INFLUENCE OF PROBABILISTIC WIND FORECAST ACCURACY IN THE OPERATIVE MANAGEMENT OF RENEWABLE ENERGY SYSTEMS WITH STORAGE

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ABSTRACT

A key feature in the management of wind energy systems with storage is the probabilistic wind speed forecast. In this paper we consider a mathematical model to determine the operative management of a wind energy system with storage. The model includes all the important elements of the energy system. Decisions take into account data concerning to the structure of selling prices and penalties as well as updated probabilistic wind speed forecast. The main focus of this work is to study the influence of the probabilistic wind forecast accuracy in the operative management of a wind energy system with storage. A simulation based optimization methodology is proposed to conduct the computational study.

Keywords: Energy, storage management, simulation, optimization

1. INTRODUCTION

Renewable energy provides valuable benefits for the environment, health and economy (produces little or no CO2 emissions, stabilizes energy prices, provides an inexhaustible energy supply, etc.). Nevertheless common problems to all renewable sources of energy are high variability in its availability; uncertainty in its forecast and then difficulty in matching production and demand. As a consequence in geographic areas with high wind energy penetration energy plants based on fossil fuels are necessary to support the network (in cases of low wind energy production), which increase the cost of the energy. In periods of high wind energy production the wind-driven generators could be disconnected because the network could not absorb all the electricity.

The storage of energy would allow solving most of the problems posed by the wind energy generation. It makes possible the management of the generated energy leading to better selling prices in the electricity market. Furthermore, the stored energy increases the reliability of the renewal energy system since it enables to correct forecasting errors by matching the output energy to the forecasted production. Lastly, it increases the wind energy penetration index: energy can be stored in periods with higher production than requirements, and then released in low production periods.

Different energy storage systems are nowadays available: lead-acid and sodium-sulfur batteries, compressed air energy storage, pumped hydro, electrolysis combined with fuel cells, and others, with different properties related with response time, storage efficiency and costs. Comprehensive technical reviews on energy storage systems can be found in (Ibrahima et al, 2008; Beaudin et al, 2010; Hedegaard and Meibom, 2012). In this work we consider hydrogen (H2) as the energy storage system, although the analysis carried out in this paper could be easily adapted to other storage systems. The hybrid wind-hydrogen energy system comprises electricity-generating wind turbines, electrolysers and hydrogen compressors to convert electricity into hydrogen (the conversion process), an H2-tank with finite hydrogen storage capacity and various energy-conversion technologies for the process of turning hydrogen into electricity (the recovery process).

Energy prices follow similar rules to the stock market. They vary with demand, and fluctuate throughout a given day while also showing variations for the same time across different days. Furthermore, prices depend on whether (or not) the amount to be sold has been pre-committed (the day before). In the case of a pre-commitment, the price is higher, but if the agreed amount is ultimately not supplied, then a penalty has to be paid. When more than the agreed amount is supplied then the surplus has a lower price. Thus, to obtain full benefit from the participation in the electricity market it is necessary to commit the electricity to be sold one day ahead.

Due to the stochastic nature of renewal sources, like wind, the exact amount of renewal energy produced cannot be known in advance. The commitments of energy have to be done by using wind speed forecast. Wind speed forecast errors lead to a mismatch between commitments and generated energy. Magnitude of errors increases as prediction horizon moves away. Probabilistic forecast becomes the most appropriate way of estimating forecast uncertainty. It provides forecast of the probability distribution of wind speed for each look-ahead time (Gneiting and Larson 2006).

A probabilistic wind speed forecast at time *t* is a set of *m* predicted wind speed trajectories for the coming future (Moehrlen 2004). They are obtained from different and coherent physical parameterizations of the meteorological model utilized. Usually, meteorological forecasts have a forecast resolution of one hour for look-ahead times up to 48 hours (Pinson and Madsen, 2009).

Storage operative management involves deciding when to use the stored energy to meet the pre-commitments. Decisions should take into account data concerning to the structure of selling prices and penalties, as well as updated wind speed forecast.

A main issue is to determine the amount of energy that should be committed one day ahead to maximize the profit. In (Aguado et al, 2009) the committed energy was obtained as solution of a sequence of linear integer programming problems which use as input data the expected wind speed in the look-ahead period. This analysis does not consider the uncertainty in the wind speed forecast and the operative management of the H2-tank is addressed in a naïve way: At time *t*, if more energy than committed is produced, then store the surplus; if the generated energy is less than commitments, then use the stored energy to correct deviations. The model provided an economic analysis of the viability of such systems and was valid as a first approximation to solve a dimensioning problem related with the facilities and necessary equipment. Nevertheless, the model was not appropriate for the system management. As a solution to those drawbacks, managers suggested a class of management policies based on a more regular and dynamic use of the tank. The new strategy, named peaking strategy, is based on the conversion of electricity into hydrogen during price troughs and the use of the stored hydrogen to produce electricity during the day's demand (thus price) peaks. These loading and unloading periods are denoted by H2-storage (valley) and H2-release (peaking) periods, respectively. Strictly speaking, peaking strategy dictates to store energy in valley hours and to release it in the peaking hour, giving no further use to the tank. However, the possibility of using the stored energy to fulfil the energy committed by correcting deviations is attractive and worthy to be investigated. This additional use for the stored energy requires making new decisions at each hour concerning with whether release energy when generated energy is below the committed energy and whether store energy in the opposite case, that is, the generated energy exceeds the committed energy. The computational implementation of the peaking strategy (Azcárate et al, 2012) allowed the capability of use the tank to match the delivery commitments but the operative decisions needed to manage the tank were fully assumed by the decision maker.

In this work, we provide the decision maker with an optimized strategy to operate the tank. Two objectives are considered: an economic one, aiming at maximizing the profit from the energy selling and a reliability one by maximizing the number of hours in which the energy commitments are fulfilled.

2. MATHEMATICAL MODEL

Optimal management policies have to make full use of the available information at the decision times. We propose operative policies for the storage management that benefit from an updated probabilistic wind speed forecast, $W(t_0)$, and take into account the structure of electricity prices, the hourly committed electricity, penalties for mismatch the commitments and the current amount of stored energy.

Two types of scenarios are considered to define an operative management policy for the tank:

- Shortage scenario (A): at time *t* the generated wind energy (*G(t)*) is less than the committed energy (*C(t)*). In this case, should the stored energy in the tank be used to match the committed energy?
- Surplus scenario (B): at time *t* the generated wind energy is greater that the committed energy. In this case, should the surplus of energy be stored in the tank for its future use?

Optimal management policies are obtained as solution of a sequence of rolling horizon stochastic optimization problems. At each time t_0, an optimization problem with decision variables $g_T(i), g_R(i),\ i = t_0, t_0+1, \dots, t_p - 1$ is formulated, where t_p represents the peaking hour. In a shortage scenario, decision variable $g_R(i)$ represents the amount of energy recovered from the tank to match the committed energy in hour i. In a surplus scenario, $g_T(i)$ represents the amount of energy stored in the tank for its future use.

Variables *T(i)* represents the amount of energy stored in the tank in hour *i*. Deviations d_i^+ and d_i^- are introduced for modeling purposes and defined by: $G(i) - d_i^+ + d_i^- = C(i)$.

The objective function includes both economical and reliability criteria. The economical objective is composed by two terms. The first one assesses the profit in time interval $[t_0, t_p]$, under management policy g, $B(t_p, g)$, by using the probabilistic forecast $W(t_0)$ and the energy prices. Energy prices include different values for commitments, surplus sales (above commitments) and penalties for shortfalls in the pre-committed energy. The second term in the economical objective function $V(T(t_p^+), g)$, is an assessment of the energy that could remain stored in the tank at the end of the peaking hour, and is expressed as follows:

$$V(T(t_p^+), g) = \gamma_V * P(t_p^*) * T(t_p^+)$$

where t_p^* represents the peaking hour of the next peaking cycle, $P(t_p^*)$ the selling price of committed energy at that peaking hour and γ_V is a parameter.

The objective function can be expressed as

$$\max_g\ E_{W(t_0)}[\, B(t_p, g) + V(T(t_p^+), g)]$$

where g is the vector of decision variables, $W(t_0)$ is the probabilistic wind speed forecast and $E_{W(t_0)}[.]$ stands for the expected value of the compound benefit function.

The consideration of only economic criteria leads to use the tank for correction of errors when these corrections provide a profit. In order to improve the reliability, the tank should be used to correct errors even with no direct economic benefit. Reliability objective function $R(t_p, g)$ aims to maximize the number of hours at which the energy commitments are fulfilled.

The constraints of the optimization problem consider the capacity of the H2-tank, the H2-tank update and the efficiencies of the H2-conversion and recovery processes.

3. PROBABILISTIC WIND SPEED FORECAST

A key feature in this management strategy model is the updated probabilistic wind speed forecast. The main focus of this work is to study the influence of the probabilistic wind forecast accuracy in the operative management of a wind energy system with storage. To conduct the computational study our model simulates the probabilistic wind speed forecast at each hour through the simulation of *m* wind forecast trajectories. The model handles prediction errors as follows. Historical wind speed data are used to simulate meteorological predictions by adding an error to each item of real energy data. The error is obtained by combining an absolute error and a relative error. The maximum relative error depends on the prediction horizon and is represented by a set of non-decreasing polynomial functions limited by the initial and final maximum relative errors. In order to smooth the predicted energy curve, we keep a record of past errors to generate an auto-correlated error series. The parameters in this error forecast simulation model are used to represent the accuracy of the meteorological forecast.

Concretely, we use the following model:

$$forecast\_wind(t) = \max\left\{\begin{array}{l} 0, true\_wind(t) + \\ + \max\{relavive\_error(t) * true\_energy(t), absolute\_error\} * \\ * (2 * pred\_error(t) - 1)\} \end{array}\right\}$$

We consider different non-decreasing functions representing *relative_error(t)*. Specifically, an initial *(IRE)* and a final *(FRE)* relative error are introduced as parameters of the model, and a set of order-two polynomial non-decreasing functions *(relative_error(t)* = $A+Bt+Ct^2$*)* limited by both *IRE* and *FRE* values are obtained as solutions of the following system of equations, where $t=1,\dots,T$ represents the forecast time horizon:

$$\begin{cases} A+B+C = IRE \\ A+BT+CT^2 = FRE \\ B+2Ct>0, \forall t=1,\dots,T \end{cases}$$

As an example, Figure 1 shows a set of functions, with *IRE=5*, *FRE=40* and *T=60*. For more details about this wind speed forecast simulation model, the reader is referred to (Mallor et al, 2009).

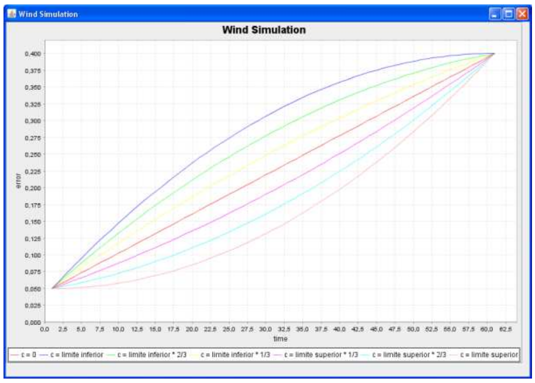

Figure 1: Relative error functions

An example illustrating the simulation of the probabilistic wind speed forecast from hour t_0 to hour t_p (band 1) and an updated probabilistic forecast at hour t_i (band 2) is shown in figure 2. The variability of the errors in probabilistic wind speed forecast decreases as the updated prediction gets closer the peaking hour.

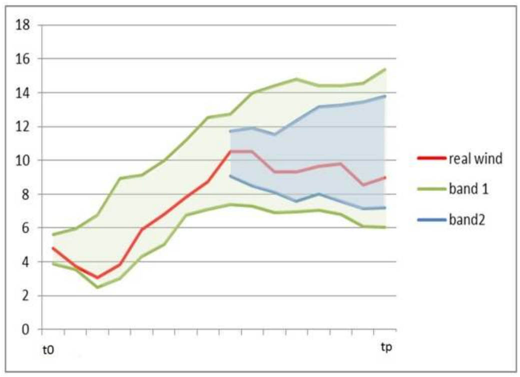

Figure 2: Probabilistic Wind Speed Forecast

4. USEFULLNESS OF THE SIMULATION-OPTIMIZATION MODEL

A simulation based optimization methodology is proposed for the assessment of the management. We develop a discrete event simulation model for a real inspired renewable energy system with H2-based storage, moving the simulation clock in 1-hour steps. The simulation model incorporates the important equipment that compose the wind-H2 energy system and the random elements of the stochastic environment in which the energy system evolves. The wind farm is characterized by its power capacity and its wind-power conversion curve; the hydrogen tank is described by its capacity; and the electrolysers, compressor and the different technologies involved in the recovery process are described both by their capacities and their efficiency curves. Our study assumes the availability of a long series of historical data containing hourly wind speed. A detailed description of such real energy systems can be found in (Aguado et al, 2009). The model allows the determination of different peaking strategies.

At each hour *t*, we simulate the wind speed forecast and then the amount of energy generated. Taking into account this amount of energy, the hydrogen stored in the tank and the pre-committed supply for this hour, the amount of energy to be stored or released into the grid is determined. This decision is made according to the optimization problem described in section 2, implying the simulation of the updated probabilistic wind speed forecast. When the simulation clock reaches the time at which the energy supply commitments for the following day must be announced, these values are determined by the cost and probability strategy described in (Azcárate et al, 2011).

Global system assessment is made by considering two objective functions: reliability and profit. Economical objective function is calculated considering energy prices for commitments, energy prices for surplus sales (above commitments) and penalties for shortfalls in the pre-committed energy. In order to compare the effect of the use of the tank to correct errors, we consider as economical objective function the ratio between the expected profit obtained with the operative management strategy and the expected profit obtained without using the tank to correct errors. Reliability objective function is measured as the percentage of hours in which commitments have been accomplished.

This proposed simulation based optimization methodology allows the assessment of the management strategy considering different price structures and efficiencies of the whole storage system. Preliminary results show that price structures with very high penalties for shortfalls in commitments and surplus with almost no value make economically attractive the use of the tank to correct errors in normal hours. This also depends on the efficiency of the whole storage system and on the probabilistic wind forecast accuracy.

5. CONCLUSIONS

In this paper we have mathematically modelled the problem of optimally operating the storage of a renewal energy system. This mathematical model describes all important elements of the energy system and, furthermore, it incorporates the variability of both energy prices and renewable resource availability. Main features of this model are the incorporation of a probabilistic forecast for the renewal energy which is dynamically updated and the simultaneous consideration of economical profit and reliability objectives.

The variability in the structure of the energy prices and penalties influences the commitment strategy and, together with the system efficiency, the cost of correcting errors. The degree of uncertainty in the renewal forecast affects the reliability of the system as provider of energy. And, of course, differences in the amount and variability pattern of the renewal resource impact in the global performance of the energy system. The consideration of all these elements together requires an extensive design of simulation experiments to assess the influence of each one of them.

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