheuristic technique is the Particle Swarm Optimization (PSO) approach, classified under Evolutionary Computation methods [94]. Particularly useful for multivariable optimization functions with multiple constrained parameters, PSO employs a group of agents to explore the solution space [95]. Each agent shares or trades the information it gathers during the search process to collectively converge towards a global optimum. PSO's simplicity and efficiency make it a valuable tool for various forecasting applications (Fig. 12).

### Markov Chain

Markov Chain models are characterized by a series of random parameters where only serial dependence between adjacent states is required to satisfy the Markov property [97]. This model represents a system comprising interconnected levels, with each level representing the state of the Markov process, determining the subsequent state [98, 99]. Transitions between states in the system are denoted as changes, and the associated probabilities for these transitions are captured in a transition matrix, as illustrated in Fig. 5. The transition matrix, associated with the initial state, delineates

the probabilities governing transitions and is instrumental in identifying the process. It is crucial to note that the Markov process accounts for every possible state and transition in its formulation, ensuring that the process continues indefinitely, evolving into the next state [99] (Fig. 13).

### Genetic Algorithm

**Genetic Algorithm (GA)** GA is a metaheuristic optimization methodology that involves the generation, systematic evaluation, and refinement of potential solutions until a specified end condition is met. The three major functions integral to the methodological technique are selection, crossover, and mutation [101] (Fig. 14).

**Selection** In the first phase, known as selection, chromosomes are transferred from one location to another based on their fitness function. This process helps propagate solutions that exhibit better fitness [102].

**Crossover** The next stage is crossover, where two chromosomes are combined to form a new and potentially improved chromosome. This operation enables the exchange of genetic information between solutions [103].

**Mutation** The stochastic nature of GA is achieved in the final step of mutation. Mutation introduces small random changes to the chromosomes, allowing the algorithm to explore new regions of the solution space and converge more swiftly to optimal solutions [104].

### Ant Colony Optimization

Ant Colony Optimization (ACO) is an efficient recovery optimization method. In the ACO operation, ants initiate their search for food from various starting places [105]. Their movements are influenced by the length of the paths they traverse, and the optimization process is guided by the collective behavior of the ant colony. ACO is particularly effective in solving combinatorial optimization problems, and its inspiration is drawn from the foraging behavior of real ants [106] (Fig. 15).

### Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a computational model that simulates the structure and functioning of the biological brain [107]. It consists of several artificial neurons interconnected with each other. The ANN is designed with three essential layers input, hidden, and output to estimate the output for a given set of inputs. The architecture of an ANN, as depicted in Fig. 13, showcases the arrangement of these layers [108]. The number of nodes chosen by the user for each layer can vary based on the specific requirements of different applications [109] (Table 4).

**Table 2** Comparison of hybrid machine learning-based prediction models

| References | Model/approach                              | Workflow/strategy                                                                                  | Datasets                                 | Implementation                  | Predicted parameters                 | Error metrics                                     | Results or remarks                                                         |
|------------|---------------------------------------------|----------------------------------------------------------------------------------------------------|------------------------------------------|---------------------------------|--------------------------------------|---------------------------------------------------|----------------------------------------------------------------------------|
| [19]       | ACPS                                        | Automatic generation of prediction models based on task characteristics                            | Google Cluster traces                    | Python                          | Response time, Cost                  | Mean error, Mean relative prediction error        | 40.86% decrease in prediction error compared to linear regression          |
| [51]       | FAHP                                        | FAHP and SVR algorithms for workload prediction, resource provisioning, and auto-scaling decisions | Clark Net, NASA, Synthetic workload      | Cloud Sim and Open source RUBIS | Request arrival, Response time, Cost | MSE, NMSE, RMSE, RMSSE                            | Decreased rent costs for cloud service providers with improved QoS         |
| [57]       | GRUED                                       | GRU encoder-decoder for workload sequence translation                                              | Google Cluster, Dinda workloads          | Python, UNIX system             | CPU, Job arrivals                    | MAE, MAPE, RMSE, root mean segment squared error  | LSTM prediction error reduction                                            |
| [58]       | LSRU: LSTM + GRU                            | Combined LSTM and GRU with statistical approaches (AR, ES, ARMA)                                   | Bitbrains, Kaggle                        | Bandwidth, Disk, Memory, CPU    | MAE, MAPE, RMSE, MSE                 | Reduced prediction error compared to LSTM and GRU |                                                                            |
| [59]       | ADRL: Deep RL+QLearning                     | RL model based on deep Q-learning for resource scalability and decision-making                     | Web-based Rice University Bidding System | Python with Java-based CloudSim | CPU, Memory, Response time           | MSE                                               | Increased stability and QoS                                                |
| [60]       | BiHyPrec: Bi-LSTM + LSTM + GRU              | Collaboration of Bi-LSTM, LSTM, and GRU units for managing time series data complexity             | Bitbrains traces                         | Python and Google Collaboratory | CPU usage                            | MSE, MAPE, MAE, RMSE                              | Outperforms ARIMA, LSTM, GRU, and Bi-LSTM                                  |
| [61]       | BG-LSTM: Bi-LSTM + GridLSTM                 | Hybrid model using Bi-LSTM and GridLSTM with Savitzky-Golay smoothing                              | Google Cluster traces                    | Python                          | CPU and RAM usage                    | MSE, RMSLE, R2                                    | Superior accuracy compared to SG-LS, SG-Bi, and SG-GridLS                  |
| [62]       | HPFDNN: Hierarchical Pythagoras + Fuzzy DNN | Combination of deep neural networks, neural representations, and Pythagorean fuzzy logic           | Carnegie Mellon University dataset       | Not mentioned                   | Number of requests                   | Accuracy cost and total cost saving               | \$202.48 savings compared to traditional techniques for real-time requests |

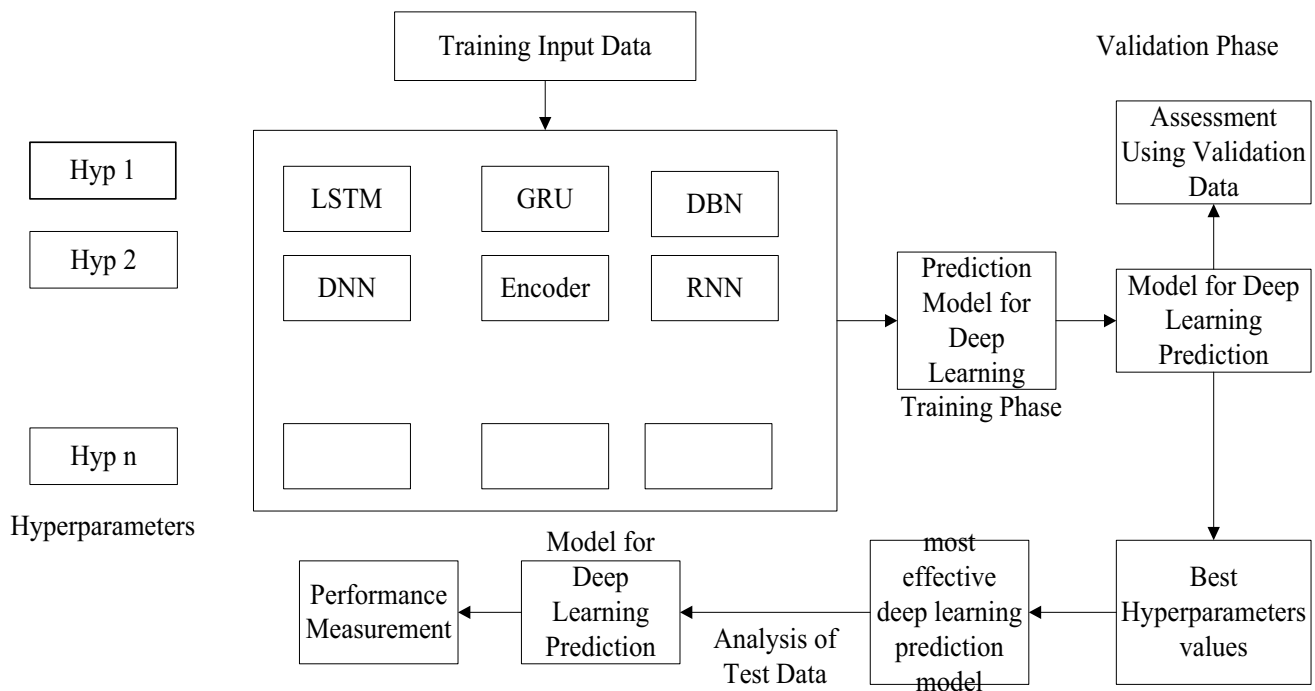


**Fig. 11** Block diagram of deep learning process [75]

## Performance Analysis of Different Forecasting Methods

Quantitative methods focus on modeling based on historical observations when predicting lighting statistical models [159]. Advanced AI strategies, such as artificial neural networks, play a crucial role in building solar predictions, which can be characterized as a form of quantitative analysis. The use of computer climate models allows for the proposal of mathematical models for solar irradiance and PV production [160].

To fulfill the requirements of the statement phase, various modeling methodologies are employed, adapting to different dimensions of climatic parameters [161]. This publication reviews state-of-the-art PV and photovoltaic forecasting approaches developed in recent years. The benefits and drawbacks of these new options are explored from both technical and philosophical perspectives [162]. Additionally, the utilization of photovoltaic forecasting in distributed generation monitoring is thoroughly examined. The performance analysis delves into comparing and contrasting the effectiveness of different forecasting methods in capturing and predicting solar energy patterns [163].

## Metrics for Evaluating the Forecasting Models

The literature has made use of statistical metrics such as co-efficacy, mean absolute error, and mean absolute percentage error to assess predicting proficiency R2, MAE, RMSE,

and MAPE were utilized in this learning since they were frequently used to measure predicting accuracy [165]. A significant source of issue is a model's training performance is evaluated (Fig. 16). It specifies the model's suitability for a practical application. Three primary performance criteria that determine the model's correctness are studied in this paper. The three performance criteria are as follows [166]:

- Mean absolute percentage error (MAE).
- Root mean square error (RMSE).
- Mean absolute error (MAPE).
- Coefficient of determination (R2).

### Mean Absolute Percentage Error

MAEs are used to determine the prediction error, or the difference between the actual data and the anticipated data [167].

$$MAE = \frac{1}{N} \sum_{i=1}^N |\bar{P}_i - P_i|$$

### Mean Absolute Error

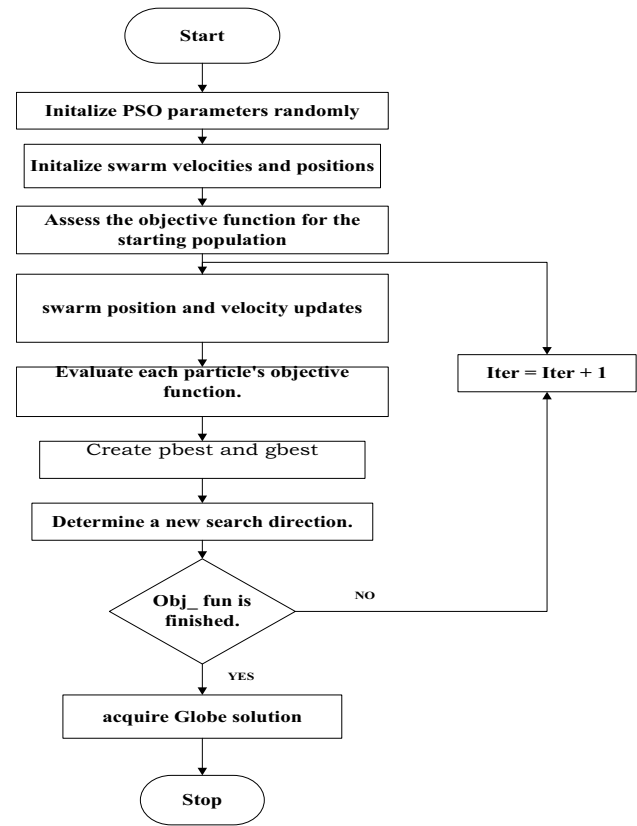
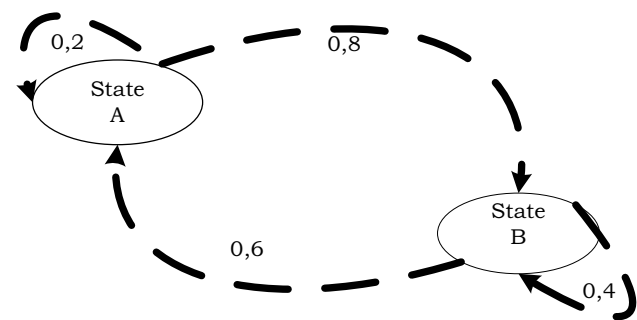
Frequently referred to as the mean absolute percentage deviation, the mean absolute percentage error is a statistician's way of gauging how well a forecasting technique, like trend estimate, will be able to predict the future. It may be

**Table 3** Detailed comparison of deep learning-based prediction methods

| References | Model              | Workflow                                                             | Datasets                              | Implementation           | Predicted Parameters          | Error Metrics        | Results or Remarks                                                                   |
|------------|--------------------|----------------------------------------------------------------------|---------------------------------------|--------------------------|-------------------------------|----------------------|--------------------------------------------------------------------------------------|
| [82]       | DBN+RBMs           | DBN identifies patterns and applies regression for prediction        | Planet Lab traces                     | Cloud SIM                | CPU utilization               | MAPE                 | Performance up to 1.3% better than the old approach                                  |
| [83]       | DNN-PPE            | Recursive Auto Encoder with pre-processed data                       | World Cup 98 (WC98), Clark net traces | Python                   | Number of requests, Power     | –                    | 79% less inaccuracy than canonical prediction                                        |
| [40]       | DBN+OED            | DBN+OED model with back propagation adjustment                       | Google Cluster traces                 | Python                   | CPU, RAM usage                | MSE                  | MSE attained in the [10p4, 10p3] range                                               |
| [84]       | LSTM/RNN           | Looping combinations of networks for pre-serving knowledge           | Web server HTTP traces                | MATLAB                   | No. of requests per unit time | MSE                  | Up to 0.00317 RMSE reduction                                                         |
| [85]       | CP auto encoder    | Features compressed with canonical polybasic decomposition           | Planet Lab traces                     | MATLAB                   | CPU utilization               | MAPE, RMSE           | Maximizes training effectiveness and predictability for industrial tasks             |
| [86]       | L-PAW auto encoder | Workload patterns extracted with TSA, predicted by GRU+RNN           | Alibaba, Google, DUX-cluster          | TensorFlow 1.4.1, Python | CPU, Memory, Disk I/O usage   | MSE, CDF             | Outperformed LSTM, RNN, and GRU accuracy                                             |
| [87]       | SG-LSTM            | S-G filter smoothens data, fed to LSTM for improved prediction       | Google traces                         | Python                   | CPU, Memory                   | Logarithmic RMSE, R2 | Fared better than LSTM, SG-LSTM, SG-BPNN, and BPNN                                   |
| [88]       | 2-D LSTM           | Input data analyzed for weak dependency, weights parallelization     | Shanghai Supercomputer workload       | Not mentioned            | Workload over days            | MSE                  | Accuracy increased for massive real-time cloud services                              |
| [741]      | Bi-LSTM            | Training data propagated through input layer, two Bi-LSTM layers     | 55,55,55 tasks traces                 | TensorFlow in Python     | Task failure rate             | F1-Score             | 93% precision and 87% task failure rate forecasted with accuracy                     |
| [89]       | DP-CUPA            | DBN anticipates load data, PSO assesses fitness of tuning parameters | Google Cluster traces                 | Not mentioned            | CPU usage                     | MSE, MAPE, MAE       | Superior to Autoregressive, DBN, and Grey models                                     |
| [90]       | Crystal LP         | LSTM trained with SGD+Adam optimizer for load pattern forecasting    | Web search archive, SPC traces        | Keras library, Python    | Request size                  | MAPE, RMSE, MAE      | 1.10% increase in MAPE demonstrated, outperformed previous techniques in MAE         |
| [91]       | Encoder LSTM       | Encoder prepares input matrices, LSTM forecasts load information     | Planet Lab traces                     | Cloud SIM and Python     | CPU, Memory, Bandwidth        | MSE, MAPE            | Decreased execution time by 13%, 11%, 16%, and 19%, along with resource improvements |

**Table 3** (continued)

| References | Model    | Workflow                                                                                    | Datasets                                    | Implementation             | Predicted Parameters             | Error Metrics                               | Results or Remarks                                     |
|------------|----------|---------------------------------------------------------------------------------------------|---------------------------------------------|----------------------------|----------------------------------|---------------------------------------------|--------------------------------------------------------|
| [92]       | DNNMVM   | Classification, pre-processing, and transmission of data to DNN-MVM                         | Grid Workload Archive (GWA) traces          | Google Colab using Keras   | CPU, Memory, Disk Utilization    | MSE                                         | Prediction accuracy of more than 85% for each resource |
| [92]       | FEMTLSTM | Feature-enhanced deep learning model for turning point prediction                           | Google Cluster, Alibaba, HPC Grid workloads | Keras library, Python      | CPU usage                        | Binary Cross-Entropy, F1, Precision, Recall | F1 score 6.6% better than current methods              |
| [93]       | es-DNN   | Multivariate data transformed into time series using supervised learning, modified GRU used | Alibaba, Google Cluster traces              | TensorFlow 2.2.0 in Python | CPU usage per time-unit interval | MAPE, MSE, RMSE                             | Lowered active hosts, decreased costs effectively      |

**Fig. 12** The flowchart of PSO [96]**Fig. 13** 2-States Markov chain [64]

computed using the method below and is frequently represented as a percentage [168].

$$MAPE = \frac{1}{N} \sum_{i=1}^N 100 \frac{|\bar{P}_i - P_i|}{P_n}$$

In this equation,  $P_n$  stands for the projected value,  $P$  for the nominal power,  $N$  for the number of test points,  $P$  stands for the anticipated value,  $N$  stands for the number of test points, and  $P_i$  stands for the value observed at the  $i$ th hour. Two benefits exist for MAPE. In the beginning, The positive

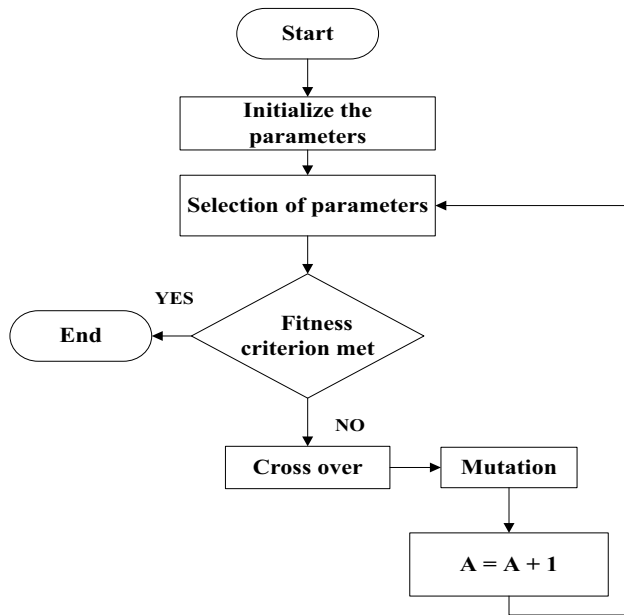


**Fig. 14** Flowchart of GA [100]

and negative mistakes are kept from canceling one another out by the absolute values. Second, this measure may be used to compare forecast accuracy across fully scaled data

since relative errors are independent of the dependent variable scale [169].

#### Root Mean Square Error

A common statistic used to compare values predicted by a model or estimator with the actual values observed is the mean square error, also known as the root mean square deviation.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \frac{|\bar{P}_i - P_i|^2}{P_n}}$$

By mixing various combinations and running several trials for the resulting models, detailed assessments are carried out [170].

#### Coefficient of Determination

It is a statistical evaluation of the variation in the expected energy generation that the feature input sets lead to in the output of the ANN models. In real-world applications,  $R^2 = 100\%$  values imply that the ANN prediction model's input parameters can fully explain the variation of the output

**Fig. 15** Flow chart of ACO [83]

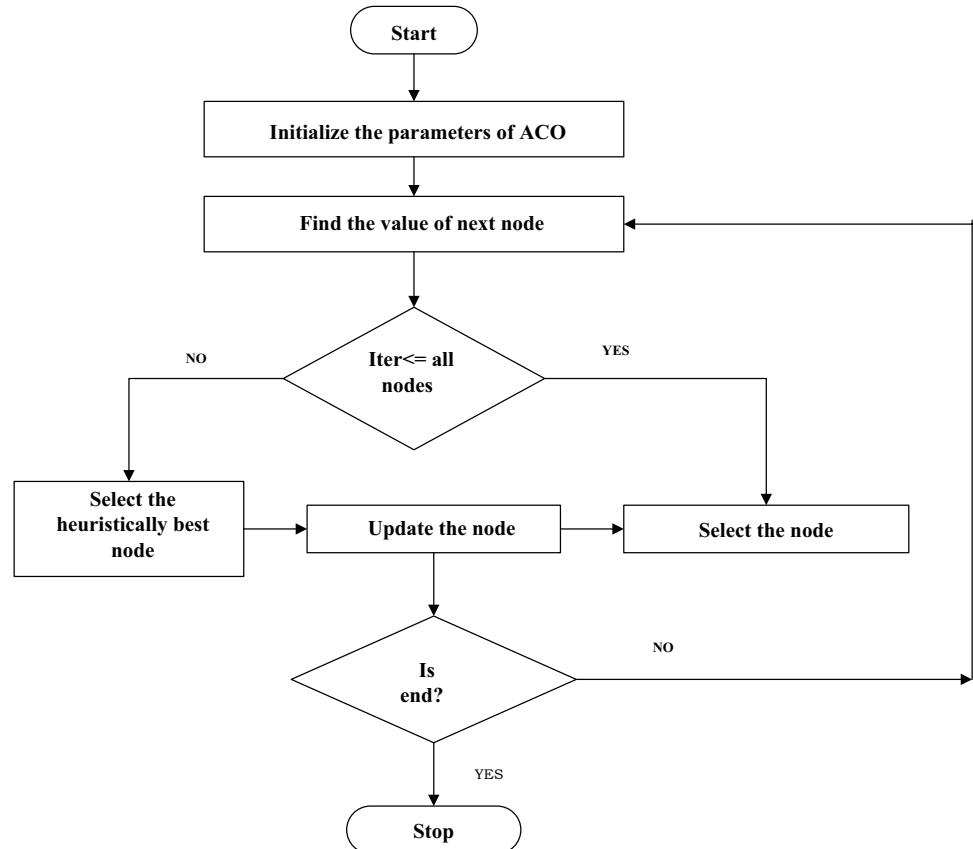


**Table 4** An overview of solar PV power forecasting techniques

| Refer-<br>ences | Forecasting<br>approach                                                                                       | Forecast<br>horizon             | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                   | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                          | Predict-<br>ing con-<br>ditions | Location                                     | Comparative tech-<br>niques                   | Merits                                          | Demerits                                                   |
|-----------------|---------------------------------------------------------------------------------------------------------------|---------------------------------|--------------------------------|---------------------------------------------------------------------------------|----------------------------|---------------------------------------------------------------------------------------------------------------|---------------------------------|----------------------------------------------|-----------------------------------------------|-------------------------------------------------|------------------------------------------------------------|
| [110]           | Building Blocks of an Artificial Neural Network with Multiple Layers of Perception                            | 24 h ahead of schedule          | MBE, RMSE, R                   | r = 98 and 99 percent on a sunny day; r = 94 to 96 percent on a cloudy day      | Ten minutes                | Daily solar irradiation average, Daily average air temperature                                                | Irradiance of the sun           | Trieste, Italy                               | K-fold cross-validation, ANN-MLP architecture | Faster computation, Generalizability            | Predictive limitations                                     |
| [111]           | Hybrid Intelligence Methodology with Wavelet, Deep Convolution Neural Networks, and Spine Quintile Regression | 15 min to 2 h ahead of schedule | MAPE, RMSE, MAE, ACE, IS, CRPS | Various improvements observed                                                   | N/A                        | PV power stats from the past                                                                                  | PV power                        | Belgium                                      | Various comparative techniques                | Improved stability, High performance            | Not suitable for PV energy forecasting, Limited to 1D data |
| [112]           | Random Forests for Wavelet-Coupled Feature Extraction and Bias Correction                                     | 1, 3, 6 h ahead of schedule     | RMSE, MAPE, MAE                | Wavelet-BCRF addresses input data sampling frequencies and forecasting horizons | N/A                        | PV system output data, Weather station sensor data records                                                    | Solar PV power                  | San Diego State University                   | Wavelet-couple SVM, RF, Transform of wavelets | Improved accuracy, Addressed data discrepancies | Limited prediction horizon                                 |
| [113]           | Kernel Techniques Extremely Intelligent Machines (Random Forests)                                             | 1 h to 7 days ahead             | MAE, MSE, NMSE, REP, PPMCC     | Various improvements observed                                                   | N/A                        | Real PV temperature, Outside temperature, Humidity, Wind speed and direction, Atmospheric pressure, Radiation | PV energy                       | Smart Polygeneration Microgrid at Savona Cam | KM, ELM, RF                                   | Improved performance with more data             | Deterioration in performance with longer time horizons     |

**Table 4** (continued)

| References | Forecasting approach                                                                    | Forecast horizon             | Performance indicators     | Measurement of forecast error                                 | Computation period | Input variables                                         | Predicting conditions | Location                             | Comparative techniques                                               | Merits                                                               | Demerits                                           |
|------------|-----------------------------------------------------------------------------------------|------------------------------|----------------------------|---------------------------------------------------------------|--------------------|---------------------------------------------------------|-----------------------|--------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------|
| [114]      | ANN and ANN+AnEn                                                                        | 72 h in advance              | RMSE/NP, CORR, BIAS/NP     | Best results with ANN+AnEn combination                        | N/A                | Temperature of the atmosphere, Elevation, Lead time     | Power from the sun    | Italy (Lombardy, Calabria, Sicily)   | ANN, As, En                                                          | Strong predicting resilience, Efficient pre-computational efficiency | Limited to specific regions                        |
| [115]      | GMDH and LS-SVM Algorithms with PCA and WD Data Pre-Processing                          | 1, 3, 6, 12, 18, 24 h ahead  | Skewness Kurtosis          | Improved performance with PCAWD                               | N/A                | Temperature outside, Solar irradiation on array slanted | PV power              | Italy                                | PCA, WD, WDPKA, PCAWD                                                | Noise removal, Dataset enlargement                                   | Limited forecasting accuracy                       |
| [116]      | Multivariate Polynomial Model with ANN Scaling                                          | –                            | NMBE, NRMSE                | Prediction error decreased with multivariate polynomial model | N/A                | PV production data, Cloud cover, Air temperature        | PV generation         | Lille, France; Guadeloupe, Caribbean | ANN, Multivariate Polynomial Model, Scaled Persistence, System Model | Simple, Versatile, No series requirement                             | Limited prediction accuracy for one input variable |
| [117]      | Forested SVRs from Random SVRs                                                          | Every day in advance         | MAE, RMSE, nRMSE (%), MBE  | SVR approach surpasses other models                           | N/A                | NWP data: GHI, Temperature, Humidity                    | Energy from sun       | Spain                                | Blended model for DNN, SVR, RF, XGB with two-day persistence         | Hybrid models maximize benefits                                      | Longer training time for ensemble Neural Network   |
| [118]      | Machine-Based Hierarchical Approach (ANN, Collaboration, Vector of Support, Regression) | 1 h, 15 min, 24 h in advance | MAE, MBE, RMSE, rRMSE, MPE | Improved performance compared to old method                   | N/A                | PV Online meteorological services                       | Power plant output    | Florida                              | Machine learning techniques                                          | Reduced error values                                                 | –                                                  |

**Table 4** (continued)

| References | Forecasting approach                                                                      | Forecast horizon           | Performance indicators          | Measurement of forecast error                                                                                                                                                                                                         | Computation period | Input variables                             | Predicting conditions     | Location            | Comparative techniques                                          | Merits                                            | Demerits                                         |
|------------|-------------------------------------------------------------------------------------------|----------------------------|---------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------|---------------------------------------------|---------------------------|---------------------|-----------------------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| [119]      | Multi-Layer Perception Neural Networks and TB K Means Clustering                          | 1, 24, 48 h in advance     | MSE, MAE, RMSE, nRMSE, Forecast | Better performance from January to October                                                                                                                                                                                            | N/A                | Solar statistics from the past              | Radiation from the sun    | Colorado states, US | K Means Clustering, MEE, ANN                                    | Efficient computational efficiency, High accuracy | Seasonal variation affects performance           |
| [120]      | Data Pre-processing with Tidal Prediction, Linear Regression, and Ridge Regression Models | 100 min ahead              | RMSE, MAE, MAPE, Bias           | RIDGE performs best overall                                                                                                                                                                                                           | N/A                | Solar radiation values, Meteorological data | Solar photovoltaic system | Aalborg, Denmark    | Comparison with linear regression, Artificial intelligence, ANN | Decreased error metrics                           | Location-specific method                         |
| [121]      | Mixed Neural Network (Grouped Days)                                                       | 2 days in advance          | RMSE, MAE, NSE, d, RAE, MAPE    | Various improvements observed                                                                                                                                                                                                         | N/A                | Temperature, Wind speed, Radiation          | PV system energy          | Tainan, Taiwan      | 3D-MHD, ANF, ML, SVM                                            | Improved accuracy, Stability                      | Limited prediction period                        |
| [122]      | Neural network ensembles                                                                  | Delivery the following day | MAE, MRE                        | A3 outperforms A2 and 1.05 percent, respectively, with 7.77 percent. Individual NN provides less precision than an ensemble of NN. The average MRE for A1, 36.48 percent for A2, and 7.18 percent for A3 is 9.43 percent in all cases | 3–10 min           | Information on prior power                  | Photovoltaic energy       | Brisbane, Australia | Single NN, Two persistence models                               | Both online and offline applications can benefit  | Longer training time for ensemble Neural Network |
| [123]      | CSOP-ELM model is a hybrid model                                                          | –                          | RMSE, MRE                       | The lowest MRE was 75%, and the lowest RMSE was 62.5 percent. Lowest MRE=75 percent in the clear sky. Lowest RMSE=62.5 percent. Lowest MRE=75 percent in the real sky. The RMSE with the lowest value is 70.83 percent                | N/A                | CSKYG information, RSKY G information       | Solar radiation from CSKY | US                  | ARMA BP Direct strategy, ARMA BP Direct approach, OPELM ARMA BP | High-dimensional input data may be inspected      | –                                                |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                                                               | Forecast<br>horizon      | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                                                                                                                                                                                          | Compu-<br>tation<br>period | Input vari-<br>ables                                                                   | Predict-<br>ing con-<br>ditions | Location          | Comparative tech-<br>niques   | Merits                                                                 | Demerits                                                                                            |
|-----------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|--------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|----------------------------------------------------------------------------------------|---------------------------------|-------------------|-------------------------------|------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| [124]           | SOM, SVR, and PSO are used in a hybrid methodology                                                                                                    | Every hour               | nRMSE, nMBE                    | In comparison to previous models, the hybrid model outperforms for 7 out of 10 months on average, with a nRMSE of 4% lower error                                                                                                                       | N/A                        | Historical data on solar irradiance                                                    | Irradiance from the sun         | USA and Singapore | ARIMA, LES, SES, RW           | Address nonstationary solar irradiation and noise in time series data  | –                                                                                                   |
| [125]           | The AR model, electrical model, and statistical model are examples of hybrid models that combine physical and statistical methodologies               | 1 to 10 h ahead          | MAE, RMSE                      | The enhancement compared to the persistent model was 57.4%, while the average improvement over the diurnal model was 34.06 percent                                                                                                                     | N/A                        | NWP Time series observations in the past (solar power)                                 | Solar energy                    | Portugal          | Nave model, Persistence model | Good way to characterize and comprehend the mechanical system          | Met heuristic optimization algorithms do not require prior knowledge of solar plant characteristics |
| [126]           | An artificial neural network and a physical model are both used in the hybrid technique known as PHANN (Physical Model and Artificial Neural Network) | Approximately every hour | NMAE, WMAE, nRMSE              | On sunny days, the accuracy is high, and the errors are low: NMAE=2.70 percent, 6.13 percent WMAE, NMAE=5.7 percent on a partly overcast day, WMAE=14.52 percent. On the first cloudy day, the NMAE was 23.61 percent, and the WMAE was 108.82 percent | N/A                        | Site coordinates and weather predictions, Date and time to find the right sun position | Photo-voltaic energy            | Italy             | EBP in its purest form        | Developed for optimal usage and management of renewable energy sources | –                                                                                                   |

Table 4 (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                                                                                                                               | Forecast<br>horizon | Perfor-<br>mance<br>indicators             | Measurement of forecast error                                                                                           | Compu-<br>tation<br>period | Input vari-<br>ables                                        | Predict-<br>ing con-<br>ditions | Location   | Comparative tech-<br>niques                         | Merits                                                         | Demerits                                                                                                  |
|-----------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------|--------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|----------------------------|-------------------------------------------------------------|---------------------------------|------------|-----------------------------------------------------|----------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------|
| [127]           | Composites of several intelligent algorithms make up intelligent hybrid algorithms. In this study, Three techniques are used: the Wavelet Transform, the Fuzzy ARTMAP network, and the Firefly optimization technique | 1 h in front        | MAPE, NRMSE, Error variance ( $\sigma^2$ ) | The proposed model exhibits decreased error variance, MAPE, and NRMSE                                                   | N/A                        | Data on solar radiation, Time series of historical PV power | Photo-voltaic energy            | Oregon     | BPNN, RBFNN, GRNN, FA WT+BPNN T+RBFNN WT+GRNN WT+FA | Improved effectiveness of the FA network                       | The TSI mirror's shadow band obscures the view of the sky dome near the sun, giving the image a poor cast |
| [128]           | Particle Swarm Optimization and Evolutionary Technique are combined in a hybrid learning algorithm to create a recurrent neural network                                                                               | N/A                 | RMSE                                       | After 100 iterations, the individual who performed the hybrid PSO-EA approaches the best achieved a total RMSE of 0.028 | N/A                        | Real-time solar radiation data                              | Radiation from the sun          | Washington | N/A                                                 | PSO develops, stores important data in local and global memory | –                                                                                                         |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                                                                               | Forecast<br>horizon             | Perfor-<br>mance<br>indicators     | Measurement of forecast error                                                                                                                                             | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                                   | Predict-<br>ing con-<br>ditions                               | Location                                                  | Comparative tech-<br>niques                                             | Merits                                                                                                                                                               | Demerits |
|-----------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------|-----------------------------------------------------------|-------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [129]           | Hybrid model:<br>Artificial<br>Neural<br>Network<br>using Hybrid<br>Evolutionary<br>Algorithm                                                                         | 1 day ahead<br>of sched-<br>ule | WMAE,<br>NMAE                      | Over a year, the PV plant's<br>NMAE mistake is more than<br>twice as great as the wind<br>farm's                                                                          | N/A                        | Weather<br>fore-<br>casting<br>service<br>provides<br>physical<br>variables,<br>Day Irra-<br>diance,<br>Tem-<br>perature<br>of the<br>environ-<br>ment | Photo-<br>voltaic<br>energy<br>– Wind<br>energy               | Italy                                                     | EBP in its purest form                                                  | Faster con-<br>vergence<br>compared<br>to tradi-<br>tional EBP<br>alone                                                                                              | –        |
| [130]           | Satellite data<br>as well as the<br>NWP model                                                                                                                         | 1 to 6 h<br>ahead               | RMSE,<br>MAE                       | 1-h=15.47 percent at C0-Pozo<br>Izquierdo Station, 6 h =<br>22.17 percent                                                                                                 | N/A                        | Data from<br>the<br>ECMWF<br>data col-<br>lection,<br>extracted<br>from the<br>satellite<br>data set<br>using<br>ground<br>data                        | Hori-<br>zontal<br>Irradi-<br>ance<br>on a<br>Global<br>Scale | C0-Pozo<br>Inquired<br>and<br>C1-Las<br>Palmas<br>Islands | Persistence, Climatol-<br>ogy, NN, NN+SAT,<br>NN+ECMWF,<br>NN+SAT+ECMWF | Combining<br>ground<br>data with<br>exogenous<br>informa-<br>tion from<br>satel-<br>lite and<br>ECMWF<br>predic-<br>tions may<br>improve<br>ANN<br>model<br>accuracy | –        |
| [131]           | Hybrid-<br>izing the<br>exponential<br>smoothing<br>state space<br>by analyzing<br>satellite pho-<br>tos and using<br>a model of an<br>artificial neu-<br>ral network | Every hour                      | nRMSE,<br>R <sup>2</sup> ,<br>nMBE | The created approach enhances<br>forecast accuracy by 6%<br>when measured against the<br>most accurate forecasting<br>performance of all available<br>statistical methods | N/A                        | Satellite<br>photos<br>from<br>Japan<br>Meteoro-<br>logical<br>Agency's<br>geosta-<br>tionary<br>weather<br>satellites                                 | Irradi-<br>ance of<br>the Sun                                 | Singapore                                                 | Models: ARIMA,<br>LES, SES, and RW                                      | Improved<br>stochastic<br>concept<br>with the<br>use of<br>state space<br>theory                                                                                     | –        |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                        | Forecast<br>horizon                                      | Perfor-<br>mance<br>indicators                                                  | Measurement of forecast error                                                                                                                | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                                              | Predict-<br>ing con-<br>ditions                                           | Location              | Comparative tech-<br>niques                               | Merits                                                                                                                                     | Demerits                                                                                                                                        |
|-----------------|----------------------------------------------------------------------------------------------------------------|----------------------------------------------------------|---------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|-----------------------|-----------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|
| [132]           | Imagery from<br>satellites and<br>an artificial<br>neural net-<br>work                                         | 30 min,<br>60 min,<br>90 min,<br>and<br>120 min<br>ahead | MBE,<br>RMSE                                                                    | Improvement in RMSE of 5 to<br>25 percent                                                                                                    | N/A                        | Cloud<br>indexing<br>(infor-<br>mation<br>gained<br>from<br>satellite<br>photo-<br>tos)—<br>Veloci-<br>metry,<br>Luminos-<br>ity                                  | Hori-<br>zontal<br>irradi-<br>ances<br>on a<br>global<br>scale            | San Joaquin<br>Valley | Other Literature<br>Review Methods,<br>Persistence Models | Enhanced<br>resilience<br>and accu-<br>racy of<br>high-fidel-<br>ity solar<br>predictions                                                  | –                                                                                                                                               |
| [133]           | Several Sky<br>Imagers are<br>mediocre                                                                         | 15 min and<br>1 s in<br>advance                          | STL, MAE,<br>RMSE                                                               | When compared to the per-<br>sistent model, improve all<br>irradiance forecasts by at<br>least 26%                                           | N/A                        | Conditions<br>of the<br>weather<br>and<br>clouds: 1.<br>Single-<br>layer<br>clouds 2.<br>Clouds<br>with<br>multiple<br>layers<br>3. It's<br>cloudy or<br>overcast | Irradi-<br>ance<br>from<br>the<br>Sun, 3D<br>Cloud<br>Track-<br>ing       | US                    | The model that holds<br>up over time                      | Reliable in<br>detecting<br>clouds and<br>tracking<br>layers                                                                               | Limited<br>FOVs for<br>observa-<br>tions,<br>viewable<br>range<br>expan-<br>sion<br>using<br>stereo<br>stitching<br>of sky<br>images            |
| [134]           | The University<br>of California,<br>San Diego's<br>Total Sky<br>Imager and<br>Sky Imager<br>were used<br>by us | 15 min<br>ahead of<br>schedule                           | Correlation<br>coef-<br>ficients<br>Pearson,<br>Spear-<br>man, and<br>Euclidean | USI: 0.70 and 0.820 correla-<br>tions in the clear sky index;<br>beats TSI: Correlations<br>between the clear sky index<br>and 0.55 and 0.69 | N/A                        | Irradiance<br>around<br>the world                                                                                                                                 | Clear Sky<br>Index<br>is a<br>measure<br>of how<br>clear<br>the sky<br>is | USA                   | Model of perseverance                                     | No informa-<br>tion loss<br>due to<br>shadow<br>band or<br>image<br>compres-<br>sion,<br>precise<br>spatial and<br>intensity<br>resolution | The TSI<br>mirror's<br>shadow<br>band<br>obscures<br>the view<br>of the<br>sky dome<br>near the<br>sun, giv-<br>ing the<br>image a<br>poor cast |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                                                                                               | Forecast<br>horizon                                                            | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                                                                                    | Compu-<br>tation<br>period | Input vari-<br>ables                                                        | Predict-<br>ing con-<br>ditions         | Location                            | Comparative tech-<br>niques                           | Merits                                                                  | Demerits                             |
|-----------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|-----------------------------------------------------------------------------|-----------------------------------------|-------------------------------------|-------------------------------------------------------|-------------------------------------------------------------------------|--------------------------------------|
| [135]           | A camera called the Total Sky Imager can record the entire sky                                                                                                                        | 30 s to 5 min ahead                                                            | Errors are few                 | Forecasting accuracy and persistence model comparison, it is lowered by 50–60%                                                                   | N/A                        | Images of the sky, The Sunshine parameter                                   | Cloud cover, Irradiance of the sun      | University of California, San Diego | Model of Persistence                                  | Short-term deterministic forecasting is possible with just this one TSI | Poor dynamic range of the CCD camera |
| [136]           | HISIMI                                                                                                                                                                                | A period of 1–24 h                                                             | Forecasting ability, nRMSE     | 36.3 percent forecast skill, 10.14 percent nRMSE. MLP and Persistence benchmark models improved by 0.80 percent and 36.30 percent, respectively  | N/A                        | Variables relating to PV plants have been measured in the past              | Photo-voltaic energy                    | Spain                               | MLP-based ANN, Classical persistence model            | Discrete probability functions for forecasting, simple database update  | –                                    |
| [137]           | GFS (global) and MM5 (mesoscale) cascaded NWP models                                                                                                                                  | 1 to 39 h ahead of schedule                                                    | RMSE                           | The best prediction model is ANN-MLP, which has forecast horizons ranging from 16 to 39 h. The rated PV power plan's RMSE value is 11.79 percent | N/A                        | Forecast values for weather variables obtained from the GFS and MM5 modules | Solar energy                            | Spain                               | ARIMA, kNN, ANN-based model, ANFIS, Persistence model | Hourly direct energy forecasts, electricity market bid offers           | –                                    |
| [138]           | Three operational NWP models were subjected to analysis and MOS correction, which included: Model North America by the Center for Medium-Range Weather Forecasts in Europe U.S. North | 1 h/36.0 h<br>3 h/84 hNAM<br>3 h/180 h<br>GFS<br>ECMWF: 3 h/144 h<br>6 h/240 h | MBE, RMSE                      | RMSE reduction is: $Nk = 20.1$<br>$Wm^2-E = 17$<br>$Wm^2-G = 25.6$<br>$Wm^2$ MBE was effectively eliminated                                      | N/A                        | Ground measurement data from SURFRAD                                        | Horizontal Irradiance on a Global Scale | Continental US (CONUS)              | Clear sky model, Persistence model                    | MOS adjustments for more accurate solar irradiance predictions          | –                                    |

Table 4 (continued)

| References | Forecasting approach                                                                                                 | Forecast horizon             | Performance indicators | Measurement of forecast error                                                                                                               | Computation period | Input variables                                                                                | Predicting conditions      | Location | Comparative techniques                                               | Merits                                                                                                                     | Demerits                                      |
|------------|----------------------------------------------------------------------------------------------------------------------|------------------------------|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------------------------------|----------------------------|----------|----------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------|
| [139]      | Regression trees that have had their strength increased by a gradient are known as gradient-boosted regression trees | 1-h time<br>1–6 h in advance | NRMSE                  | The NRMSE varied between 0.10 and 0.127 kW for lead periods $k=1$ to $k=6$                                                                  | N/A                | Measures of power from the past, Information                                                   |                            |          |                                                                      |                                                                                                                            |                                               |
| [140]      | Regression trees that have had their strength increased by a gradient are known as gradient-boosted regression trees | 1-h time                     | 1–6 h in advance       | The NRMSE varied between 0.10 and 0.127 kW for lead periods $k=1$ to $k=6$                                                                  | N/A                | Measures of power from the past Information about the location of the PV installation NPW data | Generation of Solar Energy | Japan    | Model of perseverance Recursive autoregressive model for climatology | capable of recognizing key Non-linear correlations between the input parameters and the intended outcome swiftly           | There is no easy way to update the GBRT model |
| [141]      | Splines-Based Adaptive Multilinear Regression                                                                        | 24 h ahead of schedule       | RMSE<br>MAE            | Forecasting blunders:<br>MAE=125.9 kW<br>RMSE=177.8 kW<br>Errors in the plant's daily energy production:<br>MAE=860.1 kW<br>RMSE=1094.3 kWh | N/A                | NWP data<br>Historical data on power generation                                                | PV solar energy            | Germany  | Model of perseverance                                                | Since no assumptions are made or a specific category of correlations between the input and dependent parameters is defined |                                               |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                   | Forecast<br>horizon            | Perfor-<br>mance<br>indicators | Measurement of forecast error                                     | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                                                                                                                                           | Predict-<br>ing con-<br>ditions | Location                                                                       | Comparative tech-<br>niques                                     | Merits                                                                                                                                                                                         | Demerits |
|-----------------|-----------------------------------------------------------|--------------------------------|--------------------------------|-------------------------------------------------------------------|----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|--------------------------------------------------------------------------------|-----------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [142]           | Adaptive<br>Multilinear<br>Regression<br>Using<br>Splines | 24 h ahead<br>of sched-<br>ule | RMSE<br>MAD<br>MAPE            | RMSE=119.0<br>0MAD=89.8<br>0MAPE=69.2 percent for<br>testing data | N/A                        | The typi-<br>cal, mini-<br>um, and<br>maxi-<br>mum<br>tempera-<br>tures for<br>a given<br>day<br>The tem-<br>perature<br>at the<br>dew point<br>Wind<br>velocity<br>Total<br>precipita-<br>tion Time<br>spent in<br>isolation<br>Humidity<br>Air pres-<br>sure | Solar<br>Power                  | Specified<br>Admin-<br>istrative<br>Region of<br>Coloane<br>Island in<br>Macau | Linear models<br>include those like<br>MLR, ARIMA, and<br>ARMAX | Maintains<br>the typical<br>multiple<br>linear<br>regression<br>models'<br>simplic-<br>ity while<br>dealing<br>with non-<br>linearity, a<br>sophisti-<br>cated type<br>of linear<br>regression |          |

Table 4 (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                 | Forecast<br>horizon | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                                                                                                | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                | Predict-<br>ing con-<br>ditions | Location                                                        | Comparative tech-<br>niques                                | Merits                                                                                                                                                                                                                                                                                                     | Demerits |
|-----------------|-----------------------------------------------------------------------------------------|---------------------|--------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|-------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|-----------------------------------------------------------------|------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [143]           | The study of partial functional linear regression models employs a regularised approach | a day in advance    | RMSE<br>MAD<br>MAPE            | The regularised PFLRM gives the following values: $K = 2.01$ RMSE = 59.1613 MAD = 39.125 MAPE = 0.2101 $K = 7.01$ RMSE = 58.246 MAD = 40.0159 MAPE = 0.10357 | N/A                        | Detection Constraints<br>Maximum, average, minimum, and maximum temperature deviation<br>Relative humidity<br>The use of insulation | PV power                        | The island of Coloa Macau<br>sSpecial Administrative \sRegion \ | Multiple Linear Regression Models<br>Neural Network Models | Unlike NN models, the regularised PFLRM requires no prior knowledge and provides reliable results. – It is less complicated and only requires a few settings decides which elements have the biggest influence on the response parameters automatically<br>It is feasible to model the nonlinear structure |          |

**Table 4** (continued)

| References | Forecasting approach                                                              | Forecast horizon                    | Performance indicators | Measurement of forecast error                                                                                               | Computation period | Input variables                                                                               | Predicting conditions | Location   | Comparative techniques                                              | Merits                                                                                                                | Demerits                                                                   |
|------------|-----------------------------------------------------------------------------------|-------------------------------------|------------------------|-----------------------------------------------------------------------------------------------------------------------------|--------------------|-----------------------------------------------------------------------------------------------|-----------------------|------------|---------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| [144]      | DHR is a sort of regression that is used to analyze data                          | 1–24 h in advance                   | rRMSE<br>SErMBE        | rMBE=0.241<br>rRMSE=30.011<br>International Horizontal Radiation<br>rMBE=3.785<br>rRMSE=45.969<br>Direct Normal Irradiation | N/A                | Information about solar radiation                                                             | GHI<br>DNI            | Spain      | Naïve Seasonal naïve<br>ETS inside a state space framework<br>ARIMA | In the DHR, automated identification is possible. The first model to be used to forecast sun irradiation was this one |                                                                            |
| [145]      | Spatial and temporal statistical data model                                       | From a few minutes to six hours     | nRMSE                  | Comparing the state-of-the-art forecasting methods, an improvement of 19.99% or more may be achieved                        | N/A                | Different geographic PV plant installation densities are included in the second dataset       | PV power              | France     | Random forest Autoregressive                                        | By factoring in the impact of meteorological variables like wind speed, the forecasting error can be decreased        | Data with a high number of dimensions exacerbates the dimensionality issue |
| [146]      | The ST-ARX model is a spatial-temporal autoregressive model using exogenous input | 5 min, 15.0 min, 1 h, and 2 h ahead | MAE<br>RMSE            | The ST model performs better by 1 and 2 h than the other variants                                                           | N/A                | The California Irrigation Management Information System website provided real historical data | Solar PV              | California | AR BPNN Persistence (PSS) model                                     | In the training and validation stages, quality-controlled real data is employed to increase forecast accuracy         |                                                                            |

**Table 4** (continued)

| References | Forecasting approach                                           | Forecast horizon      | Performance indicators | Measurement of forecast error                                                  | Computation period | Input variables                                                                                            | Predicting conditions | Location          | Comparative techniques                                                                             | Merits                                                                                                                                                                                                               | Demerits |
|------------|----------------------------------------------------------------|-----------------------|------------------------|--------------------------------------------------------------------------------|--------------------|------------------------------------------------------------------------------------------------------------|-----------------------|-------------------|----------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [147]      | Model of CARDS                                                 | 1 h ahead of schedule | MeAPE<br>MBE<br>NRMSE  | The CARDS model lowered the combo model's prediction error by 33.4%            | N/A                |                                                                                                            | Solar radiation       | Mildura Australia | (Other ways) Literature review                                                                     | Improve the capacity to forecast under adverse weather circumstances<br>The dynamic system model can be used to analyze data at a high frequency, such as solar irradiation                                          |          |
| [148]      | Modeling Autoregressive Data with an Integrated Moving Average | One hour later        | MBE<br>RMSE            | Miami has the lowest RMSE at 29.73 percent, while the highest is 32.80 percent | N/A                | cloud coverage<br>Horizontal global radiation<br>The usual direct irradiance horizontal diffuse irradiance | Solar irradiance      | USA               | model of persistence<br>Models for Forecasting 1 Models for Forecasting 2 Models for Forecasting 3 | The advantages of dealing with The only information needed to forecast the solar irradiance for the following hour is ground-based cloud cover data. Very useful when solar irradiance measurements are insufficient |          |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                  | Forecast<br>horizon            | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                          | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                                                                          | Predict-<br>ing con-<br>ditions                                                                   | Location  | Comparative tech-<br>niques                                                                | Merits                                                                                                                                                                                                                                     | Demerits |
|-----------------|------------------------------------------------------------------------------------------|--------------------------------|--------------------------------|----------------------------------------------------------------------------------------|----------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|-----------|--------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [149]           | Higher-order<br>Using<br>Markov<br>Chains, a<br>particular<br>sort of<br>Markov<br>Chain | 15 min<br>ahead of<br>schedule | MAE                            | With an average MAE of 2.18<br>percent, the proposed tech-<br>nique has the lowest MAE | N/A                        | PV elec-<br>tricity<br>produc-<br>tion and<br>sur-<br>rounding<br>tempera-<br>ture Solar<br>radiation<br>Solar<br>radiation<br>Solar<br>radiation<br>Solar<br>radiation<br>Solar<br>radiation | The<br>gener-<br>ated PV<br>power<br>has a<br>proba-<br>bilistic<br>distrib-<br>ution<br>function | Australia | Support Vector<br>Regression Pair<br>Copula Construction<br>Chronological Prob-<br>ability | Whatever<br>the point<br>of opera-<br>tion of the<br>PV system,<br>the PDF<br>of solar<br>power<br>generated<br>electricity<br>may be<br>accurately<br>anticip-<br>ated.<br>Sequential<br>data might<br>be used to<br>update this<br>model |          |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                           | Forecast<br>horizon                | Perfor-<br>mance<br>indicators | Measurement of forecast error                | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                         | Predict-<br>ing con-<br>ditions | Location | Comparative tech-<br>niques                                           | Merits                                                                                                                                                                                                                                                                                                                                                                                                                                                                                            | Demerits                                                                                                                                                                                                            |
|-----------------|---------------------------------------------------------------------------------------------------|------------------------------------|--------------------------------|----------------------------------------------|----------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|----------|-----------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [96]            | Generalized<br>fuzzy model<br>and density<br>hidden<br>Markov<br>model com-<br>bined in an<br>HMM | Creating<br>long-term<br>forecasts | RMSE<br>MAPE<br>R-value        | R-value=0.9921<br>RMSE=7.9124<br>MAPE=3.0083 | N/A                        | One sunny<br>hour pre-<br>vail-<br>ing tem-<br>perature<br>humidity<br>relative<br>Wind<br>velocity<br>pressure<br>in the<br>atmos-<br>phere | Radiation<br>from<br>the sun    | India    | ANFIS<br>ANN Combination<br>of inputs<br>meteorological<br>parameters | HMM offers<br>the follow-<br>ing advan-<br>tages: It<br>incor-<br>porates<br>potent<br>optimi-<br>zation<br>techniques<br>like Expec-<br>tation<br>Maximiza-<br>tion and<br>can handle<br>sequential<br>structures<br>and a high<br>level of<br>uncertainty<br>Some ben-<br>efits of soft<br>computing<br>include the<br>following:<br>GFMs<br>offer very<br>effective<br>modeling<br>structures,<br>and<br>statistical<br>distribu-<br>tions don't<br>need any<br>underlying<br>assump-<br>tions | HMM has<br>certain<br>disad-<br>van-<br>tages, such as<br>the need<br>for a<br>starting<br>assump-<br>tion when<br>modeling<br>statistical<br>distribu-<br>tions<br>and the<br>absence<br>of a<br>global<br>context |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                  | Forecast<br>horizon     | Perfor-<br>mance<br>indicators      | Measurement of forecast error                                                                                                                                                                                                          | Compu-<br>tation<br>period                                                    | Input vari-<br>ables                                                                                                                     | Predict-<br>ing con-<br>ditions | Location                                                  | Comparative tech-<br>niques          | Merits                                                                                                                                                                                                                                                                  | Demerits                                                                                                                                                               |
|-----------------|------------------------------------------|-------------------------|-------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|-----------------------------------------------------------|--------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [150]           | Regression<br>using Sup-<br>port Vectors | 15 min and<br>5 h ahead | RMSE<br>Bias                        | Combining model predic-<br>tion with reliable regional<br>estimates of PV power results<br>in an error minimization rate<br>of over 75%                                                                                                | N/A                                                                           | PV power<br>measure-<br>ments<br>NWP<br>irradi-<br>ance<br>estimates<br>Cloud<br>motion<br>vector<br>irradi-<br>ance<br>projec-<br>tions | Photo-<br>voltaic<br>energy     | Germany                                                   | Approaches to physi-<br>cal modeling | In both<br>clear and<br>gloomy<br>conditions,<br>SVR can<br>produce<br>better pre-<br>dictions                                                                                                                                                                          | The learn-<br>ing phase<br>functions<br>gener-<br>ally well,<br>especially<br>in situ-<br>ations<br>when the<br>input of<br>irradi-<br>ance is<br>relatively<br>strong |
| [151]           | Machine to<br>Support Vec-<br>tors       | –                       | RMSE<br>MRE<br>Process-<br>ing time | The MRE values for SVM<br>throughout the training and<br>testing stages last for 0.302<br>and 0.505 min. SVM predic-<br>tions data on sun radiation<br>more rapidly than ANN;<br>training takes 2.15 s com-<br>pared to 4.56 s for ANN | During<br>train-<br>ing, the<br>maxi-<br>mum<br>training<br>time is<br>2.15 s | Diffuse<br>radiation<br>Global<br>radiation<br>Direct<br>normal<br>radiation                                                             | Radiation<br>from<br>the sun    | Saudi Ara-<br>bian cities<br>of Jeddah<br>and Qas-<br>sim | ANN                                  | The SVM<br>performs<br>very well<br>because of<br>its ability<br>to maintain<br>robust-<br>ness for<br>extremely<br>small data-<br>sets. The<br>SVM can<br>be calcu-<br>lated more<br>quickly.<br>SVM<br>has the<br>potential to<br>minimize<br>computa-<br>tion errors |                                                                                                                                                                        |

Table 4 (continued)

| References | Forecasting approach                                                             | Forecast horizon  | Performance indicators             | Measurement of forecast error                                                                                                                                                                                  | Computation period | Input variables                                                                                  | Predicting conditions             | Location                       | Comparative techniques                                           | Merits                                                                                                                                                                                            | Demerits |
|------------|----------------------------------------------------------------------------------|-------------------|------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------|--------------------------------------------------------------------------------------------------|-----------------------------------|--------------------------------|------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [152]      | Support vector machines (SVMs) serve as the foundation for the Firefly algorithm | Once a month      | RMSE<br>R2<br>MAPE                 | Training: $\sqrt{\text{RMSE}}=0.60988$<br>$\sqrt{\text{R2}}=0.80240$<br>$\sqrt{\text{sMAPE}}=6.10768$<br>Testing: $\sqrt{\text{RMSE}}=1.86610$<br>$\sqrt{\text{R2}}=0.72800$<br>$\sqrt{\text{sMAPE}}=11.51920$ | N/A                | Time spent in the sun<br>Maximum and minimum temperatures                                        | Solar radiation on a global scale | Nigeria-<br>Jos, and Maiduguri | ANN<br>GP                                                        | The SVMFFA model being suggested offers an interesting methodology for projecting global solar radiation that may be applied to any case study, including those with different climate conditions |          |
| [153]      | Support Vector Machine (SVM) Least Squares                                       | Next-day delivery | RMSE<br>MRE<br>MEF<br>R2<br>CVRMSE | $\text{R2}=100.001$<br>$\text{RMSE}=0.002546$<br>$\text{MRE}=10.021$<br>$\text{MEF}=3.459$<br>$\text{CVRMSE}=0.0879$                                                                                           | N/A                | day high temperature and sunlight duration on an average day the previous day's solar insolation | Insulation from the sun each day  | Elazig city Turkey             | In the literature, there are both AI and empirical methodologies | The RBF kernel function has the following advantages:<br>1. Capable of competing effectively<br>2. Trustworthy<br>3. Keep it simple                                                               |          |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                            | Forecast<br>horizon    | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                                                                                   | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                                                                  | Predict-<br>ing con-<br>ditions | Location            | Comparative tech-<br>niques                                                                                                                                                       | Merits                                                                                                                                                                                                                                                                                        | Demerits |
|-----------------|--------------------------------------------------------------------------------------------------------------------|------------------------|--------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------|---------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [154]           | Machine to<br>Support Vec-<br>tors                                                                                 | Every day              | RMSE<br>RRMSE<br>R2            | The average RMSE is 2.094<br>mJm2, which is 10% lower<br>than the 2.323 mJm2<br>achieved by empirical models                                    | N/A                        | Time spent<br>in the<br>sun                                                                                                                                           | Radiation<br>from<br>the sun    | China               | SVM 1–7 empirical<br>models using a range<br>of input character-<br>istics                                                                                                        | Rather than<br>lowering<br>the local,<br>The SVM<br>attempts to<br>decrease<br>the upper<br>bound of<br>the gener-<br>alization<br>error by<br>reducing<br>the train-<br>ing error.<br>Because<br>the<br>optimality<br>problem<br>is so chal-<br>lenging, it<br>only has<br>one solu-<br>tion |          |
| [155]           | Back-Prop-<br>agation<br>Algorithm<br>for Artifi-<br>cial Neural<br>Networks by<br>Levenberg<br>and Mar-<br>quardt | 0–60 min in<br>advance | RMSE<br>R                      | 5 min of training<br>RMSE=19.9515W r=0.98188<br>RMSE=19.9515W RMSE=1<br>r=0.96979 RMSE=25.3816W<br>RMSE=25<br>5 min of testing<br>RMSE=35.4374W | N/A                        | tempera-<br>ture dif-<br>ferences<br>between<br>the envi-<br>ronment<br>and the<br>cell Solar<br>solar<br>panel<br>with 750<br>Wp of<br>diffuse<br>solar<br>radiation | Solar<br>power                  | Istanbul,<br>Turkey | Marquardt-<br>Liebenberg<br>The weights<br>that will<br>provide<br>the ideal<br>mapping<br>between<br>input and<br>output are<br>found via<br>back-prop-<br>agation<br>techniques |                                                                                                                                                                                                                                                                                               |          |

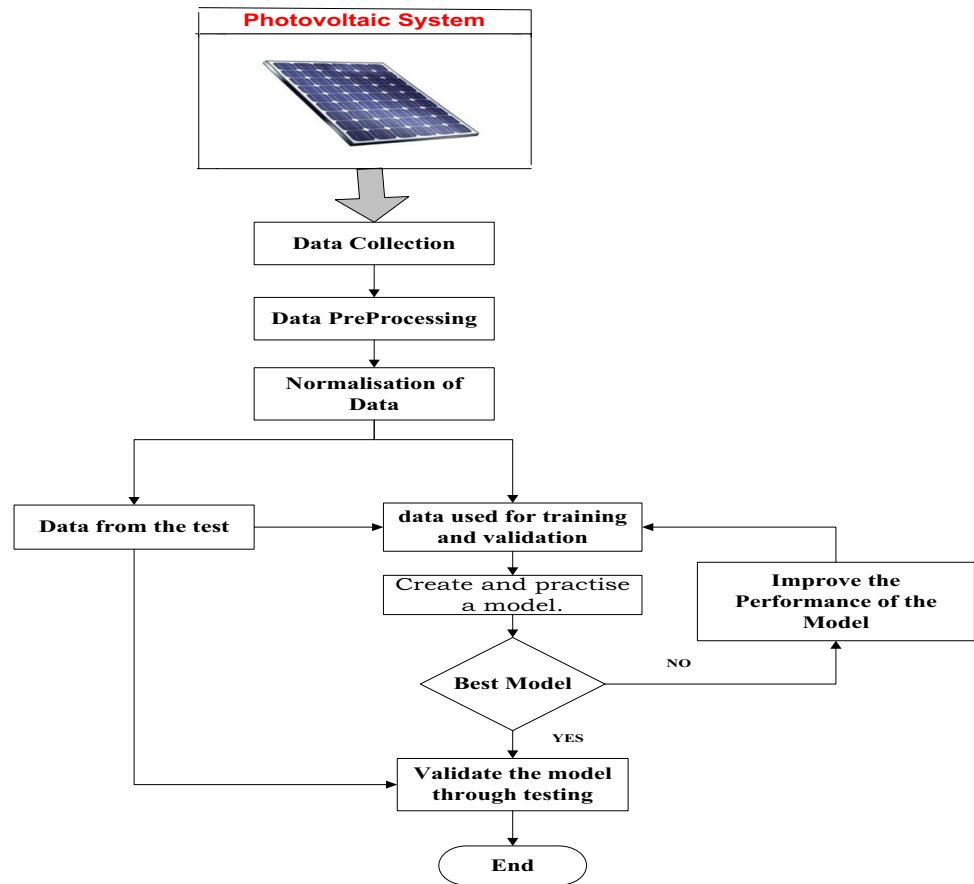
**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                               | Forecast<br>horizon                                             | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                         | Compu-<br>tation<br>period | Input vari-<br>ables                                                                                                | Predict-<br>ing con-<br>ditions | Location           | Comparative tech-<br>niques                      | Merits                                                                                                                                                                                                                                            | Demerits                                                                                                                                                                                                                              |
|-----------------|-----------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|--------------------------------|---------------------------------------------------------------------------------------|----------------------------|---------------------------------------------------------------------------------------------------------------------|---------------------------------|--------------------|--------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| [156]           | Artificial neu-<br>ral network<br>with many<br>inputs and<br>autore-<br>gressive<br>integrated<br>moving aver-<br>age | Day and<br>intra-day<br>plans are<br>in the<br>works            | NRMSE                          | Exogenous reduces NRMSE<br>SARIMA:<br>ANN=11.26–11.42 percent<br>Factor=11.12 percent | N/A                        | solar<br>energy                                                                                                     | PV power<br>conditions          | Greek<br>territory | Persistence model Pure<br>SARIMA model           | For intra-day<br>prediction,<br>the del<br>improves<br>the predic-<br>tion by<br>bringing it<br>closer to<br>the actual<br>PV<br>SARIMA<br>model is<br>unable to<br>forecast<br>day-<br>ahead PV<br>genera-<br>tion with<br>adequate<br>precision | When past<br>days have<br>irregular<br>patterns<br>compared<br>to the<br>expected<br>day, the<br>day, the<br>pure<br>SARIMA<br>model is<br>unable to<br>forecast<br>day-<br>ahead PV<br>genera-<br>tion with<br>adequate<br>precision |
| [157]           | neural net-<br>work-based<br>techniques<br>with fuzzy<br>logic                                                        | Hourly<br>starting<br>at 8:00<br>a.m. and<br>ending at<br>6 p.m | MAPE                           | MAPE=6.03–9.65 percent<br>MAPE=6.03–9.65 percent<br>MAPE=5.99–8.98                    | N/A                        | Informa-<br>tion<br>about<br>past solar<br>radiation<br>Weather<br>(sunny,<br>rainy<br>&cloudy)<br>Tempera-<br>ture | Solar<br>radiation              | N/A                | Neural Network<br>Statistical Fuzzy<br>Algorithm | A fuzzy<br>logic-<br>based<br>optimal<br>clustering<br>method<br>is used,<br>in which<br>fuzzy logic<br>is used to<br>dis-<br>criminate<br>between<br>different<br>sets of sky<br>conditions<br>and tem-<br>perature                              | For a<br>particular<br>climatic<br>circum-<br>stance,<br>fuzzy<br>logic's<br>fore-<br>casting<br>precision<br>is less<br>accurate<br>than<br>NNs'                                                                                     |

**Table 4** (continued)

| Refer-<br>ences | Forecasting<br>approach                                                                                     | Forecast<br>horizon | Perfor-<br>mance<br>indicators | Measurement of forecast error                                                                                                                                                                                                                                                         | Compu-<br>tation<br>period | Input vari-<br>ables                     | Predict-<br>ing con-<br>ditions  | Location                                     | Comparative tech-<br>niques                                                                         | Merits                                                                                                                                                                                                                                                                                                                                                               | Demerits |
|-----------------|-------------------------------------------------------------------------------------------------------------|---------------------|--------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------|------------------------------------------|----------------------------------|----------------------------------------------|-----------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------|
| [158]           | Artificial<br>neural net-<br>works of the<br>multilayer<br>perceptron<br>variety are<br>one such<br>example | Every hour          | RMSE<br>MBE<br>R               | On an overcast day, R ranges<br>from 93 to 97 percent, MBE<br>ranges from 0.7 to 1.1 per-<br>cent, and RMSE is less than<br>0.21 percent<br><br>On a bright day, R is between<br>96.7 and 97.8 percent, MBE<br>is between 0.94 and 0.98<br>percent, and RMSE is under<br>0.22 percent | N/A                        | irradiation<br>Temperature<br>of the air | PV mod-<br>ules' output<br>power | Marmara<br>University<br>Istanbul,<br>Turkey | Analytical method<br>– Polynomial and<br>multiple linear<br>regression Model<br>with a single diode | ANN mod-<br>els, unlike<br>implicit<br>models,<br>do not<br>necessitate<br>the use of<br>additional<br>variables<br>or compli-<br>cated cal-<br>culations.<br>When<br>compared<br>to a single<br>database<br>including<br>all-day<br>data,<br>categoriz-<br>ing days<br>between<br>overcast<br>and sunny<br>improves<br>ANN-<br>based<br>models<br>dramati-<br>cally |          |

**Fig. 16** The forecasting process method [164]



variable, whereas  $R^2$  100% qualities imply that numerous inputs can affect the probability distribution but were not taken into account even during the implementation of both the ANN estimation method [171]:

$$R^2 = 1 - \frac{\frac{1}{N} \sum_{i=1}^N |\bar{P}_i - P_i|^2}{\frac{1}{N} \sum_{i=1}^N |\hat{P}_i - P_i|^2}$$

### Computational Time

It is the length of time required to evaluate the built-ANN models and build viable Classification algorithms. This statistic is crucial in identifying a learning algorithm that can anticipate energy generation with the greatest accuracy and in the shortest amount of time [172].

### Conclusion

The increasing global energy consumption has led to a growing implementation of photovoltaic (PV) systems. However, predicting PV energy production remains a challenging task, prompting the development of various methodologies.

Modern solutions leverage mathematical technologies to make sense of diverse data, including irradiance, air temperature, and wind speed. Variables such as ambient temperature and wind velocity have been identified as influential in weekly power production. With extreme weather events and rising temperatures, the study of power generation and demand has become increasingly important. Fulfilling growing energy needs while addressing environmental concerns requires reliable power generation forecasts. As a result, numerous investigations have been conducted from various perspectives on this topic.

This systematic research evaluation focused on forecasting models and techniques for direct PV electricity. The study covered PV energy production, the significance of solar PV forecasts, and the integration of meteorology with analytical tools for modeling data input. The findings indicate a positive correlation between parameters utilized in the program and the output. The use of well-considered feature vectors enhances the reliability of predicted results. The research conducted a comprehensive evaluation of PV energy prediction based on a proposed categorization from various angles. The outcomes suggest that modeling techniques depend on the study's data, methodology, and prediction approach. In most instances, solar PV prediction analysis focused on a short-term prediction horizon,

and adjusting this horizon influenced the reliability of the PV energy prediction method. Recent works on the direct prediction of power production were also reviewed, highlighting the advantages and weaknesses of various methods. The precision, consistency, computing expense, and complexity of modern forecasting algorithms were explored and compared with parameter settings. Despite the rapidly changing environment, statistical techniques such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM) performed well in recent research. The PSO-based proposed technique, where maximum features were automatically tuned using the Particle Swarm Optimization (PSO) algorithm, outperformed other methods comprehensively in the current data. Intelligent Smart Energy Management systems are being developed, allowing for the prioritized switching of incoming predicted energy based on customer preferences, producing a step response. Additionally, a secure network infrastructure has been implemented to support operations such as load disaggregation and remote data processing. Overall, advancements in forecasting methodologies contribute to the efficient and reliable integration of solar energy into the broader energy landscape.

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**Declarations**

**Conflict of interest** The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

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