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A one-day-ahead photovoltaic array power production prediction with combined static and dynamic on-line correction

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ABSTRACT

In this paper we develop and verify a predictor-corrector method for a one-day-ahead photovoltaic array power production prediction. The most critical inputs to the prediction model are predictions of meteorological variables, such as solar irradiance components and the air temperature, which are the main sources of the power prediction uncertainty. Through a straightforward application of the weather forecast data sequence, photovoltaic array power production prediction is refreshed with the frequency of new forecasts generation by the meteorological service. We show that the prediction sequence quality can be significantly improved by using a neural-network-based corrector which takes into account near-history realizations of the prediction error. In this way it is possible to refresh the prediction sequence as soon as new local measurements become available. Except for predictions of meteorological variables, the prediction model itself is also a source of the prediction uncertainty, which is also taken into account by the proposed approach. The proposed predictor-corrector method is verified on real data over a 2-year time period. It is shown that the proposed approach can reduce the standard deviation of the power production prediction error up to 50%, but only for the first several instances of the prediction sequence (up to 6–8 h ahead) which are in turn the most relevant for real-time operation of predictive control systems that use the photovoltaic array power production prediction, like microgrid energy flows control or distribution network regulation.

1. Introduction

1.1. Motivation

Accurate prediction of inherently intermittent photovoltaic (PV) system power production (Eltigani and Masri, 2015) continuously gains on importance. In order to be allowed to participate in electricity markets, owners of all (renewable) power plants will have to deliver a short-term power production plan (Pineda et al., 2014; Milstein and Tishler, 2015), which will reduce the need for engagement of a costly power generation reserve (González and Lacal-Arántegui, 2016), and thus reduce the overall operating costs of the system. For a local microgrid (Justo et al., 2013) accurate prediction of power production, together with prediction of power consumption (Gulin et al., 2014), enables optimal operation of storage units (Pavković et al., 2016; Gulin et al., 2015; Parisio et al., 2014) and maximization of gain from investments in both local renewables and energy efficiency measures (Gulin et al., 2016). Information on power production and consumption prediction uncertainty can also be exploited for optimal microgrid operation in real-world conditions (Gulin et al., 2015; Su et al., 2014). Monitoring (Bizzarri et al., 2015; Firman et al., 2014) and diagnostics (Spataru et al., 2015) of a PV system can also benefit from the operational power production prediction as a continuous mismatch of predicted and actual power production beyond the prediction 99% confidence interval should in principle be characterized as a malfunction of the PV system, e.g., due to permanent shading, dirt on the active surface or contacts corrosion. For the reasons mentioned many researchers recently focus on PV system power production prediction (De Felice et al., 2015; Soubdhan et al., 2016; Yang et al., 2014; De Giorgi et al., 2015; Mellit et al., 2014; Almeida et al., 2015; Zamo et al., 2014; Zamo et al., 2014; Wolff et al., 2016).

1.2. Methodology

Since PV power production is strongly dependent on atmospheric conditions, the most critical inputs to the prediction model

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are the predictions of meteorological variables, such as solar irradiance components and the air temperature (Gulin et al., 2016). Through a straightforward application of the meteorological variables prediction sequence, the PV array power production prediction is refreshed with the frequency of new predictions generation by the meteorological service, which is usually less frequent than the discrete time step of the prediction sequence (Gulin et al., 2015). E.g., in the considered case study, a refreshed prediction sequence of meteorological variables is available every 6 h for the 72-h time period with a time step of 1 h, whereas the prediction sequence becomes available with a nearly 4-h lag. It should be noted that predictions of the PV array power production are usually very uncertain (Brancucci Martinez-Anido et al., 2016), mainly due to the uncertainty of input meteorological variables predictions (Sedić et al., 2015), but also due to the prediction model uncertainty (Gulin et al., 2016). In this paper we develop a predictor-corrector method to improve quality of the PV array power production prediction, i.e., to reduce the prediction uncertainty. Correctors are realized as neural networks which are trained, validated and tested on a real PV plant through experiments performed in the Laboratory for Renewable Energy Systems (LARES) during a 2-year time period, whereas the meteorological variables predictions are provided by the Meteorological and Hydrological Service, Croatia (DHMZ).

The proposed predictor-corrector method proceeds in two steps: (i) a prediction step calculates a rough prediction sequence of the PV array power production based on predictions of meteorological variables, which is performed as soon as new (refreshed) predictions of meteorological variables become available, i.e., in the considered case study every 6 h for the 72-h time period with a 4-h lag; (ii) a correction step refines the initial prediction sequence obtained by the prediction step as soon as a new averaged power production measurement becomes available, i.e., every 1 h for the next 24-h time period. In this way it is possible to refresh the prediction sequence as soon as new local measurements become available. Please note that here we consider only 24-h-ahead corrections of the original 72-h-ahead prediction sequence, as near-history realizations are only relevant to correct near-future predictions. A data-flow diagram of the proposed predictor-corrector method is shown in Fig. 1.

The static PV array power production model, used to calculate the PV array power production based on concurrent predicted weather conditions, is implemented as a lookup table with incident

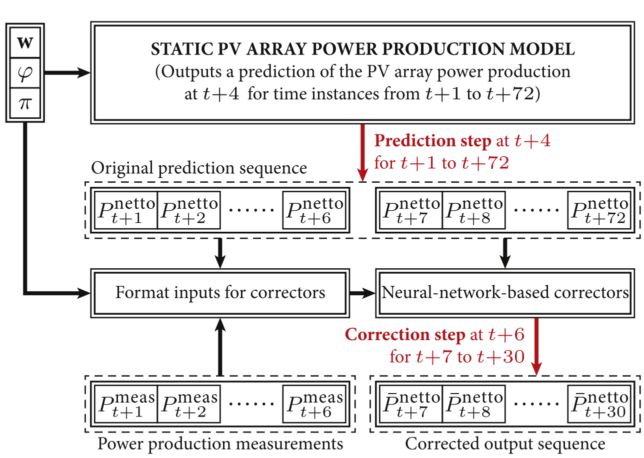

Fig. 1. Data-flow diagram of the proposed predictor-corrector method for a correction step performed at the time instant $t+6$ (**w** is predicted weather data series, including solar irradiance and air temperature predictions, φ are tilted surface tilt and azimuth angles, π are geographical and time data, whereas $t+1$ and $t+72$ are first and last time instants in the 72-h prediction sequence).

predicted solar irradiance and the PV array temperature as inputs (Gulin et al., 2016). Evolution of the PV array temperature along a prediction horizon is usually modelled by a first-order nonlinear differential equation (Gulin et al., 2013; Jones and Underwood, 2001; Kaplani et al., 2014; Torres-Lobera and Valkealahti, 2014; Vašak et al., 2011). However, these dynamic thermal models are highly complex and very difficult to tune, even in laboratory test conditions. In this paper we rather use a simple approximation of the PV array temperature with the air temperature, since our goal is to develop a concept that can be used practically for any operating conditions and environments. Prior to the predictor-corrector method analysis we also give a limit performance of such temperature approximation.

1.3. Main contributions

There are many research papers published recently for short-term power production prediction (*forecast*) of a PV array (De Felice et al., 2015; Soubdhan et al., 2016; Yang et al., 2014; De Giorgi et al., 2015; Mellit et al., 2014; Almeida et al., 2015; Zamo et al., 2014; Zamo et al., 2014; Wolff et al., 2016), which proves a great importance of this topic in the research community. For example, authors in De Felice et al. (2015) propose daily predictions of a PV array power production up to ten days ahead without using on-site measurements of meteorological variables, through support vector machine methodology on solar radiation predictions. Instead of correcting meteorological variables predictions, in this paper we directly correct the PV array power production prediction. In this way we account for meteorological variables predictions error, and the static PV model systematic error. Authors in Soubdhan et al. (2016) use a linear dynamical Kalman filter to predict photovoltaic power production up to 1-h ahead, which inherently relies on a predictor-corrector scheme. Although linear correctors are much easier to identify than nonlinear neural-network-based correctors, they cannot capture nonlinear phenomena that occur in the system, which is why they perform well only for shorter prediction horizons. Authors in Yang et al. (2014) use a black-box model to predict the PV array power production based on available weather forecasts. Black-box models do not presume any knowledge of internal characteristics and processes of the system. Since the PV array power production model can be easily identified using manufacturers' data only (Gulin et al., 2016), in this paper we propose a parallel operation of the deterministic model and neural-network-based correctors (a hybrid approach), which is proved to be more efficient, i.e., more accurate and numerically stable, and is able to operate without historical data set needed for black-box training.

The main contribution of the paper is the predictor-corrector method for the PV array power production prediction which is a novel approach, as it is based on parallel (hybrid) operation of the deterministic prediction model and correctors, whereas correctors are used to capture also those phenomena that occur in the system which are not taken into account by the deterministic prediction model. Additional contribution is the assessment of the limit performance of the prediction model, obtained through simulations on on-site solar irradiance and temperature measurements over the 2-year time period. Through this limit performance assessment we show how the tilted surface model and the PV array temperature approximation affect the prediction model quality. It should be noted that this paper does not discuss which corrector (i.e., neural network) structure or combination of inputs achieves the best performance, as we are more focused on a general idea and verification of its effectiveness. In that respect additional space for an incremental improvement of the proposed scheme exists.