Simulation of Correlated Wind Speed Data for Economic Dispatch Evaluation

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***Abstract*—The Economic Dispatch problem consists of minimizing the cost of producing the power demanded by an electrical power system, by means of the suitable dispatching of the power production between the available generators. The difficulty in predicting wind power generation means that penalty and reserve costs must be considered when it is included in the evaluation. Analyzing the output power of each wind turbine individually is not enough when evaluating these costs and the correlation between wind speed values must be considered as another input because it also has an influence. This paper introduces a new method for generating correlated wind power values and explains how to apply the method when evaluating Economic Dispatch. A case study is provided to analyze whether considering correlation in the problem has any influence or not.**

***Index Terms*—Correlation, economic dispatch, Monte Carlo simulation, Weibull distributions, wind power.**

I. Introduction

ECONOMIC dispatch (ED) consists of dispatching the power to be generated among available generators, in order to obtain the most efficient, low-cost, and reliable operation of a power system. It considers operating limits, availability, and reliability, and minimizes costs so that both load demand and losses are supplied [1]. It, therefore, plays a key role in power system planning and operation.

As wind power increases its share ratio in electrical networks, the ED problem must consider scheduled wind power and its costs. Even though wind power forecasting methodologies [2] have been considerably improved during the last years, wind power cannot be scheduled with total accuracy.

The generally used models for wind power forecasting are based on several factors: current data and atmospheric behavior, such as the numerical weather prediction (NWP); historical data, such as auto regressive (AR), auto regressive moving average (ARMA), etc.; spatial correlation; artificial intelligence; or a combination of these [3]–[6].

Therefore, taking into account that scheduled and available wind power may not coincide, the costs to be considered in the ED problem are different in nature, as will be explained later.

The ED problem is solved *a priori*, which means that the power to be produced is scheduled. Flexible plants can set output power to the required value, so both the scheduled and the produced power values coincide unless the unit is malfunctioning. There are other things to consider when wind power is taken into account because the available and scheduled powers at the corresponding wind turbine (WT) may differ and give rise to costs that must be evaluated.

Several types of procedures can be applied to solve the ED problem. Analytical solutions like those in [7] are very difficult to apply when considering wind power correlation so numerical solutions like the ones in [8] are preferred. Therefore, the ED evaluation carried out in this paper is based on four terms that depend on the following:

1) the scheduled power of flexible plants;
2) the scheduled wind power;
3) the difference between available and scheduled wind power, when it is positive;
4) the difference between scheduled and available wind power, when it is positive.

From the point of view of the system operator, there is a first term for the cost due to the sum of the power provided by the conventional generators.

The second one is due to the amount to be paid to wind power producers according to agreements established with them.

A term is included that evaluates the cost of the difference between available and scheduled wind power. These costs include the payment to the wind power producers for not using the available power, which is wasted or diverted to another generation facility like a hydro pumping station. Therefore, the third term is basically related to penalty costs due to not using all the available power in the network, i.e., it evaluates the cost of under-forecasting wind power.

On the other hand, if the wind power is over-forecasted, the power requested by the load demand has to be supplied anyway, so the power must be purchased from an alternative source. Therefore, the cost of the reserve power or the cost of the power purchased through an interconnection is evaluated in the fourth term.

So, these four terms evaluate the costs in order to solve the ED problem. However, this is a general model to evaluate ED and it is adaptable to all possible situations, so any term can be removed depending on specific cases.

Notice that if the total power generated and demanded in an electrical network were not equal, then steady-state security could be affected, because this balance is needed for keeping adequate operating conditions. Thus, the electrical network could be seriously influenced by under- or over-forecasting wind power if the steps towards achieving the balance were not taken into account.

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As explained in [8], the ED problem can be solved by taking into account the probabilistic nature of the wind speed: its statistical distribution can be approximated using a Weibull distribution and the probability density function (pdf) of the wind power can be obtained. However, the correlation between wind speed values and, consequently, between wind power values has to be included in the ED problem.

Generally, it can be said that correlation between wind speed values has great influence in electrical networks with WTs. In this paper, a method is derived to simulate series of WT output power data based on given correlated wind speed values between the locations where they are installed and also on lag-one autocorrelated values for each one. The series of WT output power data represent all possible situations. This method upgrades former approaches to this simulation in accuracy and computation time [9]–[12]. The WT output power series are used to obtain a more realistic result in the minimization of total cost, now defined on the basis of these data series.

Notice that the method proposed in this paper does not correspond to a wind power forecasting methodology but is instead a way to define all possible wind power generation states in a group of WTs.

The Interior Point Method is applied to solve the minimization problem, as it is usually used as an optimization tool for ED [13]–[16].

This paper is organized as follows: Section II explains how to simulate series of correlated and autocorrelated wind speed values; Section III outlines how to convert these wind speed series into WT output power series; Section IV describes the ED problem considering wind power and how to introduce the correlation factor; Section V shows a case study and Section VI states the conclusions.

II. Wind Speed Series

First, let us briefly comment on some of the former approaches proposed to obtain correlated wind speeds. The objective is to find a number of wind speed series where each one fulfills a given Weibull distribution, with parameters (λ, k), and the correlation coefficients are those provided by the correlation matrix.

In [9], a method that keeps the Weibull features of each of the series and obtains the exact correlation matrix is applied. However, in this method Spearman rank correlations are considered [17], so this feature must be considered when data and results are used.

Evolutionary algorithms have been used in [10] for the same purpose. They are based on the initial generation of wind speed series fulfilling the distribution features, followed by the rearranging of the values in each of the series in a trend towards obtaining the desired correlation matrix. Although the results provided by this method are very accurate, the computation time increases considerably as the number of locations rises.

In [11], a method has been proposed that is based on the sum of two squared Normal distributed variables in order to obtain the square of a Weibull distributed one, which involves solving equations by means of iterative processes. This method has nothing to do with the one proposed in this paper.

A minimization process is proposed in [12], thus using the decomposition of Weibull distribution variables as weighted sum of Uniform ones.

Except for the method proposed in [9], the time consumed by these methods tends to be increasingly greater as the number of locations increases, due to computational issues. Moreover, the accuracy of these methods depends on the error accepted by the minimization procedures. The method proposed in this paper reduces the computational time to a minimum because it does not use iteration processes, as it holds the starting correlation values, is fully accurate, and also considers parametric correlation, which is the convention.

In the methods mentioned above, only the correlation between wind speed data has been considered. However, in [11], the autocorrelation for each location has also been computed. In this paper, both types of correlation are taken into account.

A. *Conversion of Normal Distributed Series Into Weibull Distributed Ones*

The wind speed pdf at a certain location can be described by a Weibull distribution [18]–[20].

Widely used in statistics, the cumulative distribution function (cdf) of a continuous variable with a given distribution makes a transformation possible between this distribution and a Uniform one. This feature is usually used in reverse to simulate random data, when the cdf is inverted to generate uniformly distributed data between 0 and 1 so that random data can finally be created with the desired cdf.

For example, in the case of a Weibull distributed variable u, the variable F_u, obtained according to (1) is uniformly distributed

$$F_u = 1 - \exp\left(-\left(\frac{u}{\lambda}\right)^k\right) \tag{1}$$

where λ is the scale parameter and k the shape parameter of the Weibull distribution [21].

Exactly the same can be said for Normal distributions, as can be seen as follows:

$$F_x = \frac{1}{2}\left(1 + \operatorname{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right) \tag{2}$$

where F_x is the cdf of the variable x, erf( ) is the error function, defined in (3), and μ and σ are the mean and the standard deviation of the Normal distribution.

The error function, erf( ), is continuous, and its features are shown in many handbooks of mathematics [22]

$$\operatorname{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x \exp(-t^2)dt. \tag{3}$$

The reason for using the feature mentioned above is because it is intended to operate a conversion from Normal distributed data into Weibull distributions. First, the value obtained from the Normal distribution is converted into a value belonging to a Uniform one, and then this value is converted into a new one, corresponding to a Weibull distribution. So the operations involve beginning with Normal distributed data and using (2), in a direct way, and (1), in an inverse way, to obtain the Weibull