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A MIC-LSTM based parameter extraction method for single-diode PV model

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In recent years, the installed capacity of renewable energy systems has seen rapid growth, particularly in photovoltaic (PV) power. Photovoltaic modules, being the fundamental elements of the PV system, play a crucial role in determining system performance. However, the challenge arises from the inconsistent decay rates of PV modules, which significantly impact the accuracy of PV system modeling. To address this issue, this paper introduces a novel MIC-LSTM based parameter extraction method for the single-diode PV model. This method focuses on accurately deriving PV module model parameters under various decay rates. By establishing a mapping relationship between the current-voltage (I-V) curve characteristics and the five unknown parameters in the photovoltaic module model, the proposed method demonstrates high precision in parameter extraction. Simulation and experimental verifications are carried out to validate the proposed method, where the extraction accuracy is 99.3%, 98.39%, 98.85%, 97.91%, and 98.36% for the five unknown model parameters.

KEYWORDS

maximal information coefficient, LSTM, parameter extraction, single-diode PV model, feature value

1 Introduction

Modeling photovoltaic (PV) modules is a key technology for evaluating the economic benefits of PV generation systems in complex operating conditions. Accurate PV module models could depict the output characteristics of PV module under different conditions. The physical PV models can be categorized into single diode and double diode models based on the number of diodes. The single diode model can be further divided based on the number of parameters in the equivalent circuit, including the ideal model (Pavan et al., 2014), four-parameter model (Walker, 2001; Xiao et al., 2004; Chenni et al., 2007), and five-parameter model (Appelbaum and Peled, 2014; Kumar and Shiva, 2019; Muttillo et al., 2020). The ideal model regards the entire PV cell as a basic P-N junction. The four-parameter model assumes an infinite parallel resistance, thereby neglecting the leakage current of the P-N junction. Compared with ideal model, four-parameter model is more accurate with a small leakage current in the P-N junction. However, high temperatures or low irradiance can reduce model accuracy. Researchers have proposed a more complex double diode model (Cotfas et al., 2013; Babu and Gurjar, 2014) to better accurately depict the current losses in the PV module model as well as to better describe the output characteristics under low irradiance conditions. Although the double-diode model can more accurately describe the output characteristics of PV modules under certain conditions, the additional diode could increase the number of parameters in the equivalent circuit of PV module, which will lead to the increased difficulty in parameter extraction due to complex coupling relationships between parameters. Unlike the four-parameter model, the five-parameter model achieves higher modeling accuracy by introducing a parallel resistance to simulate the leakage current of the P-N junction. Therefore, the five parameter PV model could effectively balance model accuracy and difficulty in extracting model parameters, which has widely implemented.

In recent years, researchers have conducted extensive analyses on the working mechanisms and output characteristics of PV modules. Existing methods can be categorized into analytical and numerical methods. Analytical methods aim to simplify and equivalize the equivalent circuit of PV module to different extents and then analyze the output data from key points on the elementary functions and the I-V curve of PV module to obtain the unknown model parameters. Xiao et al. (2006) established a polynomial relationship between the output current and voltage of a PV module at various load under standard test conditions (STC). Although this analytical method exhibits high accuracy under standard test conditions, the model accuracy is low when weather changes rapidly. Additionally, this method requires collecting a large amount of I-V curve data to achieve a high fitting accuracy, making the data collection process over complicated. Ishaque et al. (2011); Elbaset et al. (2014); Villalva et al. (2009), and other researchers implemented standard product data sheets of PV module to extract model parameters such as open-circuit voltage, short-circuit current, maximum power point voltage, and maximum power point current. Based on open-circuit voltage, short-circuit current, maximum power point voltage, maximum power point current, voltage temperature coefficient, and current temperature coefficient, these methods established a system of equations to solve for unknown model parameters, including the series resistance (R_s) and expressing the photocurrent (I_{ph}), diode reverse saturation current (I_D), and shunt resistance (R_{sh}). However, these kinds of methods cannot take the decay of PV modules into considerations. The models established using this approach can only describe the output characteristics of the modules at the time of manufacturing and do not meet the requirements of practical applications.

Compared to analytical methods, numerical methods require analyzing the entire I-V curve of PV modules. Due to the multimodal nature of the fitness function in parameter extraction problems, intelligent optimization algorithms are widely applied, including Particle Swarm Optimization (PSO) (Soon and Low, 2012), Artificial Bee Swarm Optimization (ABSO) (Askarzadeh and Rezazadeh, 2013; Oliva et al., 2014; Garoudja et al., 2015), Cuckoo Search (CS) (Chakrabarti et al., 2016), Bacterial Foraging Algorithm (BFA) (Asif and Li, 2008; Krishnakumar et al., 2013; Rajasekar et al., 2013; Subudhi and Pradhan, 2018), Genetic Algorithm (GA) (Harrag and Messalti, 2015; Kumar and Shiva, 2019), Differential Evolution (DE) (Ishaque and Salam, 2011; Jiang et al., 2013), and Flower Pollination Algorithm (FPA) (Benkercha et al., 2018; Khursheed et al., 2021). In Ref (Soon and Low, 2012), the particle swarm optimization algorithm was employed, and the concept of inverse barrier constraints was introduced to restrict the parameter search space and thereby enhance the accuracy of parameter identification. Ref (Askarzadeh and Rezazadeh, 2013) proposed an ABSO-based technique for identifying parameters in both single and double diode models. The comparisons between the ABSO-based algorithms and the other algorithms for the single diode model parameter identification indicates that ABSO-based algorithms could achieve a higher parameter extraction accuracy. Ref (Subudhi and Pradhan, 2018) presented a novel approach to extract parameters for PV modules using the Bacterial Foraging Optimization (BFO) technique for optimal determination of parameters (R_s, R_{sh} and n) at both variable temperatures and irradiance level, which is applicable for extracting parameters of various types of PV modules. Ref (Jiang et al., 2013) presented an improved adaptive Differential Evolution (IADE)-based optimization technique to achieve parameter extraction of PV module. By using a simple structure based on the feedback of fitness value in the evolutionary process, it achieves a better extraction accuracy than other popular optimization methods such as particle swarm optimization, genetic algorithm, conventional DE, and simulated annealing (SA). In Khursheed et al. (2021), the improved Firefly Particle Algorithm (Modified FPA) is employed, introducing dynamic switch probability and step size function to enhance the accuracy of parameter estimation for photovoltaic (PV) models. This method utilizes the improved Firefly Particle Algorithm, dynamically adjusting switch probability and step size function to more effectively explore the parameter space, thereby optimizing the parameter estimation of PV models. In summary, the intelligent optimization algorithms can achieve high accuracy in parameter extraction. However, the computational cost is significantly increased due to the updating of particle positions and velocities at each step, leading to slow convergence rates. Some researchers have proposed PV module parameter extraction methods based on artificial intelligence algorithms (Gastli et al., 2015). However, the accuracy of parameter extraction in this algorithm is relatively low. In summary, existing methods for extracting parameters in photovoltaic module models still struggle to balance convergence speed and modeling accuracy.

Since the decay of photovoltaic module has a time-dependent nature, this paper introduces a MIC-LSTM based method for extracting parameters in the single-diode five-parameter PV model. This method enables parameter extraction using experimentally measured current-voltage (I-V) curves of PV modules, which could achieve the parameter extractions under any practical condition. Initially, a dataset with numerous I-V characteristic curves is created by assigning random values to the five parameters of the photovoltaic module model and extracting feature values from the I-V curves. Using these feature values as known input parameters and the five unknown parameters of the photovoltaic module model as output parameters, an LSTM training set is constructed to establish the mapping relationship between I-V curve feature values and the five unknown parameters. To enhance the prediction accuracy and reduce computational complexity, the Maximal Information Coefficient (MIC) is calculated for each of the five parameters with the I-V curve features. Feature values exhibiting high correlation with unknown parameters will be selected as input parameters for the LSTM model, facilitating the precise extraction of the five parameters in the photovoltaic module model.

2 Principle of LSTM-based parameter extraction method for single-diode PV model

2.1 Analysis of photovoltaic model output characteristics based on Newton-Raphson method

Figure 1 shows the one-diode model of a PV module. Due to its effective balance between modeling accuracy and the difficulty of parameter extraction, the single-diode five-parameter model has gained broader application. Its output characteristics are derived based on solid-state physics principles, Ohm's Law, and the equivalent circuit of the physical model of PV modules. Its I-V characteristic equation can be expressed as:

$$I = I_{ph} - I_D\left(\exp\left(\frac{q}{nkT_c}(V + IR_s)\right) - 1\right) - \frac{V + IR_s}{R_{sh}} \tag{1}$$

Where I_{ph} represents the photocurrent of the photovoltaic module, I_D is the reverse saturation current of the diode, Rs is the series resistance, R_{sh} is the parallel resistance, n is the ideality factor of the diode, q is the elementary charge constant (1.602×10^{-19} C), k is the Boltzmann constant (1.3807×10^{-23} J/K), T_c is the temperature of the photovoltaic cell, I is the output current of the photovoltaic module, and V is the output voltage of the photovoltaic module.

In Eq. 1, the photocurrent (I_{ph}), reverse saturation current (I_D), series resistance (R_s), parallel resistance (R_{sh}), and ideality factor of the Shockley diode (n) are five parameters determining the output characteristics of the PV module model. These parameters establish an effective correlation between the output voltage (V) and output current (I) of the PV module and the working temperature, irradiance, device structure, and material characteristics. This correlation provides each component in the equivalent circuit with a clear physical meaning, enabling an intuitive description of the impact of various environmental factors on the output characteristics of the PV module.

In Eq. 1, the complex nonlinearity of the I-V characteristics of the PV module makes it difficult to be solved using traditional algorithms. The Newton-Raphson method, also known as Newton's method, emerges as a crucial approach for finding roots of complex equations. Its fundamental concept involves using the first-order Taylor series expansion of the function to estimate the root iteratively, refining this estimate to converge accurately to the function's root. The computational steps are outlined as follows:

Firstly, expand the function $f(x)$ at the point x_0 using a first-order Taylor series which is expressed by Eq. 2:

$$f(x) = f(x_0) + f'(x_0)(x - x_0) \tag{2}$$

The root of the equation $f(x)$ can be expressed as:

$$f(x_0) + f'(x_0)(x - x_0) = 0 \tag{3}$$

Transforming Eq. 3:

$$x = x_0 - \frac{f(x_0)}{f'(x_0)} \tag{4}$$

Since only a first-order expansion of the function $f(x)$ has been performed, the current value of x is an approximate value of the equation's root. To enhance the accuracy of the solution, further iterative steps are required:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \tag{5}$$

When solving Eq. 1, it is necessary to construct the function for the photovoltaic cell model. By taking the output voltage of the photovoltaic model as a known quantity and the output current as an unknown which is expressed by Eq. 6:

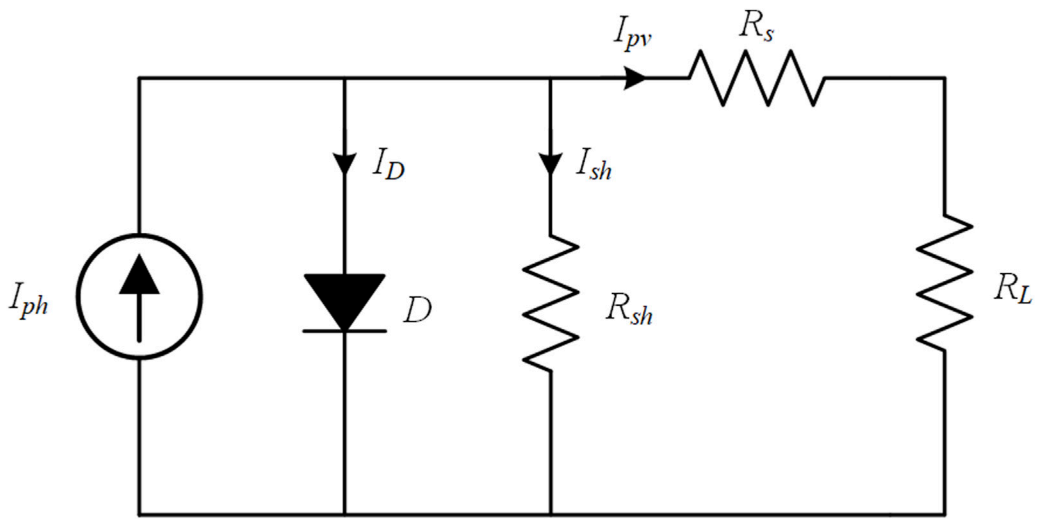

FIGURE 1
Equivalent circuit of single-diode model of PV cell.

$$f(I) = I - I_{\mathrm{ph}} - I_{\mathrm{D}}\left(\exp\left(\frac{q}{nkT_c}(V + IR_s)\right) - 1\right) - \frac{V + IR_s}{R_{\mathrm{sh}}} \tag{6}$$

Taking the derivative of the equation $f(I)$ Eq. 7 can be obtained:

$$f'(I) = 1 + \frac{qIR_s}{nkT_c}\exp\left(\frac{q}{nkT_c}(V + IR_s)\right) + \frac{R_s}{R_{\mathrm{sh}}} \tag{7}$$

Based on Eqs 4, 5, the current value for the (N+1)-th iteration can be expressed by Eq. 8:

$$I_{n+1} = I_n - \frac{f(I_n)}{f'(I_n)} \tag{8}$$

Where I_{n+1} represents the output current value of the photovoltaic cell model at a specific output voltage. The entire I-V curve of the photovoltaic cell model can be obtained by slowly increasing the voltage from zero to the open-circuit voltage.

2.2 Data processing

Due to the extensive numerical variation in the parameters of photovoltaic components, it is essential to normalize these parameters initially to enhance the training accuracy and convergence speed of LSTM. Common normalization methods include min-max normalization, Z-Score normalization. Due to the widespread utilization of the min-max normalization method in neural network systems, this paper applies it to linearly transform the model parameters of PV modules to the range of (0, 1) which is shown in Eq. 9:

$$x = \frac{x - x_{\min}}{x_{\max}} \tag{9}$$

Where x representing the normalized model parameters for photovoltaic module, $x_{\max}$ representing the maximum value within the dataset, and $x_{\min}$ indicating the minimum value within the dataset. By randomly assigning values to the five unknown parameters to the PV model and collecting multiple sets of I-V curves for photovoltaic modules, the feature values of each I-V curve can be captured. Then the data set containing various I-V curves under different decay rate can be constructed.

Sorting the data from numerous I-V curves of PV modules in the dataset based on the magnitude of I_{ph} allows for the characterization of decay RATE, which could arrange the dataset into a time series and be further processed by LSTM. Due to the large number of elements in dataset, the whole dataset is segmented into multiple subsets, where the data segmentation process is shown in Figure 2. For each subset, it contains n I-V curves with similar decay level. The blocks of each I-V curves represent the feature value drawn from each I-V curve. From subset 1 to subset n, the degree of decay increases progressively. Doing so, the degree of decay in each subset will be gradually increased, which can be easier processed by LSTM.

2.3 Data dimensionality reduction based on maximal information coefficient

The I-V curve of a PV module is shown in Figure 3. The short-circuit current and open-circuit voltage are critical characteristics that describe the module's output performance. These parameters are instrumental in deriving unknown values within the PV module. Furthermore, the voltage and current at the maximum power point, along with the slopes of the I-V curve at the short-circuit current, maximum power point and open-circuit voltage, are highly correlated with the module's output characteristics. As a result, they can also be utilized to deduce unknown parameters of the PV module. In summary, each I-V curve encompasses seven feature values, considered as known quantities. Therefore, this paper employs the derivation and computation of five unknown parameters based on seven feature values extracted from experimentally measured I-V curves to achieve precise modeling of photovoltaic modules.

Due to the substantial number of feature values and unknown parameters, along with their interdependence, this paper employs the Maximal Information Coefficient (MIC) to analyze correlations among

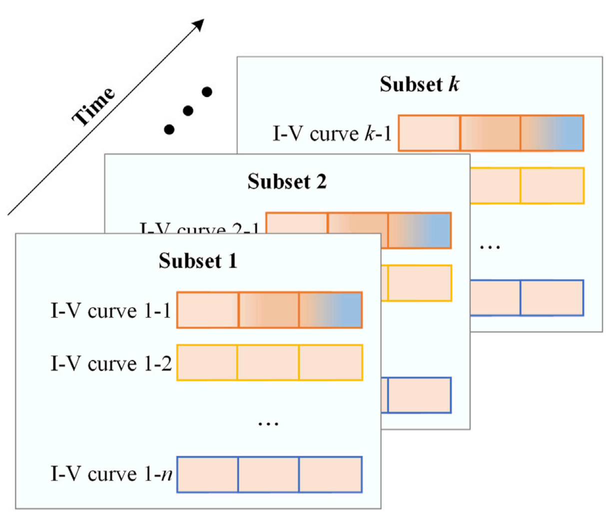

FIGURE 2
Decay-based data segmentation.

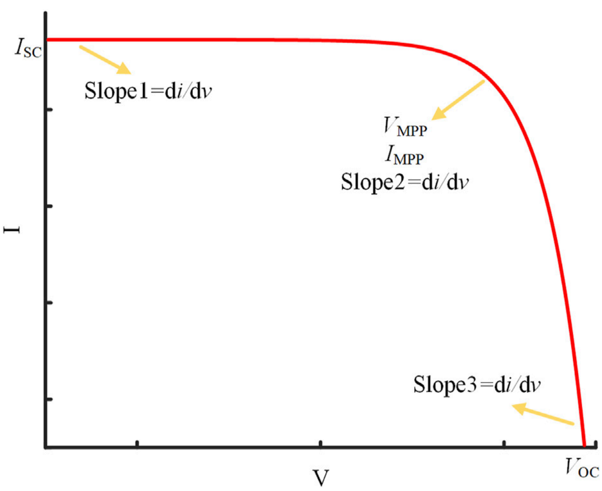

FIGURE 3
I-V characteristic curve of PV module.

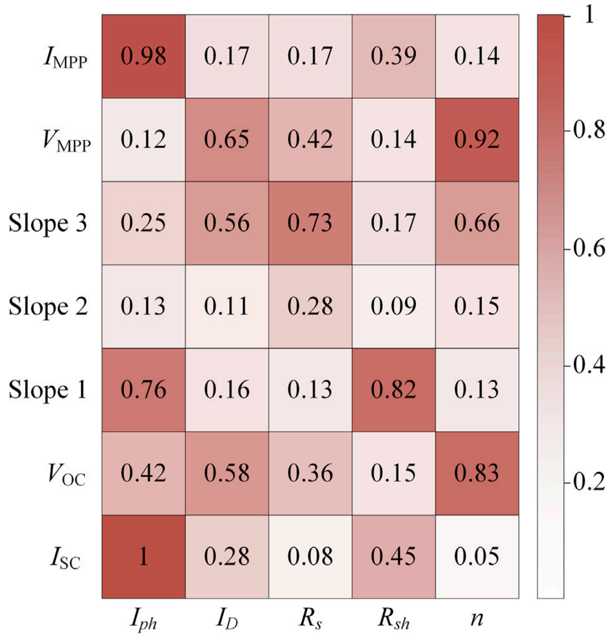

FIGURE 4
MIC analysis results between PV model parameters and feature values.

these parameters. MIC is a statistical measure utilized in data analysis to capture nonlinear dependencies between variables, with the goal of identifying and quantifying associations that may not be adequately described by traditional linear correlation measures. Given the highly nonlinear nature of the five unknown parameters among seven feature values, MIC is particularly suitable for evaluating the correlation level. Only those feature values exhibiting a high correlation with the unknown parameters will be selected as input parameters for the LSTM, facilitating data dimensionality reduction.

The procedure for computing MIC values involves the following steps:

1. Compute mutual information: Apply a specified grid scale to grid the scatter plot formed by two variables. Tally the points within each grid, calculate the joint probability of the two variables, and determine the mutual information (MI) for each grid. Select the maximum mutual information value as the MIC value for the given grid scale.
2. Standardize MIC values: Ensure a consistent range between 0 and 1 by normalizing the MIC values obtained in step 1.
3. Compute the MIC value: Adjust the grid scale from step 1 and repeat the above two steps, the largest MIC value will be the result.

The MI mentioned in step 1 can be expressed by Eq. 10:

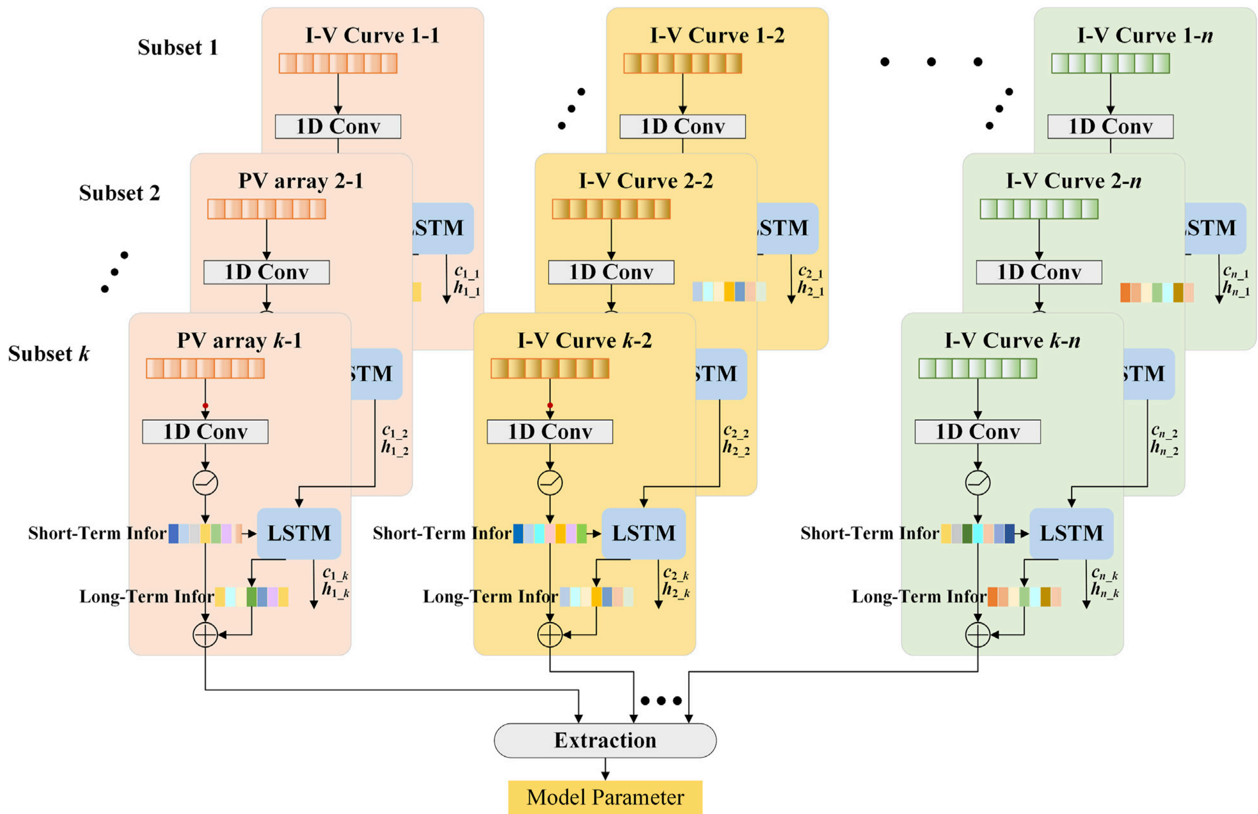

FIGURE 5
LSTM model training.

TABLE 1 MAPE of model parameter extraction by MIC-LSTM, LSTM, and ANN.

Algorithm	I_{ph} (%)	I_D (%)	R_s (%)	R_{sh} (%)	n (%)
MIC-LSTM	0.07	1.61	1.15	2.09	1.64
LSTM	0.17	2.68	1.54	3.80	3.13
ANN	0.15	1.73	1.28	3.97	3.72

$$I(x.y) = \int p(x,y)\log_2\frac{p(x,y)}{p(x)p(y)}dxdy \tag{10}$$

Where x and y represent two variables, p (x, y) represents the joint probability density distribution function of variable x and y, $p(x)$ and $p(y)$ represent the marginal probability density functions of x and y, respectively. The value of MIC can be expressed by Eq. 11:

$$\mathrm{MIC}(x,y) = \max_{a*b<B}\frac{I(x,y)}{\log_2 \min(a,b)} \tag{11}$$

where a and b represent the number of grid divisions in the x and y directions, respectively. B represents a constant, which is normally set to be 0.6 times of the dataset size. The MIC value ranges from 0 to 1. When MIC = 0, it indicates that the two variables are independent of each other. When MIC = 1, it indicates that the two variables are highly dependent of each other. Therefore, the feature values with higher MIC should be chosen as input parameters during LSTM training process.

2.4 Long-short term memory

Long-short term memory (LSTM) networks is a subtype of recurrent neural networks (RNNs). It has become widely recognized for their adeptness in capturing extensive dependencies within sequential data. The basic structure of LSTM is composed by:

Input gate which can be expressed by Eq. 12:

$$i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \tag{12}$$

This equation calculates the input gate activation, where x_t is the input at time t, h_{t-1} is the hidden state from the previous time step, W_{ii} and W_{hi} are input and hidden weight matrices, and b_{ii} and b_{hi} are the corresponding biases. σ represents the sigmoid activation function.

Forget Gate (f_t) which can be expressed by Eq. 13:

$$f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \tag{13}$$

The forget gate activation is computed to determine what information from the previous cell state should be discarded.

Cell State Update (C_t) which can be expressed by Eq. 14:

$$\tilde{C}_t = \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \tag{14}$$

The cell state is updated by combining the previous cell state (C_{t-1}) and the candidate cell state (C_t), with the forget and input gates serving as control mechanisms.

Output Gate (O_t) which can be expressed by Eq. 15:

$$o_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \tag{15}$$

The output gate activation is computed to determine what part of the cell state should be output as the hidden state.

Hidden State (h_t) which can be expressed by Eq. 16:

$$h_t = o_t \odot tanh(C_t) \tag{16}$$

The final hidden state is generated by applying the output gate to the cell state.

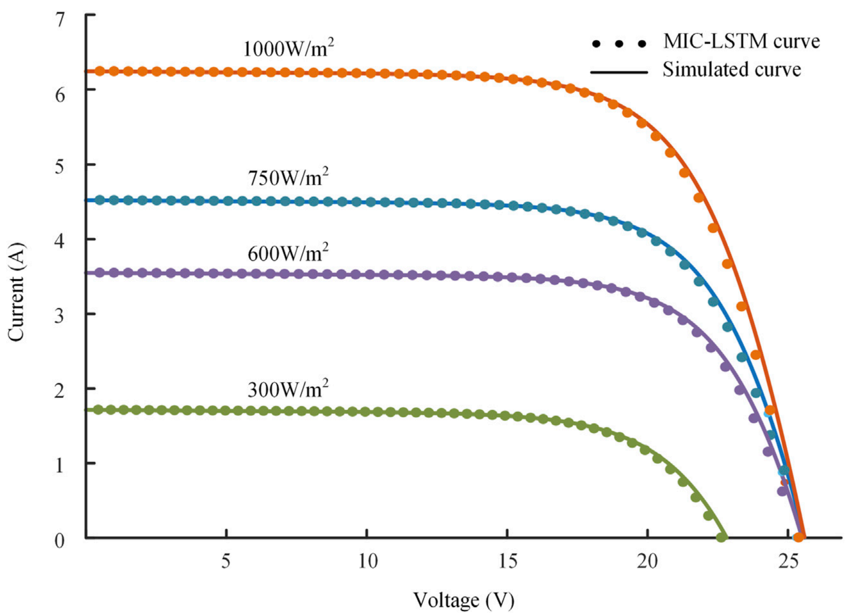

FIGURE 6
IV characteristic curve using MIC-LSTM under different irradiance.

TABLE 2 MAPE of model parameter extraction by MIC-LSTM, LSTM, and ANN.

Parameter	Value
P_{max}	100 W
V_{OC}	21.5 V
I_{SC}	6.27 A
V_{MPP}	18 V
I_{MPP}	5.55 A

The above equations regulate the information flow within an LSTM unit, which enables the network to selectively retain or discard information across multiple time steps and rendering it highly effective in managing sequential data characterized by long-range dependencies.

3 Simulation verifications

3.1 Dataset preprocessing

In this section, a dataset consisting of 10,000 I-V curves has been created. Each subset comprises 5 I-V curves, resulting in a total of 2,000 subsets. Among these, 1,800 subsets serve as the training set, while the remaining 200 subsets are designated as the validation set. Before carrying out LSTM model training, MIC is applied to achieve data dimensionality reduction. Figure 4 illustrates MIC analysis results.

As shown in Figure 4, the ideality factor n is highly correlated with V_{OC}, Slope 3 and V_{MPP} while the MIC value between n and I_{SC}, Slope 1, Slope 2 and I_{MPP} is low. In this paper, the threshold of MIC value is set to be 0.3. Therefore, the input parameters for extracting n should be V_{OC}, Slope 3 and V_{MPP}, which could effectively reduce the data dimensionality.

3.2 LSTM model training

As shown in Figure 4, the ideality factor n is highly correlated with V_{OC}, Slope 3 and V_{MPP} while the MIC value between n and I_{SC}, Slope 1, Slope 2 and I_{MPP} is low. In this paper, the threshold of MIC value is set to be 0.3. Therefore, the input parameters for extracting n should be V_{OC}, Slope 3 and V_{MPP}, which could effectively reduce the data dimensionality.

Figure 5 illustrates the training process of LSTM. Five LSTM models are constructed, where each LSTM model is applied to extract one unknown model parameter. The input data for each LSTM is those feature values whose MIC are larger than 0.3. The I-V Curve feature values in the subsets are extracted using 1-dimensional convolution (1D Conv). The dataset is segmented during data preprocessing, and each segment represents the output characteristics of PV modules for a specific decay level. Consequently, these feature values are classified as Short-term Information. To mitigate the risk of extracting inaccurate model parameter values due to poor data quality, the information from adjacent segments is incorporated as supplementary data. This helps ensure the accuracy and reliability of the extracted model parameters.

The entire dataset is divided into smaller subsets, and the data in adjacent subsets capture the characteristics of the continuous decay of PV modules. To extract the decay characteristics of adjacent data, The long-short term memory (LSTM) algorithm is employed, which is a typical recurrent neural network. LSTM could selectively remember the characteristics of the current moment and transmit them to the next moment through two transmission states: the hidden state (h) and the cell state (c). Consequently, the feature values obtained through LSTM can reflect the characteristics of a more extended period in the past, termed Long-term Information.

In order to verify the parameter extraction accuracy of the proposed algorithm, the parameter extraction accuracy of

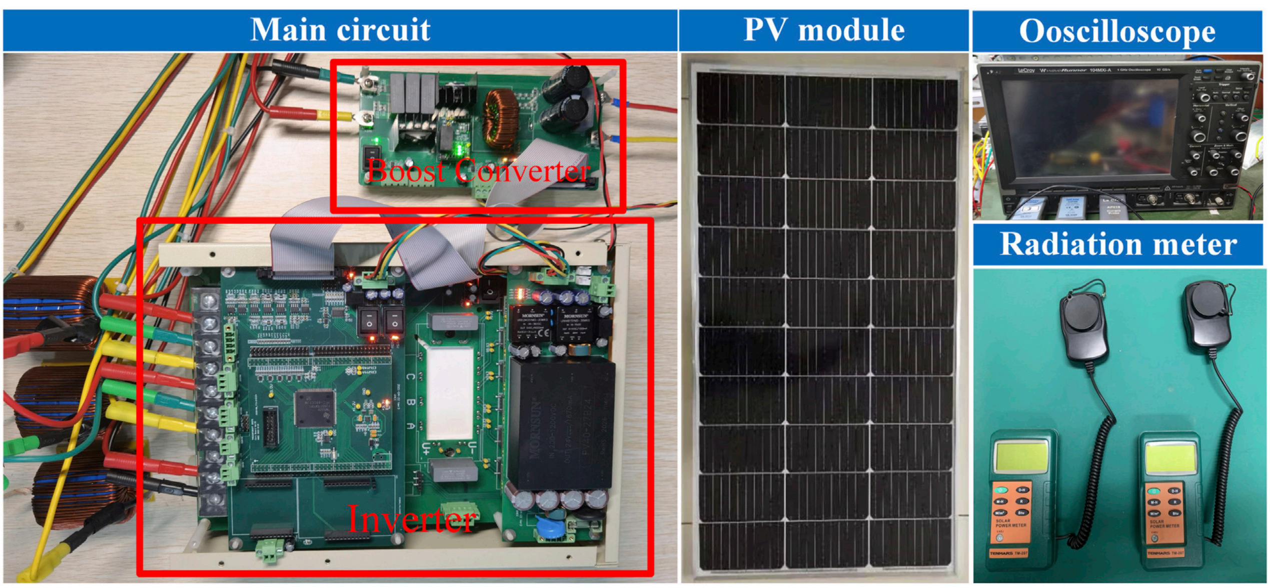

FIGURE 7
Experimental testbed.

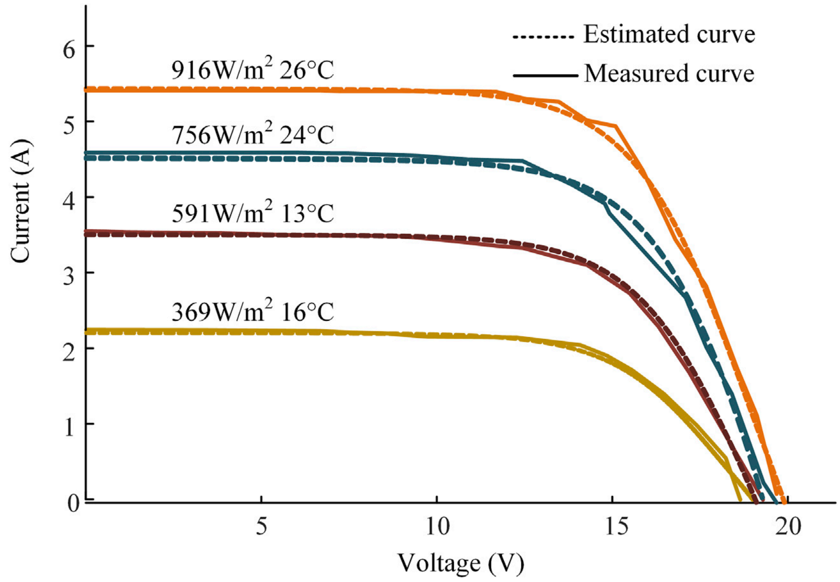

FIGURE 8
Measured and estimated I-V curve of PV module.

traditional LSTM and ANN is also evaluated, which is shown in Table 1. The comparisons indicates that the proposed could achieve a higher model parameter extraction accuracy than other algorithms. The obtained I-V curve based on extracted model parameters under different irradiance is shown in Figure 6.

4 Experimental verifications

For experimental verification of the proposed MIC-LSTM algorithm, the PV module ZY-6M-100 is applied, whose parameters is shown in Table 2.

The experimental testbed is illustrated in Figure 7. The main circuit includes boost converter and inverter, which aims to better simulate the real grid-connected conditions of photovoltaic modules. Two radiation meters are applied to measure the irradiance of PV, module. Firstly, by adjusting the duty ratio of boost converter, the I-V curve of PV, module can be obtained. The feature values of I-V curves, including V_{OC}, I_{SC}, V_{MPP}, I_{MPP}, and di/dt at OC, SC, and MPP., by continuously collecting output data from photovoltaic modules, the feature values at various irradiance levels can be obtained.

Figure 8 shows measured and estimated I-V curve of PV module ZY-6M-100 by applying the proposed MIC-LSTM algorithm under different working conditions. It can be verified that output characteristics of PV model by implementing the proposed MIC-LSTM algorithm could accurately describe the actual I-V characteristics of the PV module under various conditions.

5 Conclusion

In this paper, a novel MIC-LSTM based parameter extraction method for single-diode PV model. With the application of MIC, the dimensionality of the input parameter is reduced, which could effectively exclude the impact of low-correlation inputs on parameter extraction accuracy. With the proposed MIC-LSTM algorithm, the model parameters of PV module can be extracted based on the feature value of its I-V curves, which achieves to construct the accurate PV model at any decay level without large amount of computation. Simulations and experimental verifications were carried out, which validated the feasibility and correctness of proposed MIC-LSTM algorithm.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

XH: Data curation, Supervision, Writing–original draft, Writing–review and editing, Conceptualization, Software, Validation, Visualization. PL: Conceptualization, Data curation, Writing–original draft. YD: Methodology, Writing–review and editing. XM: Validation, Writing–review and editing.

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Conflict of interest

Authors XH, PL, and YD were employed by Ningxia Hongdunzi Coal Ind.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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