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Systematic cross-validation of photovoltaic energy yield models for dynamic environmental conditions

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ABSTRACT

The continuous growth of photovoltaic installations globally carries hope for a sustainable future but also imposes challenges on all levels of energy production and distribution. Grid operators and designers have to cooperate more closely with monitoring service providers in order to sustain a flexible scheme of energy exchange. The basis of these calculations is accurate energy yield estimation models, which are able to capture all effects of the environment. Especially for locations with highly dynamic irradiance and environmental conditions, this remains a tough challenge. All photovoltaic energy yield models presented in this work aim at accommodating the inherent dynamism of these challenging locations at small time scales. A detailed, physics based electro-thermal energy yield model is validated along with other state-of-the-art models and performs 25% more accurately. Additionally, the results from the dynamic modeling are transferred to a neural network model, increasing the accuracy further up to six times better than any parametric solution.

1. Introduction

The continuous growth of the photovoltaic energy sector, with high percentages of penetration in the grid, has created new challenges for operators of installations and distribution grid (Masson et al., 2014). The diverse scale of the installations, as well as the differences in spatial distribution, necessitates novel, modular solutions for the monitoring and control process in the form of simulation tools.

State-of-the-art PV models for energy estimation either make use of black box methods or parametric equations (Bizzarri et al., 2013; Ceylan et al., 2014; King et al., 2004). Especially the thermal part is simplified as the effects average out for coarse time resolutions, usually bigger than 15 minutes. No internal state is kept for the thermal system of the PV, leading to steady–state assumptions. Also the wind effects usually are treated as secondary, and wind direction is considered to have no significant contribution due to the high variance. Consequently, those modeling approaches are not able to calculate energy yield accurately during highly-varying irradiance or environmental conditions.

The purposes of this work are threefold: first present a thorough validation of a detailed dynamic PV model, with tight coupling between the thermal and electrical part and its capabilities, including the cross validation with recognized PV models. Second to underline the important aspects of thermal modeling for high temporal resolution models and their effect on the overall accuracy of energy yield calculations. Sources of error are recognized and solutions are proposed, in order to improve the behavior of dynamic models. Thirdly, to explore alternative configurations for neural network models and utilize the insights from the dynamic modeling in order to improve their performance.

The following sections are organized as follows: In Section 2 the state-of-the-art in energy yield modeling is explored and the motivation behind this work is developed. All the utilized methods, along with the monitored installation are defined in Section 3. The main contributions are presented in Section 4, with the analysis of the results and the recommendations for energy yield modeling.

2. Motivation

Current state-of-the-art PV energy production models can be categorized based on their intended usage as well as the implemented method. In the first case, models intended for operational

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planning or energy trading are based on parametric equations and black-box fitting tools. The temporal resolution of these models ranges from hourly to daily, therefore no dynamic effects are incorporated. Examples of such models can be identified in commercial software (e.g. PVSyst) and established open-source models (King et al., 2004). The power of these models is the speed in which they can produce fairly accurate energy production results for a given installation, given the right input. But as the PV sector expands from utility scale installations to building integrated photovoltaics (BIPV), smart grid interactions with detailed forecasting and advanced energy storage systems, the need for models that can operate on a large range of spatial and temporal resolutions is becoming more prevalent.

A major challenge lies in the thermal dynamics of the PV module, which are considered by the aforementioned class of models to be in a steady state for the purposes of hourly simulations. But as the time resolution approaches minutely or even sub-minutely scales, the dynamics of the system and therefore the calculation of the correct operating temperature become non-trivial, as already presented in (Goverde et al., 2015a). Therefore a different class of models has started to gain research interest; dynamic PV models (Bizzarri et al., 2013; Torres-Lobera and Valkealahti, 2014; Alam et al., 2015; Chopde et al., 2016). These models utilize either equivalent RC networks or state-space equations to represent the thermal properties of the module. Mostly based on previous works from (Tina, 2010; Armstrong and Hurley, 2010) these works fail to present models that can accurately traverse the temporal-spatial necessities of recent applications, usually stopping at a time resolutions of 15 min.

In contrast, this work presents the cross-validation of a coupled optical-thermo-electrical PV model versus several of the aforementioned models and outdoor measurements from a monitored installation. The term cross-validation is used in this work to describe the process of validating each model separately and then in comparison with the rest, therefore it should not be mistaken for the statistical term describing validation through re-sampling. The proposed model is fully dynamic and scalable, being suitable for simulations of a single module with a cell detail (Anagnostos et al., 2014; Goverde et al., 2015a), to even medium-size installations with many strings (Anagnostos et al., 2016). This analysis enables the recognition of the sources of errors for each class of models as well as providing solutions to mitigate these inaccuracies.

In conjunction with the produced results, additional models are trained based on neural networks. Information from the electro-thermal model is used in order to optimize the networks and achieve significant improvements in accuracy.

Summarizing the main contributions of this work, these are:

- Extensive cross-validation of different energy yield estimation models, including a novel dynamic model.
- Identification of the main sources of inaccuracy in the modeling process and ways to mitigate them.
- Development of Neural Network models with insights from the dynamic modeling in order to improve their performance.
- Exploration of a hybrid scheme for Neural Networks with utilization of relevant thermal information with the purpose of simplifying the training purpose while preserving accuracy.

3. Validation method description

This work incorporates several different models, as well as validation of the simulations with a monitored installation. The purpose of this section is to provide all the relevant details about the installation and the models used for the cross-validation.

3.1. Installation

A test-site has been operational on the rooftop of the University of Oldenburg, Germany since February 2014 with minimal interruptions, under the supervision of the Solar Energy Meteorology lab.[1] Environmental data is recorded with a frequency of 1 Hz through dedicated data loggers and stored in a server. Irradiation (global, diffuse, POA) is measured with Kipp & Zonen CM11 pyranometers, while a weather station next to the installation logs ambient temperature and wind speed and direction at 10 m above ground. The monitored module is a BP Solar 7180S 180 Wp module (Fig. 1), connected to a MPPT 3000 tracker (Chianese et al., 2008) with a resistive load, installed at 45° due South. The tracker logs voltage and current also at a 1 Hz frequency with a 2% relative accuracy. The temperature at the back surface of the module is measured by PT100 sensors at three different locations (center and top corners). All monitoring activity follows a best practice guide (Richter et al., 2015) in order to ensure the quality of the logged information.

The data used in this work corresponds to the period of April to October 2014, with only 4 days removed due to logging problems. The average POA irradiation during this period is 400 W/m^2, the average ambient temperature 18 °C and the average wind speed 1.2 m/s. However, big extremes can be observed in the dataset due to the variability of cloud coverage.

This period is chosen for two main reasons: First, production in that specific location is minimal in the months around winter so conclusions are difficult to reach when comparing the models. Second, the selected days cannot be extended to years since the machine learning techniques that are used would consume extreme computational resources when pushed to time resolutions of some seconds. Nonetheless the selected period has an average specific daily yield of 3.22 kW h/kWp and includes highly varying conditions, from clear sky days to days with broken clouds and high irradiation values to even overcast days.

3.2. Electro-thermal dynamic model

In this class, we will use the IMEC model as described in (Anagnostos et al., 2014; Goverde et al., 2015a, 2015b, 2017). This PV model is illustrated in Fig. 2 and it incorporates both the optical-thermal-electrical and spatial properties of a PV module and the relevant temporal dynamic effects. The model is constructed by coupling two (electrical and thermal) equivalent circuits, one describing the electrical part and one circuit for the thermal part of the PV module. The parameters of the optical, thermal and electrical parts of the model are determined from experimental data and from FEM models (Goverde et al., 2015a, 2015b, 2017).

The electrical model consists of an equivalent one-diode model, including the shunt and series resistances, with all the parameters extracted from either the datasheet or flash tests of the module under study. The thermal model encapsulates all effects of heat exchange to and from the environment, as well as internally in the module in all directions. Novel methodologies have been developed specifically to describe force convection at the surface of the module.

It is worth noting that the thermal model makes use of physical parameters, so all coefficients have a physical meaning and significance. So this allows not only interpolation but also extrapolation of yield trends outside the calibrated parametric ranges. Therefore, what-if analysis of different module technologies and materials is strongly enabled as it requires no additional measurements and

[1] http://www.uni-oldenburg.de/physik/forschung/ehf/energiemeteorologie/aktuelle-messungen/.