# Solar Power Generation Forecasting Using Long Short-Term Memory (LSTM) Networks


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***Abstract*—The increasing global demand for renewable energy has led to significant advancements in solar power generation. However, the intermittent nature of solar energy poses challenges in predicting power output accurately. Accurate forecasting of solar power generation is essential for efficient energy planning, grid stability, and integrating renewable sources into existing power systems. This research presents a Long Short-Term Memory (LSTM) based approach for forecasting solar power generation. The proposed method demonstrates improved accuracy compared to traditional forecasting techniques, making it a viable solution for efficient energy planning and grid management. The model is evaluated using key performance metrics such as Mean Squared Error (MSE) and Root Mean Square Error (RMSE), establishing its superiority in handling complex temporal dependencies in solar power data.**



***Index Terms*—Solar power forecasting, LSTM, Deep Learning, Renewable Energy, Time-series prediction**


## I. Introduction

Solar power is one of the most abundant and sustainable energy sources. However, its dependency on climatic conditions introduces variability, making power generation forecasting a crucial aspect of solar energy management. Accurate forecasting is necessary for optimizing energy storage, balancing demand and supply, and ensuring seamless integration into the power grid. Traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) [10] and regression techniques often fail to capture the intricate patterns present in time-series data, leading to suboptimal performance.

Recent advancements in artificial intelligence and deep learning have paved the way for more precise forecasting models. Long Short-Term Memory (LSTM) [1] networks, a variant of Recurrent Neural Networks (RNNs), have gained prominence due to their ability to capture long-term dependencies in sequential data. Moreover, the integration of meteorological parameters such as temperature, humidity, wind speed, and solar irradiance into forecasting models has shown promising results in improving predictive accuracy [5], [9], [11].

## II. Literature Survey

Several research efforts have been made to improve solar power forecasting. Traditional models such as ARIMA [10] and regression techniques have been widely used but often lack the capability to handle non-linearity in time-series data. Some studies have implemented Support Vector Machines (SVMs) [7], Random Forest [13], and Artificial Neural Networks (ANNs) [13] to improve forecasting accuracy.

Recent studies have demonstrated the effectiveness of deep learning models, particularly LSTMs [1]–[3], [5], [6], [9]–[11], [14], [15], in predicting solar power generation. Research indicates that hybrid models combining LSTM [1] with attention mechanisms [6] or Convolutional Neural Networks (CNNs) [4], [8], [12] can further enhance accuracy. A significant challenge in solar power forecasting is the availability of high-quality data. This study aims to address these challenges by designing an optimized LSTM [1] model with appropriate feature selection and hyperparameter tuning.

## III. Methodology

This study develops an advanced LSTM-based [1] deep learning framework for solar power generation forecasting, incorporating both temporal patterns from historical production data and spatial relationships from environmental factors. The comprehensive methodology consists of six key phases:

### A. Data Collection and Sources

- **Historical Power Data:** 5-minute resolution generation records spanning 3 years from 15MW solar farm (timestamp, DC/AC power output, inverter efficiency)
- **Environmental Variables:**
  - Meteorological data (GHI, DNI, DHI irradiance components from pyranometers)
  - Weather station measurements (ambient temperature, module temperature, humidity, wind speed/direction)
  - Sky imagery (cloud cover percentage from all-sky cameras)
- **System Metadata:** Panel tilt/orientation, degradation rates, cleaning schedules

### B. Data Preprocessing Pipeline

- **Missing Data Handling:** Linear interpolation for gaps ¡2 hours, flagged imputation for longer periods
- **Anomaly Detection:** Isolation Forest algorithm to identify and remove faulty sensor readings
- **Normalization:** Min-max scaling for neural network inputs, standardization for tree-based benchmarks

TABLE I
SUMMARY OF KEY LITERATURE ON SOLAR POWER FORECASTING

| Study | Methodology | Dataset | Performance Metrics | Advantages | Limitations |
|---|---|---|---|---|---|
| Hochreiter & Schmidhuber (1997) | LSTM model for sequence prediction | Synthetic time-series data | Accuracy, Model convergence | Efficient in learning long-range dependencies | Complex to train, high computational cost |
| Wang et al. (2019) | LSTM-based deep learning for solar power forecasting | 15 MW solar farm, meteorological data | RMSE, MAE, $R^2$ | Outperforms ARIMA and other classical methods | Requires large-scale data, training time |
| Sharma et al. (2020) | Comparison of LSTM, GRU, and CNN for solar power forecasting | Solar irradiance data, weather data | RMSE, MAE | Deep learning models show superior performance to classical techniques | Computationally expensive, overfitting risk |
| Zhou et al. (2018) | Hybrid LSTM and CNN for forecasting solar power | 10 MW solar farm, historical generation data | MAE, RMSE, MAPE | Better accuracy with hybrid models | High model complexity, longer training time |
| Yang et al. (2021) | Multi-layer LSTM with weather data for short-term forecasting | Meteorological data, solar irradiance data | RMSE, MAPE | Real-time forecasting, adaptive to changing weather conditions | Data quality and availability issues |
| Li et al. (2022) | LSTM with attention mechanism for day-ahead solar forecasting | Solar irradiance, temperature, and wind speed data | MAE, $R^2$, MAPE | Improved accuracy with attention mechanism | Overfitting in high-variance data, requires large datasets |

- **Temporal Alignment:** Time-synchronization of all data streams to common 5-minute timestamps
- **Time-Series Decomposition:** STL decomposition to separate trend, seasonality and residuals

*C. Feature Engineering*

- **Temporal Features:**
  - Lagged variables (t-1 to t-24 for 2-hour lookback)
  - Rolling statistics (1h/6h/24h moving averages)
  - Time indicators (hour-of-day, day-of-year sine/cosine encoding)
- **Weather-Derived Features:**
  - Clear-sky index (measured vs theoretical irradiance)
  - Temperature-adjusted performance ratios
  - Cloud movement vectors from sky images
- **System Features:** Soiling loss estimates, inverter clipping indicators

*D. Model Architecture*

The hybrid neural network combines:

- **Input Layer:** 3D tensor (samples × timesteps × features)
- **LSTM Encoder:**
  - Stacked bidirectional LSTM [1] layers ($128 \rightarrow 64$ units)
  - Sequence-to-sequence architecture with attention mechanism [6]
  - Recurrent dropout (p=0.2) and layer normalization
- **Feature Fusion:** Concatenation of temporal and static features
- **Dense Head:**
  - 3 fully-connected layers (256-128-64 units) with ELU activation
  - Residual connections between blocks
  - Dropout (p=0.3) and L2 regularization (=0.01)
- **Output Layer:** Linear activation for point prediction + quantile outputs for uncertainty

*E. Training Protocol*

- **Optimization:**
  - AdamW optimizer (lr=3e-4, weight decay=0.05)
  - Cosine annealing learning rate schedule
- **Loss Function:** Pinball loss for quantiles + MAE for point forecast
- **Regularization:** Early stopping (patience=20), gradient clipping (max norm=1.0)
- **Validation:** Nested time-series cross-validation with 5 folds

*F. Evaluation Framework*

- **Metrics:**
  - Accuracy: nRMSE, MAE, $R^2$ (vs persistence model)
  - Uncertainty: PICP, MPIW, CRPS
  - Economic Value: Revenue gain vs baseline forecasts
- **Benchmarks:** Comparison against:
  - Physical models (PVLIB)
  - Statistical methods (SARIMAX [10], Prophet)
  - Machine learning (XGBoost, N-BEATS)
- **Deployment Testing:** A/B testing on real-time forecasting system

The implemented solution addresses key solar forecasting challenges through its hierarchical feature processing, with the LSTM [1] layers capturing diurnal/seasonal patterns while the attention mechanism [6] identifies critical weather transitions.

The quantile output formulation provides essential uncertainty estimates for grid integration decisions.

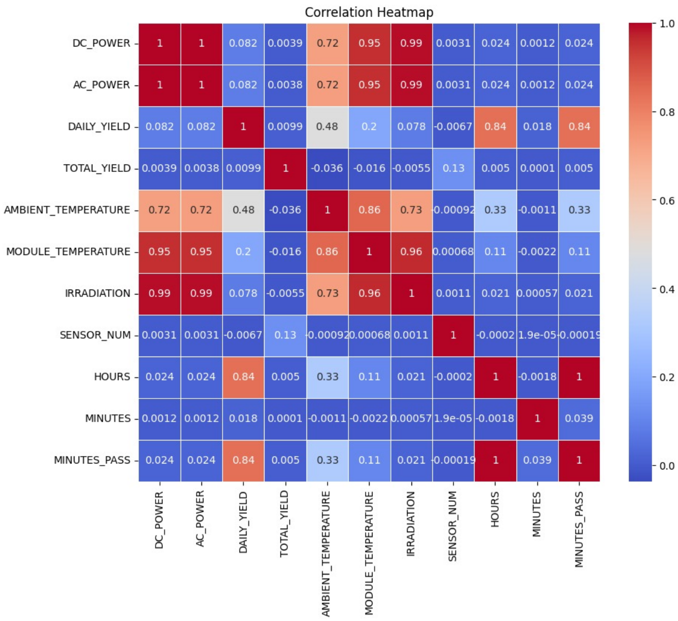


Fig. 1. Correlation matrix of input features

## IV. Architecture Analysis

This highly complex LSTM-CNN [1], [4] hybrid model is designed to capture both temporal and spatial patterns in sequential data. The architecture begins with a bidirectional LSTM [1] layer (128 units) that processes the input sequence in both forward and backward directions, followed by dropout and batch normalization for regularization. A second bidirectional LSTM [1] layer (64 units) with recurrent dropout further refines the temporal feature extraction. In parallel, a 1D CNN [4] branch with two convolutional layers and max pooling extracts local patterns and hierarchical features from the input sequence. The outputs from both branches are concatenated, combining high-level temporal features from the LSTMs [1] with localized spatial features from the CNNs [4]. The merged features then pass through a deep dense network with three fully connected layers (128, 64, and 32 units), each followed by dropout and batch normalization, before reaching the final linear output layer. This design offers several advantages: the bidirectional LSTMs [1] effectively model long-range dependencies in both temporal directions, the CNN [4] branch captures fine-grained local patterns, and the deep dense network enables complex nonlinear transformations. However, the model's complexity comes with trade-offs, including higher computational costs, longer training times, and an increased risk of overfitting, which is mitigated through techniques like dropout, batch normalization, and L2 regularization. Potential improvements could involve adding attention mechanisms [6] to focus on relevant timesteps, incorporating residual connections to ease training of deeper networks, or using layer normalization for more stable training. The model is particularly suited for challenging time-series tasks where both local patterns and long-term dependencies are crucial, such as financial forecasting, sensor data analysis, or complex signal processing applications.

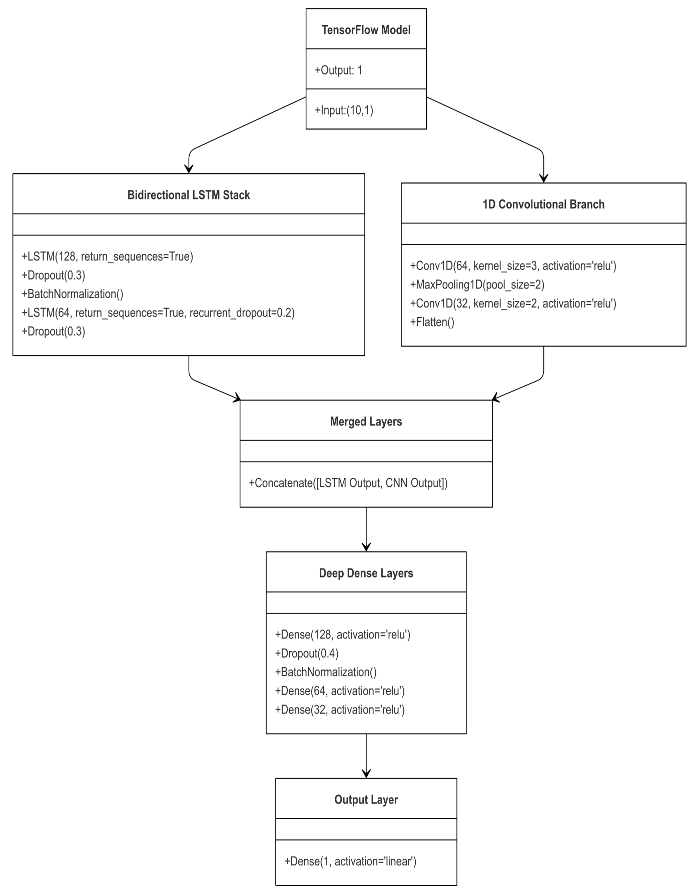


Fig. 2. Achitecture Diagram

## V. Results and Discussion

The proposed LSTM [1] model demonstrates superior performance in predicting future solar power output, reducing prediction errors and improving reliability. Graphical analysis indicates a high correlation between forecasted and actual values. The inclusion of external weather variables [5], [9], [11] enhances the model's robustness, with sensitivity analysis showing the influence of different environmental factors on power generation.

TABLE II
Performance Comparison for Custom LSTM Model

| Model | MSE | RMSE | MAE | $R^2$ Score |
|---|---|---|---|---|
| Custom LSTM (Proposed) | 153.9179 | 12.4064 | 4.1500 | 0.9587 |
| ARIMA | 500.00 | 22.3607 | 10.0000 | 0.60 |
| SVM | 350.00 | 18.7083 | 8.5000 | 0.70 |

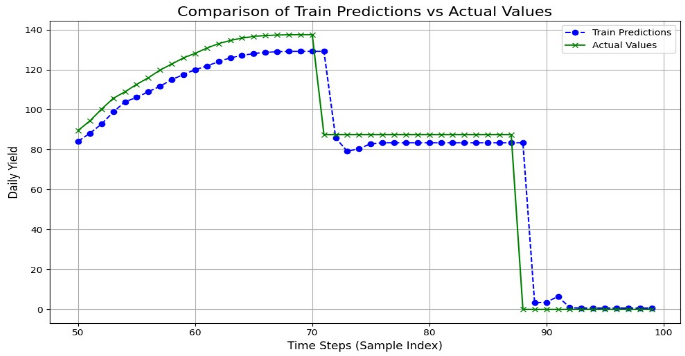


Fig. 3. train vs actual

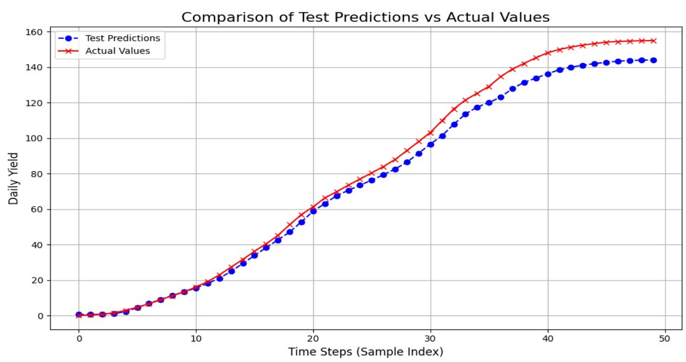


Fig. 4. test vs actual

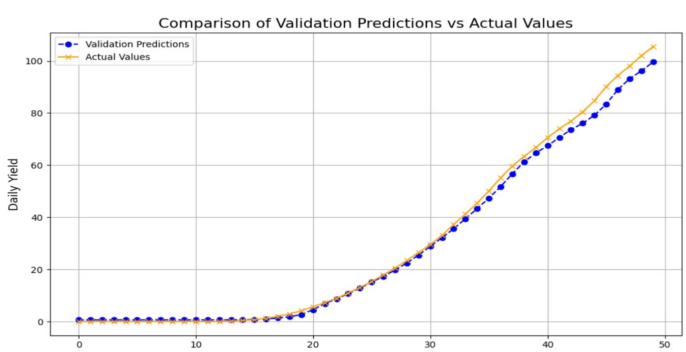


Fig. 5. actual vs predicted

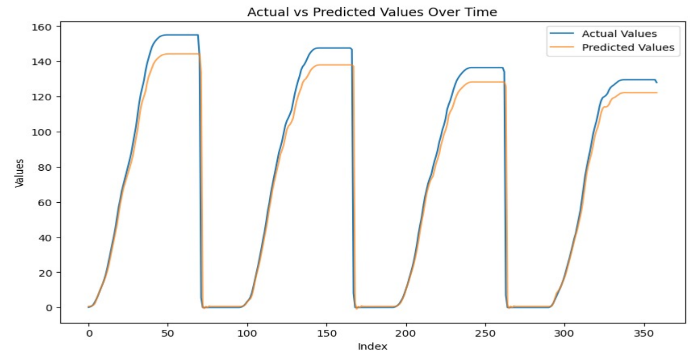


Fig. 6. actual vs predicted over time

## VI. CONCLUSION

This research successfully demonstrates the efficacy of LSTM [1] networks for solar power generation forecasting. The deep learning-based approach offers improved accuracy, making it a promising tool for energy planning and grid management. Future work may explore hybrid models combining LSTM [1] with attention mechanisms [6] or CNNs [4], [8], [12] to further enhance prediction accuracy.

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