Robust Solar Irradiation Forecasting Mechanism for Maximum Power Point Trackers: A Comparative Review

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Abstract- Solar power generation has gained worldwide attention due to high potentiality and effortless energy conversion process. However, the uncertain nature of the Photovoltaic (PV) source makes the conventional Maximum Power Point Tracking (MPPT) controllers difficult in tracking the optimal operating point under all dynamic environmental conditions, causing impacts on PV system performance. Therefore, a robust forecasting technique is suggested to predict the irradiation level using various environmental parameters. Such prediction helps the controller in quickly exploiting the optimal decisions without any false trapping and exploitation process under any rapidly fluctuating profile. For that, the probabilistic and deterministic irradiation forecasting methods are generally discussed to ensure the method's suitability. As a result, the paper mainly concentrates on Machine Learning (ML) based Artificial Neural Network (ANN) and Support Vector Regression (SVR) deterministic approaches as the most suggested prediction techniques from the literature survey for competent irradiation forecasting in PV systems in the last decades. Therefore, a comprehensive, systematic, and comparative review of ANN and SVR-based irradiation forecasting articles from 2014 to 2022 are considered, especially for PV system applications are analyzed and discussed with their benefits, demerits, and requirements in the irradiation forecasting field. It reveals that among those approaches, the performance and handling of ANN on non-linear, time series, massive as well as small datasets created wide attention than another approach confesses the suitable criteria in solving the MPPT problem stated. Also, the article conveys the formulation and functionalities of the 13 most commonly used performance indices for analyzing the responses.

Keywords Photovoltaic systems, Irradiation forecasting, Maximum Peak Point Tracking (MPPT), Artificial Neural Network (ANN), Support Vector Regression (SVR).

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1. Introduction

In recent decades, the renewable energy sector is inevitable for world countries and researchers to satisfy the increasing power crises and environmental protection [1]. The Paris agreement projects stress global warming and the need for PV integration with the grid [2]. Therefore, sustainable green energy generation will be a promising alternative to fossil fuels. Among the other energy sources, solar is considered as one of the efficient energy resources due to its high potentiality, easy adaptability, less maintenance, noise, and pollution-free nature, as stated in [3]. Among the energy sources, solar is considered as one of the efficient energy resources due to its high potentiality, easy adaptability, less maintenance, inexhaustible, and pollution-free nature, as stated in [4]. The Renewable 2020 Global status Report REN21 [5] is a globally distributed renewable energy community mainly focused on providing information on current trends, support and development in the renewable energy sector. It is observed that the contribution of renewable energy is the mainstream in the power distribution sector, where the power generation is quoted to be more than 200 Gigawatts in the year 2019. Compared to the other renewable energy systems of Wind-60GW and Hydro-16GW, the solar-based power generation is very high with 115GW. Eventually, solar energy can be used in various applications such as power generation in distribution/ residual/ commercial/ industrial sectors, operating electric vehicles, and wide applications due to the easy conversion process [6]. Many factors that could affect the performance of PV power generation include initialization cost, optimal placement, increased power quality problems, and reliability.

Moreover, the power generation in the PV system is highly vulnerable to the moment of sun, dynamic cloud motion, aerosol problems, shadows caused by trees, buildings, and seasonal changes, which creates multiple peaks in the PV system characteristics [7]. Hence it is tedious to attain optimal efficiency from a PV panel at varying environmental conditions. Such intermittency complicates the controller's performance in extracting the maximum power by choosing the global maxima among multiple peaks during power generation. Therefore, it is essential to improve the controller performance by which the power generation in PV systems gets improved. For this reason, numerous MPPT controllers have been developed to identify the exact maximum operating point of PV cells, which are integrated with the power conditioning units. Correspondingly, it is used to regulate the output power even there is a fluctuation in the input source. However, the traditional, heuristic, metaheuristic, and evolutionary algorithms face difficulties such as trapping at false maxima, slow responses, increased computational complexity, steady-state error, and oscillations during the selection of optimal operating points due to the design nature of algorithms [8]. Besides, certain power quality and energy management problems can occur due to the accumulation of uncertain renewable energy into the grid systems [9].

In recent years, some article uses the forecasting-based MPPT controllers for tracking MPP in PV systems under varying climatic conditions. In the paper [10], a comprehensive study is conducted on ML-based MPPT in a PV system, where the LSSVM (Least Square Support Vector Machine), Incremental Conductance and, Perturb and Observation methods are considered for analysis. Similarly, the Bayesian optimization technique [11] – [13] is implemented to achieve the maximum peak point in the PV systems characteristics. But most of the forecasting-based MPPT controllers are trained using irradiation and temperature or open circuit voltage and short circuit current as input parameters for getting the control variable D (Duty cycle) as the output. It signifies that the model can predict the control variable when such parameters are provided as input. Nevertheless, these models along with the controller find it difficult to adapt and respond when a rapid change in irradiation occurs. Because the model does not have any prior awareness or training on rapid change in irradiation, occurs due to changes in environmental factors, such as the Solar Zenith Angle, Relative Humidity, Ambient Temperature, Cloud cover and precipitate, etc. The schematic diagram of a standard PV system with an MPPT controller and prediction unit is shown in Figure 1.

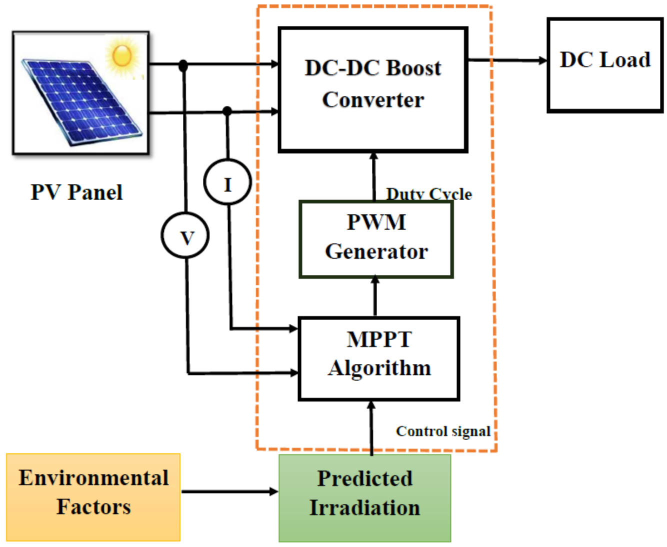

Fig. 1. Schematic of PV system integrated with an MPPT controller and prediction unit

In addition, the highly volatile, asymptotic nature of PV sources substantially causes inconvenience in the best administration of power grid for maintaining the balance between availability and production, effective energy market, and optimal power dispatch [14]. Therefore, the article [15] focuses on forecasting power output to plan for an efficient controlling of battery storage in adaptive control of grid connected PV system and, and in some cases, it is to improve electric vehicle charging in EMS, reduces the charging cost and consumption from grid, residential and commercial buildings [16]. Furthermore in [17] the SVM and ANN are implemented to predict the PV power output using several meteorological factors in Maharashtra region for improving the performance of grid tied PV system. In such processes, the performance of the controller integrated with the PV system was not taken into consideration which has great impact on PV system efficiency. As an outcome of it, the predicted power at the output side based on availability of source will not be the same as the power output of the system. This irregularity decreases the PV system and PV grid integration performance.

Therefore collectively, tunning the forecasting model using environmental factors incorporated with the controller causes the regulated output will effectively improve the conflict of tracking and equalize the above dissimilarity at the output side. Thus, this article helps in finding the exact forecasting technique for mitigating the issues mentioned above.

This investigation emphasizes that irradiation forecasting will be the looming hot area in recent trends to improve PV system performances.

As the irradiation forecasting schemes contribute to better performance in controllers, the most efficient and widely used short term irradiation forecasting model in recent years is identified by considering the review articles from 2014 – 2021. This article highly concentrates on short term irradiation forecasting, because for the instantaneous operation of controllers the prediction technique has to deliver the predicted value instantaneously. The different time horizons and their applications are discussed in section 2.2.3. Therefore, the review article by P. Singla, M. Duhan, and S. Saroha conducted a comprehensive review on finding a potential irradiation forecasting technique. The discussion includes related studies in regression, NWP (Numerical Weather Prediction), empirical, SVR, ANN, deep learning, and hybrid models. It also highlights the importance of parameters and specifications in model performance. The paper reveals that ANN-based forecasting methods are more accurate in prediction when compared with others. Likewise, [19] performed a critical review of 130 articles published between 2005-2018 reveals that SVM, ANN, GA (Genetic Algorithm) produced superior results. Here the discussion of different MLT (Machine Learning Technique) for solar power forecasting was performed. The comparison was made between ML and Time series models and are tested under five different sites in Sweden. Finally, ANN and Gradient Boosting regression Tree have better performance in all sites on average, as stated in [20]. The systematic review on impact of various irradiation forecasting techniques is analyzed and discussed in [21] for improving the prediction accuracy are elaborated.

The daily and monthly solar irradiation forecasting using 12 ML algorithms were extensively analyzed for extreme climatic conditions using metrological variables as a benefit of solar and climate-based research in [22]. Again, [23] conducted a systematic review on solar irradiation forecasting using ANN was presented. It was observed from the analysis that ANN has good prediction accuracy with an error of less than 20%. Another review was conducted on hourly solar irradiation forecasting using various MLT. It reveals that Variants of MLP (Multi-Level Perception), SVR perform better for clear sky conditions [24]. The sunshine-based GHR (Global Horizontal Radiation) prediction using empirical and machine learning models was performed [25]. It reveals that superior results were achieved in the case of ML-based models. In [26], the author summarizes solar radiation estimation in a location with no metrological station using the Artificial Neural Network technique. These paved the way

- To undergo a comprehensive, systematic and comparative review of widely suggested methods by the review article (coated above) from 2014 to 2022, especially for irradiation forecasting in PV systems.
- To perform effective analysis and discussions in identifying a suitable/robust machine learning-based short term irradiation forecasting method among ANN and SVR, especially for MPPT controllers in PV systems.

Therefore, the article is structured as follows.

- A detailed discussion characterizing various publications in recent years related to ANN and SVR in solar irradiation forecasting, its advantages, drawbacks, and requirements for the perfect design is specified.
- Overview of the studied article from each model are categorized based on specifications like location, the dataset used, forecast horizon, granularity of data, prediction variable, application, model compared, and performance evaluation metrics.
- Performance analyses are carried out on various ANN and SVR-related articles used in the study
- Discussion is made to find the superior approach among ANN and SVR based on performance metrics, dataset, input features used and feature selection process performed, especially for MPPT controllers.

The article is peculiar because

- The depth analysis was carried out on the most important forecasting techniques which have been suggested by review articles from 2014-2022
- This is the leading article where the review was performed for irradiation forecasting to solve MPPT controller problems in PV systems to the best of our knowledge.

Thus, the MPPT issues of controller and unregulated output associated with dynamic irradiation profiles can be diminished when the obtained robust forecasting model is integrated with MPPT technique. Thereby, the MPPT controller can able to track irradiation at all instances by getting the approximate instantaneous irradiation values based on environmental changes in advance. This can also help to design the hyperparameters, initialize the search agent, prevent false trapping, avoid slow response, prevent unwanted oscillations, and start the exploitation rather than normal controllers does. Hence Such smart MPPT controllers can eventually improve the converter efficiency and overall PV system performance. Furthermore, such regulated power output of controller equalizes the production and availability, can diminish the power quality, stability, variability issues faced by grid.

The paper is organized as follows: Section 2 highlights the importance of irradiation forecasting in Controller and PV system performance, and some fundamentals in the irradiation forecasting process are discussed. Also, 13 most commonly used performance metrics were formulated with their functionalities. Moreover, it summarizes various irradiation forecasting methods and detailed discussion on the distribution and contribution of various ANN and SVR approaches with their advantages, drawbacks and requirements in irradiation forecasting fields. Section 3 offers effective analysis and discussions on various ANN and SVR articles studied. Finally, section 4 presents the conclusions and future scopes of this article.

2. Materials and Methodology

2.1 Role of irradiation forecasting in MPPT controller and system performance

According to the database REN21 [5], the usage of solar PV, CSP (Concentrated Solar Power) and solar hot water in nine years from 2013 to 2021 is graphically illustrated in Figure 2. From the observation, it is identified that solar power usage has been gradually increased in these years. This investigation helps to have more interest in the PV system to improve the performance, thereby enhancing power generation. Moreover, solar energy is an essential source in PV systems, and its performance depends on the irradiation that falls on the panel. Therefore, the prediction fed controller integrated with the PV system will considerably minimize the impedance matching issues at all fluctuating irradiations.

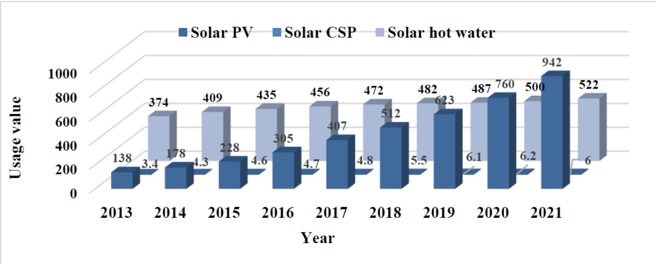

Fig. 2. Distributed usage of solar power from 2013 to 2021 [5]

Some MPPT control techniques that have been extensively used in PV systems are taken for analysis, including BPSO, ALO, CSO, PSO and MCS. The model and the parameters used to construct these MPPT controlling techniques are illustrated in Table 1. It is proven that the performance of the controlling technique purely depends on the short circuit current or irradiation, which is directly proportional to the intensity of solar irradiation falling on the panel. Typically, solar irradiation is highly vulnerable to temperature, cloud motion, humidity, sunshine hours, wind speed and direction, animal interference, and shading caused by buildings and trees. Hence highly fluctuating characteristics profile will be achieved by the PV system. So, if there is any deviation or fluctuating irradiation profile, it directly leads to a reduction in PV system performance.

Therefore, a ML technique is required to forecast short term irradiation based on environmental factors, for the next or future instances prior. This guidance helps the MPPT controller to undergo exploitation at the starting stage without exploration. Hence the controller can tune and perform under any rapid change in irradiation and find an optimal solution much better and faster, resulting in reduced power quality, variability problems when integrated with the load. Figure 3 shows the integration of machine learning with PV systems, with a detailed description of the ML model in the dashed box.

2.2 *Basic considerations in forecasting*

This section detailed some basic concepts in forecasting, which helps to understand the remaining part of the text as follows.

2.2.1 *Dataset preparation*

As the data set is the sole of all machine learning models, the model's performance exclusively depends on the data quality used for analysis. Here the dataset should be collected from the location where the PV system is mounted. As the short circuit current used for obtaining the power purely depends on the irradiation fall on the panel, the irradiation measuring instruments are costlier, leading to maintenance and technical issues more often. So, most of the metrological stations do not have an irradiation measuring facility, and hence it is required to estimate the PV irradiation via the forecasting process. For this purpose, the related data are collected from the metrological department, weather forecasting stations, and geographical locations, which are relatively used to forecast irradiation. Before processing the dataset using ML techniques, the data pre-processing must be carried out, including normalization processes (to scale the data collected from 0 to 1), cross-validation, removal of night hour data, and outlier detection.

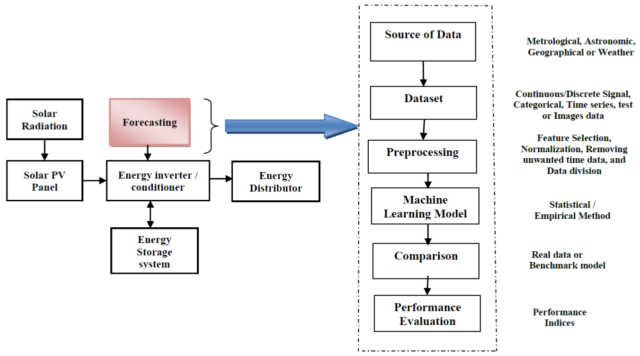

Fig. 3. Block diagram of a PV integration with ML model

Consequently, feature extraction, feature selection, and PCA (Principal Component Analysis) are performed to provide the model with more relevant inputs, ensuring the accuracy of the prediction model. After that, the data splitting is performed to categorize the data for training, testing, and cross-validation, where the training data helps in designing the model. Similarly, the testing data and cross-validation help to identify how the model works in the presence of unknown data.

2.2.2 *Types of exogenous data used*

- Astronomic data includes solar altitude angle, declination angle, solar zenith angle, and sun time.
- Geographic data includes Longitude, latitude, time zone, and altitude.
- Metrological data includes Cloudiness, sunshine duration, ambient temperature, humidity, wind speed, pressure, rainfall, wind direction, air mass and solar irradiation.

2.2.3 *Types of the forecasting horizon*

The forecasting horizon is split into four categories that include (1) very short term or ultra-short-term or immediate forecasting whose time horizon ranges from a few seconds to 30 minutes ahead especially for monitoring real-time electricity dispatch, power smoothing, PV fed electric

Table 1. Several MPPT controlling techniques and their parameters integrated with the PV system

Reference /Year	Control Algorithm	Model	Parameters
[27]/ 2011	Binary Particle Swarm Optimization (BPSO)	$P_{PV} = \eta_{PV_g} \times A_{PV_g} \times G_t$	η_{PV_g} - Efficiency of PV gen, A_{PV_g} - Area of PV gen (m^2), G_t - Solar irradiation (W/m^2)
[28]/ 2017	Ant Lion Optimization (ALO)	$P_{PV} = \begin{cases} P_{PV_r} \times \left(\frac{G}{G_r}\right) & 0 \le G \le G_r \\ P_{PV_r} & G_r \le G \end{cases}$	G – Solar radiation in a selected location (W/m^2) G_r - Rated radiation at earth's surface (1000 W/m^2) P_{PV_r} - Rated PV power for G_r .
[29]/ 2018	Cuckoo search Optimization (CSO)	$P_{PV} = \begin{cases} P_{r-PV} \times \left(\frac{R^2}{R_{STD} \times R_C}\right), & R \le R_C \\ P_{r-PV} \times \left(\frac{R}{R_{STD}}\right), & R_C \le R < R_{STD} \\ P_{r-PV}, & R \ge R_{STD} \end{cases}$	P_{PV} - Output power (MW) R_{STD} - Standard Deviation of solar radiation. R_C - Radiation at a certain point P_{r-PV} - Rated PV power
[30]/ 2018	Traditional Particle swarm optimization (PSO)	$P_{PV} = N_s \times N_p \times FF \times V_{oc} \times I_{sc}$ $V_{oc} = \frac{V_{Noc}}{1 + C_2 \times \ln\left(\frac{C_N}{G_a}\right)}\left(\frac{T_N}{T_a}\right)^{C_1}$ $I_{sc} = I_{Nsc}\left(\frac{G_a}{G_N}\right)^{C_3}$ $FF = \left(1 - \frac{R_s}{V_{oc}/I_{sc}}\right)\left(\frac{\frac{V_{oc}}{nKT/q} - \ln\left(\frac{V_{oc}}{nKT/q} + 0.72\right)}{1 + \frac{V_{oc}}{nKT/q}}\right)$	N_s & N_p - Serial and parallel PV module. G_a & G_N - Actual and nominal solar irradiance. T_a & T_N - Actual and Nominal module temperature. FF - Fill Factor of PV V_{oc} & I_{sc} - Open and closed-circuit voltage and current resp. V_{Noc} & I_{Nsc} - Nominal value of V_{oc} & I_{sc}
[31]/ 2019	Monte Carlo Simulation (MCS)	$P_{PV} = N_s \times N_p \times FF \times V \times I$ $V = V_{oc} - K_v \times T_c$ $I = S_a\left[I_{sc} + K_i(T_c - 25)\right]$ $FF = \frac{V_{mpp} \times I_{mpp}}{V_{oc} \times I_{oc}}$	K_i - Current Temperature T_c - Cell Temperature S_a -Average Solar Irradiance I_{mpp} & V_{mpp} - Maximum Power Point Current and Voltage resp.

appliances, proper PV storage control and electricity marketing in power system and smart grid. (2) short term forecasting with the prediction span of 30 minutes to a few days ahead is useful for power smoothing, electric vehicles, decision-making process performed in the electricity market, economic load dispatch and for unit commitments (3) Medium-term forecasting includes the prediction period varies from few days to one week ahead includes maintenance scheduling in conventional and non-conventional generating stations. (4) long term forecasting has the forecasting span ranging from one week to one year or more ahead for the study and design of any power farms, maintenance scheduling for obtaining optimal operating cost [32].

2.2.4 Data granularity

Generally, the data granularity is defined based on the interval between the collected data samples, where the closest samples increase the accuracy rate and storage complexity. So, selecting an appropriate granularity depends on the problem and choice of model used. For instance, min to min, hour to hour, and day to day data are the terms called in this paper as granularity.

2.2.5 Selection of machine learning model

The machine learning techniques are categorized as supervised, unsupervised, and reinforcement learning. The problem undertaken by this article is based on training with past year dataset the irradiation to be predicted when the environmental variable is provided as input. Hence the most suitable category for solving the problem stated is Supervised learning because the models use labelled datasets for training and perform prediction during testing. The supervised learning technique can be used for classification type problems (when the dependent variable is categorical output) as well as regression type problems (when the dependent variable is numerical output) based on the type of problem carried. Therefore, the most suitable class for the mentioned problem is the regression process. Because in regression the learning algorithm gets trained by finding the mapping function between input and output, then the trained model will be used for predicting the output when input is provided. Therefore, the review articles concentrating on efficient regression-based Supervised learning algorithm for irradiation prediction in PV system was analysed from 2014 to 2021. Hence the finding arrives with regression-based ANN and SVR for irradiation prediction.

2.2.6 Performance metrics

This section provides some of the performance metrics used for evaluating the performance of forecasting techniques. Typically, the predictor's output decides the efficiency of PV controllers and smooth power management in distribution systems. In addition, it indicates whether the predictor can forecast the irradiation at all environmental conditions or not. Hence, the performance of prediction techniques is validated before it is integrated with the PV controller or any other applications. For this reason, the experimental process is proceeded to find the performance accuracy of the prediction model used in the system. In general, the error indexes are used to evaluate the results based on the difference between the actual irradiation collected from the site and predicted irradiation using the forecasting techniques.

The most commonly used measures are Mean Square Error (MSE), Root Mean Square Error (RMSE), Relative Root Mean Square Error (rRMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Relative Error (MRE), and Mean Bias Error (MBE) [32]. Likewise, Relative Root Mean Square Error (rRMSE), Coefficient of Determination (R^2), Root Absolute Error (RAE), and Root Square Error (RSE) are considered for evaluation as in [33]. Also, the relative Mean Bias Error (rMBE) and relative Mean Absolute Error (rMAE) are stated in the paper [34]. The mathematical representation of these measures is formulated from equation (1 to13) as follows

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_{predicted} - P_{measured})^2 \tag{1}$$

The MSE is a simple and most commonly used measure in prediction. It is calculated based on the average squared difference between the predicted and measured values. The value of MSE is nearby 0 for the best prediction and is primarily used in very low/high dimensional data applications. Furthermore, the difference is squared for overestimation of error occurrence, easy identification and removal.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{predicted} - P_{measured})^2} \tag{2}$$

The RMSE is represented as the square root of MSE. It is the most commonly used measure which will be the difference between the predicted and measured value. It is estimated based on the concentration of data around the best-fit line, and it brings the error on the same scale as the target scale. Also, it corrects the large error values that are inappropriate in most cases and is sensitive to outliers.

$$rRMSE = \left(\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{predicted} - P_{measured}\right)^2}\right) X \frac{100}{P_{measured(\max)}} \tag{3}$$

The rRMSE is represented as the ratio of RMSE and the maximum measured value of variables. It is expressed in terms of percentage. The less nRMSE value indicates that there is less residual variance in the model.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_{predicted} - P_{measured}\right| \tag{4}$$

Typically, the MAE is calculated based on the absolute difference between the measured and predicted values, where all individual differences are treated equally on average. Moreover, it is not sensitive to outliers and does not correct any large error values.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_{predicted} - P_{measured}\right|}{P_{measured}} X100\% \tag{5}$$

The MAPE estimates the accuracy of the prediction model, which is represented in terms of percentage. It is calculated based on the difference between the predicted and measured values by summing every forecasting point in time divided and the number of fitted points.

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_{predicted} - P_{measured}\right|}{P_{total}} X100\% \tag{6}$$

MRE is based on the ratio of MAE to the mean error. It is usually expressed in terms of percentage. It states the size of an item being measured.

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(P_{predicted} - P_{measured}\right) \tag{7}$$

The MBE is used to compute the average bias of the prediction model or closeness between the mean forecast and observed forecast. It may be either positive or negative. The positive bias results indicate the overestimation, and the negative bias indicates an underestimation, then the lower error leads to the highest correlation coefficient.

$$rRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{predicted} - P_{measured}\right)^2}}{\frac{1}{N}\sum_{i=1}^{N}P_{measured}} X100\% \tag{8}$$

The rRMSE is defined as the ratio of RMSE to the mean of the measured value, which indicates that the prediction methodology is simple.

$$R^2 = \left(\frac{\sum_{i=1}^{N}\left(P_{predicted} - \overline{P}_{predicted}\right)^2 X \sum_{i=1}^{N}\left(P_{measured} - \overline{P}_{measured}\right)^2}{\left(\sqrt{\sum_{i=1}^{N}\left(P_{predicted} - \overline{P}_{predicted}\right)^2}\right)\left(\sqrt{\sum_{i=1}^{N}\left(P_{measured} - \overline{P}_{measured}\right)^2}\right)}\right) \tag{9}$$

The coefficient of determination (R^2) represents the variance of the output variable used by the regression model. If the value of R^2 is 1, the regression model can be represented as a perfect model.

$$rMBE = \frac{MBE}{P_{measured}} X100 \tag{10}$$

$$rMAE = \frac{MAE}{P_{measured}} X100 \tag{11}$$

$$RAE = \frac{\sum_{j=1}^{n}\left|P_{measured} - P_{predicted}\right|}{\sum_{j=1}^{n}\left|P_{measured} - \overline{P}_{measured}\right|} \tag{12}$$

$$RSE = \sqrt{\frac{\sum_{j=1}^{n}(P_{measured} - P_{predicted})^2}{\sum_{j=1}^{n}\left|P_{measured} - \overline{P}_{measured}\right|}} \tag{13}$$

Where, $P_{predicted}$ denotes the forecasted PV irradiation, $P_{measured}$ represents the actual PV irradiation measured, N is the number of sample points, $P_{true(max)}$ indicates the maximum of measured PV irradiation, P_{total} denotes the total installed capacity of PV plant, and $\overline{P}_{measured}$ defines the average value of measured irradiation. For an excellent prediction system, the error value should be closer to 0, and the correlation value should be 1 [35].

2.3 Classification of forecasting models

The general structure of the forecasting framework and its classifications is represented in Figure 4. It comprises the types based on variables, based on the number of time series, based on methodology, based on forecasting duration, and the predicted.

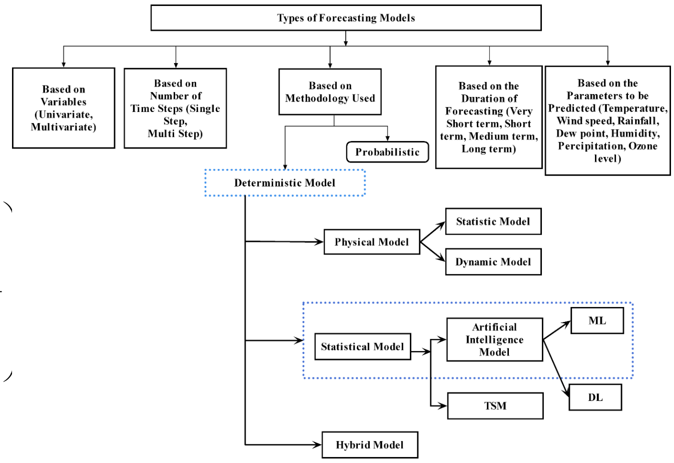

Fig. 4. Types of forecasting models based on various prediction criteria and their classifications

parameters. However, this article is highly concentrated on the forecasting model based on methodology due to advancements in machine learning in the last decades. From methodology-based forecasting, the area we are focussing on is highlighted using the dashed box. They are categorized into two types as

- Probabilistic forecasting

- Deterministic forecasting

2.3.1 Probabilistic Forecasting Model

The probabilistic model predicts the interval based on the future state of system falls. For example, using probabilistic forecasting the irradiation to be predicted on Saturday is based on data received from Sunday to Friday, whose interval is denoted by upper and lower bands. Thus, this type of forecasting technique predicts the irradiation values for the next time horizon from the present time. Figure 5 depicts the graphical representation of probabilistic forecasting models, where the day-ahead forecast of irradiation on Saturday from Friday is taken into account.

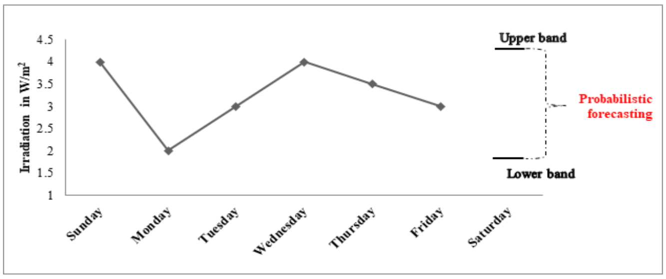

Fig. 5. Day-ahead Probabilistic forecasting of solar irradiation from Friday to Saturday

The literature related to the prediction of irradiation in PV systems based on probabilistic forecasting techniques is discussed as follows.

A review about probabilistic forecasting is conducted in [36], where the Probabilistic Solar Power Forecaster (PSPF) and Probabilistic Load Forecasting (PLF) are utilized to predict the energy consumption and load. [37] suggested a stochastic method for predicting the short-term irradiation and output power of a solar PV system using three different probability distribution functions: Gaussian, Laplace, and Uniform. These functions are utilized to find the uncertainty property in irradiation (G) and power (P), and these dynamics are tracked with the help of EM-KF (Expectation-Maximization – Kalman Filter) and PEM (Prediction Error Minimization). Moreover, it provides efficient results when compared to ARIMA (Autoregressive Integrated Moving Average). The European solar power industry utilized a probability-based approach for predicting the monthly seasonal climates [38].[39] stated the probabilistic forecasting of PV power up to 6 days using ensemble method with continuous ranked probability score process for location in France. They suggested that the method will be more suitable for both probability and deterministic evaluation tools.

The probability prediction is performed during the winter and spring seasons based on the estimation of Prediction Interval (PI) of probability by [40] with the aggregation of customers and increased PV power on netload. Here, the dynamic Gaussian processes (i.e., linear and parametric model) and QR (Quintile Regression) processes are performed with some of the identified customers (count as 300) in Sydney. To enable a stable and safe operation in power grid systems, the techniques such as RF (Random Forest), FCM (Fuzzy C-Means), SPGP (Sparse Gaussian Process), and IMGWO (Improved Gray Wolf Optimization) are hybridized in the paper [41]. The machine learning-based statistical models named NB (Naïve Bayes) and LR (Linear Regression) are utilized for the prediction interval of daily Global Horizontal Irradiation [42].

A FIG-SVQR (Fuzzy Information Granularity – Support vector Quintile Regression) mechanism is integrated for predicting the probability density of wind and solar power in [43]. Comparison of various probabilistic forecasting methods with point forecasting models for intraday solar irradiation estimation using only endogenous input. This model uses clear sky data which gives information about the situation of the sky whether it is cloudy or clear. This parameter is calculated by an index called the clear-sky index (K_c). It is the ratio of measured irradiation to the calculated irradiation during clear sky conditions at the ground level. K_c varies from 0-1, where K_c=1 denotes the sky is clear means no cloud and K_c<1 denotes the sky is cloudy means the irradiation is attenuated by clouds. It has significant impacts on the accuracy and reliability of the model because it constitutes a detailed variable for forecasting time series distribution even in case of missing data [44].

Generally, it is observed from the discussion that probabilistic forecasting models are highly dependent on the coverage probability of prediction interval and normalized prediction interval width. Typically, the prediction interval should be in the ratio of 1:0; but in most cases, the maximum interval width in PI (Prediction Interval) leads to more useless space that degrades the controller performance by wrongly choosing the maximum operating point. Also, selecting the wrong operating point will lead to power loss. Hence the overall system performance gets degraded. Thus, this article intends to implement a detailed discussion on deterministic forecasting methodology for irradiation prediction.

2.3.2 Deterministic forecasting Model

The deterministic forecasting models give a single value as output at each time horizon, also stated as point forecasting. For example, using deterministic forecasting the irradiation to be predicted on Saturday based on the data received from Sunday to Friday is indicated by the dot in Figure 6.

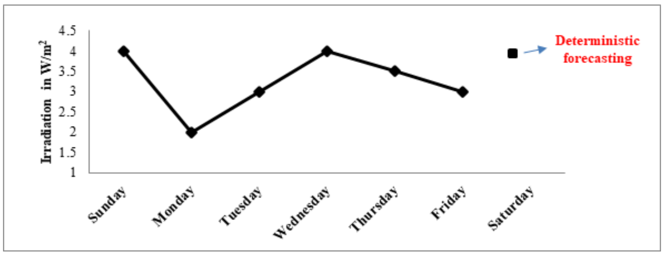

Fig. 6. Day-ahead Deterministic forecasting of solar irradiation from Friday to Saturday

Therefore, finding the most suitable point forecasting approach is imperative for solving those issues mentioned in this article. Figure 6 illustrate the graphical representation of deterministic forecasting models, where the day-ahead forecast of irradiation on Saturday from Friday is taken into account.

Some of the other point forecasting techniques apart from ANN and SVR methods are discussed in this section.

[45] aimed to predict the PV irradiation for the proper management of power in a vehicle that is tied with PV panels. Here, the 5 MMPA (Mobile Multi pyranometer Array) is used to measure the irradiation falling on the surface of the vehicle. In paper [46], the combination of the Echo state network and STESN (State Network-based Spatio Temporal) model is applied to estimate one hour ahead solar irradiation of the target station. Likewise, a simplified vector-based model [47] is recommended for predicting solar irradiation in urban areas. [48] advised a modified advection model for estimating solar irradiation with the use of PV output ground data. In addition to that, a comparison was made between three different models as the smart persistence model, ANN, and RF are used for the short-term hourly-based forecasting of PV irradiation [49]. [50] analyzed and compared various machine learning models.[51] recommended four RT(Random Tree) methods such as simple RT, RT-Pruned, RT-Boosted, RT-Bagged, and two persistence models to forecast the prediction interval of global solar irradiation and percentile estimation. [52] compared disparate algorithms such as Adaptive FoBa (Forward – Backward Greedy Algorithm), Leap Forward, Spikeslab, Cubist, and Bag Earth GCV models to predict daily global solar irradiation on the time-series dataset. [53] used an Olseth (OLS) decomposition model and Skartveit (SKA) transportation model to estimate hourly global horizontal solar irradiation.

[54] compared various soft computing techniques to predict global irradiation. [55] intended to solve the imbalance problem of grid-connected RES (Renewable Energy System) with various machine learning algorithms. [56], the historical data is analyzed along with the weather forecast variables for forecasting one hour and 24-hour solar irradiation using a random forest mechanism. Moreover, a WEKA (Waikato Environment for Knowledge Analysis) software tool [57] is used for the potential prediction of monthly solar energy/GSR (Global Solar Radiation) all over India by using the random forest technique. [58] incorporated two subsystems to predict time series surface solar irradiation based on the cloud property accessed by the satellite data. The KNN (K-Nearest Neighbour) technique is implemented in the first subsystem, and the Random Forest (RF) is employed in the second subsystem for the prediction of time-series data. [59] concentrated on the prediction of monthly solar irradiation forecasting with the help of a data integration model combined with a tree-based model named MEMD-ACO-RF. Moreover, the importance of minimizing an energy purchase from grid systems and the daily scheduling of DER (Direct Energy Radiation) in an industrial electrical system are discussed in the paper. [60] accomplishes the performance of multi period prediction using ARMA (Autoregressive Moving Average) and ARIMA (Autoregressive Integrated Moving Average) based on log-likelihood function. [61] associated the forecasting of hourly solar radiation using boosted decision tree regression model using historical data collected from Malaysia for improving the power generation.

In general, the data used for forecasting irradiation is highly volatile, time-varying, and asymmetric due to the nature of uncertainty in environmental conditions. In these cases, the above methods face difficulties in achieving better generalization at all conditions. So, there is a demand in selecting a suitable forecasting technique to satisfy the following requirements: it should handle non-linear and complex relations, outstanding generalization criteria, faster processing, no restriction in input variables, ability to learn hidden relations from data, handling data in high dimensional space, memory efficiency, robust to outliers, simple, easily updatable, less computational complexity, and increased prediction accuracy. Due to these necessities, this article intends to concentrate on two crucial ML-based point forecasting models suggested by the review article carried in the last decades for achieving efficient irradiation forecasting are

- Artificial Neural Network (ANN)
- Support Vector Regression (SVR)

2.4 Distribution of discussed article related to ANN and SVR in irradiation forecasting

In the upcoming section, we intend to focus only on the solar irradiation forecasting technique using ANN and SVR, especially for PV system applications. With a keynote of it, the recent publications from 2014 to 2022 were collected and are taken into account for the analysis in the later sections 2.5 and 2.6. The year-wise publications of ANN and SVR related articles on irradiation prediction for PV systems are illustrated in Figure 7.

From distribution, it is observed that the number of articles published related to SVR is predominantly lower when compared with ANN. The probability of combination between ANN and SVR-based publication shows variation from 2014 -2022, but the difference in the variation is major in 2019. Whereas in the year 2020 to 2022 the contribution concerning SVR is not much in the field of research, thereby we have gathered sufficient publications related to ANN which shows the developing scenario. So, it reveals that there will be a great go in ANN-based irradiation forecasting in the future era because of its simple, flexible and nonlinear problem-solving nature.

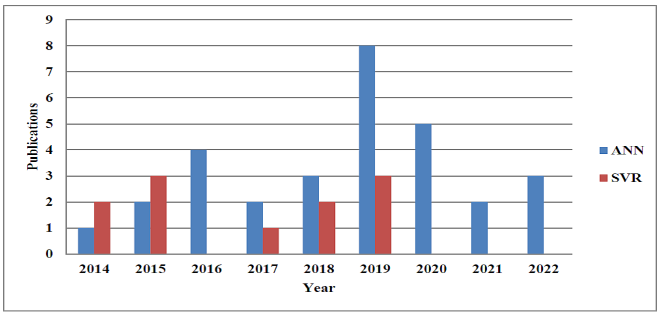

Fig. 7. Year-wise distribution of ANN and SVR related articles on irradiation forecasting for PV system

2.5 *Contribution of Artificial Neural Network (ANN) based irradiation forecasting model*

The first ANN model was developed in 1958 by Frank Rosenblatt based on the activity of the human brain. It is more commonly used in speech reorganization, image processing, financial forecasting and intelligent searching. Typically, the network is formed by connecting artificial neurons with input, hidden, and output layers. ANN mimics the activities of actual neurons and provides the output. Based on the provided input, the multiplication of weight is initialized to filter the input features based on importance and propagates the final values. The bias addition is to shift/trigger the activation function forward or backwards. Then, the activation function is utilized to generate the exact output value by introducing non-linearity. The schematic representation of an artificial neuron and general workflow procedure of ANN-based irradiation forecasting are illustrated in Figure 8 and Figure 9.

The entire process is performed by connecting each neuron to the other from the past layer through interconnected adjustable weights. Let the source x_s(s=1,2…n) represent the signal given as input to neurons. In forecasting, the input signal will be the attributes to forecast irradiation, such as temperature, pressure, humidity, etc. Then each input signal is multiplied with weight w_{ls}(s=1,2,…n). The net signal of neurons after adding bias is given by

$$N_l = \sum_{s=1}^{n} x_s w_{ls} + b_m \tag{14}$$

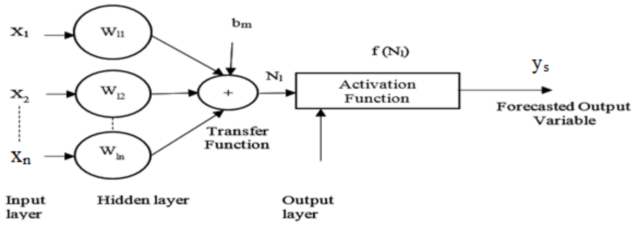

Fig. 8. Schematic representation of an artificial neuron with its layers and its functional blocks

The forecasted variable received at the output of any neuron is calculated based on the application of linear/non-linear activation function chosen based on the net response achieved in equation (14) is given by

$$y_s = f(N_l) \tag{15}$$

The operation of a Neural Network involves a 2-way process called Feed Forward-Back Propagation. The computation of weight is performed in the first process and the updation of weight is done in the second process. In the early usage of the neural network, they used only Feed Forward process. Here the function of the neuron as mentioned above is carried in each layer is continuous iteratively with the randomly assigned weights until the desired output is reached. In later years, the Back Propagation training method is practiced for faster convergence and performance improvisation. Here the weights are adjusted based on the error difference between the actual and predicted output, hence the error gets minimized considerably.

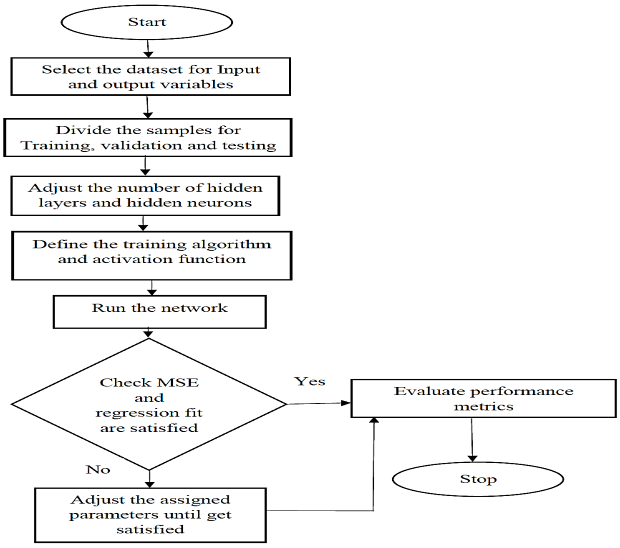

Fig. 9. General workflow diagram of ANN-based irradiation forecasting model

There are several learning algorithms used for weight modifications in the BP process. Among them, the fastest and most stable learning algorithm called Levenberg-Marquardt (LM) is used by most of the ANN-based articles in the literature. Because it has the combined advantages of both the Steepest descent algorithm and the Gauss-Newton algorithm. Hence the desired output is attained by maintaining the error within the tolerable range under minimum iterations.

Further, the selected articles related to irradiation forecasting in PV systems using ANN are discussed as follows.

[62] proposed MLP and RBF (Radial Basis Functions) based ANN technique in predicting GSR for the better utilization of solar energy in Abu Dhabi city. [63] has executed FF-LM-MLP based ANN to predict the GSR with the help of metrological data including the particulate matters in the air. It has got better improvement in prediction compared with others. The effective Comparison of FFBP (Feed Forward Back Propagation)-MLP and empirical models were made by [64]. It reveals that ANN performs with high accuracy in forecasting GSR and can be applied to all locations where the climatic parameters were similar to this article specifications.

MLP-ANN-based GSI forecasting was proposed for the proper functioning of energy management systems using metrological past data. It has attained good forecasting during the testing process. Cloudiness of the sky data is suggested for varying cloudy days for future investigation [65]. Feed Forward Multi-layered Perception-based ANN model was designed by [66] using a different combination of input variables was proposed to predict GSR for PV sites in Nepal. [67] proposed various Levenberg-Marquardt-MLP based ANN model was designed based on the different combination of input variables for predicting solar radiation to find the potential of solar energy in hilly areas of Himachal Pradesh.

Later the Feature Selection Optimization Solar Insolation Prediction (FSOSIP) based feature selection process was combined with ANN to predict accurate solar radiation in different locations of Bangladesh [68]. Another research paper performs MLP based ANN [69] in predicting DSR and normal irradiation using heterogeneous variables for the University of Salerno. Moreover, the FF-ANN method was proposed to accurately forecast daily solar radiation for 5 sites in Kuwait [70].

[71] formed a hybrid model by integrating the functionalities of Variational Mode Decomposition (VMD) and Low-rank RKELM(Robust Kernel Extreme Learning) techniques for the short term solar irradiation prediction, in which different variants such as Polynomial Kernel, Gaussian Kernel, Sigmoid Kernel, Morlet Wavelet Kernel, and Mexican Hat Wavelet Kernel are considered under different weather conditions.[72] provided a case study about the prediction of daily global horizontal solar radiation using different metrological parameters. Here, the ANN-based Back Propagation algorithm is employed to find the prediction for best combination of inputs. From the study, it is analyzed that the combination of 2 or 3 inputs like Daily Maximum and Minimum Temperature (DT) - Theoretical Sunshine Hours (Ho), and extra-terrestrial radiation (So) provides accurate daily GSR prediction. It is concluded that the outcome of (DT, So) with ANN is an excellent estimation technique for the Indian location.

[73] discussed some data-driven approaches such as MLP, SVR, and RT for predicting hourly solar irradiation using an Aerosol Optical Depth (AOD) and Angstrom exponent data along with weather variables. When compared to the other techniques, MLP provides better prediction accuracy for next hour. The article [74] performed the prediction of daily horizontal solar irradiation using GWO-MLP. Besides, a WMIM (Wrapper Technology-based Mutual Information Model) is developed by [75] for reducing the dimensionality of data used with the help of an information-based variable selection method results in a fast, computationally efficient, and accurate prediction rate, where the GHI forecasting is performed using ELM (Extreme Learning Machine) algorithms.

In [76], MLP-GA (coupled ANN) was proposed to predict GSR with high accuracy and short computational time compared with a simple ANN and empirical model. Secondly, the empirical model performs better than the simple ANN model. [77] The solar irradiation on the horizontal surface is predicted using a DBN (Deep Belief Network), categorized into two phases: pre-tuning and back prorogation phases. Here, an RBM (Restricted Boltzmann Machine) is used in an unsupervised pre-tuning phase for parameter initialization of a network and the weight values are adjusted in a supervised back prorogation phase for achieving the target. The optimal daily radiation is obtained at 3500 iterations, with the learning rate of 0.1, each layer has eight neurons, and the metrological data for three days are taken as inputs.

In addition to that in [78], a sky image-based global horizontal irradiation prediction is performed with the help of ANN. [35] integrated the ECMWF (European Centre for Medium-Range Weather Forecasting) with the ANN method for a short term daily global solar irradiation. In this paper, the NCA (Neighbour hood Component Analysis) technique is used for selecting the most suitable features for improving the prediction accuracy. Moreover, the best performance for the optimal parameters during seasonal and large climate variability are tabulated. In addition to that, a novel interval-based prediction methodology is developed in [79] for forecasting short term solar irradiation and wind speed. For this purpose, efficient techniques named Wavelet Transform, NNMFOA (Neural Network Modified Fruit Fly Optimization), and GMDHMOMFOA (Group Method of Data Handling Neural Network Modified Multi-Objective Fruit Fly Optimization Algorithm) are implemented, which exactly helps in predicting the energy consumption in a micro-grid station. At first, the data preprocessing is done using WT, and the essential features are selected using NNMFOA with a reduced error and faster rate. Finally, the GMDHMOMFOA is used to attain the optimal global solution, making the suggested framework more efficient either in both point and interval prediction.

A novel DENFIS (Dynamic Evolving Neural Fuzzy Inference System) [80] mechanism is developed to predict monthly average solar radiation, where the single variable named air temperature is considered as an input variable. Then, an evolving cluster methodology named NF (Neuro-Fuzzy) clustering is utilized for partitioning the input space. The rule base and triangular MS functions are created by using recursive clustering. The analysis stated that the suggested method works well with less input and obtain overestimated value than the observed values during summer. The high variation occurs because of the coastal area and misleading in prediction. [81] designed solar irradiation prediction using a novel CNN-GA/PSO (Convolutional Neural Network – Genetic Algorithm/Particle Swarm Optimization) and CHA (Chaos Algorithm) for a grid-connected PV system and has attained increased prediction accuracy. This technique updates the hyperparameter for improving the unsatisfactory performance of a grid system. Moreover, HAEANN (H-forecasting Horizon with Evolutionary framework with ANN) [82] generates a model based on forecasting history to forecast GHI up to 6 hours ahead. The model was tested with 24 Moroccan cities under different climates without irradiation data and has attained better prediction accuracy. [83] DENN (Direct Explainable Neural Network) with rigid function incorporated with the two-layer training process for better mapping of non-linear features. This helps to attain a clear relationship between input and output for the irradiation prediction model. Tested under different seasons has got better prediction accuracy and high training efficiency. An evolutionary NN [84] with a Radial function, Sigmoid Unit, Product Units are proposed to forecast solar radiation. The model was tested under different combinations of dataset variables to show its superiority. It reveals that EANN

(Evolutionary Artificial Neural Network) with SU-PU has achieved excellent performance with high prediction accuracy (Sigmoidal unit at hidden layer and Product Unit at the output layer).

RNN-GRU (Recurrent Neural Network-Gate Recurrent Unit) was proposed to forecast very short-term solar irradiation, with high accuracy and precession [85]. [86] proposes RE-SOINN (Regression Enhanced Incremental Self-Organizing Neural Network) for predicting hourly solar irradiation under real-time and time-series irradiation data. Before providing input to RE-SOINN, the discrete signal is converted into continuous input by the regression method and then decomposed the original input and then accessed by the model proposed, resulting in more accurate and higher forecasting performance. The optimal hyperparameters selection can be achieved using PSO for better results and presently used a grid search method. [87] proposes Multitask Hybrid Evolutionary NN for inclined solar irradiation forecasting using GHR data. MHENN (Multitask Hybrid Evolutionary Neural Network) provides two outputs, one to predict the current instance and the other for predicting the next hour value. Here evolutionary algorithm is used to adjust the parameters in NN. They were tested with ground data (whose panels are inclined, two years data from 2013 to 2014 with a resolution of 5 min) and satellite data (panel has different tilt angle, data from 2004-2006 with the resolution of 10 min). Model is performed and compared under three basic functions such as Sigmoidal units, Radial Basis function, Products unit and single model (SHRENN). It reveals that SUNN (Sigmoidal Unit Neural Network) is simple and produces computationally efficient performance.

The efficient FFBP-LM-ANN was expected by [88] with simple feature selection and optimal number of neuron selection process was performed for predicting short term irradiation forecasting in Chennai. The hourly prediction of solar radiation using ANN-BR (Bayesian Regularization) was performed in [89]. Here the research moto was to find the optimal combination of metrological variable and better BP algorithm for attaining accurate prediction. In [90] the solar irradiation prediction using ANN-LM with 1-7-1 design was implemented and achieved superior performance for the Baron Techno part location when compared with other design.

From this study, the significant benefits, demerits, and the desires to improve the performance of ANN in irradiation forecasting scenarios are analyzed clearly, and are bulleted below:

2.5.1 Advantages of ANN in PV irradiation forecasting

- It can handle non-linear data and high-level features.
- It performs well at all scales of data.
- Can handle time-series data in real-time applications.
- Uncertainty data handling capability even in case of incomplete data.
- Free from overfitting and underfitting problems.
- Manual tuning of hyperparameters will be avoided when hybridized
- Faster performance.
- High accurate prediction results for any kind of volatile, ramp up or down, high cloud variation, and seasonal climate change.
- More reliable for both short term and long-term forecasts.
- More robust

2.5.2 Drawbacks of ANN in PV irradiation forecasting

- It is challenging to interpret because it is a black-box model.
- It undergoes time-consuming and increased computation complexity.
- The data set required to be comparatively high than other ML models.

2.5.3 *Requirements for a perfect ANN design in irradiation forecasting*

- Selection of optimal number of hidden layers and hidden neurons in each layer.
- An optimal selection of activation functions is essential.
- The feature selection process should be mandatory for supplying the relevant Input variable
- Integrate the efficient training algorithm/optimization algorithm for global exploration to avoid trapping at a local max and avoid dependency on starting conditions and computational complexity.
- Effective training, testing and cross-validation must be performed for better generalization.

Detailed specifications of the discussed article on ANN-based irradiation forecasting mechanisms from 2014 to 2022 are arranged in chronological order. They are tabled based on their location, data type, prediction variable/horizon, data granularity, compared models and performance measures and applications are given in Table 2.

2.6 Contribution of Support Vector Regression (SVR) based irradiation forecasting model

The SVM algorithm was developed by Vladimir N.Vapnikin in 1963[91]. He has created non-linear classifiers by adjusting the kernel function to adjust the hyperplane. The Support Vector Regression (SVR) is the statistical prediction model that maps the future output by training the dataset, and it predicts the relevant output based on the testing sequence in future forecasting. The significant difference between the SVR and other regression models is, it tries to fit the best line within the predefined error value instead of reducing the error between the actual and predicted values. The general flow diagram of the SVR based irradiation forecasting approach is depicted in Figure 10.

Table 2. Overview of the above-discussed article based on ANN for irradiation forecasting in PV

Reference/ Year	Forecasting Technique	Location/ Latitude, longitude.	Input Variables	Forecast Horizon /prediction variable	Data granularity/Data set	Compared models/ Application	Performance measures
[62] /2014	MLP-RBFANN	Abu Dhabi city, United Arab Emirates / Lat-24° 28′ N, Long-54° 22′E	Daily T_{max}, MDWS, MDSSH, MDRH	Monthly mean/GHI	Daily mean/ 1993-2008.	Measured value, Regression model, LM-ANN/ Development and utilization of solar energy	**RMSE=294W/m^2** MBE= -0.0288 **MAPE=3.98%** **R^2=.94**
[63]/ 2015	FF-LM-MLP-NN	Tehran, Iran/ Lat-35.44E, Long- 51.23N.	WS, T_{max}, T_{min}, Particulate matters (PM10 and PM2.5)	Daily/ DiffSR, DSR, GSR	Daily/ 2012-2014	Measured value/ PV station	RMSE=0.05Wh/Cm^2 **MAPE=1.5%** **R^2=.97**
[64]/ 2015	FFBP-MLP	Qena, Upper Egypt/ Lat-26.170 N, Long- 32.70 E	SSH, T_{max}, $T_{min,}$ RH	Daily, Monthly/GHR	Daily/2001 -2013	7empirical models/Solar energy systems	MBE= -0.0692, RMSE=0.5338, MPE= -0.2647, **R^2=0.9892** NSE= 0.9890 T_{test}=2.493
[65]/ 2016	MLP-ANN	Tilos Island, Greece/ Late-36.41°N, Long-27.38°E	MOY, HOD, Ai, T, RH, BP, GSI	Mean hourly One day ahead/GSI	Min/ 17/03/2015 - 20/12/2015	Real data/ Energy management systems	**R^2=0.707** **RMSE=90W/m^2** MBE=0.033KW/m^2
[66]/ 2016	MLP-LM-BP	Kathmandu, Nepal/ Lat-27.77N, Long-85.340E	T_{max}, T_{avg}, H, RA, SSH, SR	Daily/GSR	Daily avg/ 2002-2013	Empirical models, measured data/PV sites	RMSE=0.2787 **R^2=0.976** MBE=0.0368 MAPE=12.43%
[67]/ 2016	LM-MLP	Himachal Pradesh, India/ Lat-31.63°N, Long-76.57° E	T, R, SSH, H, BP	Daily/Solar radiation	Daily/5 years	Measured value, Different combinations of input variable / Solar energy applications	**MAPE=16.45%** MSE=.0021 **R^2=0.92195**
[68]/ 2016	FSOSIP	Bangladesh / Lat-23.78N Long-90.38E.	Lat, long, RH, A, T_{max}, CI, E, MOY, SSD	Daily/Solar radiation	Monthly avg/ 2000-2014	Measured value/PV sites	MSE=0.000173% RMSE=0.013153 **MAPE=0.0868%**
[69]/ 2016	ANN-MLP-BP-LM	University of Salerno/ Lat-40°N, Long-14°E.	Lat,long,T,SSD,Pp,H,WS,H, Declination angle.	Daily and Hourly/ GSR, DNR	Daily/ 2013-2015	Related ANN for GSR and DNR /Solar residential buildings	**MAPE=5.54%** **RMSE=17.7W/m^2** **R^2 =0.991** MAE=131.2
[70]/ 2017	FF-ANN-LM	Kuwait (5 locations)	SR	Daily/ DASR	Daily/5 years	ANN-GD, ANN /Solar application	**MAPE=85.6%** MSE=43722.196 **RMSE=209.1W/m^2**
[71]/ 2018	VMD-RMWK	Odisha, India/ Lat-19.924°N, Long-85.396° E	Irradiation, AT, Current, Power	15min,1h,1d/Solar irradiation	15min,1h,1d/1st Jan 2015-31st Dec 2015	VMD-MHWK, VMD-GK, VMD-PK, VMD-SK,EMD-RMWK / Solar Power plant	**MAPE=1.162-1.523%** MAE=0.007-0.012 RMSE=0.009-0.024 **R^2=0.992** **T_r=83.70sec-196.39sec**

[72]/ 2018	ANN2 with BP-LM (TD, ETR)& ANN3 with BP-LM(TSSH, TD, ETR) with BP	Tiruchirappalli, India/ Lat-10.8050°N Long-78.69° E	GSR, TD, SSD, ETR, T_{max}, $T_{min,\ TSSH}$	Daily/GHR	5min/3 years	ANN1, ANN4, ANN5, ANN6 with Different combinations of variables/ Solar energy applications	**MAPE=5.08%** RRMSE=5.8% MPE=6.23%
[73]/ 2018	MLP	KACARE site, Saudi/ Lat-24.903° N, Long-46.39° E	AOD,SZA,WS,GHI,DNI,HOD,MOY,WD	Hourly ahead/GHI, DNI, DHI	Hourly /3 years (Jan 14, 2013, to Dec 31st, 2015)	SVR, KNN, RT/ Microgrid in the desert area	**RMSE=3.75W/m^2** FS=42.10%
[74]/ 2019	GWO-MLP	Australia	DHSR, RH, AT	Daily/ DHI	One day interval/-	Measured values/Solar energy applications	MAPE=3.025% MAE=0.022 R^2=0.9786
[75]/ 2019	WMIM-ELM	Tamanrasset, Algeria, Lat-22.79N Long-5.52E Madina, Saudi Arabia/ Lat-24.55N Long-39.70E,	Time series Solar irradiation data	5min-30min and 1h-3 hours ahead/GSR	Hourly/11 years hourly and 1 year 5 min interval data	Dimensionality reduction schemes with 50 variables,5 variables with PCA/ Electricity grid	**RMSE=8.057W/m^2** NMSE=0.06755 **R^2=0.93533** **MAPE=10.7%** FS=.25 **T_r=16.18sec**
[76]/ 2019	MLP-GA	Iran (10 locations)/ Lat-31° 20′N, Long-48° 40′ E	SSH, AT	Daily/GSR	Hourly/1992-2015	Empirical model, simple ANN/PV application	**R^2=0.92** MBE=38.4 **RMSE=185.5W/m^2**
[77]/ 2019	DBN	China, Lhasa/ Lat- 29°40′N Long-91°08′E	Daily solar irradiation data, WS, SD, DBT, RH	Daily/ Global Solar irradiation	Daily/1994-2009, and 2010-2015	BP/ Power grid	**RMSE=465.69W/m^2** MABE=1.271MJ/m^2 **R^2=0.9216**
[78]/ 2019	ANN-BP	Malaysia/ Lat-4.2105N Long-10.975E	SI, GHR	1 to 5min ahead/GHI	20sec/2016 (July to Sept)	Actual value/ Electric grid	**RMSE=143W/m^2**
[35]/ 2019	FF-ANN-LM	Queensland, Australia/ Lat-27.48S, Long-153.04 E	Ep, SR, T_{max}, SC, AT, CC, RH, SH	Daily/GIR	12 h/1979-2015	SVR, GPMC, GP and TM/ Energy modelling & utilization in power grid	**R^2=0.9351** **RMSE=448.06W/m^2** MAE=1.146MJ/m^2 rRMSE=10.55MJ/m^2 rRMAE=9.44MJ/m^2 MBE= -0.043MJ/m^2
[79]/ 2019	GMDHWFOA	Favignana Island, South of Italy/ Lat-37°55′N, Long-12°19′E	WS, SR	6 months ahead/Solar irradiation and wind speed	Monthly/ 2016	NN-GA,NN-PSO, NN-ACO,NN-FOA/ Microgrid	RMSE=0.017868 **MAPE =1.7275%** MAE =0.015095 **R^2=0.99649**
[80]/ 2019	DENFIS	Antakya and Adana,Turkey/ lat-36°33′ N, long-36° 30′ E, lat-37° 00′ N, long- 35° 19′ E	SR, AT	Monthly avg/Solar Irradiation	Monthly/1983–2010 and 1968–2015	MARS, M5Tree and LSSVR/ Modelling solar system	**RMSE=22.5W/m^2** MAE=.66MJ/m^2 NSE=.978 **R^2=0.942**
[81]/ 2020	CHA-GA/PSP-CNN	Mesonet station, America/ Lat-36.575N Long- 99.47W	SP,LWRF,AP, SWRF, W, SH, CC, AC, T_{max}, T_{min},	Yearly/ Solar Irradiation	5min/ 1994-2006, 2013-2014	ANN,KRBF,GBRT /Grid-connected and solar thermal systems	**RMSE=573.89W/m^2** MSE=4.268MJ/m^2 MAE=1.5153MJ/m^2 RS=70.89%

			CT,ST,SLR,ALR, SSR.				AER=0.14208
[82]/ 2020	HAEANN	Morocca/ Lat-30.38, long--9.57	Geographic and Climate data (BSh, Csa, BSk BWh)	Up to 6 h a head/GHI	Hourly/ 2005	Smart persistence, regression trees and random forest/Planning and modelling of Solar Technology	NRMSE=7.59%-12.49% NMAE=4.41%-8.12%
[83]/ 2020	DENN	Lyon, France/ Lat-45.786◦N, long- 4.9225◦E	SRTSD, AS, SA, DBT, H, WS,WD,T,RH ,GSR,ZI,RS	Short term/Solar irradiation	1min/ 2018	SVR, BPNN, XGBoost /PV integrated grid	**RMSE=64.01W/m^2** **R^2=0.8659** MAE=22.82W/m^2 **T_r=.7sec** Model size=22kb
[84]/ 2020	EANN SU-PU	Toledo, Spain/ lat-39◦53'N, long- 4◦ 02'E	Satellite data(Rf, CSkR, CI,GSR)	Short term/Solar Radiation	Hourly/May 2013-April 2014	ELM,GPR,MLP,SVR,EANN(SU-LO RBF-LO)/ Radiometric Station	**RMSE=51.82W/m^2** MBE=1.09W/m^2 MAE=33.46W/m^2 **R^2=0.9709**
[85]/ 2020	RNN-GRU-GA	Fes, Germany/ Lat-33.3 °N, Long—5.0 °E	Satellite data (Historical GHI-TSD, T)	Very short term/Solar irradiation	10min/ 2016-2019	Simple RNN,RNN-GA,LSTM,LSTM-GA,GRU/ Distribution Grid	**RMSE=0.05486** MSE=0.0017-0.00301 MAE=0.022-0.0311
[86]/ 2021	RE-SOINN	Samenyih, Malaysia/ Lat-2.9474°N, Long-101.9° E	SR, TSt	Hourly/Solar irradiation	One min/ April 2018-June 2018	Persistence model, Exponential Smoothing Model and Artificial Neural Networks/ Energy management systems.	**RMSE=72.658W/m^2** MASE=.81089
[87]/ 2021	MHENN with sigmoidal unit	Bouzareah, Algeria/ Lat-36.8°N, long-3.032°E	GHR, InI, SIDTA, SaD	Current and next hour /Inclined Solar Irradiation	5min,10min/ 2004-2006, 2013-2014	Sigmoidal units, Radial Basis function, Products unit and single model (SHRENN) /Solar power systems	**RMSE=108.59W/m^2** MAE=65.17W/m^2 nRMSE=18.40% nMAE=11.08 % **R^2=0.972**
[88]/ 2022	FFBP-LM-ANN	Chennai, India	SZA, RH, T, CC, Pp	Hourly/ GHI	Hourly/ 2016-2019	9 similar studies/ Solar applications	**RMSE=0.073W/m^2** MAE=0.0425W/m^2 **MAPE=44.432%** **R^2=0.979541** MBE=0.000492
[89]/ 2022	ANN-BR	Kaula Terrenganu, Malaysia/ 5°23' N, 103° 6' E.	T, RH	Daily/ SR	Daily average/ 1985-2012	4 similar works, ANN-LM, ANN-SCG/ Solar energy development	MAE=0.2015 **RMSE=0.2884** **R^2=0.86977** NSE=0.5770 **MAPE=10.64%**
[90]/ 2022	ANN-LM	Baron Techno Park, Indonesia/ 8.1324°S, 110.5437° E	T,RH,SS,UV radiation, diffused short wave radiation, WS, sea level pressure.	Hourly day ahead / SR	Hourly/ 2019(5 months)	ANN-SCG and 2 other ANN models/ Maintenance scheduling, solar power protection	**RMSE=0.15185** **R^2=0.88996** Iteration=10000

*Pp: Precipitation; Ep: Evaporation; SR: Solar Radiation; AT: Average Temperature; LWRF :Long-wave radioactive flux; SWRF: Short-wave radioactive flux; AP :Air pressure; APW: Atmospheric Perceptible Water; SH :Specific Humidity; CC: Cloud Cover; BP: Barometric Pressure; AC: Atmospheric condensate; T_{max}: Maximum Temperature; T_{min} :Minimum Temperature; CT :Current temperature; ST :Surface Temperature; SLR: Surface long-wave radiation; ALR: Atmosphere long-wave radiation; SSR: Surface short-wave radiation; MWS: Mean Wind Speed; MDSSH: Mean Daily Sun Shine Hours; MDRH :Mean Daily Relative Humidity; DAT :Daily Average Temperature; WS: wind speed; DBT :Dry-Bulb temperature; GSR: Global Solar Radiation; SR: Solar Radiation; SSC: Sunshine Coast; AT: Air temperature; GHI :Global Horizontal Irradiation; Lat: Latitude; Long: Longitude; Alt :Altitude; CI :Cloudiness Index; DNR: Direct Normal Irradiation; DHI :Direct Horizontal radiation; E :Elevation; AvgT :Average Temperature; TSSRD: Time Series Solar Radiation Data; T: Temperature; WC :Wind Chill; P: Pressure; Ti: Time; M :Month;H:Humidity; R :Rainfall; SZA: Solar Zenith Angle;; ZI :Zenith Illumination; TSD :Time series Data; RS: Radiation Shadow; Rf :Reflectivity; D :Days; MDT: Mean Daily Temperature; CSR :Clear Sky Radiation; WD :Wind Direction; AS: Azimuth of Sun; SA :Sun Altitude; GTI: Global Tilted Irradiation; AT :Air Temperature; HS-AC: Hot semi-arid climate; AD: Aerosol Data; HOD: Hour of day; MOY: Month Of the Year; TSt: Time Stamp; InI: Inclined Irradiation; SIDTA :Solar Irradiation at Different Tilt Angle; HSMC: Hot summer Mediterranean climate; CS-AC: Cold semi-arid climate; HDC: Hot Desert climate; SaD :Satellite data; Ai :Air; TD :Difference of temperature; TSSH :Theoretical Sunshine Hours;; MDWS: Mean Daily Wind Speed; MDSSH: Mean Daily Sunshine Hours; MDRH: Mean Daily Relative Humidity; RA: Rainfall Amount; SRTSD: Solar Radiation Time Series Data; ZI: Zenith Illumination; DLH: Daily Light Hours.

In addition, a detailed description and formation of SVR are given as follows:

Let us consider the training data $\{(x_1, y_1), \ldots, (x_l, y_l)\} \subset x \times R$, where x represents the space of input patterns and y_l indicates the training samples. The regression function of the SVR is represented using equation (16) as follows

$$y = f(x) = \omega^T \varphi(x) + b \tag{16}$$

Where $\varphi(x)$ represents the function to map the data, ω represents the weight value of the feature vector, and b represents the bias constant to find the relevancy factor between the training and testing set. For a better generalization of Radial Basis Functions (RBF), the kernel function is formed as follows

$$K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2} \right) \tag{17}$$

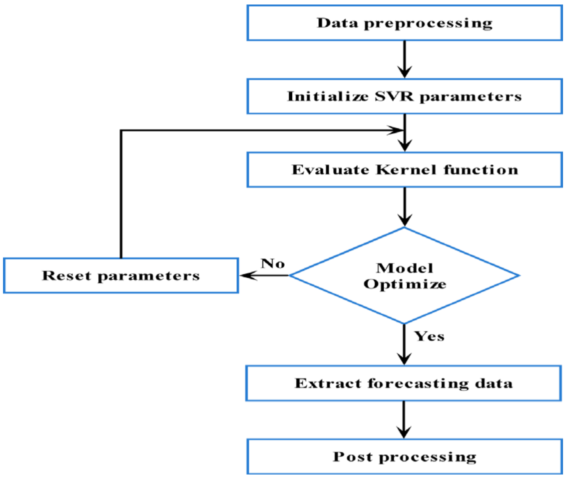

Fig. 10. General workflow diagram of SVR based irradiation forecasting model with Kernel tuning

Where $\|x_i - x_j\|$ denotes the Euclidean distance between training samples and σ is the standard deviation. In that kernel function, if the $\frac{-1}{2\sigma^2}$ is considered as γ, then the equation (17) can be written as,

$$K(x_i, x_j) = \exp\left(\gamma \|x_i - x_j\|^2 \right) \tag{18}$$

The article related to PV irradiation forecasting using the SVR model is discussed as follows:

A case study [92] about the ML technique, i.e. SVM-XGBoost (Extreme Gradient Boosting), and four empirical models such as linear temperature-based model (M1), logarithmic model (M2), exponential model (M3), and modified model of M3 (M4) is proposed for daily GSR forecasting. The evaluation results depicted that the SVM outperforms the empirical models (M1 to M4) with excellent tracking capability based on RMSE, high accuracy, stability and less computational time. [93] suggested an intelligent LS-SVM model for predicting the day ahead solar radiation. It provides better data analysis and provides a relevant feature for the regression process. During the simulation, the MATLAB tool is used for analysis, and the results proved that the LS-SVM provides the radiation for the next day with increased accuracy.

[94] introduced a hybrid SVM – FFA technique for the long term global horizontal irradiation prediction. In this work, firefly optimization is mainly used to identify the

optimal parameters used for prediction, which improves the overall performance of SVM based forecasting.

Similarly, the GA-SVR techniques are utilized in this paper [95] to predict daily GSI based on optimal parameter selection. [96] the hourly Global horizontal Radiation prediction using Forward Regression on QKSVM-FA (Quadratic Kernel Support Vector Machine-Firefly Algorithm) is employed to predict global horizontal radiation prediction. This technique intends to improve the accuracy of forecasting based on the feature selection and prediction processes. This regression model selects the vital parameter for prediction. Based on this, the SVM performs irradiation forecasting with minimized computational complexity.

[97] compared the performance of 16 SVM, 16 empirical, and 3 ANN models using the WEKA software tool to predict daily GSR. Here, the correlation and sensitivity are performed for selecting important features in forecasting. The Sunshine input data plays a dominant role in achieving efficient forecasting. In this study, SVM with the most influencing input is the best choice for a competent prediction of GSR. The benefits behind this approach are simple to use, short length in area utilization and obtaining unique solutions. [98] suggested a DCE (Decomposition Cluster Ensemble) approach in forecasting 1, 3, 6 days ahead of solar irradiation. The EEMD (Ensemble Empirical Mode Decomposition) technique decomposes the original time series data G into the IMF (Intrinsic Mode Function) and residual components. Then, the LSSVR method forecasts IMF and residual components by optimally selecting the input parameters by GSA (Gravitational Search Algorithm). Consequently, the component forecasted are clustered with the help of the k-means clustering technique, and lastly, the ensemble method is applied based on the sample weights on each cluster for obtaining the final output forecasting results. The experimental results depicted that this hybrid model is more suitable for different time horizons due to its increased accuracy and robustness.

[99] the estimation of Daily Horizontal Direct solar radiation using SVR-RBF as the kernel was modelled with the inclusion of air quality index with metrological data as an input variable, which results in high prediction accuracy. [100] utilized a hybrid SVR with the k-means algorithm for forecasting daily global irradiation, where the data is clustered based on the seasons. The SVR estimates the Daily Global Irradiation (DGI) based on the clustered data, and the 7-cross validation is performed for the hyperparameter selection process. Besides, Radial basis function-based SVR [33] was modelled for predicting direct normal radiation based on a different combination of input variables for location in Algeria.

From this study, the significant benefits, demerits, and desires to improve the performance of SVR in irradiation forecasting scenarios are analyzed clearly, and are bulleted below:

2.6.1 Advantages of SVR in PV irradiation forecasting

- It is highly efficient in handling high dimensional data.
- More robust in handling outliers.
- Better generalization
- Simple implementation and design.
- Suitable for all kinds of applications.

2.6.2 Disadvantages of SVR in PV irradiation forecasting

- Overfitting problem due to the increased *amount* of received features.
- It is not suitable for large and noisy datasets.

2.6.3 Requirements for a perfect SVR design in irradiation forecasting

- It is highly required to select the appropriate kernel function.
- Hyperparameter selection and feature selection should be made using a suitable optimization technique.

A detailed specification of discussed articles on SVR based irradiation forecasting mechanisms from 2014-2022 is arranged chronologically. They are tabled based on their location, data type, prediction variable/horizon, data granularity/dataset, compared models and performance measures are given in Table 3.

3. Analysis and Discussions

3.1. Performance analysis of ANN related articles

The preliminary information regarding various ANN-based irradiation forecasting methods, especially for PV systems, are discussed in section 2.5 and are tabulated in Table 2. The comparison cannot be made among various ANN articles due to different specifications practiced by each model. Therefore, their performance is studied by analyzing the most common performance metrics used in discussed papers, are taken into consideration. Those performance metrics are highlighted in Table 2. With this, we analyzed MAPE, R Square and RMSE metrics. To show the variability of RMSE values attained by various ANN articles in irradiation forecasting, the units used in articles for RMSE calculations were converted into W/m^2 as common traces. It is observed that the articles where the units were not mentioned for RMSE evaluation were performed before the denormalization process. Hence for a better understanding of the prediction capability of the model, we are not considering those in this analysis. The different MAPE, R Square and RMSE values of various ANN researchers regarding irradiation forecasting are put into a common platform, as illustrated in Figure11(a); (b); (C).

Table 3. Overview of the above-discussed article based on SVR for irradiation forecasting in PV systems

Reference/ Year	Forecasting Technique	Location/ Latitude, Longitude	Input Variables or Attributes	Forecast Horizon /prediction variable	Data granularity/ Dataset	Compared models/ Application	Performance measures
[93]/ 2014	LS-SVM	Elazig, Turkey/ Lat=38.6748°N, Long=39.2225°E	T_{max}, T_{min}, SSD, SI	Day-ahead/ Solar radiation	Daily/ 3 years (2000-2003)	Actual value/ PV systems	Accuracy=99.294%, RMSE=0.004384 **R^2=.99294** MRE=9.96 CVRMSE=0.094611 MEF=3.318
[94]/ 2015	SVM-FFA	Iseyin / Nigeria (Lat-7.96°N Long-3.60°E) Maiduguri/ Lat-11.83°N Long-13.15°E Jos/ Lat-9.92°N Long=8.9°E	GSR, SSD, T_{max}, T_{min}	Monthly/ GHI	Daily monthly avg/ 1987-2007	ANN and GP/ PV installation	RMSE=1.8661 **R^2=0.7280, MAPE =11.5192%**
[95]/ 2015	SVR-GA	Spain/ Lat-40.4637°N, Long-3.7492°W	T_{max}, T_{min}, T_{avg}, RH, Ri, WS,GHI,SSD	Daily/GSI	Daily/ 2013	Empirical model/Rural power generation	MAE=1.81MJ/m^2 **RMSE=722W/m^2** **R^2=0.91**
[96]/ 2017	QKSVM-FFA	Tibet, China/ Lat-87.35°E, Long-32.35°N	GHI, ZA, T, RH, WD, WS, Pp, P.	Hourly/ GHR	Hourly/ 2014	KSVM, KSVM LASSO,KSVM SCAD, KSVM-F /Designing solar power plant	MAPE=4.46% MAE=6.80W/m^2 $^+$**RMSE=9.23W/m^2** TIC=1.82 % MBE=-1.70W/m^2
[97]/ 2018	SVM	17 locations in India	M,BSSH, DL ,RH, T_{max}, $T_{min,}$ ETR	Daily/ GSR	Monthly mean/ 2000-2012	16 SVM,16 empirical and 3 ANN model/ Assessing the solar energy potential	**RMSE=322.69W/m^2** **R^2=0.9420**
[99]/ 2019	SVR(PBF)	6 location in China	T_{max}, $T_{min,}$ T_{avg}, RH, WS, AR, SSD, DOY, AQI	Daily/DHSR	Daily/ 2014-2016 years	SVR(RBF)/PV stations	**RMSE=21W/m^2** **R^2=.92756**
[100]/ 2019	K-mean -SVR	Ibadan/ lat- 7.4°N, long- 3.92°S	DAGSR, Ep, WS, RH, SSD, $T_{max,}$ T_{min}	Daily/ GSR	Daily avg/ 2010-2017	ANN, Angstrom–Prescott and ARMA /Energy planning	**R^2=0.9842, RMSE=120.55W/m^2** RRMSE=2.7498%, **MAPE=1.795%**
[33]/ 2019	SVRRBF	Ghardaia, Algeria/ Lat-+32.37°, long: +3.77°	T,H,GHI,SSD ,FD	122 future days/DNI	Daily/ 2005	Compared with different combinations of input variables/Solar power plant	NRMSE=12.94% **R^2=0.90** **RMSE=652.03W/m^2** MAE=460.26W/m^2 MBE=76.19W/m^2

*DLH: Day Light Hour; CSkSR: Clear Sky Solar Radiation; NOD: Number of Days; ETR: Extra-Terrestrial Radiation; SSD: Sun Shine duration; ETR: Extra-Terrestrial Radiation; DAGSR: Daily Average Global Solar Radiation; WS: Wind Speed; FD: Fractal Dimension; AQI: Air Quality index; DOY: Days of Year; BSSH: Bright Sunshine Hour; DL: Day length; RH: Relative Humidity; SI: Sky Image; GHR: Global Horizontal Radiation; GSR: Global Solar Radiation; T_{avg}: Average Temperature.

As MAPE defines the prediction accuracy of the model performed. It is represented in terms of percentage. Figure 11(a) illustrate the different MAPE values attained by various researchers regarding ANN-based irradiation forecasting techniques carried in this study. The plot shows that [63][71][79] have obtained a minimum MAPE of 0.015, 0.01523 and 0.0172, respectively, during irradiation prediction. It means that the designed model was better and can predict the irradiation more accurately. Comparatively higher MAPE value is attained by [70][88][67] with 0.856, 0.44432 and 0.1645 respectively. It means that the model improvisation should be required, and care should be taken to avoid input data samples with zero values to minimize the MAPE. Thereby prediction accuracy can be improved.

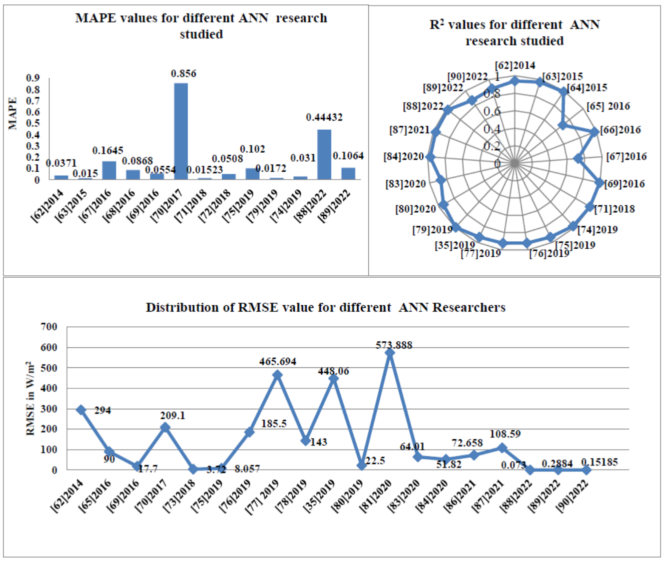

Fig. 11. Distribution of performance metrics for various ANN related irradiation forecasting articles (a) MAPE;(b) R Square;(c) RMSE

Figure 11(b) shows the distribution of different values of R square achieved by the related article of ANN studied in this review. R square denotes the amount of variance in the relation between 2 or more variables. As stated in section 2.2.6, if it is close to 1, then the designed model can tell all variability of response data. If it is 0, then the model may fail to explain the variability of response data around the mean. Figure 11(b) shows that the distribution of R square values lies between .7 to 1. However, the value close to unity is attained by [79] and [69] with .99649 and .994, respectively, during prediction. Comparatively, less value is attained by [65][67] with 0.701 and 0.7237. So proper feature selection is recommended to fine-tune the attributes to be used. Since ANN performance purely depends on input features fed into it.

As RMSE defines the average value of error obtained during the prediction process, it should always be minimum for better prediction performance. So inversely, if it is high, then the model attains more error during the prediction process resulting in poor prediction. Figure 11(c) shows the distribution of different values of RMSE for the ANN-based irradiation prediction process studied in this review. It reveals that [88], [90] has got minimum values of 0.073 W/m^2 and 0.15185 W/m^2, respectively. Moreover, very high values are noticed in the case of [81] and [77] with 573.888 W/m^2 and 465.694 W/m^2 respectively, which means the performance improvisation is suggested by concentrating on removing data outliers, skewness, selecting multiple parameters, and also selecting appropriate features could lead the model better.

3.2. Performance analysis of SVR related articles

The primary information about the related article on irradiation forecasting using SVR is discussed in section 2.6 are tabled in Table 3. It is to be noted that the comparison cannot be made among various articles of SVR due to different specifications followed by each model. Therefore, their performances are studied by analyzing the most common performance metrics used in discussed papers, which are taken into consideration. Those performance metrics are highlighted in Table 3. With this, we analyzed RMSE and R Square metrics. To show the variability and the prediction capability of the different RMSE values among the publications, the units of RMSE are converted into W/m^2 as common traces. The different RMSE and R Square values of various SVR researchers regarding irradiation forecasting are put into a common platform, as illustrated in Figure 12(a);(b).

Figure 12(a) signifies the distribution of various values of RMSE achieved by the studied articles of SVR based irradiation forecasting in PV systems. The RMSE denotes the average value of errors obtained in the prediction process. Therefore, it should be minimum for accurate prediction, as discussed in the performance metrics section 2.2.6. It is observed from Figure 12(a) that [95][33] has attained a higher RMSE value with 722 W/m^2 and 622.03 W/m^2, respectively. However, the smallest value is achieved by [96] with 9.23 W/m^2. Therefore, proper improvisation is required to minimize the root mean Square Error to attain an acceptable range.

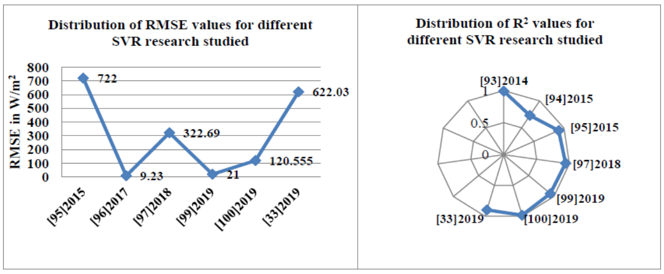

Fig. 12. Distribution of performance metrics for various SVR based irradiation forecasting articles (a) RMSE;(b) R Square.

While looking at Figure 12(b), the R square values of most researchers fall between 0.5 and 0.993. The higher value is achieved by [93] with 0.99294. Comparatively, less value is attained by [94] with 0.728. Though [93] has got a maximum coefficient of determination, proper selection of location, placing of the panel, sample data of each variable, the forecast horizon and other criteria should also be predominantly concentrated to attain better prediction accuracy.

3.3. *Analysis on input variables used*

As the performance of each model depends on the input feature used, hence it is very much mandatory to know the importance of the parameter. Therefore, the investigation is done on publications regarding ANN and SVR based irradiation forecasting models discussed in this article. Thereby we found the more frequently used parameters include Temperature, Radiation, Sunshine Hours, Humidity, Wind speed, Pressure and wind direction, which are illustrated in terms of percentage in Figure 13. Notably as a major concern in increasing the performance of PV via forecasting GHI, the temperature and irradiation parameters plays a vital contribution in deciding the system efficiency [101].

These attributes are relatively more Important to forecast PV irradiation. Apart from the above parameters, cloud cover, Days of the year, Altitude, Hours of the day, Rain, Month of the year, Zenith angle, Air particles and precipitate have two units each, which means such attributes are less important in forecasting irradiation.

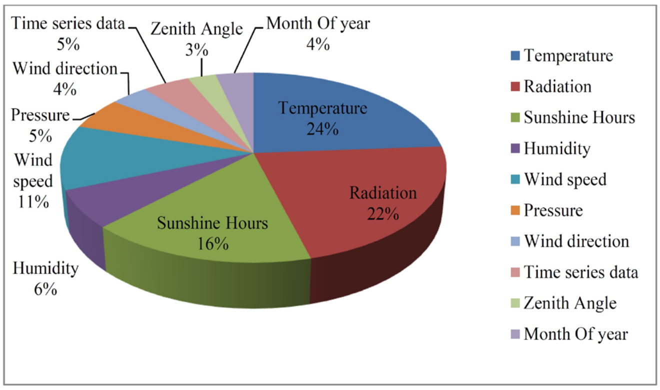

Fig. 13. Percentage contribution of various input features in predicting solar irradiation.

3.4. *Discussions*

This section discusses the findings from the article reviewed on how the ML models perform based on the dataset, input variables, and feature selection process, especially for short-term forecasting conditions. Since we are focusing our article on the solution for issues faced by MPPT controllers in PV systems as coated in section 2.1.

As ANN greatly depends on Input features and faces time-consuming issues. So, for better understanding, we are considering two kinds of data set and observing the model's performance by looking at the overview Table 2. Hence, we are taking [66][68], whose models are trained using more than a ten-year dataset. While observing the performance of [66], simple MLP-LM-BP methods are performed, but in the case of [68], has followed feature selection process additionally with ANN and has attained RMSE of 0.01315 and MAPE of 0.0868%, which are comparatively reasonable when compared with other whose values are, RMSE=0.2787 and high MAPE value of 12.43% were attained. Simultaneously, looking at small data set models [63][65] whose dataset is taken to be below two years. While observing their performance, the relevant [63] selection of input features has caused wide impacts on performance. Even though the ML model used in both papers are similar, with no sweeping change in specifications, in such case,[63] has considered very few features such as WS, T, Particulate matters (air pollutants), but in the case of [65] has considered more features such as MOY, HOD, Air, T, RH, BP, GSI. It meant to say that a better selection of relevant input features could create a wide prediction accuracy. Therefore [63] has attained RMSE of 0.05 Wh/cm^2, MAPE of 1.5% and R^2 as 0.97, which are considered to be very good compared with [65], whose RMSE is 90 W/m^2 and R^2 as 0.707. While looking at the consumption of higher computational /training time issues in ANN, most of the articles fail to mention the time consumed during the prediction process. It means that the attained time seems to be not highlightable. Moreover, very few papers like [71][75][83] have completed the training process in 83.70sec, 16.18sec and .7sec, respectively. From the above discussion, it is observed that ANN can perform better either in a huge or small dataset, only when the proper feature is selected and fetched into it. Secondly, for reducing computational time, proper selection of a training algorithm is highly recommended to train the provided network.

On the other hand, SVR faces the problem of handling big data. Therefore, we focus our discussion on short-term irradiation forecasting scenarios with a small dataset and a massive dataset from the overview Table 3. In that point of view, for short term forecasting, models used in [93][96] were trained using one to two-year datasets. [93] used least-square SVR for data analysis along with other feature selection methods, [96] used SVR with Firefly Algorithm for the feature selection process. In such cases, LSSVR achieved better performance with RMSE=0.004384 than FA with RMSE=9.23W/m^2, even though the specification is moreover similar. However, it is realized that using features such as temperature, Humidity, Sunshine duration plays a dominant role in achieving better performance as in [93] and more research articles.

Now in case, the data set used is to be more than a few years are taken into consideration. [94] uses 20 years of data with the feature selection process by optimization algorithms and [100] uses seven years of data for modelling and K means clusters are used to categorize the data, it has attained RMSE of 120.555 W/m^{2,} which is comparatively high with [94] whose value is 1.8661W/m^2. These reveal that the SVR model performs much better when better optimization methods are incorporated rather than hybridized with other ML models, even though the dataset is considerably larger.

4. Conclusion and Future directions

A comprehensive, systematic and comparative review is conducted among various ANN and SVR based irradiation forecasting for PV system applications. From performance, analysis and discussions on ANN and SVR related articles reveal that both ANN and SVR are better models for short term irradiation forecasting in PV systems. But ANN has a dominating nature of handling highly non-linear, noisy data set for mapping the relationship between input and output without any complexity and faster rate. In addition to that, the capability to handle time-series data makes the model apply to a real-time environment. Moreover, the model can be easily adopted to small as well as a huge dataset. These criteria make the model superior to SVR. Because SVR is efficient only for small datasets under parameter constraints, rather than very noisy and larger datasets. Based on these investigations, it is concluded that the ANN-based forecasting approach provides better prediction performance compared with the SVR technique. These confess that ANN based forecasting could be the efficient predictor for the researcher in forecasting the instantaneous data samples were non-linear, noisy, massive, as well as small datasets are accomplished. Hence this study confirms the ANN predictor could be an efficient irradiation forecasting technique for building a smart MPPT controllers for improving the converter efficiency and overall PV system and PV grid integration performance. Also, the regulated output eventually mitigates the mismatch between availability and production. This exact prediction can also be helpful in planning, sizing and designing of PV field installation. Moreover, the optimal power dispatch can be exactly maintained which eventually optimize the mismatch, revenue loss, timing of sale and improves the power trade.

In future, this analysis and observation will be taken forward in designing an ANN based irradiation forecasting model using various environmental variables. Then an intelligent MPPT controlling technique will be implemented by incorporating the robust irradiation forecasting model with the MPPT controller for improving the overall PV system performance. Again, in cases of grid integrated PV power generation, such smart controller can be recommended to reduce the issues related to variability, stability and power quality. Also, the performance of ANN based irradiation forecasting model can be enhanced by finding an efficient, optimization algorithm for hyperparameter tunning and feature selection process can improve the prediction accuracy of the network. In addition, the performance of model under seasonal changes should be analyzed for accessing better prediction at all climatic conditions.

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Conflict of Interest

The author declares that there is no conflict of interest.

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