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Dynamical optimal positioning of a photovoltaic panel in all weather conditions

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HIGHLIGHTS

- Described model predictive control algorithm for photovoltaic panel orientation.
- Anticipated weather forecast with its uncertainty, panel model and constraints.
- Evaluation via numerous scenarios in a year-scale simulations with benchmarks.
- Mild action towards the positioning systems which improves the overall reliability.
- Statistical properties of the future power profile facilitate smart grid integration.

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ABSTRACT

In this paper we develop and verify a model predictive control algorithm for photovoltaic panel orientation with the aim to maximize the photovoltaic system netto power production. Thereby we take into account local weather forecast with its uncertainty, thermal behavior of the panel, and the positioning system energy consumption with its technical constraints. The model predictive control synthesis procedure comprises two basic steps: (i) identification of solar irradiance model and development of the photovoltaic system model and (ii) development of predictive control algorithm for the photovoltaic panel active surface orientation, based on the obtained models. Performance of the developed algorithm is verified through year-scale simulations based on a large number of solar irradiance and other weather data patterns. It turns out that the proposed algorithm is fully competitive with the mostly used sun tracking or maximum irradiance seeking controls, and that it outperforms them. The other advantages of the proposed algorithm are: (i) the positioning system is controlled smoothly and (ii) prediction of energy yield one day ahead is available together with its uncertainty for easier photovoltaic system integration into the electricity distribution network.

1. Introduction

Importance of renewable energy sources in the world grows rapidly due to the following reasons: (i) renewable sources represent an inexhaustible potential of energy for the future, (ii) price fluctuations and limited resources of fossil fuels that are still dominant in the world's energy sources structure, (iii) the aspiration of national economies towards energy independence, etc. Among renewable sources, solar energy is one of the most promising nowadays [1] and is predicted by numerous analyses to become the mostly used energy resource by 2050 [2].

Stochastic and intermittent nature of the solar energy resource is an aggravating circumstance for the mass use of photovoltaic (PV) systems and their integration into utility grids. PV panels power production mainly depends on the available solar irradiance. The total solar irradiance that reaches the surface of the PV panel in the form of the direct and diffuse irradiance, is influenced by the PV panel active surface orientation. The computation of trajectory for the PV panel active surface orientation (in short: positioning trajectory) throughout a day can be realized in an open-loop or a closed-loop fashion. The open-loop systems precompute trajectories for the individual axes positioning systems based on weather forecast data which is refreshed once or several times a day. The closed-loop systems use the information on the current weather conditions (most usually photo sensors) to compute the trajectories.

The authors in [3] proposed closed-loop control system to maximize the solar irradiance incident with the active surface of a PV panel which is necessarily based on the maximum seeking control strategies (perturb and observe principle). Due to the permanent

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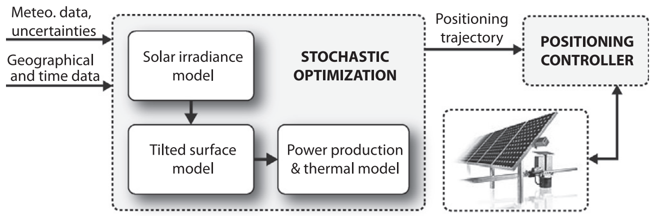

Fig. 1. Data flow diagram.

position changes, these systems can spend more energy than they gain, especially when the weather is changing. Many commercial positioning systems are realized as open-loop control systems where they use predefined trajectories for tracking the solar disk position. In this way, most of the direct irradiance is being harvested since rays of the solar disk are perpendicular to the active surface of a PV panel. However, during cloudy conditions when diffuse irradiance prevails, this algorithm does not increase energy output of a PV system. A vast majority of the developed open-loop control systems presumes clear-sky conditions [4,5]. The authors in [6,7] proposed advanced open-loop control system, where they use model predictive control for maximizing energy output of a PV system. Because of the simplicity of the used solar irradiance prediction model, proposed method is meant only for clear-sky conditions, and yet in a deterministic framework. Presuming clear-sky conditions is appropriate for climates with a large number of sunshine hours, but additional gain is achievable by taking varying weather conditions into account. The authors in [8] proposed that during the clear-sky conditions a PV panel should track the solar disk since direct irradiance prevails, while during the overcast conditions when diffuse irradiance prevails, a PV panel should be placed horizontally, since diffuse irradiance is scattered all over the sky. Although proposed method shows good results, there is no clear algorithmic distinction between clear-sky and overcast conditions.

This paper presents a method for determining the maximum netto energy gain trajectories of the open-loop dual-axes positioning system in a stochastic framework, by considering: (i) local weather forecast and its uncertainty, (ii) solar irradiance model and its uncertainty, (iii) dynamic panel temperature model, and (iv) positioning system energy consumption with its technical constraints. In the used framework of model predictive control this leads to a constrained nonlinear optimization problem, and for solving it an evolutionary algorithm called Differential Evolution (DE) [9,10] is applied. Data flow diagram of the proposed control algorithm is shown in Fig. 1.

The paper is structured as follows. In Section 2 a neural-network-based identification of parametric direct (normal) and diffuse (horizontal) solar irradiance models, along with development of uncertainty of the identified models is described. In Section 3 a PV system model is introduced, considering the uncertainty of available meteorological data and of the developed solar irradiance models. In Section 4 a method for determining the maximum efficiency trajectories of the open-loop dual-axes positioning system, based on DE, is presented. Simulation-based study of the developed algorithm and its comparison with state-of-the-art dual-axes positioning approaches is presented within Section 5.

2. Identification of neural-network-based direct and diffuse solar irradiance models

Knowledge of the local solar irradiance is essential for the proper design of model predictive control algorithm that maximizes the production of electrical power by the PV system. To this aim, a parametric model [11] for site-specific direct (normal) and diffuse (horizontal) solar irradiance as static functions of geographical and meteorological data is developed. For that purpose we use Radial Basis Function (RBF) type neural network [12,13]. Its training is performed on past geographical and meteorological data and solar irradiance measurements [14,15] taken from the National Solar Radiation Data Base (NSRDB) for Washington DC Dulles International Airport (WDC Dulles) for period 1996–2003, and its validation is performed for period 2004–2005. Input data used for neural network training are: (i) solar zenith angle, (ii) local air pressure, (iii) dry-bulb temperature, (iv) precipitable water vapor thickness, (v) aerosol optical thickness, (vi) total cloud cover, and (vii) opaque cloud cover.

Solar irradiance data available in NSRDB are in one hour resolution and represent the energy received per unit area via corresponding irradiance type within the hour-interval that ends at the time-stamp, named solar insolation [16]. This fact must be especially taken care of since our goal is to obtain the static model of the current solar irradiance that takes current geographical and meteorological data as inputs. The RBF network input data is therefore distanced one minute in time, such that linear interpolation of NSRDB full-hour data is used to compute the input meteorological data for the model. The input geographical data for the model (i.e. solar zenith angle) is obtained via known relations for calculating the sky position of the solar disk [17]. The solar irradiance neural network output data are for training reasons integrated on an hour time-scale and compared with NSRDB data. Prior to neural network training process, output data are filtered in order to retain only high-quality direct–diffuse irradiance measurement pairs for identification. For more details on used neural network structure see [18].

2.1. Objective function

The neural network is trained by numerical procedure that tends to minimize the following criterion:

$$\Im \equiv \frac{1}{2}\sum_{i=1}^{N} e^2(\mathbf{X}_i, \mathbf{\Theta}), \tag{1}$$

where $\mathbf{X}$ is the set of NSRDB input data, $\mathbf{\Theta}$ are neural network parameters, N is the number of data $\mathbf{X}_i$ in different time (full-hour) instants and the error e is defined as:

$$e_i \equiv e(\mathbf{X}_i, \mathbf{\Theta}) = I_{NSRDB,i} - \sum_{j=0}^{\tau}\left[k_j f(\mathbf{X}_{i,j}, \mathbf{\Theta})\right], \tag{2}$$

where f is the trained solar irradiance function, $I_{NSRDB,i}$ is solar insolation entry in NSRDB for either direct or diffuse solar irradiance, the sum represents a numerical integral of function f within the hour, τ is either 60 or smaller (smaller only for the cases of sunrise and sunset hours), $\mathbf{X}_{i,j}$ are input data within the hour i on the minute resolution – linearly interpolated meteorological data within the hour or the computed instantaneous solar zenith angle, and k_j are numerical integration weights given with:

$$k_j = \begin{cases} \frac{1}{2}\frac{1}{60} & \text{for } j = 0, \tau, \\ \frac{1}{60} & \text{otherwise.} \end{cases} \tag{3}$$

2.2. Identification results

Separate neural networks are trained for the direct and diffuse solar irradiance. Performance measures used for models verification on the validation data set are Mean Bias Error (MBE) and Root Mean Square Error (RMSE):