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OPINION
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Recent Photovoltaic Cell Parameter Identification Approaches: A Critical Note

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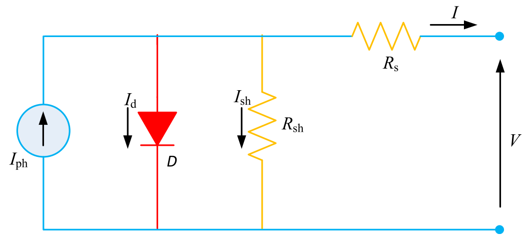
1 INTRODUCTION

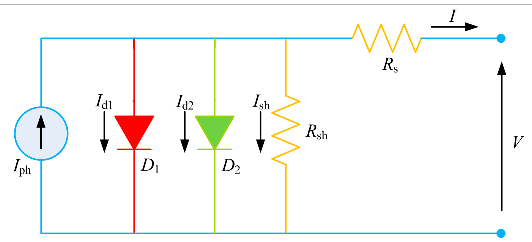
Since the 21st century, the global economy has developed rapidly, global energy resources have been decreasing and environmental problems have become increasingly prominent (Wang et al., 2020). Solar energy has become the most promising renewable energy source due to its abundant resources and wide distribution (Xi et al., 2016). Therefore, the development and utilization of solar photovoltaic technology is one of the important measures to achieve carbon peaking and carbon neutrality (Yang et al., 2020a). In particular, photovoltaic (PV) system has the characteristics of no danger of depletion, no need to consume fuel, high energy quality and short construction period, which has attracted widespread attention around the world (Yang et al., 2020b). However, PV system has highly nonlinear properties. Therefore, in order to achieve accurate modeling of PV systems, it is crucial to improve the accuracy of PV system parameter identification. So far, meta-heuristic-based parameter identification strategies for PV systems have been widely used. However, there are still many challenges to improve the accuracy of PV system parameter identification (Sun and Yang, 2020). In the current published literature, strategies to improve the identification accuracy of PV system parameters have not been fully considered, and the potential risks it brings are worth considering. This paper clarifies the above problems and puts forward some views on the problems existing in the identification of PV system parameters.

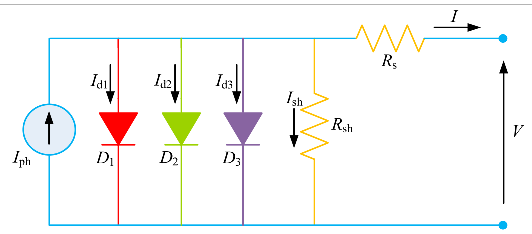
2 BASIC INTRODUCTION OF PHOTOVOLTAIC MODEL TYPES

At present, the accuracy of PV system parameter identification is improved by studying the dynamic behavior and output characteristics of different types of PV cell models under different operating states. So as to achieve accurate performance analysis, optimize design and improve the accuracy of PV system parameter identification. Among them, the most common models of PV cells are single diode model (SDM) (Sun and Yang, 2020; Yang et al., 2020c), double diode model (DDM) (Sun and Yang, 2020) and three diode model (TDM) (Kalyan and Rao, 2021). As can be seen from **Table 1**, the structures of these three PV models are basically similar, and what they have in common is that they all consist of a series resistor, a shunt resistor, and an ideal current source (Liu et al., 2021). In addition, the number of parallel diodes in the photovoltaic cell determines the model of the photovoltaic cell. Among them, the identified parameters of SDM are I_{ph}, I_0, R_{s}, R_{sh}, and a, the identified parameters of DDM are I_{ph}, I_{01}, I_{02}, R_{s}, R_{sh}, a_1, and a_2, and the identified parameters of TDM is I_{ph}, I_{01}, I_{02}, I_{03}, R_{s}, R_{sh}, a_1, a_2, and a_3. It is easy to find that the more complex the structure of PV system, the higher the complexity of modeling (Ma et al., 2014).

TABLE 1 | Three photovoltaic cell types.

<table>
<tr><th>Diode Model</th><th>Model Drawing</th><th>Output I-V Equation</th><th>Identified Parameters</th></tr>
<tr><td>SDM</td><td>


</td><td>$I = I_{ph} - I_0 [\exp(\frac{q(V+IR_s)}{aKT}) - 1] - \frac{V+IR_s}{R_{sh}}$</td><td>$I_{ph}$, I_0, R_s, R_{sh}, and a</td></tr>
<tr><td>DDM</td><td>


</td><td>$I = I_{ph} - I_{01} [\exp(\frac{q(V+IR_s)}{a_1 V_T}) - 1] - I_{02} [\exp(\frac{q(V+IR_s)}{a_2 V_T}) - 1] - \frac{V+IR_s}{R_{sh}}$</td><td>$I_{ph}$, I_{01}, I_{02}, R_s, R_{sh}, a_1, and a_2</td></tr>
<tr><td>TDM</td><td>


</td><td>$I = I_{ph} - I_{01} [\exp(\frac{q(V+IR_{s0}(1+KI))}{a_1 V_T}) - 1] - I_{02} [\exp(\frac{q(V+IR_{s0}(1+KI))}{a_2 V_T}) - 1]$ $-I_{03} [\exp(\frac{q(V+IR_{s0}(1+KI))}{a_3 V_T}) - 1] - \frac{V+IR_{s0}(1+KI)}{R_{sh}}$</td><td>$I_{ph}$, I_{01}, I_{02}, I_{03}, R_s, R_{sh}, a_1, a_2, and a_3</td></tr>
</table>

In addition, **Table 1** provides the identification parameters, model drawing and output I-V equation of the three PV cell models, where K represents the Boltzmann constant; R_{sh} denotes the shunt resistor; I_{sh} represents the current flowing through the shunt resistor; T denotes PV cell operating temperature; and V_T means the thermal voltage, the formula is as follows (Hejri et al., 2014):

$$V_T = \frac{N_s KT}{q} \tag{1}$$

where N_s refers to the number of photovoltaic cells in the photovoltaic panel; q means the electron charge, and $q = 1.6 \times 10^{-19}$C.

Moreover, the advantages of SDM are low circuit structure complexity, simple control structure, easy hardware application, and low cost (Yang et al., 2020d). The disadvantages of SDM are the non-uniform output characteristics of this model, lack of stable performance under partial shading condition (PSC), and low efficiency in replicating accurate I-V curves (Gomes et al., 2017; Qais et al., 2019). Therefore, SDM is the most widely used PV model due to its simple structure and easy application, which is suitable for PV systems that require fast response and low manufacturing cost. In addition, the advantages of DDM are that the fit of the I-V curve is high, satisfactory performance under standard test condition and simple hardware implementation (Rajasekar et al., 2013). The disadvantage of DDM is that the circuit complexity and implementation cost are slightly higher (SudhakarBabu et al., 2016), and it is necessary to ensure the normal operation of the model in a standard test condition (Askarzadeh and Rezazadeh, 2012). Therefore, in practical applications of DDM, the model has strict requirements on environmental changes, and needs to output the I-V characteristics curves accurately at low irradiation levels. Finally, the advantages of TDM are that the I-V curve fits the best among the three PV cell models (Kler et al., 2017), and it can clearly determine the current components of the PV cell (Ayodele et al., 2016). The disadvantage of TDM is that the modeling is complex, the operation and maintenance costs are high, and the hardware implementation is complex (Liu et al., 2020). In particular, TDM can be used to describe the complex physical behavior of polycrystalline silicon solar cells, which is suitable for studying the output I-V characteristics of large-area industrial silicon solar cells.

3 PARAMETER IDENTIFICATION BASED ON META-HEURISTIC ALGORITHMS

Meta-heuristic algorithm is a method inspired by the operating laws of nature or the experience and rules oriented to specific problems (Chen et al., 2018). In addition, Meta-heuristic algorithms have been widely used due to the large amount of computation of Meta-heuristic algorithms, with the development of computer technology (Xiong et al., 2021). In particular, PV system parameter identification is a multi-variable, multi-peak nonlinear function optimization problem. Thus, the Meta-heuristic algorithm has the advantages of improving the calculation accuracy, reducing the amount of calculation, fast convergence, and obtaining high-quality optimal solutions, which can make up for the above shortcomings to a great extent. So far, a variety of meta-heuristic algorithms have been applied to the parameter identification of PV systems (Erdiwansyah and Husin, 2021), e.g., biogeography based optimization (BBO) (Padhy and Panda, 2021), improved antlion optimizer (IAIO) algorithm (Muniappan, 2021), artificial bee swarm optimization (ABSO) (Niu et al., 2014a), bird mating optimization (BMO) algorithm (Wu et al., 2017), flower pollination algorithm (FPA) (Askarzadeh and Rezazadeh, 2013a), artificial immune system (AIS) algorithm (Askarzadeh and Rezazadeh, 2013b), Lozi map-based chaotic optimization algorithm (LCOA) (Alam et al., 2015).

In addition, the currently used meta-heuristic algorithms still have some shortcomings in terms of operation time and convergence accuracy, and are prone to fall into local optimum (Diabat et al., 2013). Therefore, a series of improved meta-heuristics are proposed to avoid getting stuck in local optimization and improve the convergence accuracy (Pourmousa et al., 2019). References (Muniappan, 2021), (Muhsen et al., 2015) developed an antlion optimizer (ALO) algorithm imitates the intelligent behavior of ants when hunting ants in nature, avoids local optima, and requires fewer control parameters with simplicity (Moshksar and Ghanbari, 2017). In addition, in order to improve the search efficiency of the algorithm and avoid premature convergence, an improved antlion optimizer (IAIO) algorithm was proposed (Silva et al., 2016). Compared with the original ALO algorithm, the chaotic sequence and position update formula of the particle swarm algorithm are introduced into the ant-lion optimization algorithm (Zagrouba et al., 2010). In work (Askarzadeh and Rezazadeh, 2013a), (Thanh and Pora, 2016) studied a flower pollination algorithm (FPA) mainly imitates the pollination process of flowers in nature, and iteratively executes the two operators of cross-pollination and self-pollination until the convergence conditions are met (Zagrouba et al., 2010). However, there are problems such as poor local depth search ability, slow convergence in the later stage, and low optimization accuracy. In order to solve the above problems, a new hybrid bee pollinator FPA (BPFPA) was proposed in the literature (Dizqah et al., 2014). The unique crossover between bee search algorithms, resulting in randomness to control variables, and the mutation process in local search add greater search capabilities to the BFFPA (Fathy and Rezk, 2017). References (Ismail et al., 2013), (Patel et al., 2014) adopted the teaching-learning-based optimization (TLBO) is a population-based heuristic random group intelligent algorithm (Niu et al., 2014b). Compared with other algorithms, the main advantages of the teaching optimization algorithm lie in the advantages of simple concept, small amount of hyperparameters, and fast convergence, but the initial solution set will change during the search process, and the population diversity cannot be well maintained. It will lead to unstable results and insufficient global search ability (Kumari and Geethanjali, 2017). Therefore, an improved TLBO (STLBO) algorithm (Muhsenab et al., 2015) is proposed to address the above problems. A semi-exponential step size (SESS) is adopted in STLBO, which focuses on small λ, which improves the optimization ability of the algorithm.

However, the meta-heuristic algorithm has certain defects, because the optimal solution will be affected by the number of iterations and the number of populations, so it has a certain randomness (Muangkote et al., 2019). Therefore, artificial neural network (ANN) can be considered to improve the accuracy of PV system parameter identification. In particular, there are many types of artificial neural networks. For example, Bayesian regularized neural network (BRNN), deep belief network (DBN), hidden semi-Mark model (HSMM) and Levenberg-Marquardt backpropagation (LMBP) algorithm have been successfully used to improve the parameter identification accuracy of fuel cells (Han and Ghadimi, 2022). Besides, it is necessary to fully consider the influence of noise in the experimental environment on the experimental data. The influence of noise data on the accuracy of parameter identification is unavoidable, which will greatly reduce the convergence accuracy. Therefore, it is possible to take full advantage of the combination of neural network and meta-heuristic algorithm. In addition, BRNN can be used to denoise the experimental data, and by filtering the noise data in the experimental data, the phenomenon of overfitting can be effectively prevented. Then, the processed experimental data is substituted into the meta-heuristic algorithm for optimization calculation, and finally the accurate modeling of the PV system is realized, thereby improving the parameter identification accuracy of the PV system. In addition, the influence of the temperature and pressure of the experimental environment on the parameter identification accuracy should also be considered in the parameter identification of the photovoltaic system. Therefore, the experimental temperature and pressure can be classified and studied, e.g., 1) low pressure high temperature (LPHT), 2) medium pressure medium temperature (MPMT) and 3) high pressure low temperature (HPLT), making the experimental results more convincing.

4 DISCUSSION AND CONCLUSION

In order to analyze and study the power generation efficiency of the PV system more accurately, it is necessary to accurately model the system to facilitate the study. In particular, parameter identification is required to process related parameters when modeling the PV system. Therefore, the accuracy of parameter identification directly affects the accurate modeling of the PV system. At present, there are still some problems in the convergence accuracy and practicability of the meta-heuristic algorithm widely used in parameter identification, as follows:

Only using the meta-heuristic algorithm will cause the optimization results to be highly random and prone to overfitting. And the convergence speed and accuracy of such algorithms are greatly affected by the amount of experimental data. Therefore, the artificial neural network can be considered in the parameter identification, and the experimental data can be expanded through the artificial neural network training data. In addition, when acquiring experimental data, noise data will inevitably be generated, which will affect the accuracy of parameter identification. Therefore, by combining artificial neural network and meta-heuristic algorithm, a neural network model with good generalization ability can be established first, the experimental data can be denoised, and then the processed data can be substituted into the meta-heuristic algorithm for searching. Optimized processing, thereby improving the parameter identification accuracy of the PV system. At the same time, similar to the parameter identification of fuel cells, the influence of different temperatures and pressures on the accuracy of parameter identification under experimental conditions can be fully considered. Therefore, the next task for the researchers involved is to test the feasibility of the proposed ideas in practice.

AUTHOR CONTRIBUTIONS

DL: writing the original draft and editing. BY: conceptualization. LL: visualization and contributed to the discussion of the topic. QL: investigation, validation. JD: writing-reviewing and editing. CG: revised the draft according to the others' comments.

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