

Original Article

SSLR-AE Net: Tasmanian Devil Optimized Deep Learning Architecture for Ultra-Short-Term Solar Irradiance Forecasting

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Abstract - Stable grid operation and the effective integration of renewable energy supplies depend heavily on accurate short-term solar irradiance predictions. However, accurate prediction is difficult due to the extremely nonlinear behavior of solar irradiance and the inherent unpredictability of climatic variables. This research proposes a more efficient regression-based forecasting approach by employing the integration of Tasmanian Devil Optimization (TDO) for adaptive hyperparameter tuning as well as a State-Space Latent Retention Autoencoder (SSLR-AE) network to address the aforementioned issues. The enhanced framework has been developed to perform better than the baseline SSLR-AE model as well as conventional Deep Neural Networks (DNN) in terms of a range of performance metrics, including R2, MSE, RMSE, MAE, and MAPE, respectively. The results demonstrate a substantial reduction in error rates as well as improved convergence stability. Overall, it can be observed that the proposed approach provides a reliable and accurate solution for short-term solar irradiance forecasting, and it can be used in sophisticated smart energy management.

Keywords - Solar irradiance forecasting, Deep Neural Network (DNN), Metaheuristic optimization, Renewable energy, Regression analysis, Solar irradiance.

1. Introduction

The ultra-short-term solar irradiance predictions has risen due to the rapid adoption of PV systems in traditional power grids [1]. This is because of the maintenance of system stability and the improvement of real-time grid management process. The efficacy of traditional predictive approaches is severely limited by complex factors, and it makes use of advanced data-driven and intelligent modeling applications [2, 3].

Statistical techniques and physics-based techniques, such as Autoregressive Integrated Moving Average (ARIMA), and Numerical Weather Prediction (NWP) techniques, were the backbone of preliminary research related to solar irradiance forecasting [4, 5]. Machine Learning (ML) techniques such as feed-forward neural networks, Random Forests (RF), and Support Vector Machine (SVM) were established subsequently to address non-linearities in solar-related time series data [6, 7]. Though these techniques have been developed to provide more accurate results, they are still not quite effective in modeling interdependencies between different time scales [8]. Recently, Deep Learning (DL) algorithms have become the most popular method for ultra-

short-term solar irradiance forecasting due to the strong capability of the extraction of feature characteristics [9]. To simulate the time-dependent characteristics in sequential data, Recurrent Neural Networks (RNNs), specifically, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) schemes have been widely used [10, 11]. Additionally, Convolutional Neural Networks (CNNs) have been used to record localized temporal characteristics [12]. The hybrid architectures like CNN-LSTM and CNN-GRU attain better computational overhead and are sensitive to manual tuning of hyperparameters [13]. Autoencoder-based models have gathered attention to effectively denoise solar irradiance data. Prior to the forecasting step, models like the variational autoencoder and stacked autoencoder have been employed to enhance feature extraction [14, 15]. Because these models do not adequately incorporate long-term temporal connections, and they frequently lack robustness against weather shifts. Recent studies have progressively addressed transformer-based frameworks and self-attention mechanisms to better capture long-range temporal dependencies in time-series data [16]. While these methods exhibit robust representational capabilities and facilitate effective parallel processing, they usually necessitate substantial training datasets and



hyperparameter tuning to attain the best possible accuracy. Although recent Deep Learning (DL) models have brought substantial improvement to ultra-short-term solar irradiance prediction, there are still some inherent challenges that need to be addressed. Current models using RNN architecture, such as LSTM and GRU networks, mostly concentrate on capturing temporal dependencies while having poor representation capability for the nonlinear dynamics of the system. The transformer models can capture long-term dependencies effectively, but their high complexity and training time make them less suitable for forecasting applications in real-time. Likewise, traditional autoencoder models are able to represent features concisely but typically do not have any method for retaining the temporal memory during latent representation learning. Additionally, most of the current approaches make use of manually designed hyperparameters and causing high sensitivity in the performance of the models due to their dependency on empirically tuned values. It is clear that there is a need for a universal forecasting framework which is capable to learn temporal dynamics, developing informative latent representations and maintaining long-range dependences. In light of the above, this research introduces an advanced deep learning approach to enhance the accuracy and reliability of ultra-short-term solar irradiance forecasting.

1.1. Major Contribution

The major contributions of this study are summarized as follows:

- A nonlinear state-space representation encoder, a compressed latent autoencoder module, and a retention-driven memory unit are all integrated into a single architecture to provide a revolutionary SSLR-AE Net

framework for ultra-short-term solar irradiance prediction.

- The main parameters of the SSLR-AE Net are tuned by employing a Tasmanian Devil Optimization (TDO). The use of the TDO optimization approach accelerates the convergence rate under nonstationary and changing solar irradiance, respectively.
- Stable training dynamics and enhanced generalization performance are ensured by this methodical pipeline, which includes temporal alignment, stationarity augmentation, informative feature transformation, and normalizing processes.

1.2. Organization of the Research

Section 2 defines the related work, Section 3 defines the proposed methodology, Section 4 highlights the result and discussion, and Section 5 ends with conclusion and future scope.

2. Related Work

To handle the significant nonlinearity and quick variations of solar radiation, DL and hybrid modeling techniques have become more and more important in recent advancements. In order to improve short-term predicting accuracy, researchers have looked into CNN, recurrent architectures, ensemble learning systems, and multimodal data fusion approaches. Notably, forecasting efficiency has significantly improved with the combination of temporal sequence modeling, hybrid learning paradigms, and spatial feature extraction. Recent state-of-the-art techniques are compiled in Table 1, which also highlights their goals, methodological advancements, benefits, and related drawbacks.

Table 1. Comparative summary of existing ultra-short-term solar irradiance forecasting models

Reference	Goal	Methodology	Key Contributions	Merits	Demerits
Elmoussaid et al. (2024) [17]	Improve ultra-short-term GHI forecasting accuracy	Hybrid GRU-TCN deep learning model	Combines GRU temporal learning with TCN for long-range dependency modeling	High forecasting accuracy; effective temporal feature extraction	Increased model complexity; requires careful hyperparameter tuning
Liu et al. (2023) [18]	Enhance forecasting using spatial cloud dynamics	Spatiotemporal modeling using sky image sequences	Exploits sky image correlations to capture cloud motion	Strong performance under fast-changing cloud conditions	Requires expensive sky imaging systems; high computational cost
Wang et al. (2026) [19]	Improve prediction robustness using multimodal data	Multimodal deep learning with sky images and weather sequences	Fuses visual and meteorological information	Improved robustness and accuracy	Complex data fusion; dependency on multiple sensors
Li et al. (2024) [20]	Develop an efficient and lightweight forecasting model	Hybrid K-means clustering with Extreme Learning Machine (ELM)	Enhances ELM efficiency via clustering-based preprocessing	Fast training; low computational cost	Limited temporal dependency modeling capability

Wang et al. (2025) [21]	Improve cloud feature representation	Integrated framework with novel textural convolution kernel	Introduces texture-aware convolution for cloud feature extraction	Improved cloud pattern representation	Specialized kernel design; limited generalizability
Ma et al. (2025) [22]	Enhance PV power forecasting accuracy	Multimodal data fusion with ensemble learning	Combines multiple learners and data sources	High robustness; reduced variance	Increased computational overhead; complex deployment
Huang et al. (2023) [23]	Capture spatial-temporal irradiance dynamics	3D ConvLSTM-CNN with multi-channel color extraction	Joint spatial-temporal modeling using 3D convolutions	Strong performance under dynamic weather	High memory usage; computationally intensive
Alorf and Khan (2025) [24]	Improve ultra-short-term solar irradiance forecasting through advanced temporal sequence learning.	Temporal Fusion Transformer (TFT) incorporating attention mechanisms for multi-horizon forecasting.	Introduced a transformer-based framework capable of capturing long- and short-term temporal dependencies for improved forecasting accuracy.	Excellent temporal feature learning, interpretable attention mechanism, and improved prediction performance.	High computational complexity, increased training time, and sensitivity to hyperparameter selection.
Gao et al. (2023) [25]	Develop an interpretable model for solar irradiation prediction by jointly exploiting spatial and temporal information.	Spatio-temporal interpretable neural network based on transformer architecture.	Combined spatial and temporal feature learning while improving model interpretability for solar irradiation prediction.	Effective modeling of spatio-temporal dependencies and enhanced interpretability.	Requires high-quality spatial information and involves considerable computational overhead.
Zhang et al. (2024) [26]	Improve forecasting performance under incomplete data scenarios.	Hybrid transformer-based forecasting framework with mechanisms for handling missing data.	Enhanced robustness of transformer models for solar irradiance forecasting when data are incomplete or noisy.	Strong robustness against missing data and improved prediction accuracy.	Complex architecture with higher computational cost and implementation complexity.
Naveed et al. (2024) [27]	Enhance solar irradiance forecasting using hybrid deep learning techniques.	Transformer-infused recurrent neural network integrating attention with recurrent feature learning.	Combined recurrent learning and transformer attention to capture nonlinear temporal dependencies more effectively.	Improved nonlinear temporal feature extraction and forecasting performance.	Requires large-scale training data and careful hyperparameter optimization to achieve optimal performance.

2.1. Research Gaps and Motivation

The reviewed works highlight a significant advancement in ultra-short-term solar radiation prediction using recurrent neural networks, hybrid approaches, multimodal learning, and attention mechanisms. However, current models largely focus on the problem of increasing prediction accuracy via feature extraction and temporal dependencies. The hybrid recurrent neural network models, such as GRU-TCN and ConvLSTM, perform well in modeling the temporal information but are

usually complex in terms of computation and need to be manually optimized. In the same manner, the feature redundancy and noise are eliminated by the autoencoder-based technique, but they fail to maintain the temporal information in the process of latent representation learning.

On the other hand, the recent transformer architecture is efficient in capturing the long dependencies, but they suffer from the issue of computational cost. In order to address these

shortcomings, this research presents the SSLR-AE Net framework for irradiance forecasting, which combines the features of nonlinear state-space modeling, latent feature learning, retention-driven temporal memory, and intelligent hyperparameter tuning.

More specifically, the nonlinear state-space encoder is able to model the complicated irradiance dynamics, whereas the latent autoencoder filters out any superfluous information and retains the informative latent features. Moreover, the retention-driven memory system improves the temporal consistency and also considers both the short-term and long-term irradiance dynamics. In addition, the TDO technique selects the optimal values for hyperparameters and thus enhancing the stability of convergence and reducing the dependence on manual tuning. The combined effect of the integration of all these elements makes it possible to forecast ultra-short-term solar irradiance in an accurate manner.

2.2. Novelty of the Proposed Work

The uniqueness of the proposed work is in the unified approach to the nonlinear state space model, latent autoencoder-based representation learning, memory-centric temporal representation, and metaheuristic hyperparameter tuning for ultra-short-term solar radiation forecasting. While

several previous research works have focused on recurrent neural networks, transformer-based architectures, multi-modal learning, and autoencoders individually, very little attention has been paid towards modeling the nonlinear temporal dynamics and latent memory while tuning network parameters automatically. The SSLR-AE Net is able to achieve this by adopting an end-to-end forecasting framework. Moreover, the inclusion of TDO allows for automatic determination of hyperparameters, and it results in better convergence stability and better prediction accuracy.

3. Proposed Methodology

Figure 1 illustrates the SSLR-AE Net framework, and it achieves a unified and streamlined design. Raw solar irradiance data is pre-processed and segmented to provide temporally matched input sequences. A latent autoencoder bottleneck with a retention-driven memory mechanism captures both long-term trends and short-term alterations to maintain temporal coherence. To create accurate ultra-short-term predictions, the latent features are decoded. In parallel, the TDO algorithm is used to enhance the stability and accuracy of the predictions in highly variable atmospheric conditions by optimizing key hyperparameters, such as learning rate, latent dimension, and retention coefficients, in a balanced exploration-exploitation manner.

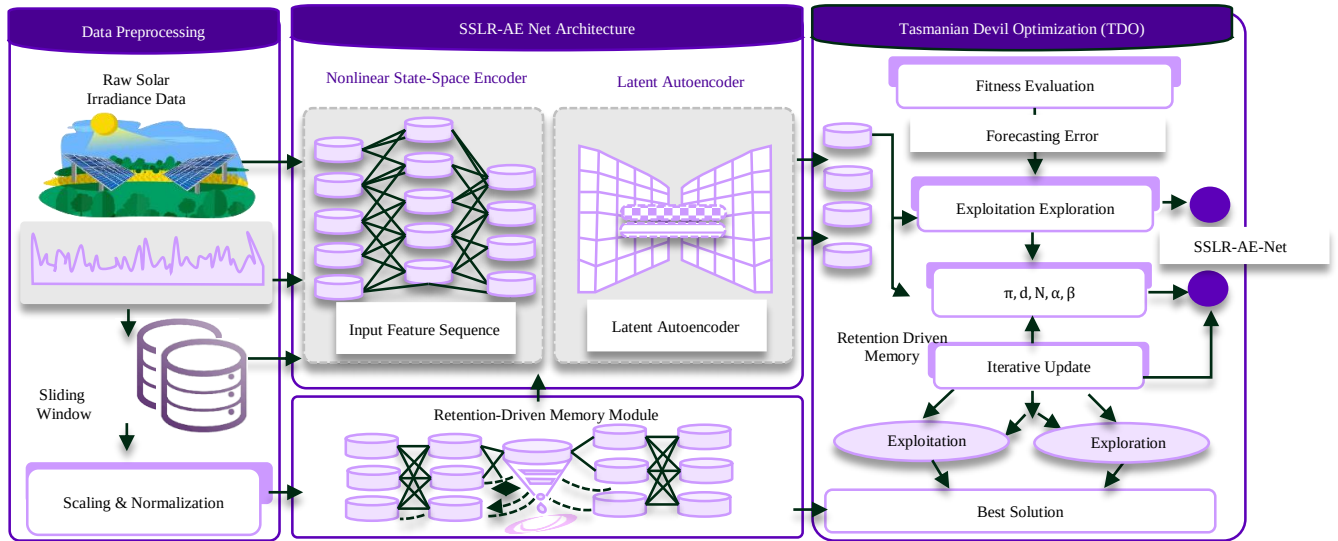


Fig. 1 Overall proposed framework

3.1. Problem Definition and Assumptions

The objective of this research is to design a strong DL model for ultra-short-term forecasting of solar irradiance through precise prediction of future irradiance values from the past records of solar irradiance along with meteorological parameters. The input would be a time series of irradiance values along with meteorological data, while the output would be the forecasted solar irradiance values. The following assumptions are introduced to define the forecasting problem:

- The measured data for solar irradiance and meteorology are temporally aligned and reflect the actual conditions in the environment.
- Dealing with missing data and outliers is efficiently done during the preprocessing phase before the training process.
- There is enough temporal information available in the past records to learn future solar irradiance patterns

- Both training and testing phases use separate datasets, and all preprocessing processes take place without information leakages.

3.2. Data Preprocessing

The quality of the input data is the most important factor that influences the accurate prediction of the weather. In the case of solar irradiance, the fluctuating weather causes noisy data, missing values, misalignment of the data, and non-stationary behavior. All these steps are collectively referred to as data cleaning and improves stationarity.

3.2.1. Data Cleaning

Measurements of solar irradiance often have anomalous spikes and missing data because of communication failures, shadowing, or malfunctioning sensors. The time series of raw irradiance can be represented as $\{G_t\}_{t=1}^T$. Where T is the total number of observations and $G_t \in \mathbb{R}$ is the measured global solar irradiance at time index t . G_t is considered to be missing when it is not specified or falls outside of physically significant bounds. Using linear interpolation, these values are substituted, and the result is expressed below:

$$\hat{G}_t = G_{t_1} + \frac{t-t_1}{t_2-t_1}(G_{t_2} - G_{t_1}) \quad (1)$$

Where the interpolated irradiance value is stated as $\hat{G}_t$, the nearest valid observations before and after time t is denoted as G_{t_1} and G_{t_2} consecutively. A statistical threshold is used to identify outliers brought on by unusual sensor activity, and it is defined as

$$|G_t - \mu_G| > k\sigma_G \quad (2)$$

Where the mean of the irradiance series is defined as μ_G , the standard deviation is stated as σ_G and k specifies the predefined constant. To maintain the data's temporal structure, observed outliers are either smoothed or replaced with nearby legitimate values.

3.2.2. Temporal Alignment

Time series are consistently spaced and are necessary for ultra-short-term forecasting models to accurately learn temporal dependencies. The irradiance series is resampled using interpolation or aggregation to a set time resolution Δt . Let τ_j represent the aligned timestamps with constant interval Δt and t_i represent the original sampling timestamps. The definition of the temporally aligned irradiance series is

$$G(\tau_j) = \mathcal{A}(G(t_i) \mid t_i \in [\tau_j, \tau_{j+1})) \quad (3)$$

Where the aligned irradiance value at time τ_j is defined as $G(\tau_j)$, $\mathcal{A}(\cdot)$ specifies the aggregation function, and the resampling interval is specified as $[\tau_j, \tau_{j+1})$. For the state-

space and recurrent parts of the forecasting model, this alignment guarantees constant temporal spacing.

3.2.3. Stationarity Enhancement

Because of seasonal fluctuations, weather patterns, and diurnal cycles, solar irradiance time series are intrinsically non-stationary. Forecasting accuracy and model convergence may suffer from non-stationary data. In order to improve stability, the aligned irradiance sequence undergoes a differencing process. The first-order derivative series is defined as

$$\Delta G_t = G_t - G_{t-1} \quad (4)$$

Where, differenced irradiance signal at time t is stated as ΔG_t and the irradiance value at the previous time step is denoted as G_{t-1} . Furthermore, normalization is used to limit the input features to a predetermined range:

$$G_t^* = \frac{G_t - \mu_G}{\sigma_G} \quad (5)$$

The normalized irradiance value is stated as G_t^* .

3.3. Feature Engineering

Feature engineering is used to further enhance the cleaned and temporally synchronized solar irradiance measurements. This study uses feature engineering, which combines feature encoding and feature scaling to increase the representational capacity and enhance the SSLR-AE Net framework's numerical stability.

3.3.1. Feature Encoding

A feature encoding technique based on sliding windows is used to capture short-term temporal correlations. Assume that the pre-processed irradiance time series is given as follows: $\{G_t^*\}_{t=1}^T$. An input feature vector $\mathbf{x}_t \in \mathbb{R}^L$ for every predicting instant t is constructed, and it is defined below:

$$\mathbf{x}_t = [G_{t-L}^*, G_{t-L+1}^*, \dots, G_{t-1}^*] \quad (6)$$

Where L specifies the window length and $\mathbf{x}_t$ defines the encoded temporal feature vector. The matching forecasting goal is described as:

$$y_t = G_t^* \quad (7)$$

Where y_t represents the normalized irradiance value to be predicted at time t . The SSLR-AE Net can simulate the nonlinear link between historical irradiance behavior and future solar circumstances due to this input-output mapping.

3.3.2. Feature Scaling

To guarantee that every encoded feature contributes equally during model training, feature scaling is enforced in

this stage. Each encoded feature vector is subjected to min-max scaling, and the scaled feature value is defined as

$$\tilde{G}_t = \frac{G_t^* - G_{\min}}{G_{\max} - G_{\min}} \quad (8)$$

Where the scaled irradiance value is stated as $\tilde{G}_t$, minimum and maximum values of the irradiance series is defined as $G_{\min}$ and $G_{\max}$ respectively. Because of this, all input features are limited to the interval $[0, 1]$, which enhances the computational reliability and makes learning faster and more dependable.

3.3.3. Final Feature Representation

The final input dataset, following feature encoding and scaling, is shown as follows:

$$X = \{x_t \mid t = L + 1, L + 2, \dots, T\} \quad (9)$$

with corresponding targets

$$Y = \{y_t \mid t = L + 1, L + 2, \dots, T\} \quad (10)$$

Where the set of linked prediction targets is called Y, and the set of input feature vectors used for testing and training is called X, respectively. The flow diagram of data processing and feature engineering is illustrated in Figure 2.

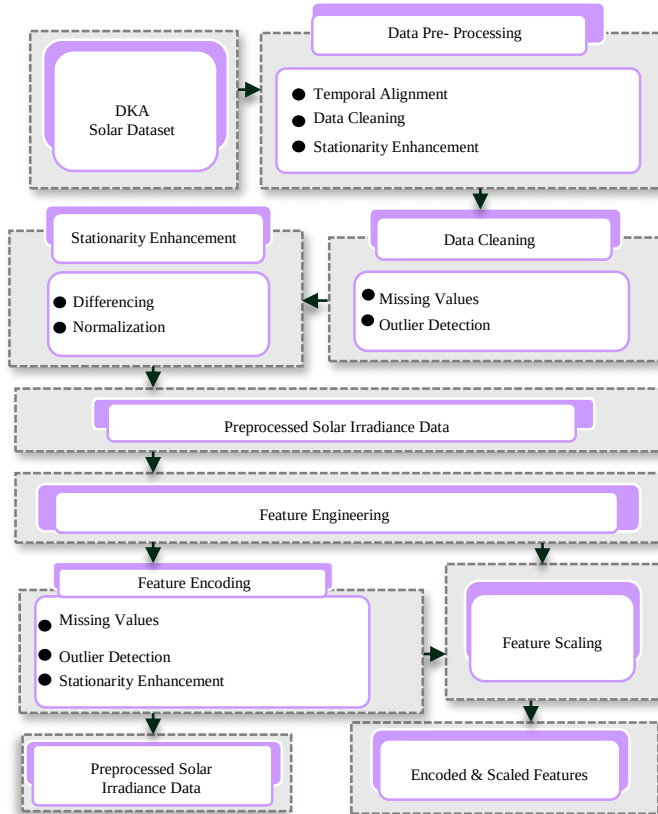


Fig. 2 Data processing and feature engineering flowchart

3.4. SSLR-AE Net Architecture

To explicitly handle the inherent nonlinearity in ultra-short-term solar irradiance time series, the SSLR-AE Net was developed.

Four closely related components are integrated into the architecture:

- (i) an adaptive decoder to provide accurate ultra-short-term forecasts
- (ii) a latent autoencoder to enforce compact and noise-robust representations;
- (iii) a retention-driven memory mechanism to regulate temporal persistence;
- (iv) and a nonlinear state-space encoder to describe irradiance dynamics.

3.4.1. Input Representation and Temporal Context

Let the engineered input sequence be defined as

$$X = \{x_t \in \mathbb{R}^L \mid t = 1, 2, \dots, T\} \quad (11)$$

Where T is the sequence length, L is the feature dimension, and x_t is the encoded and scaled feature vector at time t .

3.4.2. State-Space Temporal Encoding

Additionally, SSLR-AE Net uses a discrete-time nonlinear state-space formulation to explicitly describe the temporal development of solar irradiance. The latent state of the system $h_t \in \mathbb{R}^d$ is defined below:

$$h_t = \phi(Ah_{t-1} + Bx_t + \eta_t) \quad (12)$$

Where, state transition matrix encoding temporal dependencies is termed as A , B projects input characteristics into the latent dynamic space, $\phi(\cdot)$ is a nonlinear activation function, and η_t represents stochastic perturbations brought on by atmospheric variability.

3.4.3. Latent Autoencoder Representation Learning

Redundancy and measurement noise in solar irradiance signals can spread via extensive networks and reduce forecasting precision.

A latent autoencoder bottleneck is incorporated into the state evolution process to solve this problem. The latent state is compressed by the encoder with fewer dimensions:

$$z_t = \phi(W_e h_t + b_e), z_t \in \mathbb{R}^k, k \ll d \quad (13)$$

W_e and b_e are encoder parameters. The decoder reconstructs the state approximation, and it is defined below:

$$\tilde{h}_t = \phi(W_d z_t + b_d) \quad (14)$$

By suppressing noise and unnecessary fluctuations, this reconstruction constraint compels z_t to maintain the most informative temporal features.

3.4.4. Retention-Driven Memory Dynamics

It is necessary to preserve both gradual irradiance patterns and quick transient fluctuations for ultra-short-term forecasting. A learnable retention method that actively regulates memory persistence is introduced by SSLR-AE Net, and the updated retained latent memory $m_t \in \mathbb{R}^k$ is

$$m_t = \alpha \odot m_{t-1} + (1 - \alpha) \odot z_t \quad (15)$$

Where the learnable retention vector is specified as α , temporally smoothed irradiance data is stored in m_t . For the purpose of modeling heterogeneous solar dynamics, this formulation makes it possible for various latent dimensions to preserve information at various time scales.

3.4.5. Adaptive State Evolution Mechanism

The reconstructed state $\hat{h}_t$ and preserved memory m_t are rapidly merged to provide strong temporal consistency, and its expression is given below:

$$s_t = \psi \left(W_s \begin{bmatrix} \hat{h}_t \\ m_t \end{bmatrix} + b_s \right) \quad (16)$$

Where the evolved latent space is stated as $s_t \in \mathbb{R}^d$ and the non-linear activation function is termed as $\psi(\cdot)$. By using this fusion method, the network can dynamically modify state transitions according to both the historical perspective and the dynamics of the system.

3.4.6. Prediction Decoder and Output Generation

The irradiance output space is translated to the final developed state by means of a linear regression decoder:

$$\hat{y}_t = W_o s_t + b_o \quad (17)$$

Where, the predicted ultra-short-term solar irradiance is stated as $\hat{y}_t$ and the trainable output parameters are stated as W_o and b_o consecutively. Latent autoencoding, explicit state-space dynamics, and retention-driven memory modeling are all smoothly combined in the SSLR-AE Net a unified DL framework. This architecture performs better under dynamic solar circumstances than traditional recurrent and attention-based methods. The architecture of SSLR-AE Net is illustrated in Figure 3.

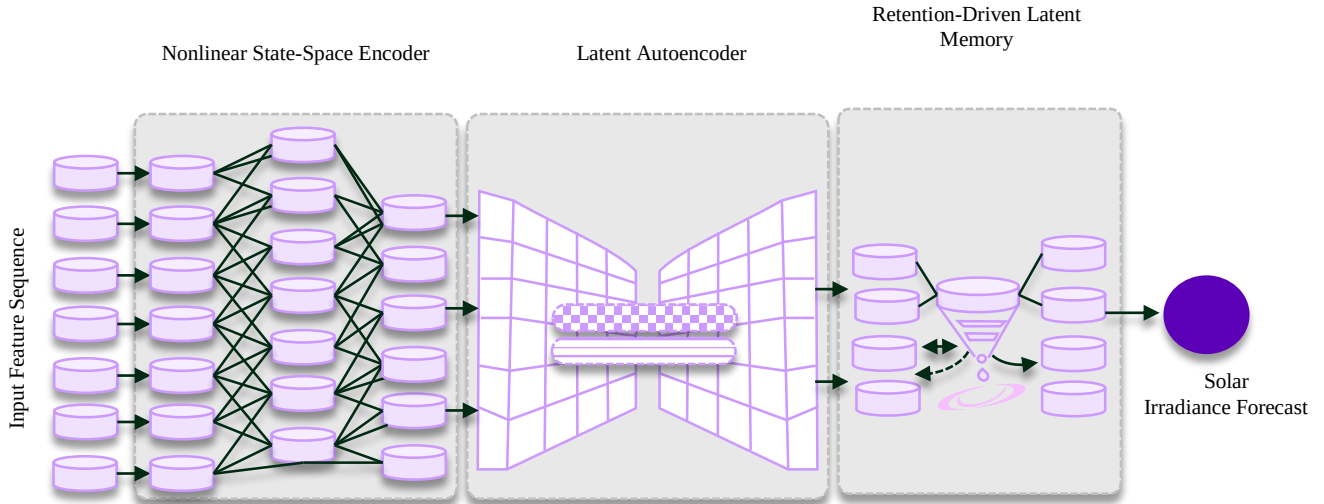


Fig. 3 Architecture of SSLR-AE Net

3.5. Stage IV: Hyperparameter Optimization using Tasmanian Devil Optimization (TDO)

Learning rate, number of hidden units, latent dimension size, retention coefficients, and batch size are some of the hyperparameters that have a significant impact on SSLR-AE Net's performance. TDO is a population-based metaheuristic that draws inspiration from Tasmanian devils' aggressive foraging strategies and survival tactics. TDO was chosen due to the excellent balance of exploration and exploitation of the algorithm, which proved to be useful when dealing with high-dimensional hyperparameters of DL model. TDO has a more

adaptive search process compared to traditional metaheuristic algorithms, and providing better stability in convergence without risk of premature convergence to local optima. Such properties made it suitable for hyperparameters tuning in ultra-short-term solar irradiance forecasting, where model accuracy depends greatly on choice of learning parameters.

Thus, the use of TDO improves the reliability of proposed SSLR-AE Net through optimal hyperparameters determination.

3.5.1. Population Initialization

Consider the Tasmanian devil as a potential solution, which can be represented as a hyperparameter vector:

$$D_i = [\eta, N_h, k, \alpha, B] \quad (18)$$

Where the learning rate, number of hidden units in the state-space encoder, latent bottleneck dimension, retention coefficient and mini-batch size are specified as $[\eta, N_h, k, \alpha, B]$ consecutively.

3.5.2. Fitness Evaluation

The SSLR-AE Net is configured and trained using each candidate solution D_i . A validation dataset is used to assess the forecasting performance, and the fitness function is described as follows:

$$\mathcal{F}(D_i) = \frac{1}{T_v} \sum_{t=1}^{T_v} (y_t - \hat{y}_t)^2 \quad (19)$$

Where, the number of validation samples is specified as T_v and both the actual and predicted irradiance is specified as y_t and $\hat{y}_t$ respectively. Forecasting accuracy is increased by minimizing $\mathcal{F}(\cdot)$.

3.5.3. Exploration Phase (Scavenging Behavior)

Tasmanian devils mimic scavenging behavior during the exploration phase by approaching randomly chosen individual in an attempt to search the global solution space:

$$D_i^{(t+1)} = D_i^{(t)} + r_1 (D_{rand}^{(t)} - D_i^{(t)}) \quad (20)$$

Where, the randomly selected solution is stated as D_{rand} , and r_1 specifies the random coefficient.

3.5.4. Exploitation Phase (Aggressive Feeding Behavior)

An exploitation technique is used to improve promising solutions by approaching the individual who is currently functioning at the highest level:

$$D_i^{(t+1)} = D_i^{(t)} + r_2 (D_{best}^{(t)} - D_i^{(t)}) \quad (21)$$

Where, r_2 controls the step size and D_{best} denotes the best solution. The convergence toward ideal hyperparameters is accelerated by this technique.

3.5.5. Adaptive Balance between Exploration and Exploitation

An adaptive probability factor that changes with iterations governs the transition between exploration and exploitation in order to dynamically balance local refinement and global search. Strong convergence behavior is ensured by emphasizing exploitation in later rounds and favoring exploration in earlier iterations.

Until the convergence conditions are met or a maximum number of iterations is attained, the optimization process keeps going. Using the entire training dataset, the final SSLR-AE Net is trained using the best hyperparameter vector, D_{best} . The algorithm of hyperparameter strategy is shown in Table 2.

3.5.6. Hyperparameter Configuration of Tasmanian Devil Optimization

The effectiveness of the TDO algorithm relies on the proper tuning of its optimization parameters. In the process of optimization, each candidate solution is a full set of SSLR-AE Net hyperparameters such as learning rate, latent dimension, hidden units, retention coefficient, and batch size. Candidate solutions are randomly generated within the given search spaces to guarantee enough diversity in the initial stage of optimization.

In the optimization process, the population is iteratively optimized according to the exploration and exploitation methods explained in Sections 3.4.3 and 3.4.4. The optimization process is stopped either when the predefined maximum number of iterations is reached or the improvement in the validation loss becomes insignificant. Finally, the selected hyperparameters of the SSLR-AE Net are optimized via the TDO. In addition, the process of optimization adopts a convergence condition, which is defined based on the number of optimization steps and the lack of substantial improvement in validation loss for each iteration. The proposed convergence condition ensures that unnecessary optimization is avoided while achieving stable convergence to an optimal setting of hyperparameters.

Through its adaptive exploration-exploitation strategy, the TDO algorithm makes it possible for the optimization process to perform efficient global search in the early stages of the iteration. The convergence analysis of the proposed model is illustrated in Figure 16.

Table 2. Algorithm of TDO-based hyperparameter optimization

Input:	
•	Raw solar irradiance dataset $\mathcal{D}_{raw}$
•	Sliding window length L
•	Forecast horizon H
•	Population size P
•	Maximum TDO iterations T_{max}

Output:

- Forecasted solar irradiance $\hat{y}_{t+H}$
- Trained SSLR-AE Net model

Begin

// ----- **Stage I: Data Preprocessing** -----

Load raw dataset D_raw

Remove missing and noisy observations

Align data temporally to uniform resolution

Enhance stationarity using normalization

Construct sliding window sequences of length L

Split dataset into training, validation, and testing sets

// ----- **Stage II: Feature Engineering** -----

Encode temporal and meteorological features

Apply feature scaling to all input variables

Form final feature matrix X and target vector y

// ----- **Stage III: SSLR-AE Net Initialization** -----

Initialize nonlinear state-space encoder

Initialize latent autoencoder bottleneck

Initialize retention-driven recurrent memory module

Initialize adaptive latent decoder

// ----- **Stage IV: Hyperparameter Optimization (TDO)** -----

Initialize TDO population with candidate hyperparameter sets

For iteration = 1 to T_max do

For each candidate solution do

Configure SSLR-AE Net with candidate hyperparameters

Train model on training set

Evaluate validation loss

Update candidate position using TDO rules

End for

Update global best hyperparameter set

End for

Select optimal hyperparameters

// ----- **Stage V: Model Training** -----

Configure SSLR-AE Net using optimal hyperparameters

Train final model on training dataset

Validate model and apply early stopping

// ----- **Stage VI: Forecasting and Evaluation** -----

Generate ultra-short-term irradiance forecasts on test set

Compute MAE, MSE, and RMSE performance metrics

End

Return trained model and forecast results

4. Result and Discussion

This section evaluates the performance of the suggested model in comparison to existing models. The evaluation is done by using statistical values, convergence, and graphical outcomes to check the accuracy and consistency of the models.

The effectiveness of the suggested optimization strategy is validated by evaluating the DNN, the SSLR-AE model, and the TDO-optimized SSLR-AE model. The results clearly show that the forecasting accuracy is enhanced with reduced prediction errors and faster convergence. Tables 3 and 4 show the final optimized results and the training parameters.

Table 3. Training configuration

Parameter	Value
Optimizer	Adam
Learning Rate	Optimized via TDO
Population Size	20 Devils
Maximum Iterations	30
Search Strategy	Exploration & Exploitation
Fitness Function	Validation MSE
Initialization	Random
Metric	Mean Absolute Error (MAE)
Batch Size	32
Epochs	10

Table 4. Final optimised results

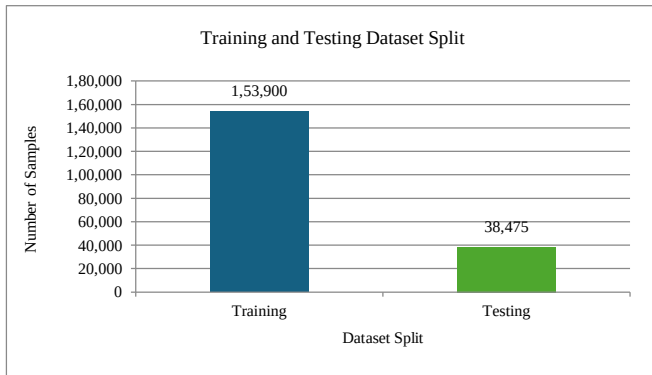
Hyperparameter	Optimized Value
Latent Dimension	44
RNN Units	54
Learning Rate	0.0005725

4.1. Dataset Description and Experimental Setup

The dataset used for the trials is the Short-Term Solar Irradiance Forecasting dataset, which is openly accessible on the Kaggle website. This dataset consists of time-stamped Photovoltaic (PV) power generation records accompanied by relevant meteorological and solar radiation measurements. The following properties are recorded: Weather_Daily_Rainfall, Radiation_Global_Tilted, Radiation_Diffuse_Tilted, Wind_Speed, Weather_Temperature_Celsius, Weather_Relative_Humidity, Global_Horizontal_Radiation, Diffuse_Horizontal_Radiation, Wind_Direction, and Timestamp.

4.1.1. Data Splitting and Reproducibility Details

For the sake of reproducibility of the introduced forecasting approach, all experiments have been carried out within the same implementation environment. The dataset was split into the training set, 153,900 (80%) and test set, 38,475 (20%), whereas model selection was carried out based on the validation dataset with respect to hyperparameters tuning. In the process of the network training, a batch size of 32 was used, while the learning rate was automatically tuned using the TDO technique. The tuning process was stopped after a predetermined number of iterations or absence of improvements in the validation loss value. To reduce randomness in the training process, identical methods for data preprocessing, feature extraction, and optimization were used in all experiments. The aforementioned implementation settings allow the reproducibility of experiments and provide a fair comparison between the proposed SSLR-AE Net architecture and the traditional DNN approach. The proposed approach has been described comprehensively in terms of preprocessing technique, network architecture, optimization approach, parameter setup, training, and evaluation process. The dataset split analysis is shown in Figure 4.

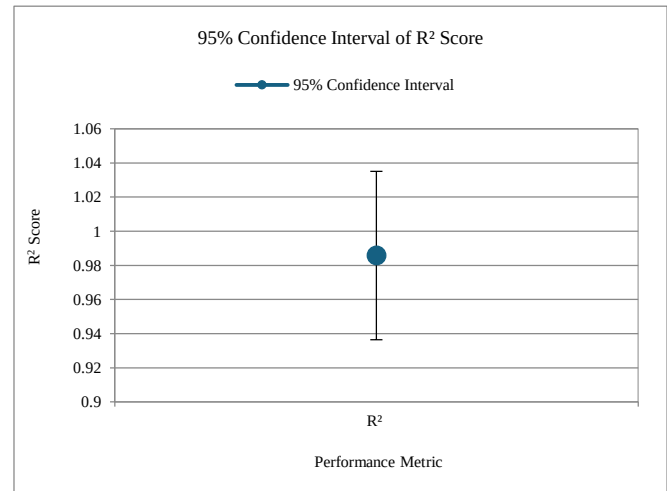
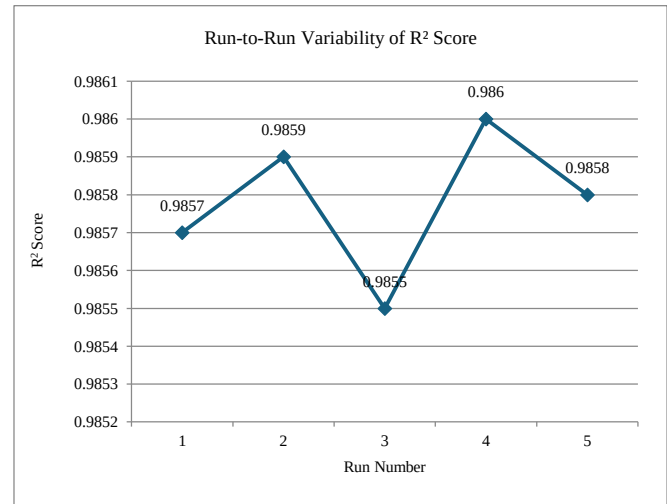
**Fig. 4 Dataset split analysis**

4.1.2. Statistical Reliability and Uncertainty Analysis

To examine the stability and consistency of the presented SSLR-AE Net model, the experiments were performed under the same conditions but with different random initialization of network parameters. The stable performance between the different runs proves that using the TDO algorithm helps to choose consistent hyperparameters and makes the forecasting model insensitive to the random initialization. Also, the confidence interval analysis and the Run-to-Run variability of R^2 score is shown in Figures 5 and 6, respectively. The statistical reliability of the proposed model is illustrated in Figure 7.

Table 5. Performance stability over multiple runs

Run	R^2	MSE	RMSE	MAE
1	0.9857	0.001517	0.03895	0.01856
2	0.9859	0.001498	0.03870	0.01831
3	0.9855	0.001529	0.03910	0.01873
4	0.9860	0.001490	0.03860	0.01842
5	0.9858	0.001513	0.03890	0.01855

**Fig. 5 Confidence interval analysis****Fig. 6 Run-to-run variability of R^2 score.**

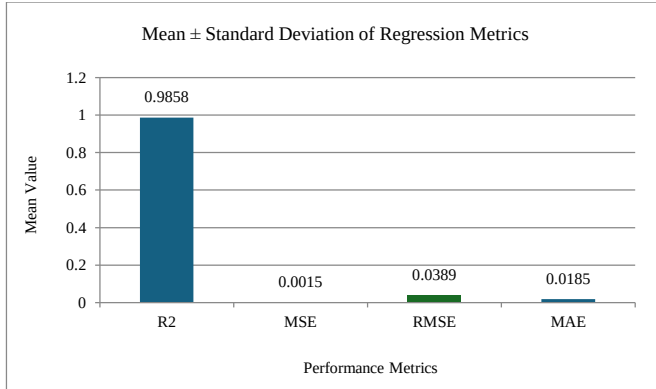


Fig. 7 Statistical reliability of the proposed model

4.2. Exploratory Analysis of Power Output and Meteorological Variables

The statistical properties and frequency distribution patterns for active power generation and important meteorological factors in the dataset are simultaneously

depicted by the four graphs in Figure 8. The active power distribution displays a highly skewed pattern with a large concentration of values near zero, suggesting nighttime or low-irradiance instances. This suggests that power output exhibits notable nonlinearity and intermittency.

The weather relative humidity histogram shows a wide distribution over the whole humidity range, with greater frequencies at lower to moderate humidity levels. This suggests that different atmospheric conditions affect the availability of solar radiation.

In contrast to diffuse tilted radiation, global tilted radiation exhibits a more prominent peak at moderate radiation levels, according to the density plots of the two types of radiation. These findings support the data's complexity, nonstationarity, and extreme skewness, highlighting the necessity of reliable feature learning and temporal modeling for ultra-short-term solar irradiance forecasting.

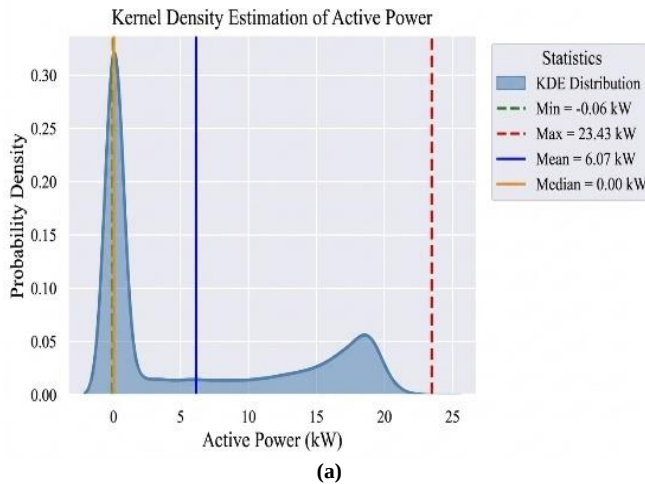
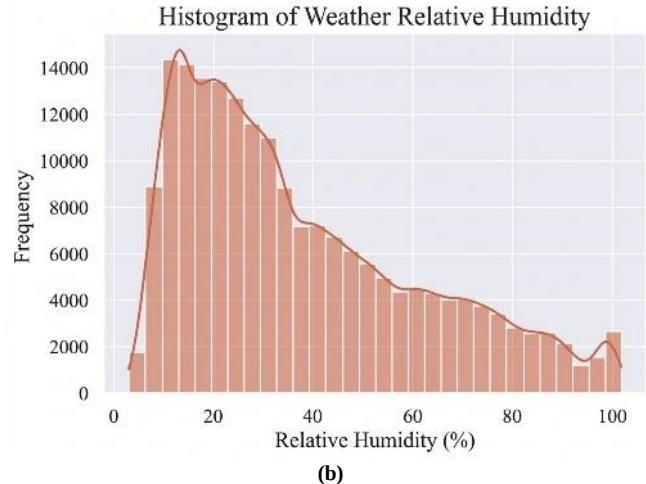
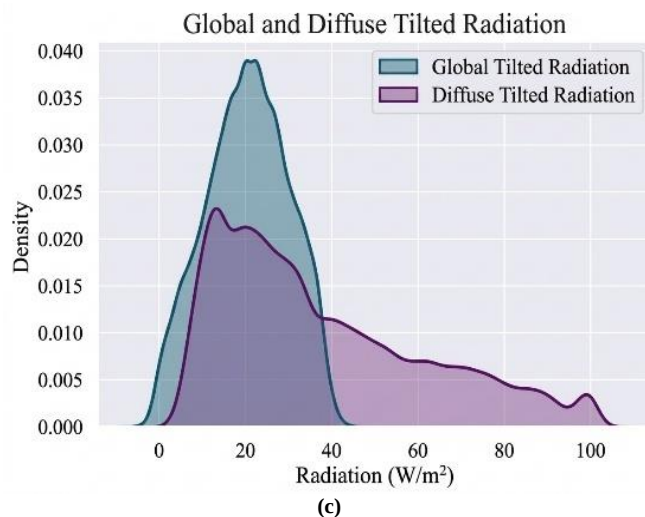
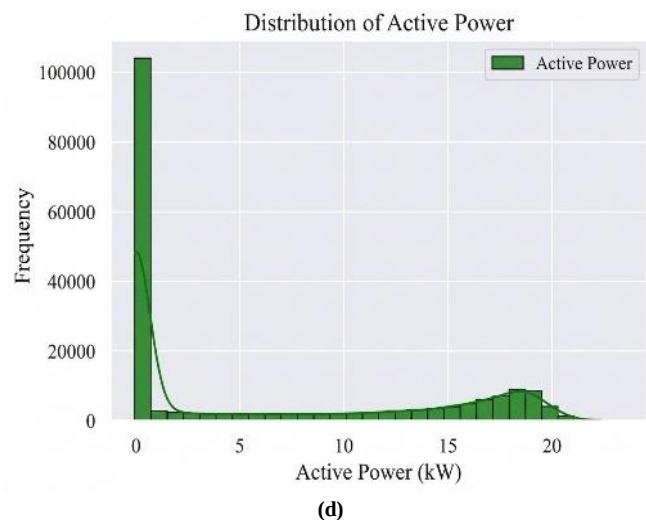


Fig. 8 Exploratory data analysis illustrating the statistical distributions. (a) Kernel density estimation and statistical distribution of active power output, (b) Histogram showing the distribution of weather relative humidity values, (c) Density comparison of global tilted radiation and diffuse tilted radiation, and (d) Frequency distribution of active power illustrating data imbalance and intermittency.

4.3. Relationship between Meteorological Variables and Active Power

The statistical distribution of daily rainfall, its indirect impact, and the correlation between weather temperature and active power generation are depicted in Figure 9.

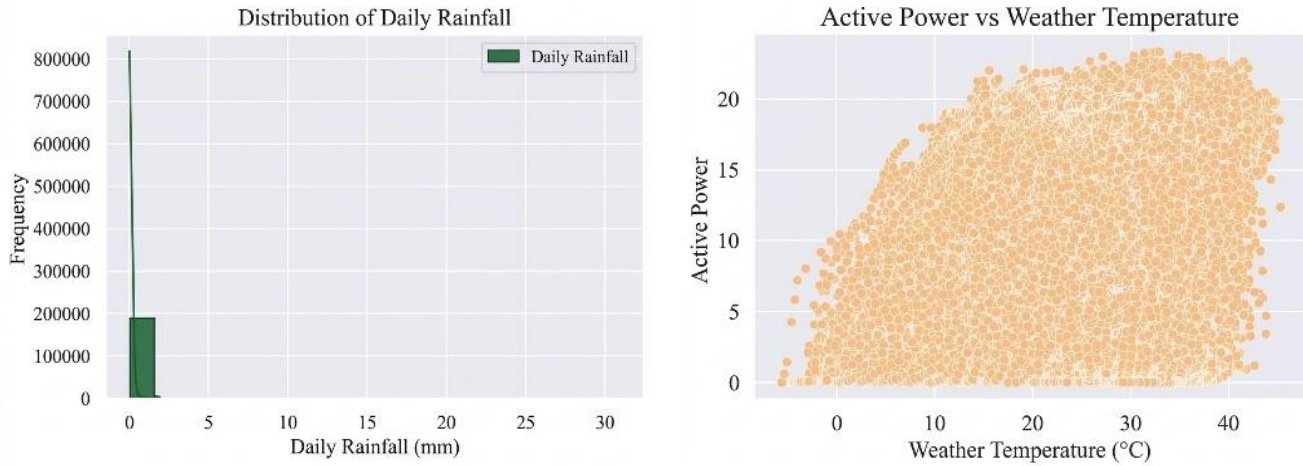


Fig. 9 Statistical distribution of daily rainfall and the relationship between weather temperature and active power generation

4.4. Distribution of Global and Diffuse Solar Radiation

The statistical distributions of diffuse and global horizontal radiation in the dataset are shown in Figure 10. The diffuse radiation distribution reflects the contribution of scattered solar energy under cloudy and partially cloudy

situations, exhibiting a wider spread with a more progressive drop. These features highlight the importance it is to use reliable nonlinear modeling approaches in ultra-short-term solar irradiance forecasts that can capture a variety of radiation regimes.

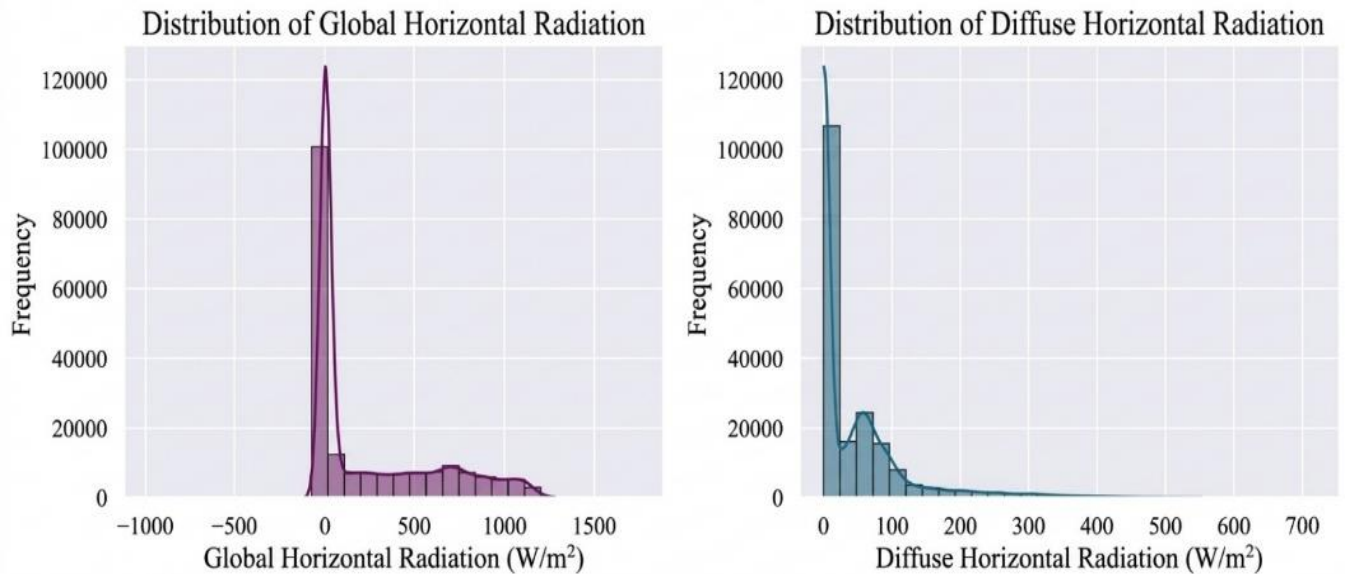


Fig. 10 Statistical distributions of global horizontal radiation and diffuse horizontal radiation in the dataset

4.5. Temporal Variation of Active Power Output

The active power output over time-series pattern for the specified period is displayed in Figure 11. The curve's frequent rise and fall represents normal cycles, whereas erratic variations are brought on by transient weather phenomena.

Maintenance or missing data could be the cause of a dramatic decline around the end of the year.

Ultra-short-term solar power forecasting is difficult due to the time-series data's general nonstationary and variability.

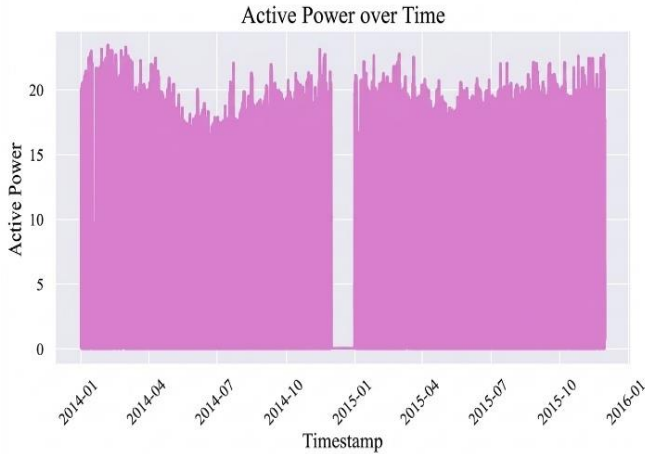


Fig. 11 Time-series variation of active power output over the observation period

4.6. Temporal Pattern of Daily Weather Rainfall

The daily rainfall time series and its three-day moving average are shown in Figure 12. Rainfall occurrences become weaker and less frequent in later stages.

In ultra-short-term solar power projection, this emphasizes the necessity for forecasting models that can manage weather changes.

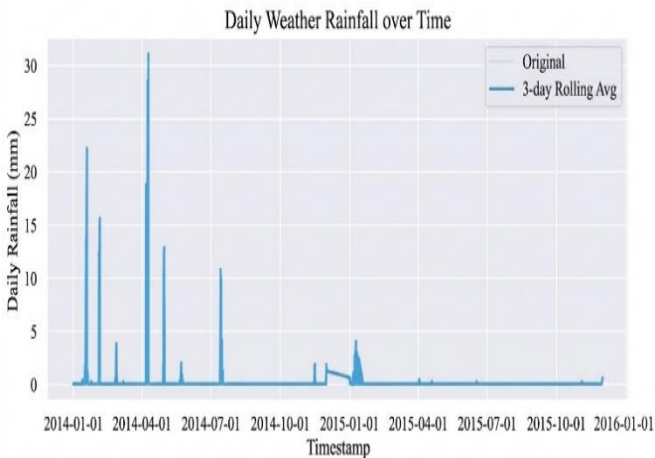


Fig 12 Time-series representation of daily weather rainfall and its three-day rolling average

4.7. Correlation Analysis between Power Output and Meteorological Variables

The correlation heatmap between power output and meteorological variables is shown in Figure 13. Diffuse horizontal radiation (0.53), wind speed (0.34), and ambient temperature (0.49) also show moderately positive associations, indicating that they contribute to system performance in a secondary way. Conversely, there is a moderately negative connection (-0.46) between relative humidity and active power, suggesting that irradiance output is decreased in humid or overcast situations.

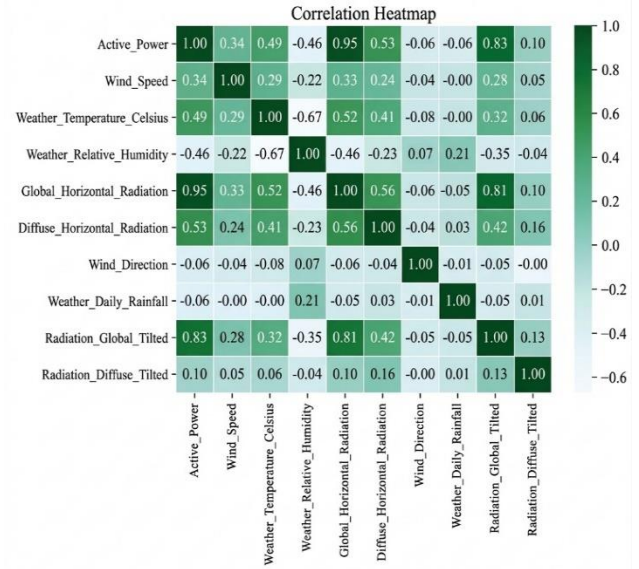


Fig. 13 Correlation heatmap showing relationships between active power output and meteorological variables

4.8. Statistical Characteristics of Weather Relative Humidity

Four important metrics, minimum, maximum, mean, and median, are used in the radar map in Figure 14 to characterize the statistical distribution of meteorological relative humidity. The fact that the greatest humidity value is nearly 100% suggests that extremely humid circumstances were present during the study period.

On the other hand, the minimum humidity is comparatively low, indicating significant fluctuations in the amount of moisture in the atmosphere.

Extreme humidity circumstances appear to be less common than moderate humidity levels, based on the intermediate mean and median readings. The wide range of values between the lowest and maximum indicates significant variation in relative humidity, which can affect the availability of solar irradiance and, in turn, affect the efficiency of power generation.

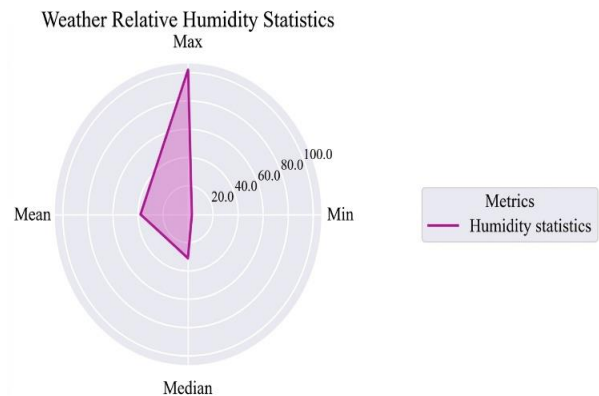


Fig. 14 Radar chart showing minimum, maximum, mean, and median statistics of weather relative humidity

4.9. Comparison of Model Training Performance across Different Architectures

Figure 15 shows the loss and Mean Absolute Error (MAE) trends of three models-SSLR-AE Net with TDO, SSLR-AE Net, and a Deep Neural Network (DNN) across training epochs to compare their training and validation performance. A consistent decrease in training and validation loss is shown by all models, suggesting efficient learning and

convergence behavior. With training and validation curves that nearly overlap, the SSLR-AE Net optimized with Tasmanian Devil Optimization exhibits the best generalization and the least amount of overfitting among them achieving the fastest and most consistent drop in loss and MAE. Despite significantly larger oscillations in its validation MAE, the conventional SSLR-AE Net also achieves satisfactory convergence.

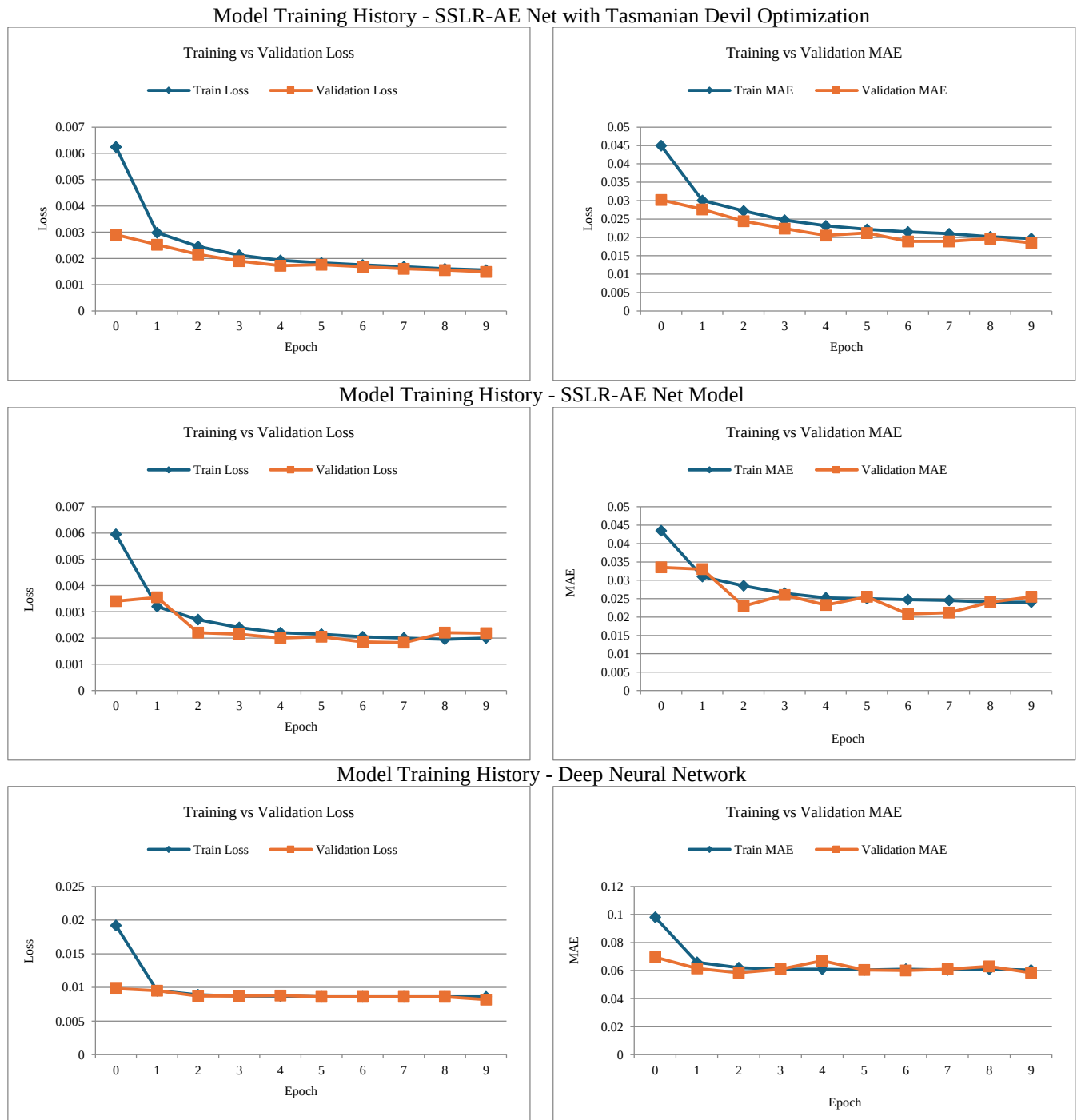


Fig. 15 Training and validation loss and MAE curves for SSLR-AE Net with optimization, SSLR-AE Net, and Deep Neural Network models

4.10. Tasmanian Devil Optimization Convergence Behavior

Considering Mean Squared Error (MSE) acting as the optimization goal, Figure 16 shows how the TDO algorithm converges over the course of multiple rounds. Due to the fact the optimizer is exploratory, the error is initially rather low but shows a modest increase throughout the first few rounds. Effective exploitation and progress toward an ideal parameter configuration are shown by the MSE's steady fall as the process proceeds, which reaches its minimum during the third iteration. A slight increase in the last iteration indicates more research, showing that the technique prevents premature convergence and encourages strong parameter improvement.

Stabilization of the objective function in the final stages of the optimization process suggests that the proposed TDO algorithm converges stably without oscillations by optimizing the hyperparameters of the SSLR-AE Net effectively. Also, the hyperparameter search stability is illustrated in Figure 17.

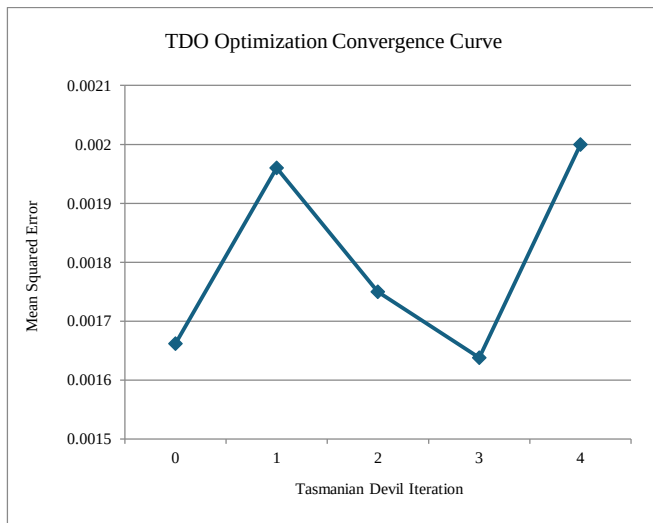


Fig. 16 Convergence curve of the Tasmanian devil optimization algorithm showing MSE variation across iterations

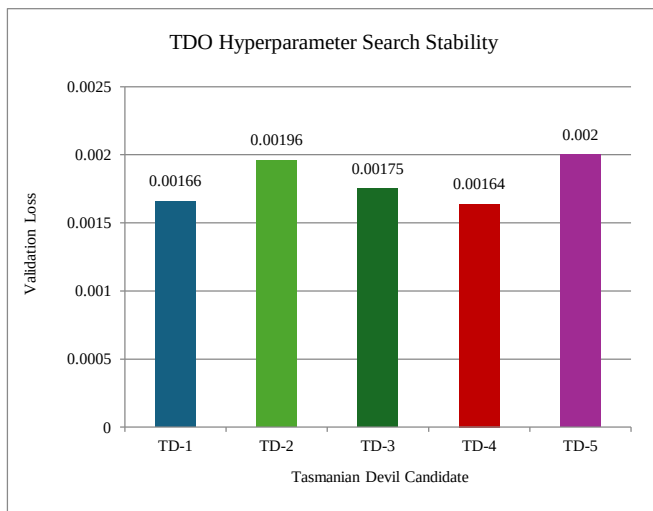


Fig. 17 Hyperparameter search stability

4.11. Comparison of Actual and Predicted Power Outputs across Models

Three models have their actual and expected power outputs compared in Figure 18. Under both peak and low power conditions, the SSLR-AE combined with TDO exhibits excellent prediction accuracy with little divergence in the first subplot. Although the unoptimized SSLR-AE network largely catches the broad trend, the second subplot reveals moderate prediction errors due to notable departures at multiple peak locations. The third subplot shows that the DNN has relatively less generalization capacity, as shown by greater differences between real and predicted values, especially during times of sharp oscillations.

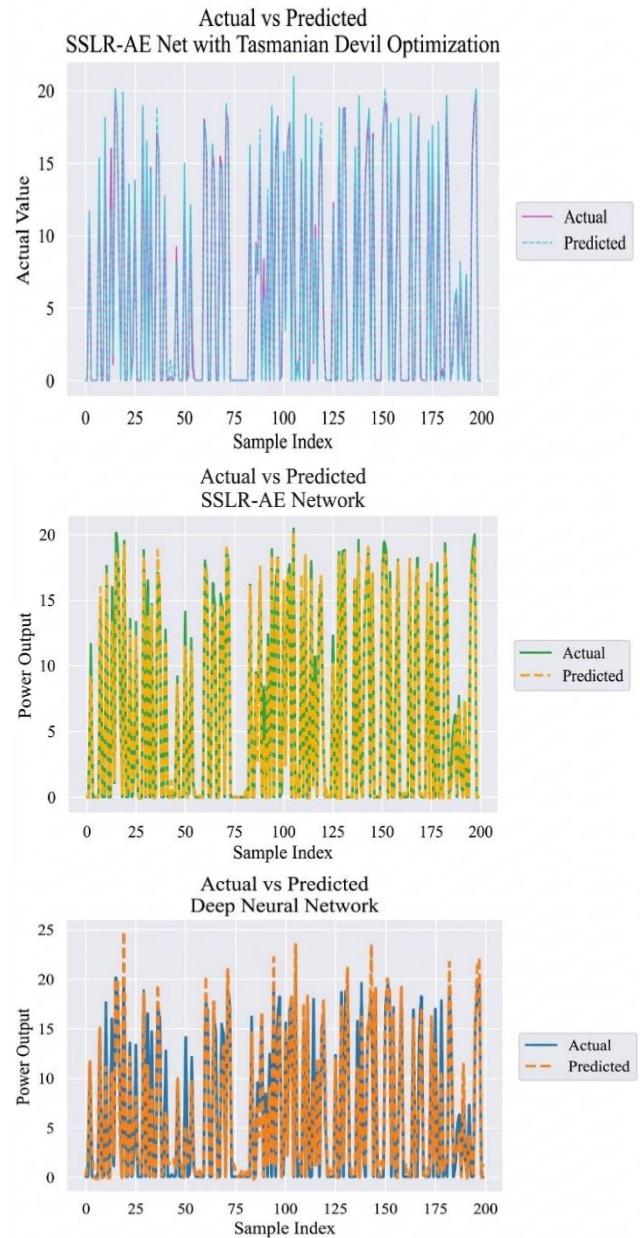


Fig. 18 Actual versus predicted power output comparison for SSLR-AE with TDO, SSLR-AE, and Deep Neural Network models

4.12. Regression Performance Comparison using Error Metrics

Numerous error metrics, such as MAPE, MSE, Median Absolute Error, MAE, RMSE, and Maximum Error, are employed in Figure (19) to assess the regression performance of the DNN, SSLR, and SSLR-TDO models. The SSLR-TDO model offers outstanding prediction accuracy and robustness, as seen by its lowest error values across nearly all criteria. Specifically, significant decreases in MAPE, MSE, MAE, and RMSE demonstrate how well the optimization approach works to enhance model learning. Across all criteria, the standard SSLR model exhibits substantial error reductions and constantly outperforms the DNN.

The DNN, +, shows the greatest error values, indicating a very poor level of predicting accuracy. The overall superiority of SSLR-TDO for short-term solar irradiance forecasting is confirmed by its competitive performance, even if the maximum error values are quite similar among models. According to the Table 6, the suggested SSLR-TDO model performs best overall, achieving the lowest error values and the highest R^2 score across the majority of metrics (MSE, RMSE, MAE, MAPE, and Median AE). The efficacy of the enhanced SSLR approach for precise solar irradiance forecasting is confirmed by the fact that the SSLR model outperforms the baseline DNN while the DNN exhibits most significant errors.

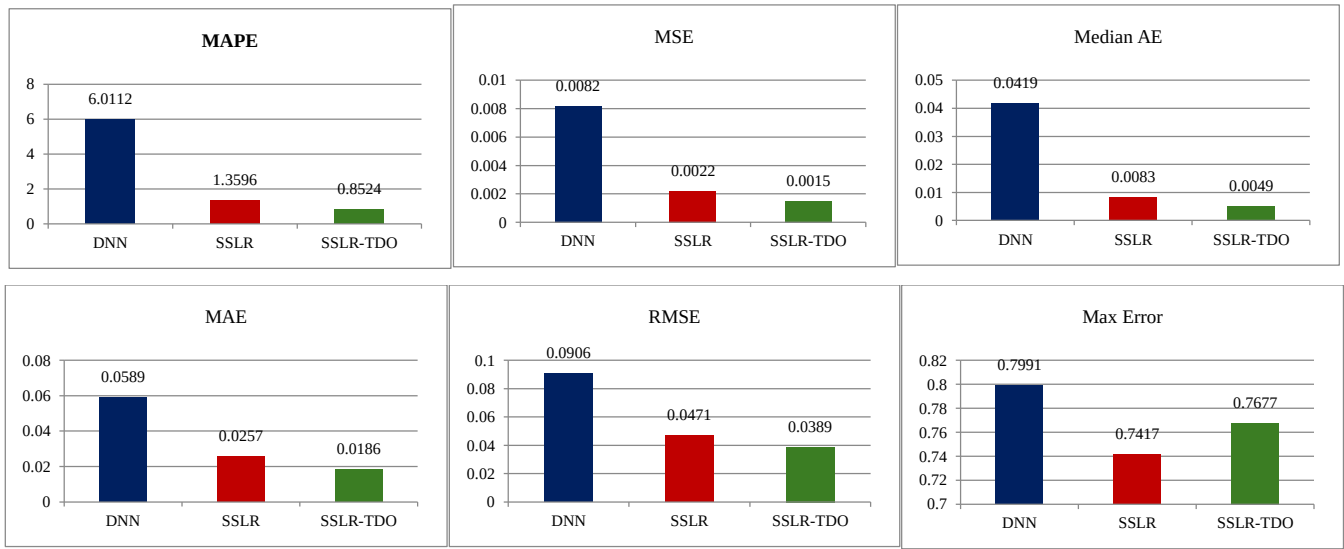


Fig. 19 Comparison of regression error metrics for DNN, SSLR, and SSLR-TDO models

Table 6. Comparison of regression performance metrics for DNN, SSLR, and SSLR-TDO models on short-term solar irradiance forecasting

Regression Metrics Comparison across Models			
Metric	DNN	SSLR	SSLR-TDO
R^2 Score	0.9226	0.9791	0.9857
MSE	0.0082	0.0022	0.0015
RMSE	0.0906	0.0471	0.0389
MAE	0.0589	0.0257	0.0186
MAPE	6.0112	1.3596	0.8524
Max Error	0.7991	0.7417	0.7677
Median AE	0.0419	0.0083	0.0049

The comparative analysis shows that the SSLR-AE Net performs significantly better than other existing state-of-the-art prediction models for all evaluation criteria. This is due to the synergistic combination of different parts of the architecture. The first component is the state space latent retention system, which is capable of capturing both the short-term and long-term dependencies present in solar irradiance data. Secondly, the latent autoencoder produces efficient feature representations to preserve the temporal nature of the

inputs. In addition, the adaptive state evolution process is able to refine the latent representations of the system to improve its generalization under varying weather conditions. Lastly, the TDO model finds an optimal configuration of hyperparameters in an automated manner by ensuring better convergence behavior and minimizing the possibility of sub-optimal outcomes from manually tuned parameters. As a result of the interaction between all these elements, the

proposed model is able to obtain better forecasting results than existing methods based on deep learning and transformers.

This indicates that the combination of these techniques leads to better performance for ultra-short-term forecasting of solar irradiance than architectural improvements alone.

4.13. Ablation Study

An ablation study was performed to analyze the role played by each of the components of the proposed SSLR-AE Net in terms of their contributions to the model's performance, and it is shown in Table 7.

The analysis was carried out in terms of the effect of the latent autoencoder, the retention-driven memory module, the adaptive state evolution mechanism, and the TDO hyperparameter optimization. RMSE, MAE, MSE, and R^2 were used to measure the performance of each of the variations of the model.

From the results, it is clear that each of the components plays an important role in improving the model's performance, while the complete SSLR-AE Net performs better than any other model. In addition, the usage of the TDO algorithm improves hyperparameters tuning and consequently enhances the convergence of the network.

Table 7. Ablation study of the proposed SSLR-AE Net

Model Variant	MSE	RMSE	MAE
Baseline Deep Neural Network (DNN)	0.008214	0.090633	0.058855
State-Space Network	0.004872	0.069799	0.041278
State-Space + Latent Retention	0.003064	0.055353	0.031864
State-Space + Latent Retention + Autoencoder	0.002214	0.047055	0.025714
Proposed SSLR AE Net	0.001517	0.038947	0.018559

4.14. Sensitivity Analysis

Table 9. Computational resource analysis

Model	Training Time (min)	Testing Time (s)	GPU Memory (GB)	Parameters (M)
DNN	12.4	0.45	1.10	0.82
StateSpace	18.6	0.58	1.42	1.31
SS+Latent	22.3	0.64	1.76	1.84
SSLR	27.8	0.71	2.08	2.17
SSLRTDO	30.5	0.75	2.14	2.19

Experimental results show that the forecasting performance of the proposed SSLR-AE Net is much better than that of other baseline methods through all evaluation metrics. The proposed approach shows a better performance compared to other existing methods since it provides low prediction errors and higher accuracy due to its efficient latent

To study the effectiveness of the proposed SSLR-AE Net model, a sensitivity analysis was performed by changing their values while keeping all other parameters constant. Particularly, five different values of the learning rate are considered, and the prediction accuracy is investigated in terms of R^2 and MSE measures is shown in Table 8. Also, the sensitivity analysis of dropout rate is illustrated in Figure 20.

Table 8. Sensitivity analysis of SSLR-AE Net under different learning rates

Learning Rate	R^2	MSE
0.0001	0.9792	0.00231
0.0003	0.9828	0.00191
0.0005	0.9857	0.00152
0.0007	0.9848	0.00161
0.0010	0.9816	0.00195

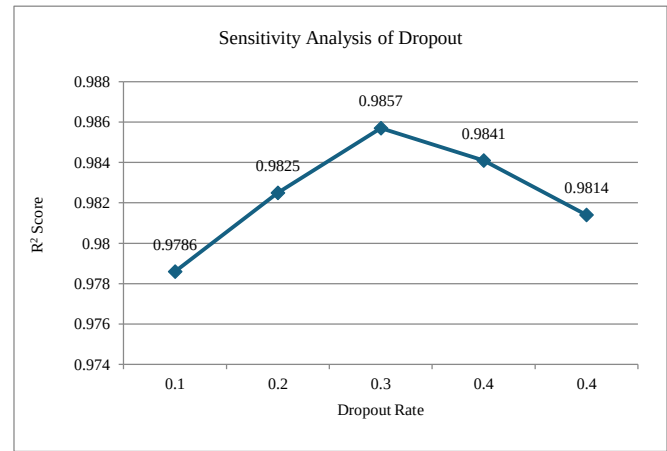


Fig. 20 Sensitivity analysis of dropout rate

4.15. Computational Resource Analysis

To determine the computational efficiency of the SSLR-AE Net, computational resource analysis was conducted based on a comparison of training time, inference time, and memory usage against baseline forecasting methods under an identical computational environment. The results are presented in Table 9.

representation learning and adaptive optimization of the hyperparameters.

It can be observed that convergence analysis proves the stability of the optimization process, and the statistical reliability analysis verifies the reliability of the results.

4.16. Discussion on Model Robustness and Generalization

The experimental results shown that the proposed SSLR-AE Net is capable of achieving stable forecast performance under various weather conditions that are associated with changes in solar radiation, humidity, precipitation, and temperature. It is achieved because of the effectiveness of the non-linear state space encoder can model complex temporal dependencies, whereas the retention-based memory system helps to maintain both long-term and short-term dependency relationships required for robust forecasting under atmospheric conditions. The use of TDO has enhanced the stability of convergence due to the automatic selection of appropriate hyperparameters.

4.17. Practical Implications and Computational Analysis

The proposed model is intended to be used in practical applications within smart-grids in which the precise prediction of solar irradiance is crucial for energy planning and ensuring stability of the grid. Though adding nonlinear state-space learning and latent representation to the model makes it more complicated than a traditional DNN. Once the optimal hyperparameters are determined, the actual forecast phase requires only one iteration through the network and making real-time deployment feasible. In addition, the enhanced convergence during the training process decreases the cost of the optimization process and increases the forecast accuracy.

4.18. Limitations of the Present Study

Although the performance of the framework is quite promising, there are some limitations in the current research. First, the framework has been tested on one publicly available dataset for solar forecast, and testing on other geographic datasets can prove its generalizability. Furthermore, no computations have been made regarding the performance of

the framework on resource-constrained edge devices. The following limitations will be considered in future studies for improving the applicability of the framework proposed.

5. Conclusion and Future Scope

This study integrated the SSLR-AE network with TDO for optimal parameter tuning, leading to an improved short-term solar irradiance forecasting framework. Across all evaluation measures, the suggested SSLR-TDO model outperformed the baseline SSLR and traditional DNN models in terms of predictive performance. A more accurate and stable regression model resulted from the integration of TDO, which also enhanced convergence behavior and decreased prediction errors. The efficiency of the chosen input features and the suggested learning architecture was further confirmed by the significant correlation between radiation features and active power. In terms of statistics, the suggested SSLR-TDO outperformed SSLR (0.9791) and DNN (0.9226) with an R2 score of 0.9857. It also reduced RMSE to 0.0389 as opposed to 0.0471 (SSLR) and 0.0906 (DNN). Furthermore, the MAPE was much reduced to 0.8524%, indicating strong and accurate predicting. Moreover, the details of implementation settings and configurations have been included in the research to enhance the replicability of the suggested framework.

5.1. Future Scope

Future research might concentrate on improving temporal feature learning with the use of sophisticated attention-based processes. The suggested framework's scalability and adaptability would also be demonstrated by validating it on large-scale or geographically dispersed solar farms. Deploying the system in smart grid scenarios with edge computing or IoT-enabled technologies may also provide real-time operational optimization.

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