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A REVIEW ON OPTIMIZATION TACTICS FOR RESTRICTION VALUATION & MAXIMUM POWER POINT TRACKING (MPPT) OF PHOTOVOLTAIC SYSTEMS THROUGH ARTIFICIAL INTELLIGENCE.

Meghana Mishra[1]

Research Scholar, Department of Electrical Engineering, SKU Chhatarpur[1], M.P. India

Abstract

PV power systems are electrical power systems energized by PV modules or cells. This thesis starts with the introduction of PV modeling methods, on which our re- search is based. Parameter estimation is used to extract the parameters of the PV models characterizing the utilized PV devices. To improve efficiency and accuracy, we proposed sequential Cuckoo Search (CS) and Parallel Particle Swarm Optimization (PPSO) methods to extract the parameters for different PV electrical models. Simu- lation results show the CS has a faster convergence rate than the traditional Genetic Algorithm (GA), Pattern Search (PS) and Particle Swarm Optimization (PSO) in se- quential processing. The PPSO, with an accurate estimation capability, can reduce at least 50% of the elapsed time for an Intel i7 quad-core processor.

Keywords: - Artificial intelligence (AI), Bio-inspired (BI), Classical techniques MPPT techniques, Photovoltaic (PV), Renewable energy resources

Introduction

This chapter first presents the background and motivation of the thesis work, which is followed by this project's aims and objectives. We highlight the main contributions on the topic of the application of artificial intelligence algorithms to parameter estimation and maximum power point tracking methods. A conclusion and future work of the thesis are provided at the end of the chapter.

Literature Review

The primary purpose of this chapter is to review the studies on PV parameter esti- mation and Maximum Power Point Tracking (MPPT) methods with respect to their motivation and strategies. To this end, this chapter first introduces the most widely used electrical models for Photovoltaic (PV) devices which our research is based on. It then proceeds to present the state and progress of the current literature on the related work documented in this thesis.

Part of the content of this chapter has been published in the following review paper:

Jieming Ma, Ka Lok Man, Tiew On Ting, Hyunshin Lee, Taikyeong Jeong, Jong- Kug Sean, Sheng-Uei Guan, and Prudence W. H. Wong, Insight of Direct Search Methods and Module-Integrated Algorithms for MPPT of Stand-Alone Photo- voltaic Systems, Lecture Notes in Computer Science (LNCS2012), vol. 7513, pp. 468-476, 2012.

A Review of Modeling Methods for Photovoltaic (PV) Cells

Although PV module prices fell by 74% from 1995 to 2011 [20], the initial cost of a PV system is still relatively high. An accurate assessment of the electrical character- istics is therefore indispensable in the system design [21]. PV manufacturers usually provide typical electrical characteristics of their PV modules, such as the current at Maximum Power Point (MPP) Imp, the voltage at the MPP Vmp, the power at MPP Pmax, the open-circuit voltage Voc and short-circuit current Isc. These values are generally measured at the Standard Test Conditions (STCs) which correspond to a module temperature of 25 and an irradiance of 1000 W/m2 at 1.5 air mass spectral distribu- tions. The current and voltage (I-V) characteristic curves under several different test conditions may also be presented by manufactures. Despite this, the data available in manufactures' data sheet are still limited and usually cannot fulfill the engineering requirements because PV modules always operate under environments far from these test conditions.

Any PV device can be modeled using the equivalent circuit models [22]. These electrical models, with the ability to predict I-V characteristics of a PV cell or module under the working environment other than STCs, are predictive performance tools that allow PV system designers to understand, optimize, and develop PV power generation systems. They are broadly applied to estimate whether a PV power generation

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sys- tem is economically feasible. Recently, many MPPT techniques have been proposed to overcome the problems caused by partial shading conditions and rapidly changing environmental conditions [7, 10, 11, 23, 24]. For instance, Chen et al. [10] utilized model-based Particle Swam Optimization (PSO) to search the Global Maximum Power Point (GMPP). In [25, 26], the PV array was adaptively reconfigured by a control algorithm integrated with emulated PV module models. These methods have high-lighted the need for a reliable PV electrical model with high accuracy but very complex.

Significant research efforts have been made to develop electrical models of PV systems [27]. These models include analytical models based on PV cell physics, empirical models, and a combination of these two approaches [22]. Their mathematical expres- sions formulate the terminal current I with the most crucial technical characteristics and environment variables, such as terminal voltage V , the ambient temperature T , and the irradiance G. Even though the other environment factors (e.g. dust and wind velocity) may change the electrical characteristics of PV modules, it is quite impossible to obtain a model that accounts for every single effect on the performance of a PV model [28]. Among numerous modeling approaches, the Ideal Single-Diode (ISD) model achieves the lowest computational complexity. The Single-Diode (SD) model is usually considered to offer a good compromise between simplicity and accuracy [29]. In con- sideration of the recombination loss in the depletion region, Sah [30] introduced a more accurate model known as Double-Diode (DD) model. The Three-Diode (TD) model can be found in [31]. Although it takes into account the influence of grain boundaries and leakage current through the peripheries, the extra diode increases the number of

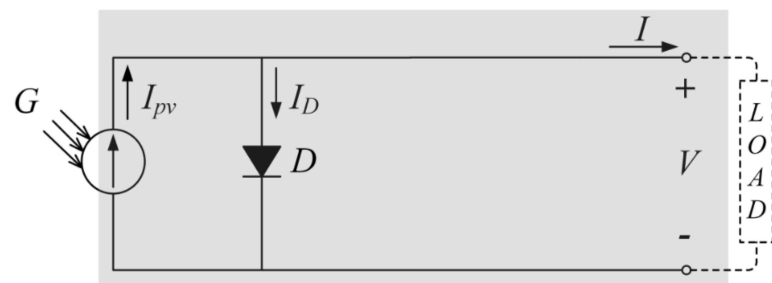

Figure 2.1: Electrical diagram of the ideal single-diode model.

parameters. Accordingly, more computational effort is needed to predict the electrical characteristics via a TD model. In the next three subsections we will present through a variety of PV electrical models, including the ISD model, SD model and DD model. Since the TD model has complex non-linear analytical expressions and not suitable for fast computation, it is not studied in this thesis.

Research on Parameter Estimation for PV Electrical Models

As discussed in the previews section, PV electrical models involve a series of parameters. These models cannot be directly used because of lack of proper model parameters characterizing the PV cells. Parameter estimation is a discipline that provides tools for estimating constants appearing in the model [53]. With the parameters obtained in such a way, the difference between the simulated and experimental data can be minimized.

In the literature [54, 55], conventional parameter estimation methods are classified into two categories:

Analytical techniques [56–60];

Numerical extraction techniques [16, 61–65].

Analytical Techniques

An analytical technique utilizes mathematical equations to describe the parameters of PV electrical models. There is much research on addressing the parameter estimation problem by analytical expressions in terms of the physical parameters, such as the coefficient of diffusion of electrons in the semiconductor, lifetime of minority carriers, the intrinsic carrier density, etc. [31]. However, the values of these physical parameters are normally not provided by manufacturers, which impels researchers to explore an alternative way of formulating the parameters by using the information available in datasheet (e.g. short circuit current coefficient Ki, open circuit voltage coefficient Kv, Isc, Voc, Vmp, Imp, etc.). In [21], the Iph is stated in relations of a linear meaning as:

$$I_{ph} = (I_{phn} + K_i \Delta T) \frac{G}{G}, \quad (2.12)$$

where Iphn, Gn, and Tn are used to denote the photocurrent, solar irradiance, and cell temperature measured at the STCs, respectively. ΔT is the difference between T and Tn.

Based on the diode theory, Messenger and Ventre [2] presented an approximate linear expression for the diode saturation current Io1 , which can be expressed as Based on the diode theory, Messenger and Ventre [2] presented an approximate linear expression for the diode saturation current Io1 , which can be expressed as

$$I_o1 = I_{on}1 \frac{T}{T_n} e^{[(qE_g/A_1k)(1/T_n - 1/T)]}, \quad (2.13)$$

where Eg is the material band gap. Usually, Eg is set at a reasonable level depending on the semiconductor materials (Eg = 1.12 eV for the polycrystalline Si at 25) in simulation and design tools [66]. De Soto et al. [58] accessible an guesstimate method for Eg in a varied temperature range:

$$E_g = E_{gn}(1 - 0.0002677\Delta T), \quad (2.14)$$

where Egn is a normal value at the STCs (Egn = 1.12 eV for silicon cells and Egn = 1.6 eV for the triple intersection nebulous cells).

The value of ideality factor is empirical. Numerous authors discussed the means of estimating the correct value of this constant [29, 67]. For simplicity, the A1 can be assumed to be independent of temperature and set the value in the range 1 $\leq A_1 \leq 2$[21].

A large number of analytical methods have been applied to determine the values of Rs and Rp over the years. In [28], mathematical formulas are derived to predict Rs and Rp. However, the slopes at the open-circuit and short-circuit points are not usually given in I-V datasheets. Iterative process was proposed in [21] and [50] based on several analytical conditions. This approach may obtain lower absolute error, not at the expense of increased computation complexity. Considering the fact that Rs and Rp vary in almost inverse linear mode with the solar irradiance, Brano [50] demonstrated an improved expression for the series and shunt resistances:

$$R_s = \frac{Gn}{G} R_{sn}, \quad R_p = \frac{Gn}{G} R_{pn} \quad (2.15)$$

where the values of the resistances Rsn and Rpn are evaluated under the STCs. By using the aforementioned relations, the model is able to analytically describe the I-V characteristics of a PV generator for each generic condition of operative temperature and solar irradiance [58].

The analytical techniques conclude approximate relations with the experimental data. Though modest, they are mostly reliant on on the key points on the I-V curve.

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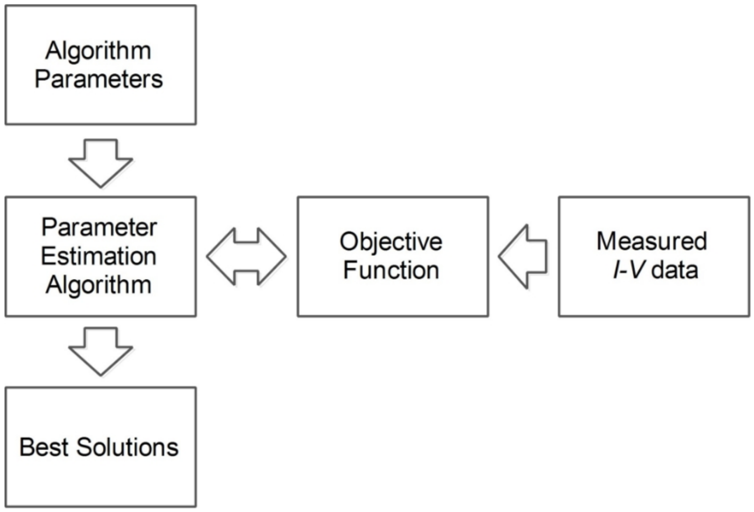

Figure 2.4: Block diagram of the restriction evaluation method for PV electrical models.

The blunders can be momentous & cannot be extra amended if these key points are mistakenly specified.

Numerical Techniques

Assisted by a statistical method, numerical extraction techniques fit a great many operating points on the *I-V curves* to obtain a more accurate solution [61–63, 65]. These curve fitting methods minimize the Root Mean Square (RMS) error ε *given* in [28] as:

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{d=1}^{N}\left(I_d - \hat{I}_d\right)^2} \qquad (2.16)$$

where d (d = 1, 2, ..., N) is the number of measured I-V data. The simulated and measured data are denoted by Id and Id, respectively.
The numerical abstraction practices are normally measured as accurate tactics in parameter assessment since all the unrushed data can be used in calculation. How- ever, it is axiomatic that their performance is also related to the type of fitting al- gorithm, the cost function as well as the initial values of the parameters to be ex- tracted [61]. The non-linear curve-fitting procedures are quite complicated both math- ematically and in terms of computer code [68]. Additionally, the systems can be com- putationally exclusive as the size of essential data is greatly large.

Evolutionary Algorithm Techniques

Evolutionary Algorithm (EA) techniques are very efficient in optimizing real-valued multi-modal objective functions [12, 13, 69, 70]. To date, Genetic Algorithm (GA) [18], Particle Swarm Optimization (PSO) [17, 71, 72], Bacterial Foraging Algorithm (BFA) [73], Simulated Annealing (SA) [74] , Pattern Search [19], Differential Evolution [75,76] have been hired for assessing parameters of several PV electrical models due to their capacity to handle non-linear roles without needing derivatives information. PV parameter estimation is basically a process that minimizes the difference be- tween the calculated and measured data by adjusting the normal PV parameters [77]. Figure 2.4 shows the flow diagram of a typical parameter estimation process for PV devices. After importing several constants or parameters, the parameter estimation algorithm starts evaluating possible solutions by using the objective function with the measured I-V data. In general, the objective function is formulated by the RMS er- ror which serves to aggregate absolute differences into a single measure of predictive power. If the number of experimental data is denoted by N , the RMS error can be mathematically formulated as the following equation:

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{d=1}^{N}(f_d(\hat{V},\hat{I},\mathbf{X}))^2}, \tag{2.17}$$

where $\hat{V}$ and $\hat{I}$ denote the measured voltage and current, respectively. $f_d(x)$ is the objective function for the d^{th} data. $\mathbf{X}$ is a path representing the classical parameters.Take the SDC model for example. $f_d(V, I, \mathbf{X})$ is a homogeneous form of Equation (2.5), namely:

$$f_d(\hat{V},\hat{I},\mathbf{X})_{SD} = I_{ph} - I_{o1}\left(e^{\frac{\hat{V}+\hat{I}R_S}{A_1V_t}} - 1\right) - \frac{\hat{V}+\hat{I}R_S}{R} - \hat{I}. \tag{2.18}$$

In the above equation, X is a vector involving the model parameters Iph, Io1 , A1, Rs, and Rp.

The EA techniques may obtain the most accurate solution compared with the other methods if their initial points and algorithm parameters are set properly. On the other hand, most of these methods apply multiple agents or particles in random search and do not provide a significant improvement in computational efficiency. Taking into account the fact that extraction is the main component of a PV system simulator, the overall simulation speed would be greatly compromised [75].

Research on Maximum Power Point Tracking (MPPT) Methods

In a P -V characteristic curve of PV cells or modules, there exists only operating point where the power is maximum. This point is known as the MPP. As shown in Figure 2.5, the MPP locus, denoted by circles, varies with different atmospheric conditions.

Figure 2.5: Electrical characteristic curves of a MSX60 PV module under different atmospheric conditions: (a) I-V curves under various irradiance levels; (b) P -V curves under various irradiance levels; (c) I-V curves under various temperatures; (d) P -V curves under various temperatures.

PV modules are usually connected in series to scale up the voltage because their open circuit voltage is independent of the module area and is limited by the semicon- ductor properties [33]. In an outdoor environment, the whole or some parts of the PV array may be under a non-uniform irradiance condition caused by passing clouds, high buildings, trees, etc. In this case, the series connected PV array is in open circuit, which is known as "hot spot" [33]. To dodge this problem, sidestep diodes are customarily sited

Conclusions

The Cuckoo Search (CS) algorithm has been applied to estimate the parameters for PV electrical models. The CS algorithm is based on the cuckoo breeding behavior. Instead of conventional isotropic random walks, the algorithm uses Lévy flights. The simulation results showed that CS algorithm outperforms Genetic Algorithm (GA) [18], Chaos Particle Swarm Algorithm (CPSO) [17], and Pattern Search (PS) [74] methods. At a certain irradiance level, the CS obtained slightly lower RMSE for model parameters, recording 0.0010 in numerical value, and its convergence speed was slightly faster than the CPSO. Moreover, the validity of the CS algorithm was evaluated using KC200GT PV module operating under different environmental conditions. In statistical analysis, the CS algorithm recorded the lowest RMSE value compared with other algorithms such as the GA, CPSO andPS.

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