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Correlated wind-power production and electric load scenarios for investment decisions

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HIGHLIGHTS

- ▶ Investment models require an accurate representation of the involved uncertainty.
- ▶ Demand and wind power production are correlated and uncertain parameters.
- ▶ Two methodologies are provided to represent uncertainty and correlation.
- ▶ An accurate uncertainty representation is crucial to get optimal results.

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ABSTRACT

Stochastic programming constitutes a useful tool to address investment problems. This technique represents uncertain input data using a set of scenarios, which should accurately describe the involved uncertainty. In this paper, we propose two alternative methodologies to efficiently generate electric load and wind-power production scenarios, which are used as input data for investment problems. The two proposed methodologies are based on the load- and wind-duration curves and on the K-means clustering technique, and allow representing the uncertainty of and the correlation between electric load and wind-power production. A case study pertaining to wind-power investment is used to show the interest of the proposed methodologies and to illustrate how the selection of scenarios has a significant impact on investment decisions.

1. Introduction

One key issue when dealing with investment problems is the modeling of the uncertain parameters that influence the investment decisions. These parameters include electric load, investment costs, fuel prices, market participants behavior, etc.

Two main techniques are available in the technical literature to deal with optimization problems involving uncertain data, namely stochastic programming [1,2] and robust optimization [3–5]. Stochastic programming, which is used in this paper, represents the uncertainty in the input data via scenarios [1] and thus, an adequate modeling of these scenarios is essential to achieve the best investment decisions. The selection of these scenarios and their influence on investment decisions are analyzed in this paper.

As an example, we consider a wind-power investment problem, which seeks to determine the wind-power capacity to be built in an existing electric energy system. Among the references addressing this problem [6–8], in this paper we consider the model proposed in [8] consisting in a stochastic mathematical program with equilibrium constraints (MPEC). In this particular model, there are two parameters subject to uncertainty that significantly influence the investment decisions: the electric load and the wind-power production.

Wind-power, as other renewable sources, is subject to uncertainty and thus requires models rather different to those developed for conventional generating units [9,10]. Moreover, wind-power production for the same facility is different in different locations depending on the wind-power conditions. These wind-power conditions can be represented via scenarios, which are generated using historical data in the location under study.

On the other hand, we face the uncertainty of the electric load of the system that has an important impact on market prices, which in turn modify the investment decisions. The electric load uncer-

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tainty can also be represented through scenarios based on historical data.

Finally, we should note that in most systems electric load and wind-power production are not statistically independent magnitudes. Low values of electric load usually occur during the night, when wind-power production is comparatively higher. Thus, considering electric load and wind-power production as independent phenomena may render suboptimal and inefficient investment decisions. It is thus necessary to properly represent the statistical correlation between electric load and wind-power production.

We propose two methods to address the uncertainty of and the correlation between the electric load and the wind-power production in different locations of an electric energy system: the load- and wind-duration curves technique [8] and the K-means clustering technique [11–13].

These methodologies use as input historical data of electric load and wind-power production in different locations of an electric energy system, and provide as output a reduced data set of electric load and wind-power production in different locations that keeps the information and correlation of the historical data. This reduced data set consists of a set of scenarios, each one comprising a value for the electric load and wind-power production in each location of the system. Note that each set of values of electric load and wind-power production in different locations represents a system operating condition, i.e., a scenario. For example, the K-means technique is used in [12] to generate load and wind input data for the probabilistic evaluation of the total transfer capability in power systems.

Within the context above, the contributions of this paper are threefold:

1. To propose, analyze and compare in detail two methodologies to precisely characterize the electric load and wind-power production in several locations of an electric energy system, considering the uncertainty of and the correlation between these two uncertain parameters.
2. To use these two methodologies to derive electric load and wind-power production scenarios used as input data for an investment decision problem (i.e., a long-term planning problem).
3. To analyze through a case study how different scenario representations of the electric load and the wind-power production influence wind-power investment decisions.

The remaining of this paper is organized as follows. In Section 2, we describe two techniques to characterize electric load and wind-power production uncertainty, as well as the correlation between the two parameters. In Section 3, these two techniques are used to characterize the electric load and the wind-power production in a given electric energy system. These data are then used to solve a wind-power investment problem in Section 4. Finally, Section 5 concludes the paper with some relevant remarks.

2. Techniques

In this section, we describe the two techniques used to represent the uncertain nature of the electric load and the wind-power production as well as their correlation: the load- and wind-duration curves and the K-means technique.

2.1. Load- and wind-duration curves

The first method to model the uncertainty and correlation of the electric load and the wind-power production at each bus of an existing electric energy system is based on the load- and wind-duration curves. Both electric load and wind-power production are jointly modeled as described below.

We consider available historical data of electric load consumption throughout one or several years in the electric energy system under study. These historical data are adequately scaled to account for demand growth. Using these scaled data, we build a load–duration curve as represented by the continuous curve in the lower plot of Fig. 1. This load–duration curve is approximated by a set of demand blocks, e.g., four blocks. Note that the first block is narrower (in terms of hour span) than the others in order to represent the peak load. Since the peak load can have a great impact on system-wide decisions, it should be adequately represented. The electric load uncertainty within each demand block is represented by considering different demand levels. In order to do this, we build the cumulative distribution function (cdf) of the electric load within each block, as depicted in Fig. 2. This cdf plot is divided into a selected number of segments (three in the example of Fig. 2), each one with an associated probability. The average values of the values within each segment give the electric demand levels represented in the lower plot of Fig. 1.

Once the electric load of the system is represented, we model the wind-power production. As explained in the introduction of this paper, wind-power production is correlated with the electric load of the system and thus, electric load and wind-power conditions have to be jointly represented.

We use historical data of wind-power capacity factors (defined as the wind-power production divided by the installed wind-power capacity) throughout the same period as the electric load. For each demand block used to adjust the load–duration curve, we consider the corresponding wind-power capacity factors (i.e., the wind-power capacity factor realizations corresponding to each

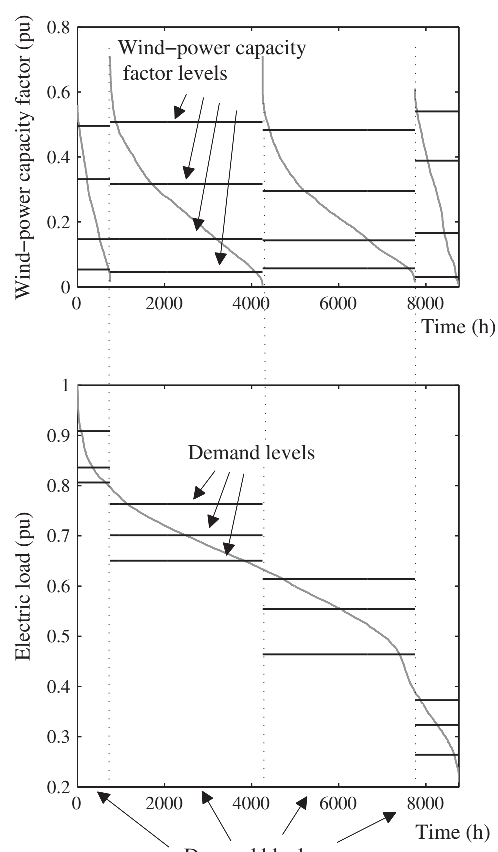

Fig. 1. Load- and wind-duration curves.