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Enhanced Fault Detection in Solar Photovoltaic Modules Using VMD-LSTM Model

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Abstract— Detection of solar PV faults in an Accurate and versatile technique are essential because the safety and efficiency of solar photovoltaic (PV) modules greatly depend on efficient fault identification. However, because it can be challenging to identify complex operating patterns and detect tiny faults, currently methods frequently have low accuracy. This may make it more difficult to validate the models, which would limit their usefulness in the actual world. This paper presents a new fault detection method that combines Empirical Mode Decomposition (EMD) with the power of Long Short-Term Memory (LSTM) networks. Critical features are efficiently extracted from the data by use of an adaptive decomposition of voltage and current signals into Intrinsic Mode Functions k(IMFs) through the use of EMD. An LSTM network that has been trained to recognize complex patterns and periodic connections then processes this information. Our model which has been validated using a PSCAD simulation model, shows notable improvements in accuracy and durability of more than 92% after undergoing thorough testing on a simulated PV system that allows for several fault types and their severities when compared to existing methods.

Keywords: Current signal, EMD, IMF, LSTM, PSCAD simulation, Solar Photovoltaic.

INTRODUCTION

Detecting faults is essential to the operation of the electrical system. The goal of utilities is to lessen the number of natural disaster-related outages that might affect their customers financially and cause lengthy disruptions [1] [2]. Depending on the kind of consumer and season, the cost of a one-hour outage might vary from USD 13 to USD 81,000 [3]. Utility companies can reduce unplanned outages, assign repair teams, and properly sequence activities by forecasting faults and their duration [4]. Numerous nations have already made the production of new energy their primary source of power due to the ongoing use of fossil fuels and the global degradation of ecosystems. Recent years have seen a global increase in the use of solar energy as a clean, environmentally acceptable energy source for photovoltaic power generation. As a result, photovoltaic power generation is currently developing at a faster rate. Furthermore, by the end of 2019, the total installed capacity of solar power generation in China had increased to 204.3 GW due to the growing trend of solar power station installed capacities [5]. Because of the way our nation is shaped, building photovoltaic power plants is

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typically given priority in the Northwest, which has an abundance of solar energy. Unfortunately, the majority of this region is made up of harsh environments like deserts and plateaus, which negatively affect photovoltaic modules and raise the risk of module failure. In addition, these environmental conditions make life more difficult for humans and make it more difficult to operate and maintain photovoltaic power plants, which leads to longer cycles and a decrease in power generation. The most recent data indicates that the yearly output power reduction rate of solar power plants with varying settings and locations ranges from 0.6% to 1.0%, which has a significant impact on the total photovoltaic power plant's power generation capacity. They propose a fault detection approach for solar modules based on SP structure, which primarily depends on the modulating electrical properties of the modules [6].

Determine the extent to which the solar module has failed, commencing with and identifying the solar module's weak points [7]. To enhance the previously discussed techniques and suggested a reconstruction topology structure. First, each solar string has current sensors inserted inside of it. Subsequently, the acquired current values underwent preliminary training and verification. Ultimately, the photovoltaic module's fault localization could be more precise. By altering the range of voltage values in each section of the photovoltaic module presented a zoning evaluation of photovoltaic arrays based on the SP structure, which locates faults precisely [8]. Developed a new photovoltaic module fault detection technique based on the CTCT structure and built a CTCT structure based on the TCT structure foundation. The precise procedure involves installing m layers of current transformers in a series of photovoltaic module installations between every two rows and using the current values detected by the installed current transformers to pinpoint the position of the problem area. Through the construction of a CTCT structure comprised of TCT structure and SP structure, a new approach for diagnosing faults in solar modules [9]. This method is based on the CTCT structure. The primary target of this technique is the growing quantity of solar panels in use today. This technique can cut the number of sensors to between 50% and 80% of what it was before.

The solar module fault detection and positioning techniques mentioned above are limited to basic fault positioning tasks; they are unable to identify the specific type of fault that arises. However, suggested a problem detection technique for solar modules based on the SN-TCT structure [10]. By carefully fusing sensor data with environmental data, this diagnostic technique enhances the capacity to identify problem modes and, eventually, the precision of fault localization for solar modules. Furthermore, as computers have advanced in China and other nations, research has suggested the use of time series convolution neural networks (CNN) as a progressive step towards more advanced time series deep learning models like RNN, LSTM, GRU, and so on particularly when handling challenges involving the prediction of time series data [11] [12]. Time series data is the fundamental component of current data in solar power plants. Simultaneously, there is an issue with inadequate accuracy in data collection equipment because photovoltaic modules are typically operated under extremely harsh climatic conditions nowadays.

Additionally, there is a lot of noise in the present data needed for research because aging equipment causes problems with data transfer as well. Vibration signals were suggested and complex performance characteristics and high noise signals were also superimposed on the current data of photovoltaic power plant branches [13]. Temporal convolutional neural networks' ability to learn can be significantly harmed by noise. The temporal convolutional neural network's ability to learn can be significantly harmed by noise. A soft thresholding temporal convolutional neural network (ST-TCN) fault diagnostic model for photovoltaic modules has already been proposed [14]. It has a high fault detection accuracy and a rapid convergence speed.

This research presents a fault detection technique for solar photovoltaic modules that combines Long Short-Term Memory Network (LSTM) and Maximum Empirical Mode

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Decomposition (EMD) based on the previously mentioned approaches. First, the voltage and current signals under normal and fault situations were gathered, and the characteristic curves under various operating conditions were examined. The gathered signals were adaptively divided into K IMF components using EMD. After that, feed the IMF component into the LSTM neural network that has been trained to detect faults. Ultimately, a PSCAD/EMTDC simulation model was created to confirm the method's correctness and viability. The outcomes demonstrated that this technique can accurately identify faults in solar modules.

METHOD

Modeling is the process of creating mathematical simulations that forecast the performance of photovoltaic (PV) cells under various conditions, such as temperature changes and light exposure. PV system fault analysis is concerned with finding problems such as soiling on modules, shading effects, and short- and open-circuit faults. The efficiency of PV cells can be greatly decreased by these faults. To ensure the durability and efficiency of photovoltaic cells, it is imperative to optimize their performance and mitigate potential faults through regular maintenance and effective modeling. In order to simplify comparison with the latest detection techniques, the PV system under examination has a similarity to that found in [15] [16]. In Fig. 1, this PV system is display under considered faults. The simulated PV specifications Module specifics are given in [17].

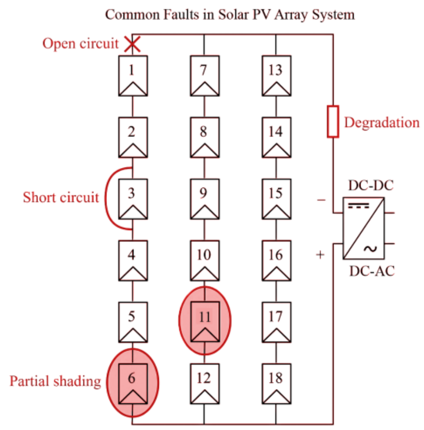

Figure 1. Common PV faults in Solar array system

Open-circuit: faults are a major problem with photovoltaic (PV) systems. These failures result in interruptions in the electrical continuity, which cause large decreases in power output. Short-circuiting: problems in which accidental direct connections result in excessive current flow and possible component damage, are a different one, more uncommon fault. Degradation: The system's efficiency and energy yield decrease with time due to cause by elements including UV exposure and thermal cycling. Shading: it reduced output power and hot patches can also result from dust on the panels, buildings, or trees create [17].

It is essential to attend to these faults through regular maintenance, careful system design, and prompt fault correction in order to maintain the optimal performance of PV systems. The PV system in Fig. 2 is simulated in 23 different configurations: no fault, two open circuit severities, and four severities of all other fault categories. Severity is defined as the average drop in power production that the issue causes. For ten years of publicly available weather measurements, every configuration is simulated.

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A. Modeling of photovoltaic modules

Two diode circuit models can be used to explain the physical properties of the solar cells in photovoltaic modules. As seen in Figure 1, the two-diode circuit model is composed of a current source, parallel diodes, and series parallel resistors.

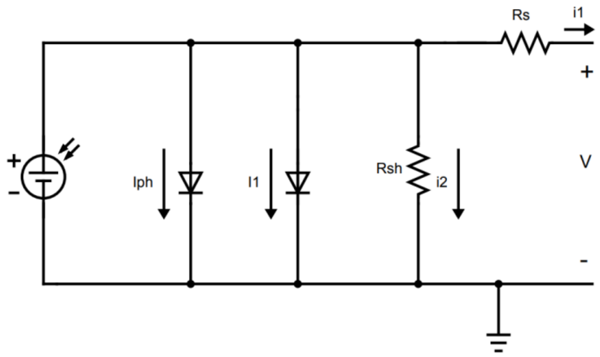

Figure 2. Dual Diode Equivalent Circuit Model for Photovoltaic Cells

In this research, a PSCAD model for a photovoltaic module is established, and a photovoltaic cell with four parallel photovoltaic arrays is constructed. Each array is made up of 10 modules connected in series, which are then connected in 250 parallel configurations. In Figure 3, the constructed solar array model is displayed as shown.

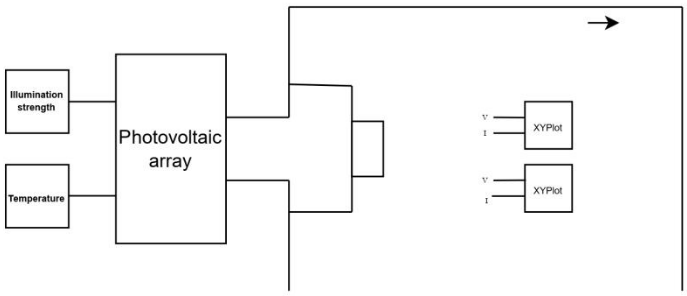

Figure 3. Photovoltaic array model

B. Output characteristics of photovoltaic components during normal operation

In addition to their basic characteristics, the environmental circumstances surrounding solar arrays have a significant impact on their output characteristics. At a temperature of 30 °C, Figure 3 displays the output characteristic curve of the solar array model with variations in irradiance. Figure 3 illustrates how the solar array's short-circuit current (I_{sc}) decreases linearly with decreasing irradiance, whereas the open circuit voltage (V_{oc}) declines non-linearly. While the maximum power point voltage essentially stays constant, the maximum power (P_{max}) drops as the irradiance lowers.

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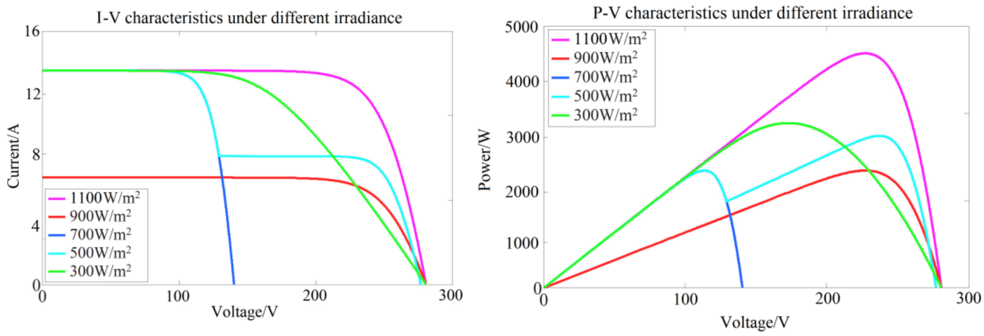

Figure 4. Output characteristic curve of PV model with changes in irradiance at temperature of 30℃

C. Fault output characteristics of photovoltaic modules

As the external environment's operational time grows, so does the probability of failure. During an examination of the functioning of current solar power facilities, it was discovered that faults including soiling, shadows, open circuits, and coloration frequently arise in solar arrays. Energy loss results from the photovoltaic power generation system's efficiency declining when a problem happens. Furthermore, significant failures have the potential to harm components and result in dangerous accidents like fires. Among the most common kinds of PV module failures that occur nowadays are open circuit, short circuit, degradation, shading, and bypass. The P-V and V-I diagrams of the photovoltaic modules in each fault are obtained by simulating these kinds of faults in this article, as seen in the following graphs.

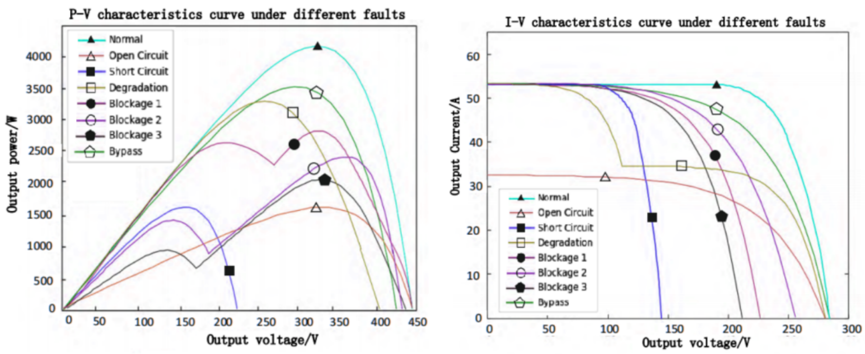

Figure 5. Voltage and current fault output of photovoltaic array at a temperature of 30℃

RESULT AND DISCUSSION

A. Workflow for PV Fault Detection model

The fault detection workflow for a photovoltaic (PV) system utilizing Empirical Mode Decomposition (EMD) and PSCAD Inputting sensor-derived time-series data. inherent Mode Functions (IMFs), or inherent oscillatory components, are extracted from the data by EMD. A Long Short-Term Memory (LSTM) neural network, which is adept at identifying salient characteristics and capturing temporal patterns, is then used to process each IMF. The way these features are arranged into vectors makes them essential for the PSCAD platform's simulation phase. The PV system's electrical behavior under simulated fault scenarios is carefully modeled and examined in PSCAD. Next, the result of the simulation is assessed for definitive fault discovery. Reiterating the procedure from a relevant previous phase, like feature extraction or EMD decomposition, can help to improve the analysis if the results are unclear. The workflow proceeds to the last step, where the state of the PV system is determined, describing the kind and details of the issue, once a fault has been positively discovered. As shown in Figure 6, the procedure ends in a systematic and accurate diagnosis of the PV system condition.

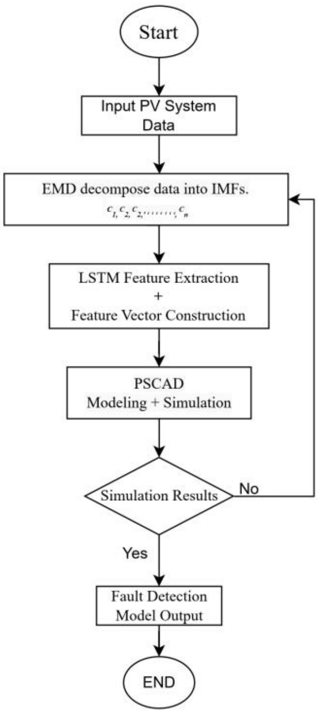

Figure 6. Model of EMD-LSTM

B. Empirical Mode Decomposition (EMD)

Huang et al. [18] presented the EMD technique, which breaks down a signal into a few different k IMFs. An IMF is a function that satisfies the following two requirements:
(1) The number of extrema and the number of zero-crossings must be equal throughout the data set, or differ by no more than one.
(2) The mean value of the envelope defined by the local minima and local maxima must always be zero.
A basic oscillatory mode included in the signal is represented by an IMF. The EMD approach was developed to break down a signal into its individual IMF components, based on the basic premise that any signal consists of various simple IMF's. Its mathematical expression is in [18].

$$X(t) = \sum_{i=1}^{n} c_i + R_n \tag{1}$$

where, c is the intrinsic mode function, n is number of IMF's, Rn is residue, may be a constant or the mean trend.

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Even though the actual EMD technique involves continuous sifting, which cannot be simply expressed by a single mathematical expression, this formula is the summative outcome of applying EMD to a signal. The algorithm identifies and extracts each ci from X(t) using a data-driven procedure; the residue is what's left over after all potential IMFs have been extracted.

C. Long Short-Term Memory Network (LSTM)

Long Short-Term Memory networks (LSTM) are an excellent fit for time series data with high volatility. They essentially consist of modifying the recurrent layer neurons of the RNNs. The RNN is a specific type of artificial neural network (ANN) that stores recent input events as activation through feedback loops. Moreover, able can establish a correlation between the network's current and historical data. Although it has difficulties with gradient exploding and fading, the RNN can also learn any length. The specific RNN architecture brought forward by Hochreiter and SchmidHuber (1997) can get around this by substituting a gated cell known as a Long Short-Term Memory network LSTM for the RNN cell [19] [20]. LSTMs are composed of intrinsic neurons arranged in linked subnetworks that are connected to each other. LSTMs analyze data by taking into account both the current moment information and all previous historical information as inputs, in contrast to typical neural networks that can only map current input data to outputs. This method greatly improves the recognition accuracy of the network by partially resolving the problem of vanishing gradients in RNNs [21]. As seen in Figure 5, the recurring modules in LSTMs consist of four interacting layers: three sigmoid and one tanh layer. Their unique interaction style makes it easier for information to be updated or forgotten. In Figure 5, σ stands for the hyperbolic tangent function, which compresses values between -1 and 1, and tanh for the sigmoid activation function, which compresses values between 0 and 1.

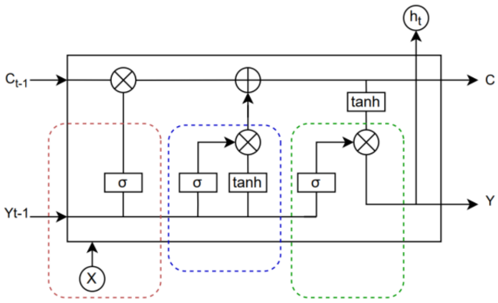

Figure 7. LSTM structure diagram

D. Model parameter settings

A signal can be naturally broken down into a finite number of Intrinsic Mode Functions (IMFs) using EMD, an adaptive data analysis technique, depending on the properties of the signal itself. An over-decomposition may result from extracting too many IMFs (K), thereby hiding important fault information in the noise. On the other hand, if too few IMFs are extracted, important signal components can be missed, which would reduce the fault detection accuracy. Since the process of EMD does not impose a convergence tolerance or an artificial number of modes, these problems are naturally avoided by design. The optimization terminates by the signal characteristics and particular EMD convergence conditions, guaranteeing a compromise between computing efficiency and decomposition fidelity. Based on our calculations, we find that the best compromise between noise and detail is achieved with 6 IMFs. To create a strong

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fault detection system, the LSTM model's parameters—which include 100 units with a 'Relu' activation function, a 'Softmax' output layer, a learning rate of 0.001, a batch size of 300, and the 'Adam' optimizer—complement the EMD procedure. Table 1 provides an overview of the particular parameter configurations.

Table 1. Parameter configurations

Parameter	Value
IMFs Extracted	Variable
EMD Stopping Criterion	Native EMD stopping conditions
LSTM Units	100
Activation Function	Relu
Output Activation	Softmax
Learning Rate	0.001
Batch Size	300
Optimizer	Adam

E. Model of Training

The preliminary features extracted by EMD can be incorporated into LSTM to further deepen the analysis of time series data. This can help extract more abstract features, reveal complex relationships between data samples, and significantly improve the model pattern recognition accuracy [22]. Figure 6 shows the network structure diagram.

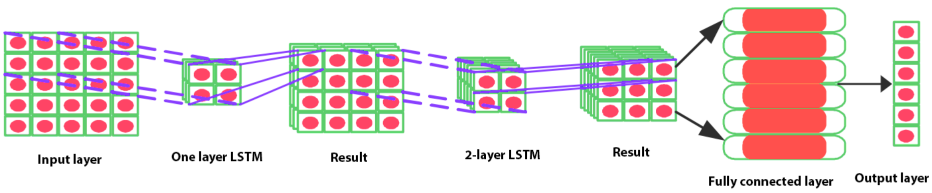

Figure 8. EMD-LSTM network architecture diagram

In this research, the 20 kHz sample frequency is used, and fault events happen every 1 second, or 20,000 sampling points. In order to improve the network's accuracy in locating fault zones, normalization is applied to the input data X due to the notable variance in the input values. Equation (3) provides the method for conducting the normalization. A variable number of IMFs are produced by the EMD process in response to the signal's inherent properties. These features may include fault indicators in the case of PV systems. After then, the LSTM network is trained to identify intricate temporal and sequential patterns in these IMFs that could be associated with various fault types. By utilizing the temporal learning capabilities of LSTM networks, this integrated EMD-LSTM technique improves fault identification by analyzing the time-dependent behavior of the IMFs extracted by EMD. The balance between computing efficiency and model complexity must also be taken into mind. The complexity of the EMD-LSTM model should be not too high to make real-time analysis impossible, but still sophisticated enough to catch the subtleties of the signal. In order to make sure the network does not overfit to the training set and that it generalizes well to new data, model validation and testing are therefore essential throughout the training phase. In order to create the EMD-LSTM network model, 1,200 sets of training samples are generated through fault simulations performed on the PSCAD platform in the present study. The raw time series data is

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preprocessed by extracting Intrinsic Mode Functions (IMFs) using the Empirical Mode Decomposition (EMD). These IMFs are essential for identifying the traits of PV system problems. By putting the IMFs into the LSTM network requires normalization first. Thus min-max normalization method is used on the majority of datasets:

$$x_i = \frac{x_i - min(X)}{min(X) - min(X)} \tag{2}$$

By normalizing the values of Xi to a range of [0,1], this equation guarantees a constant scale for the input of the LSTM. To standardize the data in the event of outliers, z-score normalization may be utilized instead:

$$z_1 = \frac{x_i - \mu}{\sigma} \tag{3}$$

where σ and μ are the dataset's standard deviation and mean, respectively.

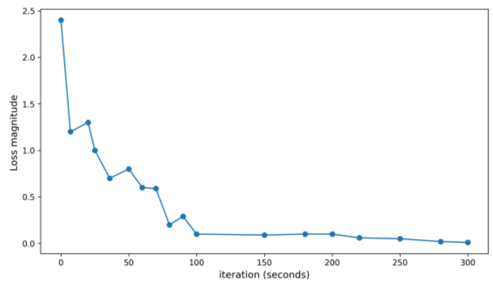

Figure 9. Training Set Loss Value Curve

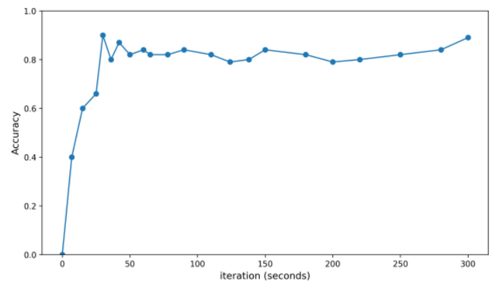

Figure 10. Accuracy variation curve

Figures 9 and 10 illustrate how the LSTM network, trained on these normalized IMFs, is adjusted to identify fault patterns across iterations, with accuracy considerably increasing beyond 200 iterations. To guarantee model consistency, the same normalization must be applied to every data collection. In order to properly apply the normalization parameters to new data during operational deployment, they must be kept after training.

RESULT AND DISCUSSION

With the utilization of the PSCAD/EMTDC-built solar array output characteristic simulation model, simulations are performed with irradiance levels ranging from 300 W/m² to 1200 W/m² and temperature conditions ranging from 25°C to 50°C. 200 data sets are collected for each of the six operational states of the solar array, which are mainly monitored to obtain the open-circuit voltage (V_{oc}) and short-circuit current (I_{sc}) values. A total of 1200 data samples were collected, of which a third were randomly picked to create the training set, and the remaining quarter was used as the test set. In this research, the EMD LSTM network ($X = [V_{oc}\ I_{sc}]$) receives the fault voltage and current signal as inputs. The output quantity is $Y = (y_1, y_2, y_3, y_4, y_5, y_6)$, and the detection results are displayed in Table 2 when the fault occurs. The EMD-LSTM network design used in this paper has six output results in order to detect the fault type.

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Table 2. Shows VMD-LSTM test results

Fault Type	y^1	y^2	y^3	y^4	y^5	y^6
Efficiency	1	0	0	0	0	0
Short Circuit	0	1	0	0	0	0
Open Circuit	0	0	1	0	0	0
Degradation 1 (70%)	0	0	0	1	0	0
Degradation 2 (50%)	0	0	0	0	1	0
Degradation 3 (30%)	0	0	0	0	0	1

The EMD-LSTM network utilizes the natural advantages of LSTM in pattern recognition, which are further supported by the initial features that EMD extracts from Voc and Isc signals. These signals are normalized, using either z-score normalization or min-max normalization, before being fed into the LSTM network in order to maximize network performance and guarantee data consistency. As the network's repeated training advances, Figures 7 and 8 illustrate the excellent prediction accuracy of the EMD-LSTM model, whose efficacy is tested against the test set. This comprehensive technique highlights the EMD-LSTM network's resilience and dependability, which has been fine-tuned to precisely detect and categorize faults under a variety of PV module operating conditions.

CONCLUSION

This study presents an EMD-LSTM based fault detection system for solar modules that can successfully identify six main situations of the modules: normal operation, open circuit fault, short circuit fault, and shadow occlusion fault. The study used a dataset of voltage and current signals preprocessed with EMD for feature extraction to train the model, which was then used to develop an EMD-LSTM-based fault diagnosis model and a PSCAD/EMTDC simulation model to collect electrical data from solar modules under various operating conditions. By closely matching the non-stationary and non-linear character of signal data, the EMD facilitates the adaptive extraction of Intrinsic Mode Functions (IMFs), which significantly reduces mode mixing and facilitates better breakdown of fault signals for more effective feature extraction. As a result, the suggested approach significantly outperforms traditional methods in terms of fault detection durability and accuracy. After extensive evaluation on a simulated PV system with various fault types and severities, this novel approach validated using a PSCAD simulation model demonstrated notable improvements in accuracy and durability of over 92%, showing its potential for real-world applications where effective fault identification is essential for the safety and efficiency of solar photovoltaic modules.

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