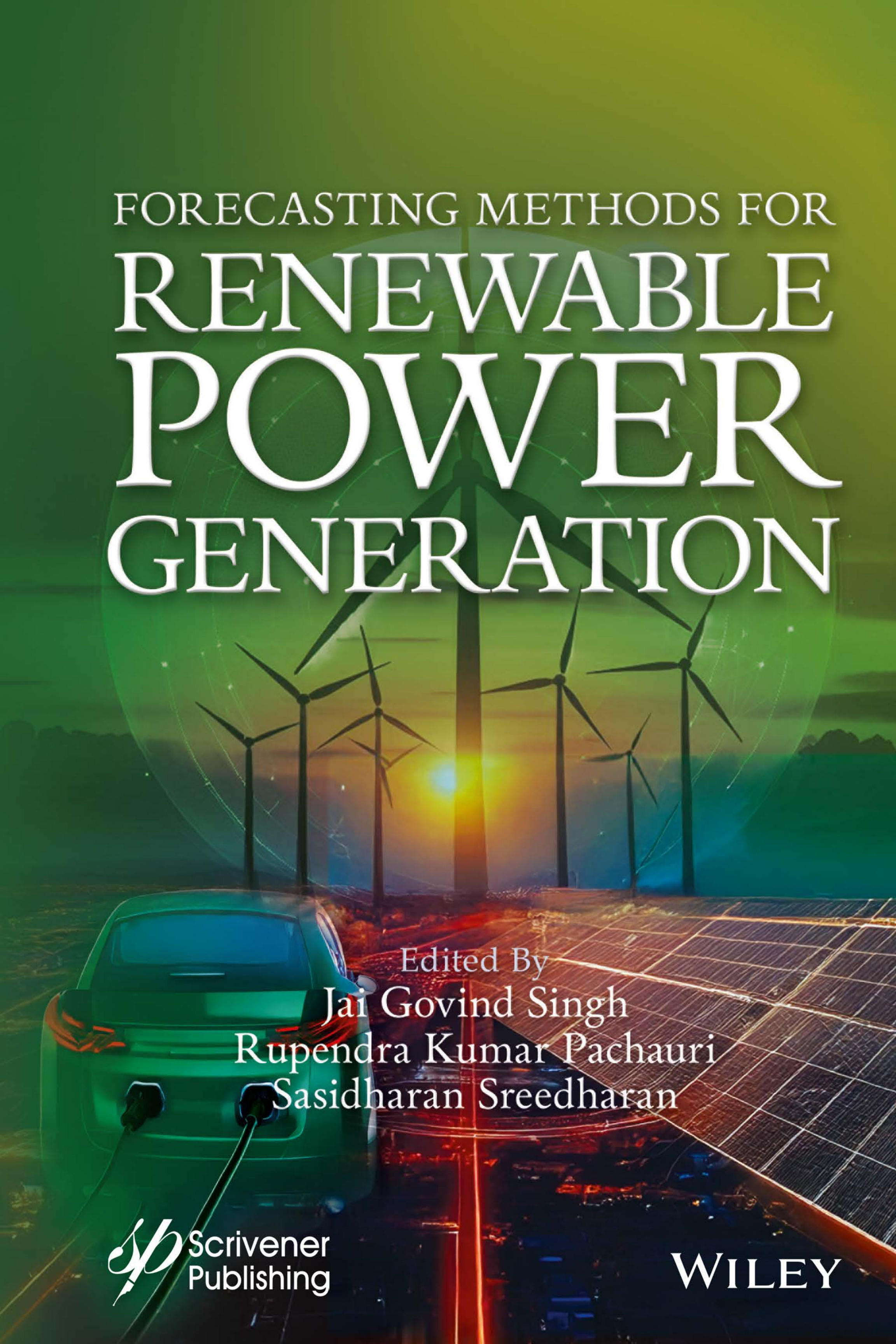

FORECASTING METHODS FOR RENEWABLE POWER GENERATION

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Preface

As we stride toward a sustainable future, the integration of renewable power sources into our energy mix becomes increasingly pivotal. However, the intermittent nature of these resources poses unique challenges for power system operators, planners, and policymakers alike.

Forecasting Methods for Renewable Power Generation emerges as a comprehensive guide to navigating these challenges. In this edited book, we delve deep into the realm of forecasting techniques tailored specifically for renewable energy, demand, and electricity price. This book serves as a platform for experts from diverse backgrounds, including academia, industry, and research institutions, to share their insights, methodologies, and practical experiences in forecasting renewable power generation, demand patterns, and electricity prices. By integrating theoretical foundations with real-world applications, it offers the readers a holistic understanding of the complexities involved in predicting variables crucial for the efficient operation and planning of modern power systems.

The chapters in this volume cover a wide spectrum of topics, ranging from statistical methods to cutting-edge machine learning algorithms and hybrid models. Each chapter not only elucidates the underlying principles but also provides extensive guidance on implementing these methods using various software tools and platforms. Furthermore, this book explores the interdisciplinary nature of forecasting in the context of renewable energy, drawing connections between meteorology, economics, and engineering. By fostering collaboration and knowledge exchange across disciplines, it aims to accelerate the development and adoption of innovative forecasting solutions that can drive the transition toward a more sustainable and resilient energy landscape.

Whether you are a researcher, practitioner, policymaker, or student, ***Forecasting Methods for Renewable Power Generation*** offers valuable insights and practical strategies to address the forecasting methods in renewable energy integration. We hope that this book serves as a catalyst for further advancements in the field.

Editors
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1

Solar Power Forecasting Using Hybrid Deep Learning Networks Combined with Variational Mode Decomposition

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Abstract

Solar power forecasting is beneficial for better operation of electrical systems to satisfy the rising energy demand using renewable energy. However, the uncertainty of solar irradiance degrades the prediction accuracy and model generalization ability. Therefore, hybrid deep learning methods with decomposition techniques are proposed here to ease the impact caused by the nonlinearity and nonstationarity of solar radiation. Firstly, the historical time-series solar power data is decomposed into band-limited intrinsic mode functions using variational mode decomposition. Secondly, the band-limited signals and the multivariate meteorological and time features are independently predicted using the hybrid network; finally, the aggregation results in the solar power prediction. The outcomes are compared with other benchmarked models.

Keywords: Solar power forecasting, hybrid deep learning networks, variational mode decomposition, recurrent neural networks (RNN), long short-term memory (LSTM) networks

1.1 Introduction

Solar power forecasting (SPF) is a rapidly evolving field driven by the growing importance of solar energy in the transition to sustainable and

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renewable power sources. It helps grid operators manage the integration of variable solar generation into the grid while ensuring grid stability and reliability. Precise solar power forecasts allow operators to proactively respond to output variations and balance supply and demand in real time, minimizing grid disruptions and ensuring smooth operation [1]. Furthermore, forecasting solar power generation is crucial for facilitating renewable energy integration, energy trading, providing stakeholders with information to facilitate informed decision-making, improving system reliability, and unlocking the full potential of solar energy as a clean and abundant resource [2, 3].

There are several types of SPF methods, each with its characteristics, advantages, and limitations. Based on the time horizon, forecasting methods are divided into three types: long-term, medium-term, and short-term power forecasting [4]. Short-term forecasting predicts solar power output over a horizon ranging from a few minutes to several hours ahead. It is essential for operational planning and real-time control of solar power plants, allowing grid operators to optimize energy scheduling and manage grid stability. Medium-term forecasting predicts solar power output over a horizon of several hours to several days ahead. It helps renewable energy developers, grid operators, and market participants make informed decisions about resource allocation, energy trading, and investment planning. Long-term forecasting predicts solar power output over days to weeks or even months ahead. It supports strategic decision-making, such as capacity planning, infrastructure development, and policy formulation, by providing insights into long-term trends and variability in solar power generation [3, 5]. Deterministic forecasting aims to estimate future solar power output based on historical time-series data and meteorological forecasts [6].

The forecasting models are divided into physical, statistical, and deep learning [7]. Physical models of solar irradiance forecasting leverage knowledge of atmospheric physics, radiative transfer processes, and solar geometry to simulate solar radiation under different weather conditions. They account for atmospheric scattering, cloud cover, and terrain effects, offering valuable insights into solar irradiance variability. However, physical models require detailed input parameters and may be computationally intensive [8].

Early research in SPF predominantly relied on statistical methods, such as time-series analysis, autoregressive integrated moving averages, and exponential smoothing techniques. While effective for short-term forecasting, statistical methods may struggle to capture nonlinear and complex relationships in solar irradiance data [9, 10]. Machine learning (ML) techniques, particularly artificial neural networks (ANNs), have gained popularity in solar power and irradiance forecasting owing to their ability to model complex, nonlinear relationships [11]. ANNs, including feedforward and recurrent neural networks (RNNs), have been extensively used to predict solar power based on meteorological data, such as temperature, humidity, and cloud cover. Random forests, K-nearest neighbor, support vector machines, and gradient boosting algorithms are also employed for solar power or irradiance forecasting [12–15]. ML approaches often outperform traditional statistical methods, especially in capturing nonlinear dependencies and improving forecast accuracy [16].

Hybrid forecasting approaches aim to overcome the limitations of individual methods and improve forecast accuracy across different time horizons. In recent years, with the emergence of deep learning, RNN [17], long short-term memory networks (LSTMs) [18], and convolutional neural networks [19–21], have become the essential units of hybrid models in renewable energy forecasting. Furthermore, integrated hybrid models may leverage the distinct characteristics of many models to predict future data patterns based on historical data. However, relying solely on hybrid models will not yield all the useful information in the dataset. As a result, integrated hybrid models frequently combine with data decomposition to strengthen their anti-interference capacity. Signal decomposition, therefore, becomes a critical component of data processing. Wavelet decomposition [22], empirical mode decomposition [23], and variational mode decomposition (VMD) [24] are commonly used decomposition methods. Combining these methods with deep learning models achieves better accuracy and performance.

1.2 Methodology

This section presents the models and theories used in the proposed forecasting framework.

1.2.1 Variational Mode Decomposition

VMD [25] decomposes a signal into a specified number of band-limited intrinsic mode functions (IMFs) or modes that represent the underlying oscillatory components of the signal. VMD decomposes a real-valued input signal f into discrete sub-signals or modes, u_k, with specific sparsity properties. Each mode k is considered compact around a central pulsation ω_k, which will be determined alongside the decomposition. The goal is to determine a specific set of IMFs u_k and associated center frequencies

ω_k that yield the minimum value for the constrained variational problem, defined by

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \Sigma_k \left\| \partial_t [(\delta(t) + \frac{j}{\pi t}) * u_k(t)] e^{-j\omega_k t} \right\|_2^2 \right\} \quad (1.1)$$
$$\text{subject to } \Sigma_k \, u_k = f$$

where $\{u_k\}=\{u_1,\ldots, u_k\}$ and $\{\omega_k\}=\{\omega_1,\ldots, \omega_k\}$ are the set of all modes and their center frequencies, respectively, δ is Dirac function, $\|.\|_2$ represents the L2 distance, and * represents the convolution operation.

The constraint variation problem is transformed into a nonconstraint variation by using the second penalty component α and the Lagrangian multiplication operator λ(t).

$$\mathcal{L}(\{u_k\},\{\omega_k\},\lambda) = \alpha \, \Sigma_k \left\| \partial_t [(\delta(t) + \frac{j}{\pi t}) * u_k(t)] e^{-j\omega_k t} \right\|_2^2 + \| f(t) - \Sigma_k u_k(t) \|_2^2 + \langle \lambda(t), f(t) - \Sigma_k u_k(t) \rangle \quad (1.2)$$

The "saddle point" of the expanded Lagrange formula is found by updating u_k^{n+1}, ω_k^{n+1}, and λ_k^{n+1} using the alternate direction method of multipliers (ADMM). In order to update the mode $u_k(t)$, the following sub-optimization problem is considered at the *n*-th iteration.

$$u_k^{n+1} \leftarrow \arg\min_{u_k} \mathcal{L}(\{u_{i<k}^{n+1}\},\{u_{i\geq k}^{n}\}\{\omega_i^n\},\lambda^n) \quad (1.3)$$

This is resolved in the spectral domain in VMD, leading to an update in the frequency domain.

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \quad (1.4)$$

In the next step, the center frequency ω_k is updated by solving the following sub-optimization problem iteratively

$$\omega_k^{n+1} \leftarrow \underset{\omega_k}{\arg\min}\, \mathcal{L}(\{u_i^{n+1}\},\{\omega_{i<k}^{n+1}\}\{\omega_{i\geq k}^{n}\},\lambda^n) \tag{1.5}$$

to get an update for ω_k^{n+1} in the dual frequency domain.

$$\omega_k^{n+1} = \frac{\int_0^{\infty} \omega\,|\,\hat{u}_k(\omega)\,|^2\, d\omega}{\int_0^{\infty} |\,\hat{u}_k(\omega)\,|^2\, d\omega} \tag{1.6}$$

The new frequency is estimated as the centroid of the power spectrum of the associated modes. Overall, the VMD updates all of the sub-signals constantly via the frequency domain and subsequently converts them into the time domain using the inverse Fourier transform.

1.2.2 Long Short-Term Memory

The RNN effectively models time-series data. Unlike traditional feed-forward neural networks, the output is feedback to the input, acting as dynamic memory to process the input sequence. RNN comprises an input layer, an output layer, a recurrent layer, a series of weight matrices, and activation functions. The weights are shared between hidden units across each time step, and the network produces the same outcome by performing the same task on all layers as shown in Figure 1.1. For each time step t, the activation function and the predicted output $\hat{y}$ are expressed as follows:

$$h_1 = g(W_x X + b_h) \tag{1.7}$$

$$h_t = g(W_x X + W_h h_{t-1} + b_h) \tag{1.8}$$

$$\hat{y}_t = softmax(W_y h_t) = \frac{e^{W_y h_t}}{\Sigma_1^j e^{W_y h_{tj}}} \tag{1.9}$$

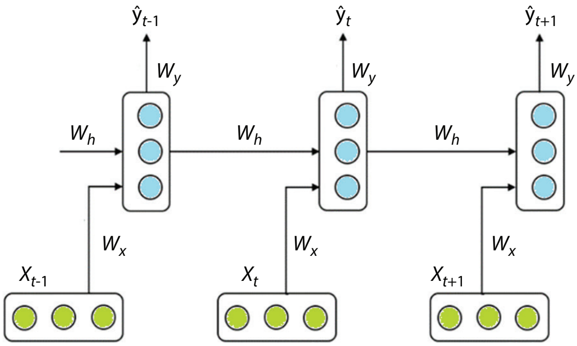

Figure 1.1 Traditional RNN.

where X is an input vector, h_t is a hidden state vector at time t, g is the logistic function, $\mathfrak{b}$ are bias vectors, and W_x, W_h, and W_y are weight matrices shared across time steps. The model sets the weight matrices during training to minimize an overall loss function. Errors must be propagated over many steps to compute gradients concerning inputs. The contribution of gradient values diminishes gradually as the computation propagates to previous time steps, thus decreasing the capability to learn long sequences. A powerful variant of the RNN, the LSTM, is used to model time-series forecasting to overcome the long-term dependency and vanishing/exploding gradient problems.

Employing LSTM units in RNN layers will allow errors to propagate throughout the entire network. The LSTM introduced in [26] is designed to store information for a long period. LSTM addresses gradient issues by introducing an additional cell state C in the hidden layer(s).

The structure of an LSTM network in Figure 1.2 consists of cells that form the memory blocks, and are recurrently connected comprising of gates, namely, forget gates, input gates, and output gates. For each gate in the network, the input weights W and bias $\mathfrak{b}$ are all initialized as a column matrix, respectively, as below.

$$W = \begin{bmatrix} W_f \\ W_i \\ W_C \\ W_O \end{bmatrix}, \beta = \begin{bmatrix} \beta_f \\ \beta_i \\ \beta_C \\ \beta_O \end{bmatrix} \tag{1.10}$$

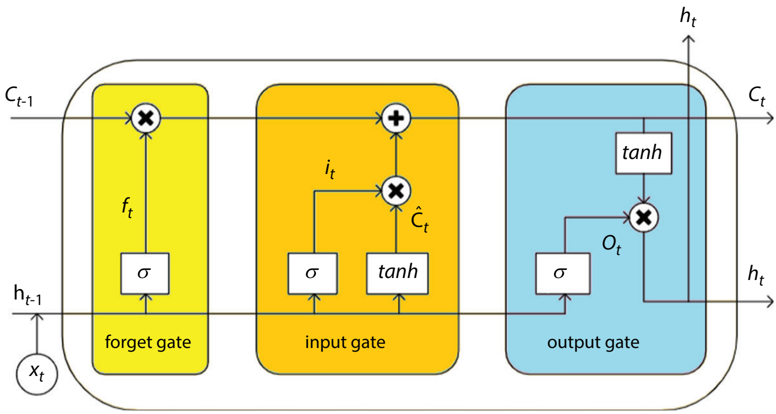

Figure 1.2 Structure of an LSTM cell.

The forget gate eliminates unnecessary or trivial information by multiplying the hidden layer's previous state h_{t-1} and the current input x_t with the weight matrices and by adding a bias. It uses a sigmoid function, producing values between 0 and 1 for each cell status. An output of 0 for a particular cell state means that information is forgotten and outputting 1 means that information is retained for future use.

$$f_t = \sigma(W_f \,.\, [h_{t-1}, x_t] + \beta_f) \tag{1.11}$$

An input gate adds useful information to a cell state controlled by a sigmoid function acting as a filter alike the filter gate. The cell state is updated using the *tanh* function. The cell state can be updated by adding a *tanh*-activated vector containing all possible values of previous hidden state and current input. The *tanh*-generated vectors are multiplied with regulated values. The following represent the cell state equations:

$$i_t = \sigma(W_i \,.\, [h_{t-1}, x_t] + \beta_i) \tag{1.12}$$

$$\hat{C}_t = tanh(W_C \,.\, [h_{t-1}, x_t] + \beta_C) \tag{1.13}$$

$$C_t = (f_t . C_{t-1} + i_t . \hat{C}_t) \tag{1.14}$$

The output gate determines and presents the valuable details from the current state of the cell as outputs. The information is processed through the sigmoid function and filtered based on previous hidden state h_{t-1} and current input x_t. The *tanh* function, responsible for cell activation, results in the final output after dot multiplication.

$$O_t = \sigma(W_O . [h_{t-1}, x_t] + \beta_O) \tag{1.15}$$

$$h_t = O_t . tanh(C_t) \tag{1.16}$$

Given an input sequence at time t, $X_t = [x_1, x_2, \ldots x_t]$, the final prediction of an LSTM layer is a vector of all the outputs, represented by $\hat{y}_t = [h_1, h_2, \ldots h_t]$.

1.2.3 Gated Recurrent Units

GRUs combine the input and forget ports from LSTMs into one update gate. The update port retains previous state information it receives. On the other hand, the reset port decides whether the current state should be combined with the information earlier. The functions are outlined below:

$$z_t = \sigma(W_z . [h_{t-1}, x_t] + \beta_z) \tag{1.17}$$

$$s_t = \sigma(W_r . [h_{t-1}, x_t] + \beta_r) \tag{1.18}$$

$$\tilde{h}_t = \tanh(s_t W . [h_{t-1}, x_t] + \beta) \tag{1.19}$$

$$h_t = (1 - z_t)\tilde{h}_t + z_t h_{t-1} \tag{1.20}$$

where W_z, W_r, and W denote the weight matrices; σ denotes the logistic sigmoid function; β_z, β_r, and β are the bias; z_t, s_t, h_t denotes the update gate, reset gate, and hidden layer, respectively.

GRU demonstrates the potential to capture long-term dependencies from massive sequential data without excluding information from the earlier part of the data sequences. GRU is used to capture the temporal dependencies in the data.

1.3 Proposed Methodology for Solar Power Forecasting

Hybrid deep learning models enhance time-series forecasting. Deep learning approaches are employed for enhancing forecasting precision and resilience. Utilizing LSTM and GRU models, the proposed hybrid system aims to capture diverse solar power patterns and correlations within time-series data. The LSTM and GRU models are well adapted to the vanishing gradient problem and the long-term dependencies. Therefore, hybrid techniques synergistically use the merits of different architectures to enhance prediction accuracy. To do this, the proposed approach combines the predictions of these models.

A hybrid deep learning approach using LSTM-GRU models for day-ahead SPF is implemented in this study. The original time-series solar power data is pre-processed to make the data suitable for VMD decomposition. Neural networks require data to be normalized within the range [0 1]. In this framework, the solar power prediction is divided into two stages. The decomposition of the dataset into *n* subseries called IMFs using VMD is the first stage. The *n* number of IMFs is expressed as IMF_1, IMF_2,…IMF_{n-1}, IMF_n. The IMFs are separated into relatively high-frequency (*h*) and low-frequency (*k*) subseries. The lower-order IMFs are high-frequency useful information, and the higher-order IMFs are the low frequency subseries. An *h* number of independent LSTM models is built and trained for the high-frequency subseries and a *k*-independent GRU model for the low-frequency subseries. LSTM modules produce *h* predictions and GRU modules produce *k* prediction values. These *h*+*k* prediction results from each component are aggregated to obtain the final prediction results. The framework of the proposed prediction model is shown in Figure 1.3.

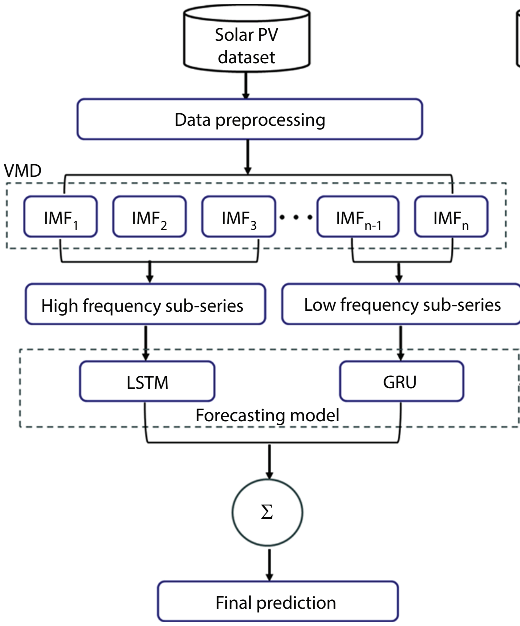

Figure 1.3 The framework of the proposed prediction method.

1.4 Experimental Results and Discussion

1.4.1 Solar PV Dataset

This study is based on historical solar power generation data collected from a 4-kW plant from January 2019 to December 2022, with a resolution of 5 min. The features of the dataset include the status of the day (day or night), day temperature (°C), dc power from panels to inverter (W), solar radiation (W/m^2), and panel temperature (°C). Figure 1.4 shows the variability of the power generation in typical days of April 2022. There is volatility in solar power generation in these three successive days. The hourly distribution of PV power production reaches its maximum at midday and falls to zero at night. One-hour data is derived from the real-time 5-min interval dataset as the average value for corresponding time intervals.

Solar power generation depends on many factors, mainly solar irradiation. Figure 1.5 (a and b). shows the mean solar power generated by hours for summer and winter, which indicates that the generation is low for winter. Figure 1.6 shows the mean solar radiation by month. Solar radiation is particularly low in January, February, and December, resulting in reduced power generation during these winter months.

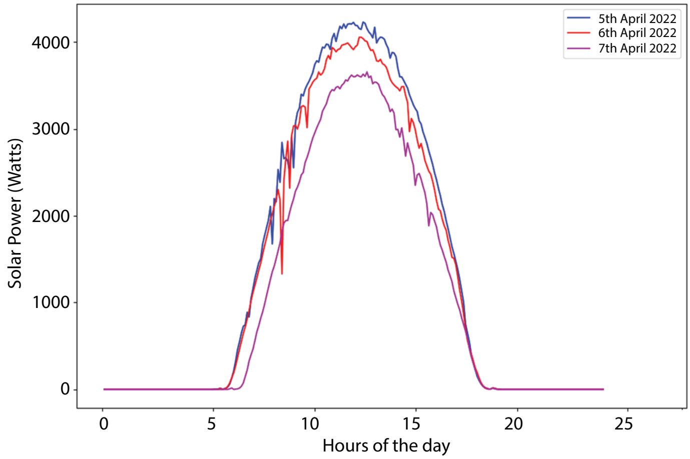

Figure 1.4 Solar power generation on typical days.

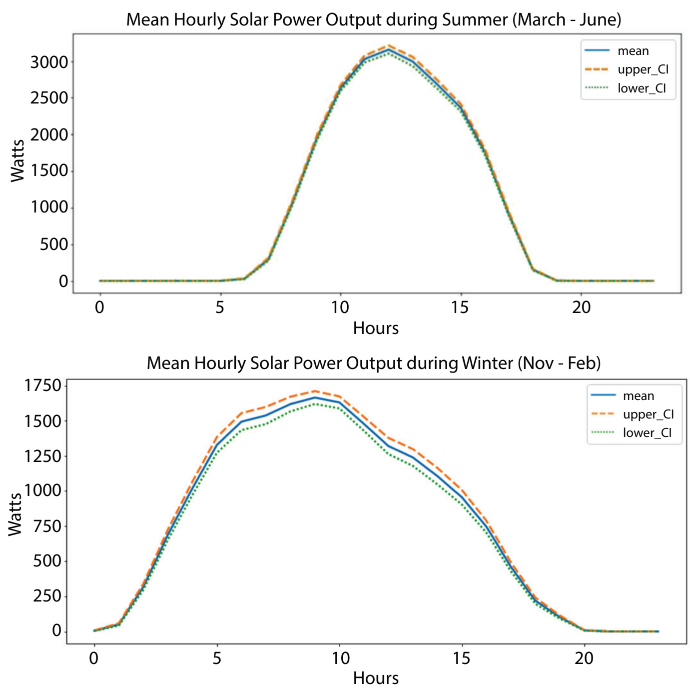

Figure 1.5 Mean solar power generated by hour for (a) summer and (b) winter.

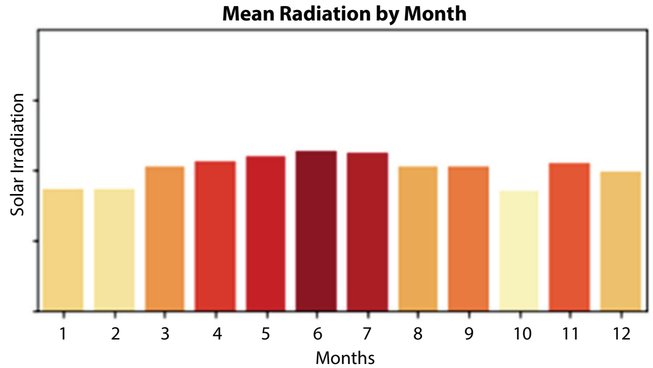

Figure 1.6 Mean solar radiation by months.

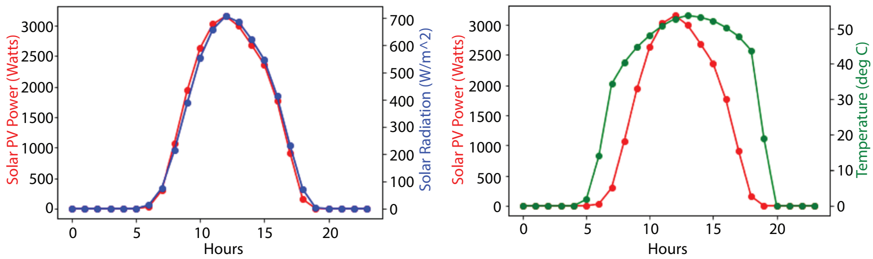

Figure 1.7 Correlation between mean solar power, irradiation, and temperature.

Figure 1.7 shows the relationship between the mean values of solar power output with solar irradiation and temperature by hours. The scatter plot in Figure 1.8 shows the correlation of the meteorological factors plotted against the solar power. Solar power output is highly correlated with three important features: solar irradiation, day temperature, and panel temperature. The model uses the status of the day, temperature, solar radiation, panel temperature, and solar power output as inputs.

1.4.2 Experimental Setup and Model Training

In the training phase of recurrent models, optimization algorithms are used to minimize the error rate. The performance of an optimizer is generally characterized by the speed of convergence and the model's capabilities. Adaptive moment estimation (Adam) is the gradient-based optimizer for model instantiation and training. The activation function used here for determining the final response of the network is sigmoid,