

Key Parameter Identification and Optimization of Photovoltaic Power Plants Based on Genetic Algorithm

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Abstract. As the penetration rate of the photovoltaic power continues to grow, its impact on the stability of the power system becomes more considerable ever than before. However, due to the relatively low accuracy of the parameters, the traditional electromagnetic transient simulation used to assess the impact is biased. Therefore, it is of great importance to perform key parameter identification and optimization on a solar power plant containing many photovoltaic panels, which can avoid the problem of combination explosion. In this paper, a scheme of key parameter identification is proposed. Then, an optimization method based on genetic algorithm is also established to improve the accuracy. Simulation tests validate the effectiveness of the proposed method.

1. Introduction

The penetration of photovoltaic (PV) power is increasing rapidly in recent years. However, PV power is different from conventional power sources including thermal and hydro power, in two aspects. Firstly, the generation of PV is intermittent and fluctuating, which depends on the irradiance of the sun. Secondly, PV power plants utilizes a wide range of power electronic devices, making the whole system coupled more intensely. All these characteristics of volatility and uncertainty may impose a strong impact on the secure and stable operation of power systems, and thus bring new challenges. Therefore, it is essential to model and simulate PV power plants to analyse the impact before the integration of them.

It is obvious that the accuracy of the simulation parameters directly affects the outcome of the simulation. Inaccurate parameters will have a negative impact on the calculation and even mislead the determination of the stability. However, the complexity of the electromagnetic transient model and the diversity of integrated power electronic devices suppliers, the parameters of PV cannot be as accurate as conventional synchronous generators. This issue makes the analysis difficult. As a result, it is necessary to carry out key parameter identification for PV power plants.

A series of methods of parameter identification of generators [1] - [5] are proposed. A method of square-root unscented Kalman filter is proposed in [1], where a step-by-step method based on the trajectory sensitivity is presented in [2]. In order to improve the noise tolerance of the identification results, a multi-parameter identification method based on spectral information is established in [3]. Ref [4] - [5] introduce different curve fitting methods to identify multiple parameters respectively. These



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methods are focused on a single generator. In contrast, a series of related works have been done by using the data from Phase Measure Unit (PMU), hybrid simulation method has been successfully applied in parameter identification of synchronous generator model [6] - [8]. Nonetheless, it is difficult to directly apply this method to PV power farms due to complexity of electromagnetic model.

In order to improve the accuracy of simulation model parameters efficiently, a novel solution to key parameter identification of PV power plants based on genetic algorithm is proposed in this paper. Firstly, hybrid simulations using the ideal voltage source method are run under different parameters and given operation point. The deviation between simulation trajectory and wave recorded can be mapped into the distance between two points and it is easy to find out the key parameter. At last, the key parameter is adjusted by optimization method.

The rest of this paper is organized as follows. Section 2 presents the parameter identification and optimization method based on genetic. Then section 3 introduces the model of PV power plant. Section 4 gives out the test results in a real PV power plant. Finally, Section 5 concludes this paper.

2. Problem Description

Parameters are identified through disturbances. To ensure the validity of identified parameters, the simulation should fully consider the interaction between the PV station and the integrated grid. In this paper, two kinds of disturbances are designed as follows:

1) Large disturbances, including: three-phase to ground short circuit fault, single-phase to ground short circuit fault and sharp voltage drop. If these disturbances are not tackled in time, the stability of the grid will be endangered.

2) Small disturbances, including: active/reactive power control, irradiance disturbance and small voltage deviation from the grid side. The state of the system may remain at the original operational point after this type of disturbances.

Hybrid simulation method is used to link simulation results and obtained waveform. In the simulation, different disturbances can be imposed to establish the relationship between indices and parameters. Once these relationships and indices are obtained, the dominance of each parameters will be assessed to identify key parameters, which are important and have major impacts on the waveform indices. Thus they should be optimized to make the estimated waveform fit the original one better. In this way, the accuracy of the simulation is improved.

2.1. Identification of parameter dominance based on PCA

Theoretically, parameters of a large-scale PV station can be identified individually. However, it usually has hundreds of inverters, meaning at least thousands of parameters. So it is very complicated to identify all the parameters by this raw method. Meanwhile, due to the limitation of observability, not all of them can actually be identified. Therefore, some key parameters must be extracted. Parameters with high dominance indicates major impacts on the waveform indices. In this paper, an identification method based on principle component analysis (PCA) is constructed.

PCA is a broadly used data dimension reduction method, which utilizes an orthogonal transformation to convert a set of possibly correlated variables into a set of values of linearly independent variables called principal components (PCs). Each PC is a linear combination of the original variables, and all the principal components are orthogonal to each other. The transformation is defined in such a way that PCs are sorted by their variance in descending order. That is, the first principal component has the largest possible variance, which accounts for as much of the variability in the data as possible, that the second has the second largest possible variance, and so forth. PCA can be implemented by the singular value decomposition (SVD) of a data matrix \mathbf{X} , which is n -by- p , with rows corresponding to n observations and columns to p variables

$$\mathbf{X} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T \quad (1)$$

where $\mathbf{U} \in \mathbb{R}^{n \times n}$ and $\mathbf{V} \in \mathbb{R}^{p \times p}$ are orthogonal matrices, and $\mathbf{\Sigma} \in \mathbb{R}^{n \times p}$ is a diagonal matrix. If only the first r principal components is needed, a truncated transformation is constructed by using only the first

r columns of Σ as (2) and then the n -dimension observations (parameters) can be reduced to r -dimension ones.

According to the results of the PCA, composite indices (CIs) are constructed, because not all indices are equally important. Then by distributing CIs' importance to their member parameters, the dominance of each parameter is identified. Details of the CI construction is available in our previous work [9].

2.2. Optimization of key parameters based on genetic algorithm

The accuracy of the PV model can be improved by parameter optimization after identifying key parameters p_{key} . To this end, waveform-matching indices are constructed to quantitatively depict the difference between simulation results and recorded waveform, according to the aforementioned disturbances. For large disturbances, peak value, time of peak value, and transient time are considered. As for small ones, transient time and increment/decrement after disturbance are analyzed. The weighted index can be constructed as follows

$$f(p_{key}) = \sum_{j=1}^n w_j I_j(p_{key}) \quad (2)$$

where the f is the weighted index, w_j is the weight of the single waveform-matching index I_j . Obviously, f is a function of key parameters p_{key} . The value of w_j depends on the test case.

The process of parameter optimization is regarded as the following minimization problem

$$\min_{p_{key}} f(p_{key}) \quad (3)$$

However, the traditional gradient descent method is not suitable for this optimization, because there is no analytical expression. In this paper, the genetic algorithm (GA) is used to solve this problem. GA is based on the biological evolution process of natural selection, which can find a solution close to the optimal solution by simulating the evolution of the population. In the genetic algorithm, each individual has a set of "genes" that represent a set of parameters. Individuals constitute a population, and the algorithm ends after several generations of the population evolution. In each generation of evolution, individuals in the population are subject to genetic recombination, genetic mutations, and natural selection (survival of the fittest), and the same descendants are produced by naturally selected individuals to form the next generation.

3. Control Model of PV Power Plant

The general model of the PV power station is shown in figure 1, which consists of PV cells, the substation-level control, the active/reactive power control and the PWM inverter control.

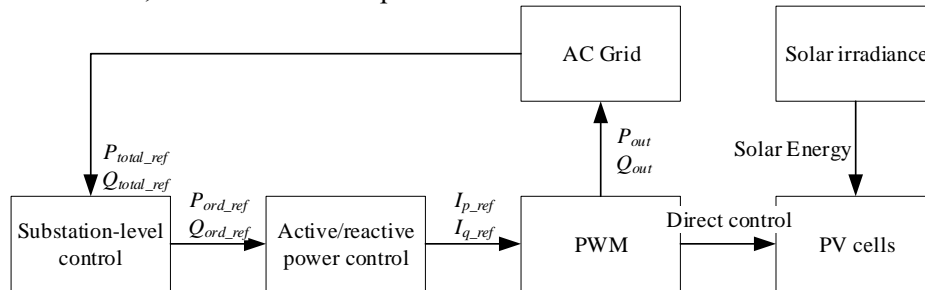


Figure 1. General model of PV power station

3.1. PV cell

The model of PV cell used in this paper considers the intensity of the solar irradiance but ignores the variance of environmental temperature. The maximum of the output of a PV cell is

$$P_m = U_{m_sta} I_{m_sta} \frac{S}{S_{sta}} (1 + b(S - S_{sta})) \quad (4)$$

where S is the solar irradiance, S_{sta} is the rated value, b is the battery material constant.

3.2. Active/reactive power control

The diagram of active/reactive power control is shown in figure 2, which has two loops.

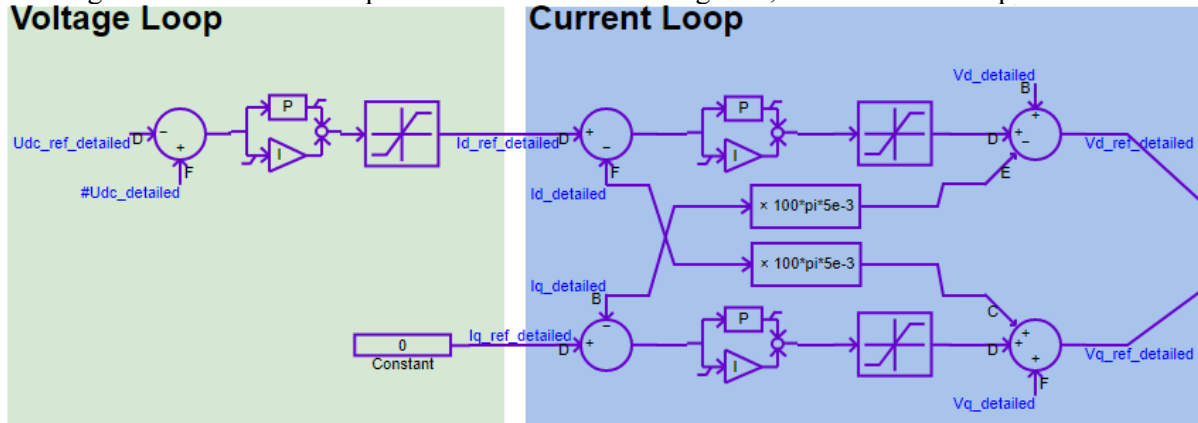


Figure 2. Active/reactive power control

The reference of active and reactive power is converted to that of voltage and current. The active control loop can be configured as the fixed active power control mode or the maximum power tracking mode. The reactive power control loop can be configured as the fixed reactive power control mode, the fixed power factor control mode, or the blocked mode.

3.3. Substation-level control

The substation-level control deals with power distribution, which is used to simulate the response characteristics of the centralized active/reactive control systems of the entire PV station.

3.4. PWM inverter control

The PWM inverter tracks the given current control commands I_{p_ref} and I_{q_ref} by current control loop, and output active and reactive power to power grid.

4. Case Study

4.1. Case setup

A PV station containing an array of 29×3 cells is tested on the platform CloudPSS [12]. In this case, one large and one small disturbances are imposed. The type and time of these disturbances are listed in table 1. The total simulation duration is 6s.

Table 1. Imposed disturbances

Type	Value	Time/s
Voltage drop	1p.u. → 0.8p.u.	1
Output power drop	0.051p.u. → 0.042p.u.	3
Output power rise	0.042p.u. → 0.052p.u.	4.9

According to Section 2.2, there are 7 (3+2+2) waveform-matching indices. Meanwhile, the parameters of PI, amplification limit and gain process are selected as parameters to be identified, denoted as P, L and G.

4.2. Identification of parameter dominance

Perform PCA on the 3-by-7 matrix. Then 3 PCs are obtained. However, they explain different percentage of the total variance of waveform-matching indices, which is shown in figure 3. The first 2 PCs explain more than 99% of the variance. Besides, they both chiefly consist of P and L.

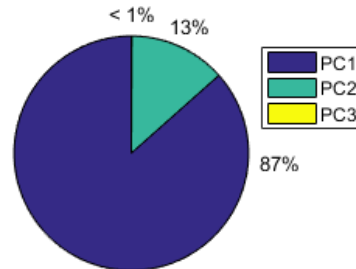


Figure 3. Percentage of total variance explained by each PC

Next, according to the CI proposed in [9], the dominance of P, G and L is identified, as shown in table 2. According to the results, P and L take the most part of dominance. That is, they play a dominant role in affecting the simulated waveform. Therefore, they are key parameters of the PV power station.

Table 2. Parameters and their dominance

Parameter	Dominance/%
P	49.38
L	1.5
G	49.12

4.3. Optimization of key parameters

In this part, a scenario where the parameters of the PV station diverge from their original values is set. The original and actual values are listed in table 3.

Table 3. Divergence of parameters

Parameter	Original value	Actual value
P	5	6
L	0.15	0.2
G	100	200

Since the parameters have varied, the simulated waveform does not match the measured one. The difference is shown in figure 4.

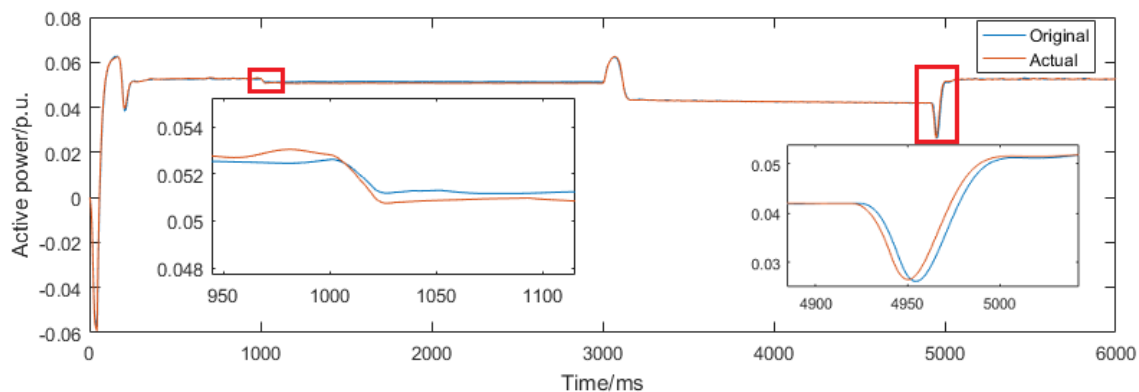


Figure 4. Percentage of total variance explained by each PC

To optimize the parameters, the weighted waveform-matching index is defined as follows

$$f(p_{key,original}) = \sum_{j=1}^7 \sqrt{|I_{j,original}^2 - I_{j,actual}^2|} \quad (5)$$

Then optimization can be performed based on the genetic algorithm. The optimized results are shown in table 4.

Table 4. Optimized parameters

Parameter	Original value	Optimized value	Actual value
P	5	5.98	6
L	0.15	0.18	0.2
G	100	119	120
weighted waveform-matching index f	0.4062	0.3492	

After the optimization, the parameters are nearer to actual values, which validates the feasibility of the proposed scheme. Moreover, because of the low dominance of L, the difference of L between optimized and actual values is the largest.

5. Conclusions

A novel key parameter identification and optimization method for PV power plant based on genetic algorithm is proposed in this paper. Firstly, waveform-matching indices are constructed to quantitatively describe the difference between simulation results and measures. Secondly, parameter identification is modelled as an optimization problem, which is solved by genetic algorithm. Finally, test results of a real PV power plant validate the feasibility of the proposed method.

Acknowledgments

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