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Data driven prediction based reliability assessment of solar energy systems incorporating uncertainties for generation planning

Rohit Kumar[1], Sudhansu Kumar Mishra[1], Amit Kumar Sahoo[2]✉, Subrat Kumar Swain[1], Ram Sharan Bajpai[3], Aymen Flah[4,5,6,10,11], Mishari Metab Almalki[7], Habib Kraiem[8] & Mohamed F. Elnaggar[9]

In the era of renewable energy integration, precise solar energy modeling in power systems is crucial for optimized generation planning and facilitating sustainable energy transitions. The present research proposes a comprehensive framework for assessing the operational reliability of solar integrated systems, validated using the IEEE RTS 96 test system. A robust uncertainty model has been developed to characterize variations in solar irradiance to address the uncertainties in solar panel output, followed by a multi-state modeling approach to account for the dynamic nature of solar panel output. The research introduces a time series-based 'non-linear autoregressive neural network' (NAR-Net) to forecast the solar irradiance levels five days ahead to optimize solar power efficiency. A comparative analysis has been conducted of three other state-of-the-art approaches, such as auto-regressive (AR), auto-regressive with moving average, and multi-layer perceptron, for predicting solar irradiance. Performance metrics, including mean square error, regression, and computational time, were evaluated to demonstrate the efficacy of the NAR-Net. The proposed prediction-based approach enhances the reliability of power generation planning by integrating modeling, which is based on forecasting. It is found that the proposed method achieves an accuracy of 98% w.r.t its counterpart. Moreover, the assessment to optimize the operational reliability of solar-integrated systems and improve generation planning for a sustainable energy future is achieved.

Keywords Artificial neural network, Frequency domain, multi-state model, Operational reliability, Solar energy system

In recent years, solar energy has emerged as a promising and sustainable power source, driving advancements in power systems that integrate renewable energy. These advancements have led to the development of solar integrated systems, which utilize photovoltaic (PV) panels to convert solar irradiance into electricity and contribute to sustainable energy generation. These systems are broadly classified into three categories: Hybrid Solar Systems, Grid-Connected Solar Systems, and Utility-Scale Solar Power Plants. However, unlike conventional energy sources, renewable energy like solar is inherently variable, requiring efficient strategies for grid operation

[1]Birla Institute of Technology, Mesra, Ranchi 835215, India. [2]Department of EEE, Centurion University of Technology and Management, Bhubaneswar, Odisha, India. [3]Department of Electrical & Electronics Engineering, Shri Ramswaroop Memorial University, Lucknow 225003, India. [4]Applied Science Research Center, Applied Science Private University, Amman 11931, Jordan. [5]Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura 140401, Punjab, India. [6]ENET Centre, CEET, VSB-Technical University of Ostrava, Ostrava, Czech Republic. [7]Department of Electrical Engineering, Faculty of Engineering, Al-Baha University, 65779-7738 Alaqiq, Saudi Arabia. [8]Department of Electrical Engineering, College of Engineering, Northern Border University, Arar, Saudi Arabia. [9]Department of Electrical Engineering, College of Engineering, Prince Sattam Bin Abdulaziz University, Al-Kharj11942, Saudi Arabia. [10]Jadara University Research Center, Jadara University, Irbid, Jordan. [11] National engineering school of gabes, University of gabes, Gabes, Tunisia. ✉email: amitkumar2687@gmail.com

and integration. Solar power is harnessed through photovoltaic (PV) panels, which convert solar irradiance into heat or electricity, and these systems are increasingly employed in residential, commercial, and industrial applications[1]. However, the intermittent nature of solar irradiance, influenced by weather, seasonal changes, and daily variations, significantly impacts the efficiency and reliability of solar energy systems. Studies have explored various methods to address these challenges, including forecasting solar irradiance using artificial intelligence techniques such as seasonal auto-regressive models, which enhance system reliability[2]. To further tackle these issues, conducting uncertainty analysis of solar irradiance and developing robust prediction models, including time-series forecasting, is crucial. These efforts improve reliability and support informed decision-making, enabling the seamless integration of solar farms into energy grids while projecting the overall performance and dependability of solar energy systems[3].

Literature survey

Climatic conditions significantly impact reliability forecasting for solar integrated systems, resulting in power generation fluctuations. Various methods handle dynamic models, including auto-regressive with moving average (ARMA), autoregressive integrated moving average (ARIMA), autoregressive moving average model with exogenous inputs (ARMAX), autoregressive integrated moving average with explanatory variable (ARIMAX), and stochastic state-space models[4]. However, the complexity of the irradiance pattern poses challenges in designing accurate regression models. Unpredictability in solar irradiance patterns due to instrument or human errors can lead to model failures. Forecasting methods like artificial neural networks (ANN), kernel recursive least squares algorithm and support vector machines (SVM)[4–7] are used for prediction. These models are trained by recognizing patterns in time-series data and forecast future values. These techniques aid in producing accurate predictions, supporting decision-making and planning in various fields. Hybrid models and ANN-based methods[8] are gaining popularity for their ability to train effectively and reduce reliance on complex mathematics, showing promise for solar irradiance forecasting. However, effectively incorporating a time-series-based prediction method is crucial to address the non-linearity within solar irradiance data[9]. This is essential as solar irradiance patterns often exhibit complex and non-linear behaviors influenced by various factors, including meteorological conditions, time of day, and seasonal variations. A more suitable network must be implemented to better capture and model these dynamics, improving the accuracy and reliability of solar irradiance forecasts.

Recent research focused on reliability modeling of solar irradiance and its integration with conventional systems. The aim is to track maximum irradiance for solar power maximization[10–12], evaluate reliability based on power loss due to variable insolation[13], assess electric vehicle reliability[14–16], and optimize cost for reliability assessment[17]. However, a significant challenge for current and future grid-connected solar distributed generation (DG) systems is reliably meeting load demands[18]. While ample research exists on adequacy assessment for solar farm integrated power systems[19,20], limited work addresses solar DG adequacy, considering solar irradiation's intermittent nature. PV cell power generation depends on solar irradiation intensity, which varies with the solar unit's location. Uncertainty in solar generation is represented by probability density functions, changing with seasonal variations[21]. Normal and Weibull distribution functions[22,23] represent global solar irradiation data. Thus, a standardized model is needed to represent solar data for seamless integration with conventional reliability assessment methods. Adequacy assessment schemes also require further attention and refinement.

Here are some gaps found from the above existing literature:

i. Reliance on computationally intensive convolution-based techniques with limited research on simplified multi-state modeling for solar-integrated systems.
ii. Inadequate probabilistic frameworks for accurately capturing and quantifying solar power fluctuations caused by intermittency.
iii. Limited focus on developing reliable two-day-ahead forecasting models, such as NAR-Net, for solar irradiance and power generation, and their seamless integration into practical energy grid management and operational planning to support proactive energy management.

Motivation

In sustainable energy exploration, the central objective revolves around enhancing the reliability of solar-integrated power systems. Solar energy, while environmentally conscious, presents challenges stemming from its inherent unpredictability. Short-term solar irradiance prediction typically leans on time series analysis techniques involving mathematical modeling, using the Kalman filter and linear regression, to tackle these challenges. However, traditional methods are susceptible to inaccuracies due to rounding errors and fluctuations in solar irradiance, potentially overlooking various influencing factors. To address these limitations, machine learning (ML) and artificial intelligence (AI) methods have been widely implemented in recent years. However, their approaches could be more complex and computationally inferior. Notably, artificial neural networks (ANN), such as the multi-layer perceptron (MLP), are employed to develop predictive networks with less complexity. It's important to acknowledge that MLP is more effective due to its multiple layers and nodes. In our research, we employ a single-layer neural network, i.e., a non-linear autoregressive neural network, for time-series data prediction. This network is well-known for its ability to account for non-linearity in data patterns, enhancing its capacity to model and predict solar irradiance with greater accuracy and reliability.

Contribution of the work

Certainly, here are the key contributions of the work.

i. Simplified reliability evaluation through multi-state modeling for solar-integrated systems, shifting away from conventional convolution-based techniques[25].

ii. Development of an extended probabilistic framework that allows for accurate evaluation of fluctuations in solar power generation due to solar intermittency[24].
iii. Two-day-ahead solar irradiance and power generation prediction using the NAR-Net for facilitating proactive energy integration and operational reliability projection[26].

Thus, Table 1 shows the comparison of the proposed work with the existing state-of-the-art Sect. Uncertainty modeling of solar irradiance and prediction model for reliability analysis encompasses solar energy and prediction model reliability analysis. Section Prediction using Non-Linear autoregressive neural network discusses the NAR-Net used in predicting the solar irradiance. Section Case studies and results presents the case studies and a detailed discussion of the proposed methodology. Finally, Sect. Conclusion provides a summary of the conclusions derived from the case studies and analysis.

Uncertainty modeling of solar irradiance and prediction model for reliability analysis

In the pursuit of a sustainable energy future, the integration of solar power systems stands as a promising solution to meet global energy demands. However, reliably harnessing the solar power for electricity necessitates meticulous attention. Ensuring the dependability of solar-integrated power systems requires an exploration of the uncertainties tied to solar irradiance, the lifeblood of solar energy generation. Thus, this section deals with uncertainty modeling of solar irradiance, multi-state power generation and lastly, reliability assessment using the Fourier domain approach.

Uncertainty modeling of solar irradiance for generation planning

Solar energy relies on understanding solar irradiance dynamics, influenced by weather, time of day, and location, introducing uncertainty into energy output. Reliability assessment of solar-integrated power systems requires a comprehensive grasp of these uncertainties. To model solar irradiance uncertainties, Eq. (1), a Weibull probability density function (PDF), denoted as $f\left(x\right)$, is employed.

$$f\left(x\right)=\frac{1}{\sigma\sqrt{2\pi}}e^{\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^{2}\right)} \tag{1}$$

The Weibull distribution is commonly used in solar irradiance modeling due to its ability to capture the variability and uncertainty in solar energy generation. With two shape parameters, it models both typical and extreme irradiance events, such as sudden spikes or drops. It depends on various meteorological and environmental factors, with x representing irradiance values, μ as the mean, and σ as the standard deviation. One study used the Weibull distribution to estimate solar energy yield by analyzing irradiance values over selected days[27]. Another study found the Maximum Likelihood method best fit global solar irradiance data in France, enhancing PV energy output reliability[28]. Further research compared Weibull, Rayleigh, and Lognormal distributions, with Weibull providing useful insights for PV power generation prediction[29]. A probabilistic model based on the Weibull distribution was also developed to improve grid-connected system simulations by calculating Weibull parameters and assessing irradiance smoothness and continuity[30]. Thus, this approach seamlessly incorporates uncertainty into solar irradiance modeling, addressing data variability efficiently. Thus, adopting of this distribution not only accounts for central tendencies but also comprehensively addresses data variability and uncertainty. Finally, it allows the computation of forecasted values of probabilistic energy generation by estimating the likelihood of extreme events and by conducting sensitivity analyses efficiently, capitalizing on the mathematical properties of the Weibull distribution.

Multi-State modeling for variable solar power generation

The inherent variability in solar panel power generation is attributable to the dynamic nature of solar irradiance. Thus, a comprehensive approach is required to capture the intricate dynamics of solar irradiance fluctuations. As a result, a multi-state model is utilized to effectively characterize the diverse solar power output states that arise due to changes in solar irradiance[25]. To capture this variability, we use a multi-state model. This model illustrates different solar power output states resulting from irradiance fluctuations, covering a wide range of data points (up to 5σ), is expressed in Eq. (2). The decision to use 5σ is guided by its capacity to capture extreme values, which are rare but may have significant implications for system performance. For shape parameters $k>1$, the Weibull distribution becomes more symmetric, and 5σ effectively encompasses nearly the entire range of the data, akin to the normal distribution. Thus, the Weibull distribution has been divided into N_a intervals,

Proposed Work				Existing Work	
State-of the-art	**Proposed Work**	**State-of the-art**	**Proposed Work**	**Reliability analysis for power system**	**Time-series solar irradiance Forecasting**
Proposed work	✓	✗	✓	✓	✓
[20]	✗	✗	✗	✗	✓
[23]	✓	✗	✗	✗	✗
[25]	✗	✗	✗	✗	✗
[26]	✗	✓	✗	✓	✗

Table 1. Comparison of the proposed work with the existing state-of-the-art.

each spanning $\frac{5\sigma}{N_a}$, with midpoint values as SMP_N for $s = 0,\ 1,\ 2,\ \ldots\ ,\ 9$. Equation (3) generates SMP_N values for even and odd N positions.

$$SMP_N = \frac{5\sigma}{2N} + \frac{5\sigma}{N}(N-1) \tag{2}$$

$$SGP_N = \begin{cases} \frac{SP_R \times SMP_N{}^2}{SI_{cin} \times SI_{cout}}, & 0 \le\ SMP_N \le\ SI_{cin} \\ SP_R\left(A\frac{SP_R \times SMP_N}{SI_{cin} \times SI_{cout}}\right) & ,\ SI_{cin} \le\ SMP_N < SI_{cout} \\ SP_R, & SI_{cout} < SMP_N \end{cases} \tag{3}$$

This approach models solar irradiance intermittency and facilitates efficient convolution. Equation (3) [22] represents solar power generation (SGP_N) in response to cut-in, nominal, and cut-out irradiance, where, SP_R is the rated solar power, $SI_{cin}$and $SI_{cout}$is cut-in and cut-out solar irradiance. Segmenting the solar irradiance model into discrete bands based on standard deviation, optimizes the modeling, improving solar power prediction and reliability assessment. Equation (4) evaluates each state's probability (P_N), crucial for modeling, using simulated solar irradiance within SMP intervals. Thus, the multi-state modeling approach enhances our understanding of solar power generation dynamics, advancing solar energy prediction and management.

$$P_N =\ N/N_{ys} \tag{4}$$

Operational reliability evaluation for solar energy system using fourier approach

Getting generation and load in sync is essential for incorporating solar power variability into power networks. A quantized probabilistic load model (QPLM) that incorporates both conventional and non-traditional generating units has been created in order to address this problem. The QPLM has been formulated as a probability distribution $pb = f(x) = \frac{F(x)}{T}$ of load sampled at intervals of $T_s\ MW$, for conventional units, which typically operate in either a normal or failure state. Here, pb stands for the probability distribution of load values, $F(x)$ for the cumulative distribution function of load, and T for the sampling interval. As illustrated below in Eq. (5), the QPLM has been iteratively developed for each unit with the inclusion of a generator outage. Here, $f_i(x)$ represents the QPLM following the factorization of unit G_i failure with an outage capacity of PG_i, l_i denotes the likelihood that a generating unit G_i will be in a normal state, and m_i denotes the likelihood of its outage. However, in order to account for the uncertainty surrounding the generation of non-conventional solar power, a multi-state modeling technique has been implemented. The "s states," or solar power states, are related to probabilities SGP_N. The convolution of all these states with the previously derived load model is taken into consideration in the QPLM technique for a solar farm, as indicated by Eq. (6)[26], where $f_k(x)$ stands for the QPLM for the solar farm. SGP stands for the state $\prime N \prime$ s generating capacity.

$$f_i(x) = f_{i-1}(x) \otimes\ \ Gi = l_i.\ f_{i-1}(x)\ \ + m_i.\ f_{i-1}(x - PG_i) \tag{5}$$

$$f_k(x) = \sum\ _{N=1}^{N}[SGP_N f_{k-1}(x - WGP_N)] \tag{6}$$

As explained earlier in Eqs. (5) and (6), traditional convolution techniques grow more complex as the number of generating units increases, requiring significant storage for reliability evaluations. The procedure has been moved from the time domain to the frequency domain in order to address this, using the Fast Fourier Transform (FFT) approach[26]. As a result, Eq. (7) is used to determine the discrete-time and frequency responses, and Eq. (8) describes the use of the Inverse Fast Fourier Transform (IFFT).

$$F(K) = \sum\ _{i=0}^{N_{samp}-1} a_i W^{-Ki} \tag{7}$$

$$\left.\begin{array}{l} q_i = \sum_{n=0}^{N_{samp}-1} P(n)\, W^{ni} \\ f(k) = \sum_{i=0}^{N_{samp}-1} q_i \times\ \delta\ (x - i\Delta\, x) \end{array}\right\} \tag{8}$$

The frequency domain approach[21] simplifies the convolution involved in reliability analysis. System dynamic reliability is quantified using loss of load probability (LOLP) and expected energy not supplied (EENS)[17]. Reliability indices are computed from the final discrete probabilistic load model $f_\alpha\ (x)$ resulting from the convolution of all generating units, given $''\alpha\ ''$ generating units and total generation capacity (PG_T). The maximum load in the final DPLM is $(x_{max} + PG_T)$. Therefore, EENS and LOLP is assessed using Eqs. (9) and (10).

$$EENS = \sum\ _{PG_T}^{(x_{max}+PG_T)} f_\alpha\ (x) \tag{9}$$

$$LOLP = f_\alpha\,(PG_T) \tag{10}$$

Optimal replacement of generating unit with renewable energy sources

The generation planning problem is a challenging task that involves selecting the optimal combination of generators to meet the power system's energy demands while ensuring its reliability and security. Renewable energy's technical and financial viability must be evaluated to achieve an optimal solution for improved generation expansion planning. Thus, the Power Set[31] concept and Linear Programming[32,33] can be used to find the optimal solution for better generation expansion in the power sector. The power set concept can help to determine all possible combinations of power generation sources that can be used to meet the demand. These combinations can then be evaluated using Linear Programming, which can identify the optimal solution to optimize the cost of interrupted energy and expected energy not served for each combination while meeting the demand. Linear Programming uses a set of constraints to ensure that the solution is feasible and realistic. The conditions of the problem ensure the power demand is always met, the system remains within its operating limits, and sufficient reserve capacity is available to respond to unexpected events. By combining the Power Set concept with Linear Programming, it is possible to find the best mix of power generation sources that will maximize efficiency, enhance system reliability and minimize costs while meeting the energy needs of consumers. Hence, for better planning, integrating wind energy sources is required to meet the maximum demand with low generation costs and low energy losses.

Prerequisite

Creation and technologies used in solar farm

The virtual solar farm has been created by carefully considering several factors such as the capacity factor, the type of generator to be replaced, the amount of generation required to meet existing conventional generation needs, and the duration of available solar irradiance. This approach ensures a robust modeling of the solar farm's capacity to supplement or replace conventional energy sources. The modeling, testing, and execution of the solar farm were performed using MATLAB/SIMULINK, which provides a comprehensive simulation environment to model real-world conditions and the performance of photovoltaic (PV) systems.

In the virtual solar farm, the solar technology used is based on photovoltaic (PV) modules. The simulation considers various parameters like solar irradiance, cell temperature, and electrical characteristics of PV modules to evaluate their performance in real-world conditions. Below is a table outlining the numerical models and specifications for the solar technologies used in the farm, including both input parameters (such as solar irradiance and temperature) and output metrics (such as PV voltage and current). These models ensure that the performance of the farm is accurately simulated under different environmental conditions. Thus, Table 2 shows the details and specifications of solar PV System.

Prediction model for solar irradiance

Solar power is vital in the global transition to cleaner energy production. Accurate solar irradiance prediction is crucial for efficient energy management, grid stability, and optimizing solar power generation. This study focuses on the importance of precise solar irradiance prediction in ensuring reliable solar-integrated power systems. We use advanced forecasting techniques and data-driven models, including auto regression with moving average (ARMA) and nonlinear autoregressive neural network, to improve predictability and resilience in solar energy systems, contributing to future sustainable energy. Adaptive-based methods have emerged as highly effective tools for solar irradiance prediction, offering the capability to model complex and nonlinear relationships within the data. Among these neural network models, two prominent approaches are auto regression (AR), auto regression with moving average (ARMA), Multi-Layer Perceptron (MLP), and nonlinear autoregressive neural network.

Sl. No.	Category	Parameter	Details/Specifications
1	**Input Parameters**	*Solar Irradiance (W/m²)*	Scalar input, range: [0, 1000]; defines the irradiance applied to solar panels.
		Cell temperature (°C)	Scalar input; can be negative, zero, or positive, indicating actual cell temperature.
2	**Output Metrics**	*PV Array Voltage (V)*	Output voltage of the PV array under specific environmental conditions.
		PV Array Current (A)	Output current from the PV array based on irradiance and temperature.
		Diode Current (A)	Current flowing through the internal diode of the PV module, critical for accurate modeling.
		Effective Irradiance (W/m²)	Measured irradiance applied directly to the PV array, recorded during simulation.
		Operating temperature (°C)	Temperature of the PV module during operation, influencing performance.
3	**System Design**	*Parallel Strings*	40 parallel-connected strings of series-connected PV modules.
		Modules per String	10 series-connected PV modules per string forming a larger array.
4	**Module Attributes**	*Maximum Power (W)*	213.15 W, representing the maximum power output under standard conditions.
		Open Circuit Voltage (Voc, V)	36.3 V, voltage when the circuit is open, with no current flow.
		Short Circuit Current (Isc, A)	7.84 A, current when the circuit is shorted.
		Voltage at Maximum Power (Vmp, V)	29 V, voltage at which maximum power output is achieved.
		Current at Maximum Power (Imp, A)	7.35 A, current at which maximum power output occurs.
5	**Temperature Factors**	*Voc Coefficient (%/°C)*	-0.36099; defines the variation in Voc (open-circuit voltage) as temperature changes.
		Isc Coefficient (%/°C)	0.102; defines the variation in Isc (short-circuit current) as temperature changes.
6	**Advanced Features**	*Robust discrete Model*	On; iterates to resolve algebraic loops during simulations for accurate results.
		Measurement filter time constant (s)	5e-5; used for filtering measurement data during simulations.
		I-V and P-V Charac-teristics	Displayed for individual modules or arrays at 1000 W/m² and specified temperatures.

Table 2. Details and specifications of solar PV system.

i. *Auto Regression (AR).*

Auto Regression (AR) is a data-driven method for predicting time-dependent data like solar irradiance. It relies on the idea that a time series data on solar irradiance, is a data-driven approach intricately linked to its past values. AR helps us understand patterns and trends by comparing current and past observations at different time steps. Its simplicity and adaptability are valuable for short-term solar irradiance prediction, capturing daily, seasonal, and weather-related changes, ultimately enhancing the reliability and efficiency of solar-integrated power systems. The AR model, typically denoted as $AR(p)$ captures the future value of a time series, solar irradiance data Y_t, as a linear combination of its past values at different lags $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})$. Mathematically, the $AR(p)$model can be expressed as $(Y_t = c + \varphi_1 \times Y_{t-1} + \varphi_2 \times Y_{t-2} + \ldots + \varphi_p \times Y_{t-p} + ?_t)$, where "$c$" represents a constant, "φ" denotes the model coefficients, "p" signifies the order of the model, and "ϵ_t" is a white noise error term.

ii. *Auto Regression with Moving Average (ARMA).*

The ARMA model combines Autoregressive (AR) and Moving Average (MA) components to forecast solar irradiance more accurately. This integration offers a versatile framework for understanding temporal patterns. ARMA uses past values and errors to predict future data points in a time series, improving solar irradiance predictions and enhancing solar-integrated power system efficiency. Mathematically, the ARMA model can be expressed as an ARMA *(p, q)* model as shown in Eq. (11).

$$(Y_t = c + \varphi_1 \times Y_{t-1} + \varphi_2 \times Y_{t-2} + \ldots + \varphi_p \times Y_{t-p} + ?_t + \theta_1 \times \epsilon_{t-1} + \theta_2 \times \epsilon_{t-2} + \ldots + \theta_q \times \epsilon_{t-q} \quad (11)$$

where, "Y_t" is the solar irradiance at time "t", "c" is a constant, ϵ_t" represents the white noise error term at time "t, and $(\varphi_1, \varphi_2, \ldots, \varphi_p)$ are autoregressive coefficients for past values up to lag "p". Additionally, $(\theta_1, \theta_2, \ldots, \theta_q)$ represent moving average coefficients for past error terms up to lag "q". This equation illustrates how ARMA combines past time series values and error terms to forecast future values, making it an effective tool for capturing and predicting temporal patterns in the time-series data.

iii. *Multi-Layer Perceptron (MLP).*

The Multi-Layer Perceptron (MLP) for solar irradiance prediction involves understanding its core operational principles. The MLP consists of interconnected layers: an input layer, one or more hidden layers, and an output layer, each containing multiple artificial neurons. Input data, including historical irradiance values and weather conditions, enters the input layer, undergoes weighting and summation within neurons, and encounters a nonlinear activation function (typically sigmoid or ReLU) for introducing nonlinearity. This process repeats through the hidden layers, where each layer extracts abstract features from the data. The final output layer generates predictions based on learned patterns. The MLP's strength lies in adapting its internal weight parameters during training, minimizing prediction errors, and capturing complex dependencies within solar irradiance data. Mathematically, this process can be expressed using Eq. (12), where Z_j represents neuron output j, X_i is the input features, W_{ij} is the weights, b_j is the bias, and f is the activation function.

$$Z_j = f(\sum {}_{i=1}^{n} X_i \times W_{ij} + b_j \quad (12)$$

Consequently, the training phase involves iteratively adjusting these weights to minimize prediction errors, enhancing the MLP's capacity to capture intricate patterns in solar irradiance data and enabling precise forecasts.

Prediction using Non-Linear autoregressive neural network

In the domain of renewable energy management, the accurate forecasting of solar irradiance is a pivotal endeavor. Solar irradiance, the radiant energy received from the sun, directly influences the efficiency and reliability of solar energy systems. The inherent complexity of solar irradiance data, marked by nonlinear and dynamic patterns shaped by diverse variables like cloud cover, diurnal variations, and seasonal fluctuations, necessitates advanced modeling techniques. Within this context, nonlinear autoregressive neural networks (NAR-Nets) emerge as a powerful, cutting-edge approach. These networks are meticulously designed to handle the complexities of solar irradiance data and uncover the nonlinear relationships. NAR-Nets operate on historical solar irradiance data, ingeniously organized in input sequences to furnish the necessary historical context for accurate predictions. Mathematically, a NAR-Net commences with the input sequence, as shown in Eq. (13), undergoing a nonlinear transformation via a neural network layer. This transformation is pivotal, introducing nonlinearity to the model as mathematically represented in Eq. (14), where $H(t)$ represents the hidden state of the network at a given time "t". The activation function f introduces nonlinearity, while W and b denote the weight matrix and bias vector, respectively.

$$X = [x(t-1), x(t-2), \ldots, x(t-n)] \quad (13)$$

$$H(t) = f(W * X + b) \quad (14)$$

Subsequently, the forecasted solar irradiance at the next step, $x(t+1)$, is crafted as a linear combination of the hidden state $H(t)$ through an output layer, as shown in Eq. (15), where U signifying the weight matrix for the output layer.

$$x(t+1) = U * H\,(t) \tag{15}$$

In the context of training NAR-Nets, Bayesian regularization, a statistically grounded technique, is employed to optimize internal parameters, notably W and U, by minimizing a suitable loss function like mean squared error (MSE) or mean absolute error (MAE). The model's performance is rigorously evaluated through validation on an independent dataset and testing on unseen time-series data to ensure its ability to generalize to new situations. Furthermore, fine-tuning hyper parameters, encompassing different aspects, like the number of hidden layers, neuron counts in each layer (10 neurons), and the learning rate, is a critical facet of optimizing NAR-Nets. Additionally, a lag window of 2 delays accommodates historical observations in the predictive process, enhancing the model's contextual understanding. Thus, in solar irradiance forecasting, NAR-Nets manifest a remarkable capacity to capture complex and non-linear trends, enabling improved management and the utilization of solar energy resources. The algorithm for non-linear autoregressive neural is presented in Fig. 1.

However, it is imperative to recognize that NAR-Nets demand substantial historical data and computational resources for effective training. This underscores the necessity for judicious application within the renewable energy sector, considering the balance between their potential advantages and available resources. These cutting-edge methods promise a more efficient, reliable, and sustainable future for solar energy management. Thus, Fig. 2 shows the block diagram representation for the evaluation of operational reliability using NAR-Net.

Case studies and results

This study aims to implement and validate the operational reliability of a solar-integrated system using the IEEE-RTS framework[33,34]. With 32 generating units and a total installed capacity of 3405 MW, the IEEE RTS can handle peak loads of 2457 MW. In the revised configuration, a 350 MW conventional energy source is replaced by a 1130 MW solar farm. Each turbine is stationed at bus number 15, which operates at a capacity factor of 0.31. Thus, the modified IEEE-RTS encompasses various generator types, i.e., coal/steam, hydro, nuclear, and oil/steam, alongside their generation capacities.

In Sect. Uncertainty modeling of solar irradiance and prediction model for reliability analysis, MATLAB is used to simulate a virtual solar farm. We evaluated the solar power generating data over a two-day period thanks to this simulation. The study uses the time series non-linear autoregressive neural network (NAR-Net) technique to forecast the irradiance conditions for the next five days based on the historical data. A time series of hourly data for four years (2019–2023) from New Hampshire, US, has been utilized in the study. The solar

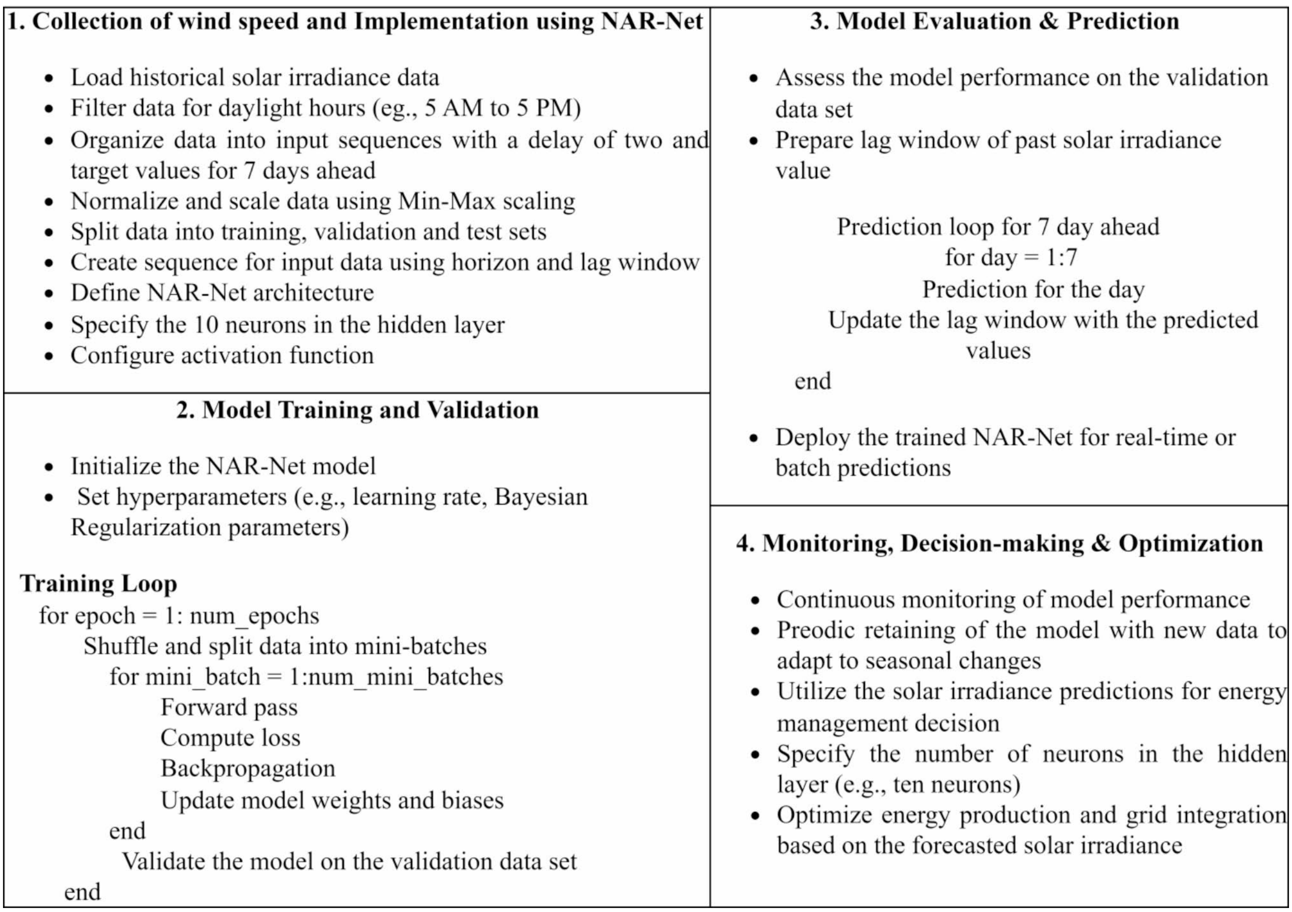

Fig. 1. Algorithm for a non-linear autoregressive neural network for solar irradiance prediction.

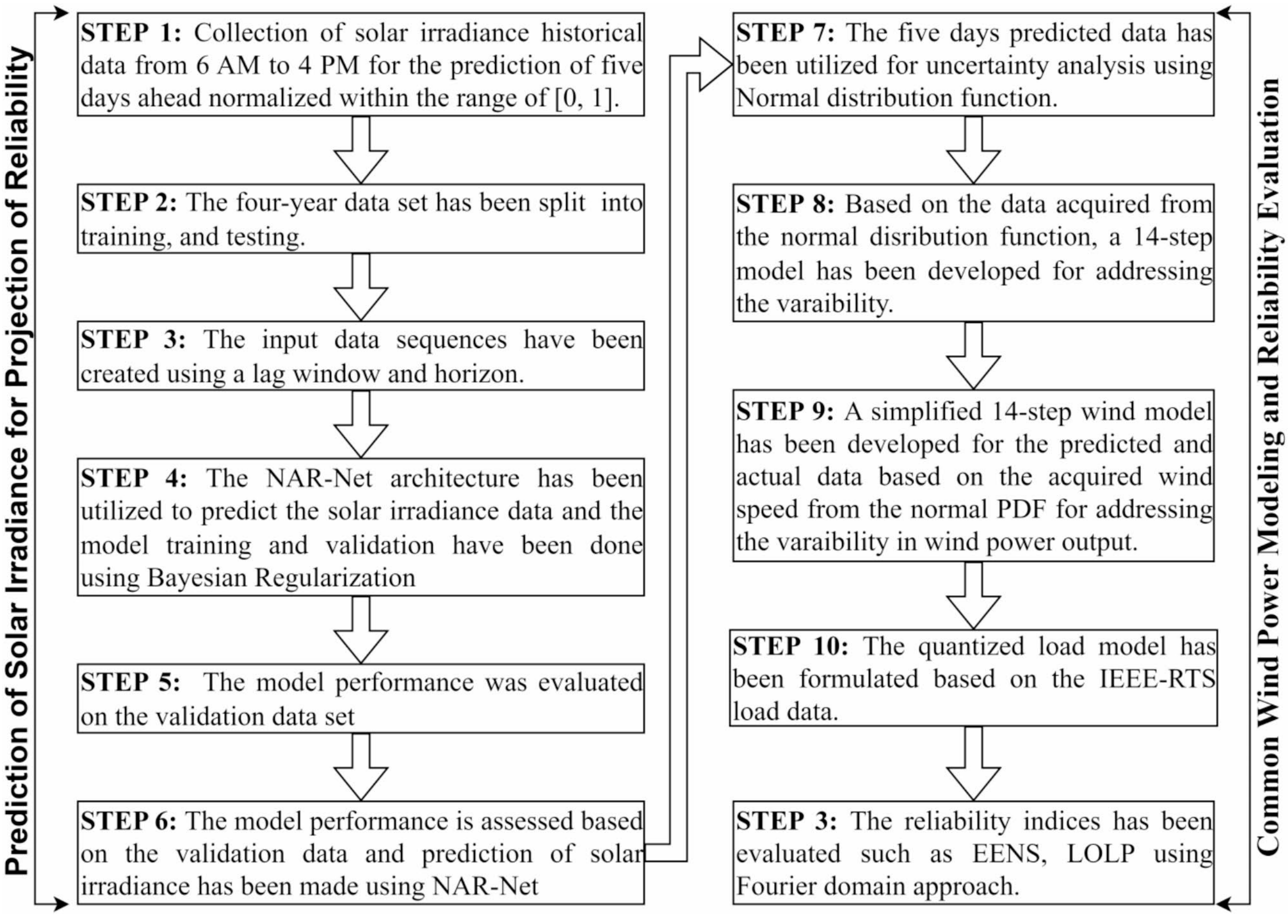

Fig. 2. Block diagram representation for operational reliability evaluation using NAR-Net.

irradiance dataset is split into training (70%) and testing (30%) subsets. It is found that for the training set, MSE and R are 2726 and 0.9818, respectively, and for the testing set, "MSE" and "R" are 2888 and 0.9815, respectively. The testing subset features a mean solar irradiance of 170.254 Wh/m^2 and a variance of 118.0394 Wh/m^2. The training dataset's loss function, as shown in Fig. 3, utilizes ten input neurons, and the mean square error is evaluated to analyze the model's behavior.

Hence, it can be observed from Fig. 3 that the model gives the best training performance, i.e., MSE = 2726.8836 Wh/m^2 at 661 epochs. Thus, Fig. 4 shows regression R for training testing, and the overall values are 0.98189, 0.98154, and 0.98182, respectively. Consequently, as Fig. 4 illustrates, a strong 98% correlation between predicted and real solar irradiance has been discovered. Additionally, Fig. 5; Table 3 represent the hourly average predicted and actual solar irradiance data for five days with a time-stamp (6 AM to 4 PM). It can be observed that the solar irradiance data for actual and predicted values are very close to each other. The predicted data follows the trend of the expected solar irradiance pattern. The utilization of the predicted value assists operators in making informed decisions to reduce variability in the system.

Three artificial neural network (ANN) techniques were compared, and the results showed that NAR-Net performed better than the other two, including the non-linear input-output neural network and the non-linear regression neural network. Table 4 illustrates this superior predicted accuracy, with the MSE that NAR-Net obtained being 1.21 times lower than that of NAR-Net. NAR-Net significantly outperformed a non-linear input-output neural network with 1.88 times lower MSE. Furthermore, NAR-Net provides enhanced regression accuracy and computational efficiency compared to existing techniques, making it a favourable choice for the problem domain for the evaluation of operational reliability.

As previously mentioned, a predictive model for solar irradiance has been developed using historical solar irradiance data. This model forecasts solar irradiance levels up to five days in advance. Both the actual and predicted solar irradiance data have been utilized to assess the variability in solar irradiance for power generation. This analysis is facilitated through the utilization of a Weibull distribution function. The outcome of this analysis is illustrated in Fig. 6, where a Weibull distribution plot is presented.

Following the uncertainty analysis employing the Weibull distribution, the mean and variance data are utilized to establish a multi-step model for variable power generation. This comprehensive 14-step modeling process is meticulously executed, ensuring the accurate characterization of power states. Thus, Table 5; Fig. 7 show probability, mid-point value, and power for each of 14-state for both actual and predicted solar data which has been utilized in this modeling approach.

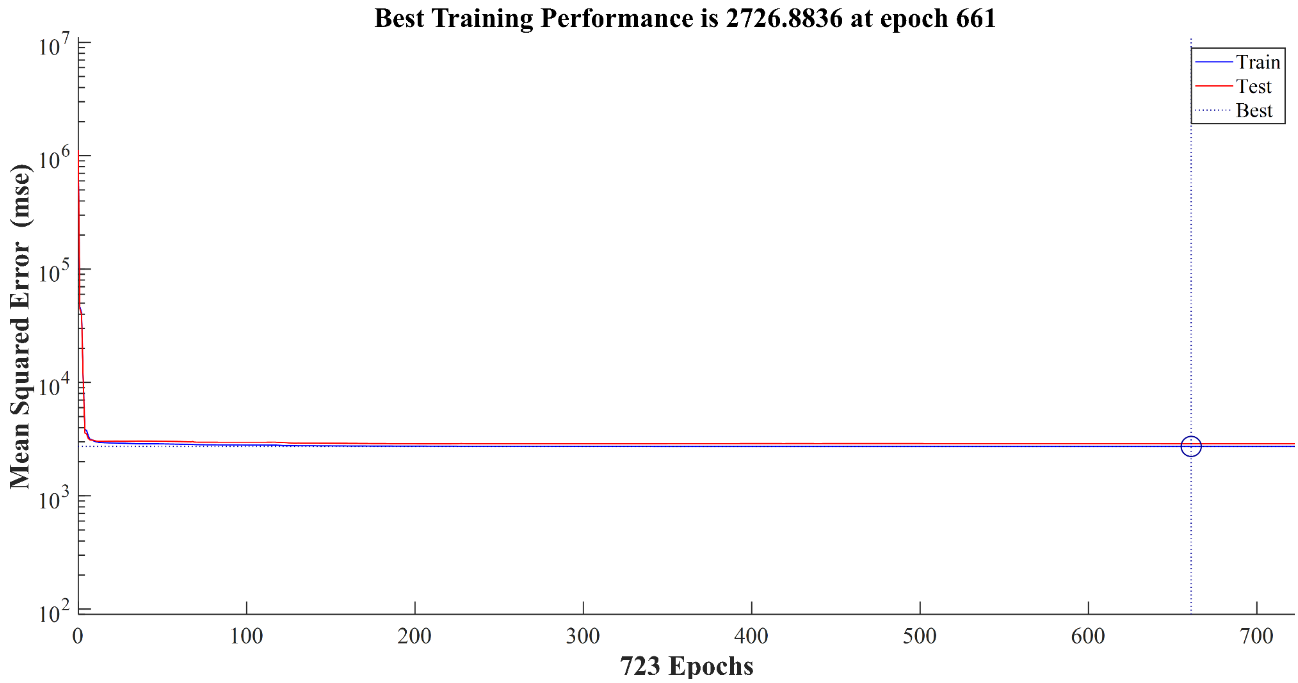

Fig. 3. Training Performance plot of solar irradiance using NAR-Net.

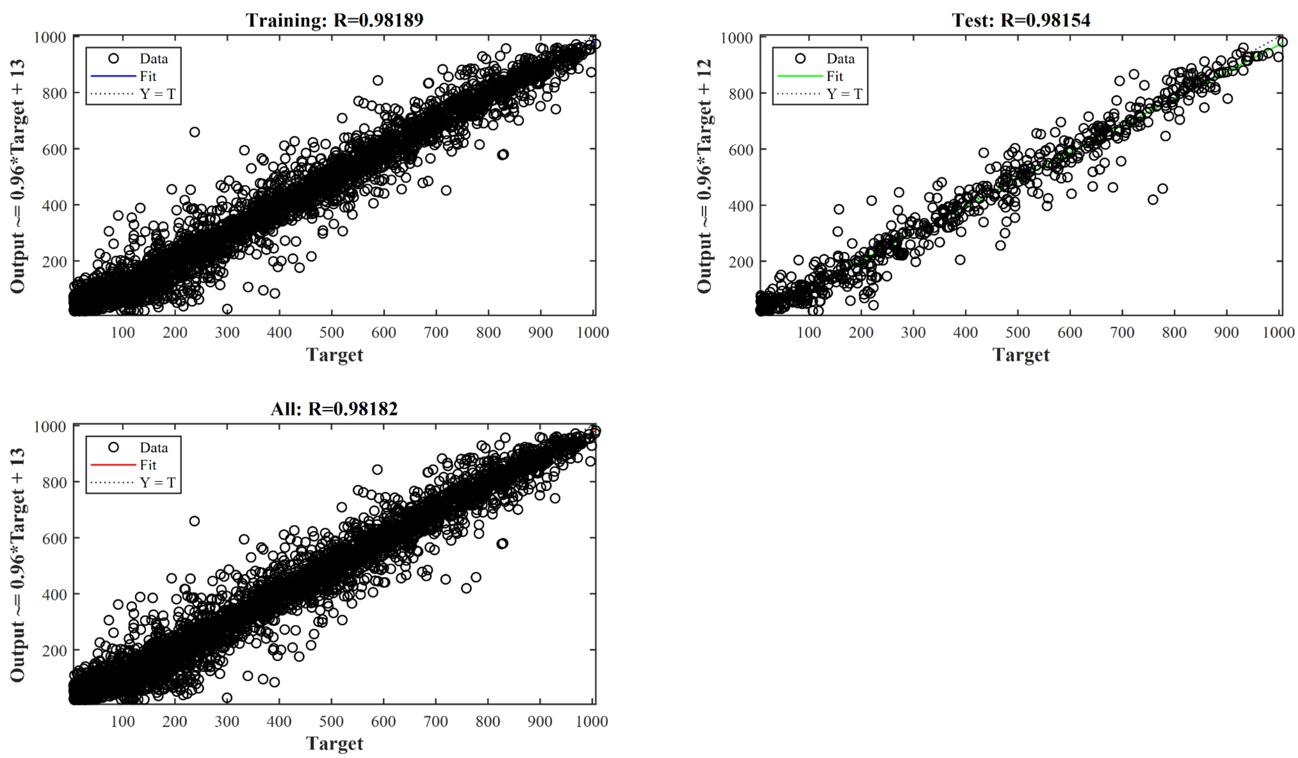

Fig. 4. Analysis of the correlation between forecasted and real solar irradiance data.

As a result, Fig. 7and Table 3 and is a valuable resource, offering a comprehensive view of the solar farm's probabilities across a range of distinct solar irradiance values, correlated power levels, and associated probabilities.

During the investigation of the proposed approach for solar integrated system, the reliability indices of the IEEE-RTS (Institute of Electrical and Electronics Engineers Reliability Test System) and its modified counterpart were scrutinized, employing QPLM techniques. To assess the impact of solar energy on the power system, a modified reliability test system was developed by integrating a 1130 MW solar farm into conventional power

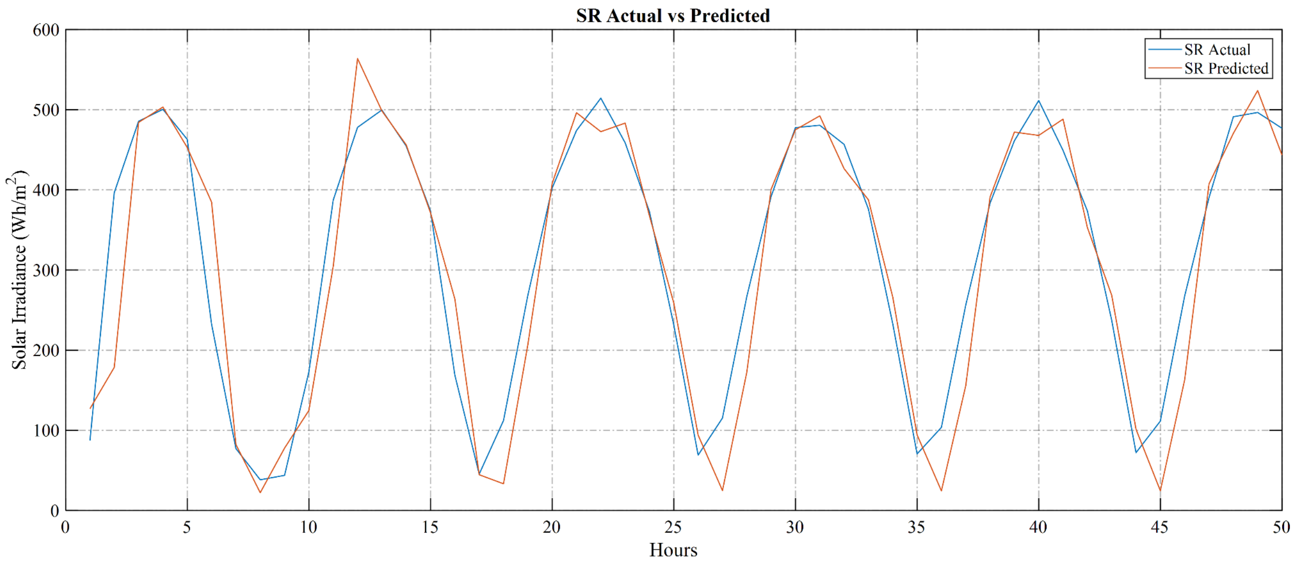

Fig. 5. Time series forecasting using ANN.

No. of Procured Data	Time (hh: mm: ss)	True Solar Irradiance (Wh/m^2)	Predicted Solar Irradiance (Wh/m^2)	No. of Procured Data	Time (hh: mm: ss)	True Solar Irradiance (Wh/m^2)	Predicted Solar Irradiance (Wh/m^2)
1	0:0:00	9.42	9.89	**.........**	....	....	....
2	1:00:00	11.26	11.95	**45**	43:00:00	6.75	6.85
3	2:00:00	11.43	11.32	**46**	44:00:00	6.39	6.27
4	3:00:00	11.51	11.5135	**47**	45:00:00	7.5	8.04
5	4:00:00	11.69	11.75	**48**	46:00:00	6.29	5.67
6	5:00:00	11.6	11.47	**49**	47:00:00	5.63	5.17
...	....	....	....	**50**	49:09:00	6.15	6.50

Table 3. True and predicted hourly solar irradiance and corresponding solar irradiance with a time-stamp for five days.

Sl. No.	Methodologies	Neurons	MSE	Regression (*R*)	Computational time (seconds)
1.	MLP	10	3217.746	0.57725	25.2
2.	Auto Regression	NA	3377.397	0.88963	23.5
3.	Auto Regression with Moving Average	NA	2958.685	0.91963	21.4
4.	NAR-ANN	10	2726.883	0.9818	18.6

Table 4. Comparison of the proposed method with the counterpart method.

systems, replacing 350 MW of coal-based energy. In this setup, all six hydro units were considered continuously, as they represent renewable energy sources. Additionally, the two nuclear units were always included in generation planning, given their lower carbon emissions and compliance with regulatory requirements. To explore various generator combinations, the remaining 24 generators (out of 32) were grouped using the power set technique, and these combinations were analyzed via linear programming. A power generation constraint of 3350 MW was set, based on a maximum load demand of 2850 MW and the highest capacity generating unit of 1130 MW. Consequently, the 1130 MW was considered as reserve from a reliability perspective. Combinations where the generation capacity fell below 3700 MW were excluded. In the end, 101 viable combinations remained. The optimal combination for minimizing interrupted energy costs and expected energy not supplied was identified by replacing a 350 MW conventional generator, leading to a more efficient generation plan with the integration of solar energy. As a result, maximum demand was met with reduced energy losses. A comparative analysis for reliability indices under varying load conditions is presented in Table 6. These indices, which hold paramount significance in power system performance evaluation with a particular emphasis on reliability and resilience, reveal noteworthy trends. A reliability indices for three load scenarios have been evaluated i.e., 80%, 100%, and

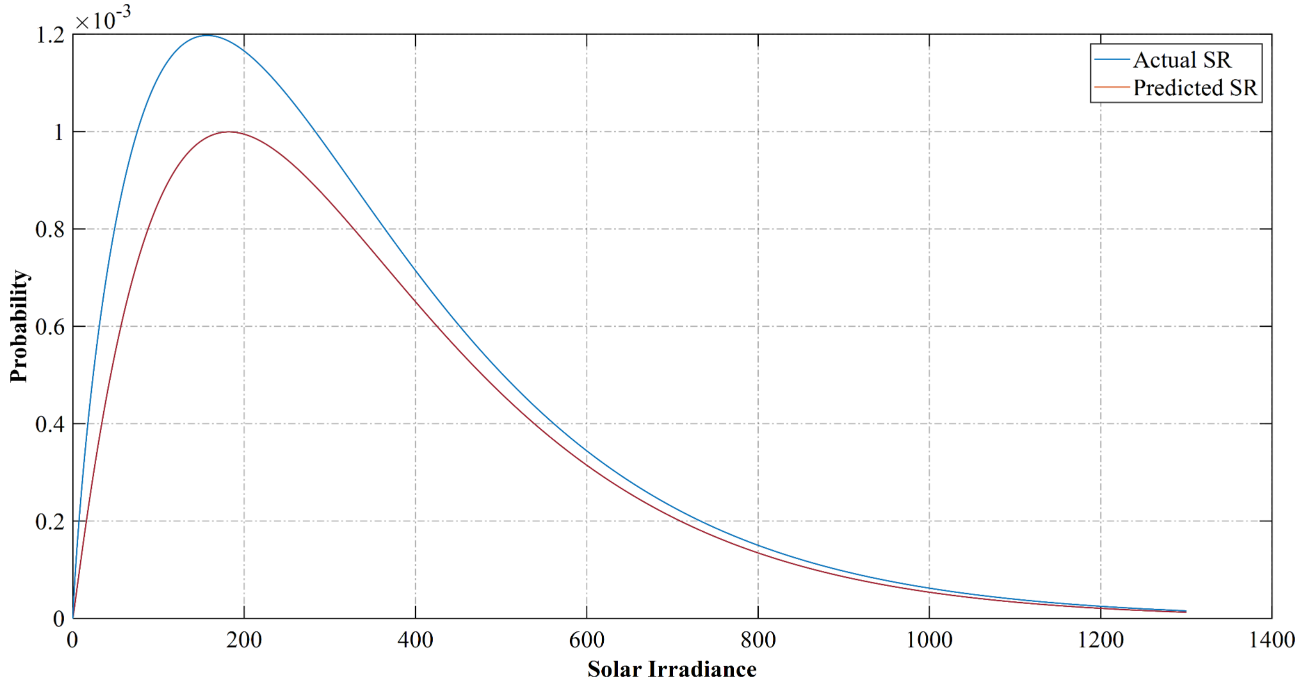

Fig. 6. Weibull distribution function for predicted solar irradiance.

Steps	Probability for Actual Solar Irradiance (SR)	Actual Mid-point for SR (Wh/m^2)	Probability for Predicted Solar Irradiance (SR)	Predicted Mid-point for SR (Wh/m^2)
State 1	0.06	25.2942	0.12	31.0067
State 2	0.1	75.8825	0.1	93.0202
State 3	0.08	126.4708	0.12	155.0337
State 4	0.04	177.0591	0.02	217.0472
State 5	0.08	227.6475	0.1	279.0607
State 6	0.08	278.2358	0.06	341.0742
State 7	0	328.8241	0.14	403.0877
State 8	0.2	379.4124	0.24	465.1012
State 9	0.04	430.0008	0.08	527.1147
State 10	0.28	480.5891	0.02	589.1282
State 11	0.04	531.1774	0	651.1417
State 12	0	581.7657	0	713.1552
State 13	0	632.3541	0	775.1687
State 14	0	682.9424	0	837.1822

Table 5. Probability and its corresponding solar irradiance mid-point for 14-step model.

120%. Under an 80% load variation, the predicted expected energy not supplied (EENS) and loss of load probability (LOLP) exhibit a subtle conservatism, as the predicted values are marginally higher than the actual readings. This suggests a prudent approach to reliability estimation, ensuring preparedness for potential uncertainties. Moving to full load conditions (100%), this inclination towards conservatism persists, with predicted EENS and LOLP values exceeding actual levels. This consistency underscores the cautious stance adopted in the prediction of reliability indices. Similarly, when confronted with a 120% load variation, the predicted EENS and LOLP values maintain their slightly conservative pattern, surpassing the actual data. These observations reinforce the overarching trend of prudence in estimating reliability indices across various load conditions, reflecting a commitment to ensuring system reliability and resilience in the face of potential challenges.

Table 7 compares the proposed and existing methods in terms of the expected energy not served (EENS) (MWh/day). The proposed method demonstrates a significant improvement over the existing methods, with percentage improvements of 14.03%, 17.54%, and 13.01% compared to the Analytical Method, Monte Carlo Simulation, and Crude Monte Carlo Simulation, respectively. Additionally, for the NARX-ANN and Non-linear

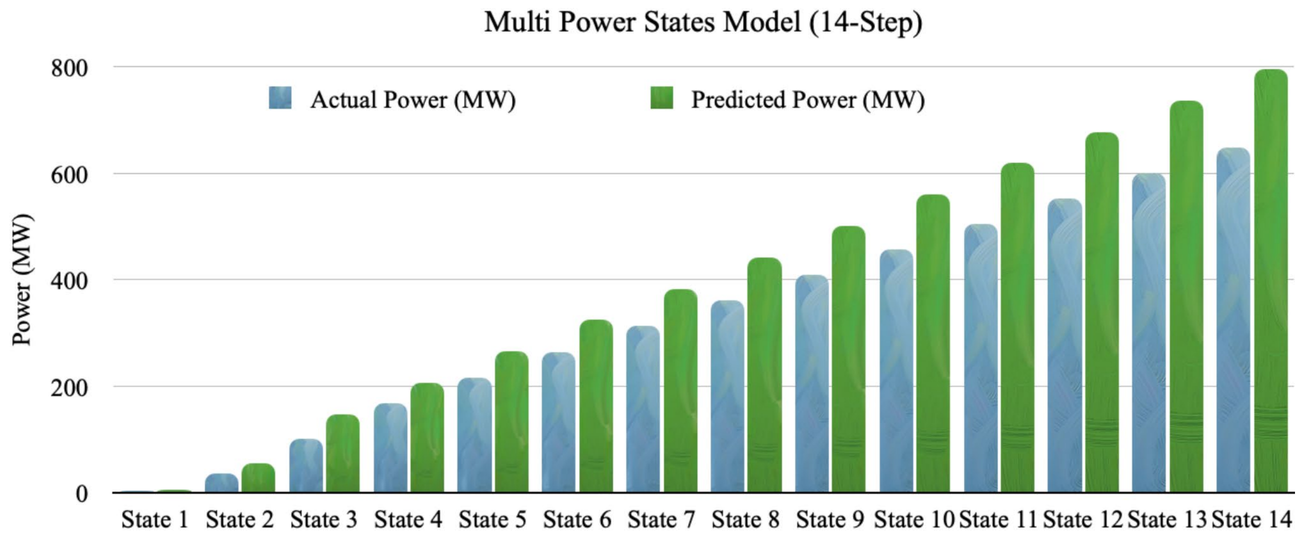

Fig. 7. 14-step power states model for actual and predicted solar irradiance.

Load Variation (%)	Solar farm capacity (MW)	Solar penetration percentage	Reliability Indices	Actual Reliability Indices	Projected Reliability Indices
80%	950	27.9	**EENS**	0.75608	0.79192
	950	27.9	**LOLP**	0.0001488	0.0001584
100%	950	27.9	**EENS**	0.9451	0.9899
	950	27.9	**LOLP**	1.86E-04	1.98E-04
120%	950	27.9	**EENS**	1.13412	1.18788
	950	27.9	**LOLP**	0.0002232	0.0002376

Table 6. The indices for the projected operational reliability of the proposed solar system under 80%, 100% and 120% loading.

	Methods		Results		
	Existing Methods	Proposed Method	Existing	Proposed	Percentage Improvement
Expected Energy Not Served (EENS) (MWh/day)	Analytical Method, Monte Carlo Simulation, Crude Monte Carlo Simulation	QPLM using FFT	1.078 1.1109, 1.0681 (MWh/day)	0.9451 (MWh/day)	14.03%, 17.54%, 13.01%
	NARX-ANN, Non-linear input output-ANN	NAR_ANN	Regression: 0.967, 0.586	Regression: 0.98154	1.48%, 40.29%

Table 7. Comparison of proposed method with the existing method.

input-output ANN methods, the proposed NAR_ANN shows a percentage improvement of 1.48% and 40.29% over the existing methods. These results highlight the effectiveness of the proposed methods in reducing the expected energy not served when compared to existing approaches.

Thus, from the above study it has been found that accurate prediction of solar irradiance is crucial for enhancing the reliability of power systems incorporate solar energy. By forecasting solar irradiance two days in advance using a Nonlinear Autoregressive Network (NAR-Net), operators can anticipate variations in solar power generation, which directly depends on irradiance levels. This foresight enables the assessment of operational reliability for the current day and projections for the subsequent two days, facilitating informed decision-making and optimized generation planning. Consequently, operators can implement proactive measures to maintain grid stability, allocate resources efficiently, and ensure a consistent power supply, thereby improving the overall reliability of the power system.

Conclusion

The transition to sustainable, renewable energy sources, particularly solar power, is pivotal in mitigating climate change and securing a dependable future energy supply. This study addresses key challenges in solar irradiance variability, operational reliability, and computational efficiency for integrated systems. A simplified reliability evaluation approach, utilizing multi-state modeling, has been proposed and validated using the IEEE RTS

96 test system, demonstrating its scalability and reduced computational complexity compared to traditional convolution-based methods. An extended probabilistic framework for modeling solar power fluctuations due to intermittency was developed, accurately capturing and quantifying variations in solar irradiance and power generation. Additionally, a non-linear auto-regressive neural network (NAR-Net) was employed for two-day-ahead solar irradiance and power generation forecasting. The proposed model achieved an accuracy of 98%, outperforming traditional methods such as AR, ARMA, and MLP in terms of predictive accuracy, correlation, and computational efficiency. The comparative validation of the NAR-Net highlights its effectiveness in facilitating proactive energy management and operational reliability projection. The integration of the multi-state reliability model and the extended probabilistic framework enabled accurate reliability assessment and operational planning for solar-integrated systems, bridging the gap between theoretical predictions and practical energy grid management. The incorporation of uncertainty modeling with the forecasting approach is found to be relevant for enhancing the operational reliability of solar integrated systems. Hence, the analysis of the proposed work gives valuable guidance for the adoption of solar power and other renewable energy sources, ensuring a sustainable and dependable future.

Future work

This study has certain limitations, particularly in modeling solar power generation, as rapid fluctuations in solar irradiance were not considered, and the impact of these fluctuations on the prediction model was not addressed. Additionally, transmission losses were excluded in the IEEE RTS-96 system due to the absence of load flow analysis. These aspects present important areas for future work, where the incorporation of rapid irradiance fluctuations and transmission losses could improve the accuracy and reliability of solar power generation models. Exploring these factors will further enhance the understanding of dynamic changes in solar power predictions and system performance.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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Author contributions
Rohit Kumar and Sudhansu Kumar Mishra presented the conceptualization, data collection, methodology, designing, analysis, and original draft preparation; Amit Kumar Sahoo and Subrat Kumar Swain involved in original draft preparation, results, and discussion; Ram Sharan Bajpai involved in revised manuscript preparation, review process, editing, and discussion; Aymen Flah and Mishari Metab Almalki handled in reviewing, visualization, editing, and funding acquisition; Habib Kraiem and Mohamed F. Elnaggar handled in reviewing, visualization, editing, and funding acquisition. All authors have read and agreed to the published version of the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Correspondence and requests for materials should be addressed to A.K.S.