INCLUDING RELIABILITY IN THE ANALYSIS OF MARKET DRIVEN RENEWABLE ENERGY SYSTEMS WITH STORAGE

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ABSTRACT
The possibility of renewable energy systems to store energy facilitates their participation in the electricity market as well as to control the forecast errors in the renewable source and then to increase the reliability of the system as provider of energy. This paper optimizes the management of this energy system considering simultaneously both goals, an economic goal and a reliability goal. Policies to provide the electricity dispatch schedule for the day ahead (tactical decisions) and to control the energy storage each hour (operational decisions) are obtained from a sequence of mathematical problems. A simulation model is developed to assess the performance of these policies in a stochastic framework that considers the variability and uncertainty in the renewable source.

Keywords: Energy Storage System (ESS), Renewable Energy Management, Tactical and Operational Decisions, Simulation and Optimization

1. INTRODUCTION

The aim of electricity companies is to get as much profit as they can by selling the product they commercialize: the electricity. However, as any other company in every economic sector, they are also obliged to provide a service of quality (by contractual enforcement or simply because it is a strategic requirement to survive in a competitive environment). An important part of the service quality provided by a company in the energy sector is to supply energy whenever it is demanded. However, a handicap for renewable energy companies is that the sun does not always shine and the wind does not always blow when they are required. Cost-effective energy storage technologies help to overcome this problem enabling the management of the generated renewable energy.

The stored energy can be used to improve achievements in the two above mentioned objectives: the economic one by storing the energy when prices are low and selling it when prices are higher, and the reliability one by supplying the demanded energy when the renewable sources are not available. Furthermore, the storage facilitates the participation of the electricity companies in the day-ahead electricity market. The grid operator receives the electricity dispatch schedule from the wind farm managers in advance. When the power output of the wind farm differs from the schedule submitted the wind farm owner is financially punished.

This paper simultaneously deals with the problem of determining the number of kWh that should be committed by an electricity company in the day-ahead electricity market and the operational management of the energy storage system (ESS), with the aim of simultaneously achieving a maximum economic return as well as a maximum reliability. Thus this bi-objective optimization problem is simultaneously of tactical and operational nature. Furthermore, decisions about how much electricity to commit each hour of the day-ahead is based on available forecasts for the renewable energy resource. That is, our analysis incorporates both forecasting and uncertainty in resource availability into the analysis which allows a more realistic assessment of the reliability of the energy system. However, the inclusion of the stochastic environment in which the energy system evolves also leads to the formulation of more complex mathematical models.

Many papers have studied the management of renewable energy systems with ESS, (see Connolly et al., 2010, the reviews Luo et al., 2015, and Zhao et al., 2015, and the references therein) some focused on the tactical problem and optimizing the economic problem as for example Aguado et al. (2009), where a mixed integer linear programming model was used embedded in a simulation model. This model was improved in Azcarate et al (2012) to incorporate a probabilistic wind speed forecast (PWSF). Operational decisions were not optimized in either of these two articles, which consider only simple strategies oriented towards fitting the committed energy as much as possible. A type of parametric operational strategies for the ESS was studied in Mallor et al (2015), but the commitments were obtained independently of the implemented operational management. In Kou, Gao, and (2015) an operational strategy for the management of a set of batteries connected to a wind-farm is proposed to control the deviations from a dispatch curve, and then paying more attention to the reliability goal.

In this paper we propose a bi-objective stochastic linear problem to model the operational and tactical problems which incorporate a PWSF. They are solved by using a rolling horizon strategy, which allows the assessment of the reliability of the ESS achieved in the recent past for building the subsequent optimization problems that drive the tactical and operational policies. The sequence of stochastic linear problems is solved by a method inspired by the Stochastic Approximation Average (SAA) technique (see Kim, Pasupathy, and Henderson, 2015, for an explanation of this mathematical method to solve stochastic optimization problems). We particularize the mathematical model to a wind energy system with ESS based on hydrogen (H2) technologies. A discrete event simulation model is developed to mimic the operation of such wind energy system with storage. Using this simulation model we can assess, under different stochastic scenarios, the performance of the management policies obtained from the solution of the optimization problems. Nevertheless, the models can be easily adapted to other intermittent renewable energies and ways of energy storage.

The paper is organized as follows. In Section 2, the management problem of an energy system with storage, regarding economic and reliability goals, is defined. In section 3 we present the two stochastic mathematical linear problems that model the tactical and operational problems, respectively. In Section 4 a simulation framework is built to assess and to calibrate the management policies obtained as outcome of the optimization problems. Simulation results are included in Section 5 to illustrate the capability of our mathematical approach to get optimal operational and tactical management policies. The paper ends with some remarks and conclusions.

2. PROBLEM DEFINITION

In this Section the economic and stochastic environment context of the wind farm with ESS is described, particularly, the economic rules that govern the grid connected electricity market, the variability and uncertainty of the wind resource and related reliability issues. All these factors strongly influence the performance of the adopted operation and control strategies for the ESS. Next subsections describe their mathematical modelling.

2.1. Electricity Market and Economic Assessment

We consider an electricity company owning a wind energy system grid-connected with ESS based on the production of H2. The electricity dispatch schedule of the wind farm has to be submitted in advance to the grid operator. In this way, the company participates in the electricity market through committing energy to be sold for the day ahead. These commitments are made once per day by declaring the amount of energy that they are selling in each one of the 24 hours of the following day. Specifically, let Y_i be the amount of kWh committed for selling at hour i. The revenue obtained from the selling of Y_i kWh at hour i is $C_{c_i}Y_i$, where C_{c_i} is the unit price of a committed kWh at hour i. Let Z_i be the amount of kWh ultimately sold at hour i. Deviations of the dumped energy Z_i from the committed energy Y_i have a penalty: when the sold energy Z_i is less than Y_i, an amount C_{p_i} should be paid for each kWh committed and not supplied (furthermore, the renewable energy system becomes a non-reliable energy supplier). For the case in which the dispatched energy Z_i exceeds the committed energy Y_i, the selling price of each kWh in excess, C_{s_i}, is less than the committed kWh price, C_{c_i}. Thus, the total economic revenue at hour i with Y_i committed KWh and Z_i kWh sold is:

$$C_{c_i}Y_i + C_{s_i}d_i^+ - \left(C_{c_i} + C_{p_i}\right)d_i^- \qquad (1)$$

where

$$Z_i + d_i^- - d_i^+ = Y_i, \quad \text{with} \quad d_i^-, d_i^+ \geq 0$$

Here, the deviational variables d_i^- and d_i^+ express the negative and positive deviations of the supplied energy with regard to the commitments. Clearly, from an economic point of view the greatest revenue are obtained when variables Y_i take values as highest as possible and the deviation variables take value zero. The quotient d_i^-/Y_i measures the lack of reliability of the system at time i.

The dispatched energy Z_i is the result of adding the X_i^O kWh obtained from the ESS to the G_i kWh generated from the renewable source at hour i and subtracting the amount X_i^I of kWh stored in the ESS.

That is,

$$Z_i = G_i - X_i^I + X_i^O$$

Determining the values for X_i^O and X_i^I are the decisions that constitute the operational decision making. Determining the values of Y_i (once per day, in the day-ahead electricity market), for each one of the 24 hours of the day ahead are the decisions that constitute the tactical decision making.

2.2. Variability and uncertainty

The decision-making is performed in a stochastic environment, which has to be taken into account to obtain meaningful results. The value G_i is not known with certainty in advance. Decisions are made based on a forecast of the renewable resource, which is subject to errors. Specifically, we assume that a Probabilistic Wind Speed Forecast (PWSF) at each time t is available: a set of *m* predicted wind speed trajectories for the near future. These *m* different forecasts for the wind speed are used as inputs of the power curve, which converts wind speed to power generation. After this transformation, we obtain a probabilistic forecast of the amount of electricity produced for each of the next *n* hours: $G_m = \left\{G_{ij},\ i = 1, \dots, n\right\}_{j=1}^{m}$, where G_{ij} is the KWh generated at hour i associated with the j-th predicted wind speed curve.

2.3. Reliability Assessment

In regions with high penetration of renewable energy it is necessary to measure the capacity of the generation system to cover the load without unexpected imports.

In the literature two main measures are used to assess the reliability of any energy generator system (see Callaway, 2010): the expected time that the system does not supply the demanded energy (the Loss of Load Probability - LOLP) and the expected amount of demanded energy not supplied by the energy system (the Loss of Load Expectation - LOLE). Both are used to assess the performance of the system in the long term. In our analysis we need to adapt these measures to get a local measure of the energy system reliability performance in order to drive tactical and operational decisions to meet reliability goals at every moment over time.

We propose the following index R_t^E to measure the local reliability at time t:

$$R_t^E = 1 - \frac{\sum_{k=0}^{t-1} \lambda^k (Y_{t-k} - Z_{t-k})^+}{\sum_{k=0}^{t-1} \lambda^k Y_{t-k}}$$

where,

$0 < \lambda \leq 1$, and $(Y_{t-k} - Z_{t-k})^+ = \max\{Y_{t-k} - Z_{t-k}, 0\}$

When λ is 1, this index calculates the ratio of committed energy not supplied by the energy system, and then it corresponds with an estimation of the long term reliability measure LOLE. When $\lambda < 1$, a geometric moving average is defined where the reliability behavior of the system in the far away past contributes to the index result less than its reliability behavior in the recent past and present. The greater the value of λ the greater the influence of the reliability in the past in the present value of the reliability index. That is, λ represents a memory-size parameter.

Similarly, we define a local version R_t^P of the LOLP

$$R_t^P = 1 - \frac{\sum_{k=0}^{t-1} \lambda^k 1_{\{Y_{t-k} > Z_{t-k}\}}}{\sum_{k=0}^{t-1} \lambda^k}$$

If R^E denotes the reliability goal for the amount of committed energy supplied by the renewable system (that is, for the LOLE value) then,

$$\varphi_t^E = \begin{cases} \dfrac{R_t^E}{R^E} & \text{when } R_t^E < R^E \\ 1 & \text{when } R_t^E \geq R^E \end{cases}$$

is a reliability ratio that measures at time t the deviation of the system from the general reliability goal. This index can be calculated at every time t, and it is introduced in the mathematical optimization problem to induce outcomes providing management policies supporting the increase of the reliability goal.

3. MATHEMATICAL OPTIMIZATION PROBLEM

In this section we propose a mathematical optimization problem whose solution provides the tactical (Y_i values) and operational (X_i^I, X_i^O values) management of the energy system. The mathematical model deals with the uncertainty in the wind speed forecast by considering that a PWSF is available, and includes both objectives the economic and the reliability one.

3.1. Formulation of the Optimization Problem for the Energy System Operational Management

Let suppose, without loss of generality, that the present time is denoted by t, that the commitments of energy Y_i are known (they are determined by a similar problem described in next section concerning the tactical problem). A reliability goal R^E is fixed and it is know the reliability ratio φ_t^E. The operation of the ESS in the next hour (denoted by index 1) is determined by the values of the decision variables X_1^I, X_1^O obtained as solution of the following mathematical problem.

Problem [OP]:

$$\begin{aligned} Maximize \sum_{i=1}^{n} C_{c_i} Y_i + C_{s_1} \frac{1}{m} \sum_{j=1}^{m} d_{1j}^+ - (C_{c_1} + C_{p_1}) \frac{1}{m} \sum_{j=1}^{m} d_{1j}^- \\ + \sum_{i=2}^{n} \left(C_{s_i} d_i^+ - (C_{c_i} + C_{p_i}) d_i^- \right) \\ - (1 - \varphi_t^E) C_R \left(\frac{1}{m} \sum_{j=1}^{m} d_{1j}^- + \sum_{i=2}^{n} d_i^- \right) \end{aligned}$$

Subject to

$$G_{1j} - X_1^I + X_1^O + d_{1j}^- - d_{1j}^+ = Y_1 \quad j = 1, \dots, m \qquad (1)$$

$$T_1 + efI\ X_1^I - efO^{-1}\ X_1^O = T_2 \quad j = 1, \dots, m \qquad (2)$$

$$G_{ij} - X_{ij}^I + X_{ij}^O = Z_{ij} \quad i = 2, \dots, n, \ j = 1 \dots, m \qquad (3)$$

$$T_{ij} + efI\ X_{ij}^I - efO^{-1}\ X_{ij}^O = T_{i+1\,j} \quad i = 2, \dots, n \quad j = 1 \dots, m \qquad (4)$$

$$Z_i = \frac{\sum_{j=1}^{m} Z_{ij}}{m} \quad i = 2, \dots, n, \qquad (5)$$

$$Z_i + d_i^- - d_i^+ = Y_i \quad i = 2, \dots, n \qquad (6)$$

$$X_1^I, X_{ij}^I \leq Cap_{transf}/efI \quad i = 2, \dots, n, j = 1 \dots, m \qquad (7)$$

$$X_1^O,\ X_{ij}^O \leq Cap_{Recovery} * efO \quad i = 2, \dots, n, j = 1 \dots, m \qquad (8)$$

$$T_{ij} \leq Cap_{Tank} \quad i = 2, \dots, n, j = 1 \dots, m \qquad (9)$$

$$Z_i, Z_{ij},\ d_{1j}^+,\ d_{1j}^-, d_i^-, d_i^+, X_1^O, X_1^I, X_{ij}^I, X_{ij}^O, T_{ij} \geq 0$$

Observe that constraints (1) determine the deviation variables associated to the operational decision variables X_1^I, X_1^O which will be the only ones that will be implemented in practice. The other decision variables, X_{ij}^I, X_{ij}^O, are only used to evolve the system in the future to evaluate the consequences of the present decisions. Constraints (2) update the state of the energy storage system. Constraints (3) define the amount of kWh to be released in the future according to each wind trajectory, (4) assures that the employed policies are feasible, (5) estimates the expected kWh released into the grid and (6) evaluates the deviations of this average with respect to the committed kWh. The remaining constraints, (7), (8) and (9), are the capacity constraints.

3.2. Formulation of the Optimization Problem for the Energy System Tactical Management

Once per day, the managers should decide how much energy to commit for each of the 24 hours of the day ahead. Suppose that the decision is made every day at 12 a.m., then i=1 corresponds to the hour from 12 a.m. to 1 p.m., i=2 to the hour from 1 p.m. to 2 p.m., and so on. The commitments for the 12 hours ranging from 12 a.m. to 12 p.m. are known because they were fixed the day before. This problem is solved by formulating a problem similar to the previous one, where the decision variables of interest to determine the electricity dispatch schedule are $\mathrm{Y_i}, i = 13, \dots, 36$. These values define the tactical decisions because they are considered as the electricity selling commitments. There are two differences respect to the problem [OP]:

- the $\mathrm{Y_i}$ are known parameters for the indices i corresponding to hours of the current day, $i = 1, \dots, 12$, but they are decision variables for each of the 24 hours of the day ahead, that is, indices $i = 13, \dots, 36$.
- the reliability influence on the tactical decisions is modeled by modifying the constraint (5) in the following way:

$$Z_i = \left(\varphi_{\mathrm{t}}^{\mathrm{E}}\right)^{W_t} \frac{\sum_{j=1}^{m} Z_{ij}}{m} \quad \mathrm{i} = 2, \dots, \mathrm{n}$$

where $W_t = \sum_{k=0}^{t-1} \lambda^{\mathrm{k}} 1_{\{\mathrm{Y_{t-k}} > \mathrm{Z_{t-k}}\}}$.

When the reliability goal is not being achieved then the factor $\left(\varphi_{\mathrm{t}}^{\mathrm{E}}\right)^{W_t}$ induce a reduction in the amount of released electricity and then also in the value of the scheduled energy, favoring in this way the ultimate supply of the scheduled energy.

Then the mathematical problem to obtain the tactical management of the renewable system is:

Problem [TP]:

$$\mathit{Maximize} \sum_{i=1}^{n} C_{c_i} Y_i + C_{s_1} \frac{1}{m} \sum_{j=1}^{m} d_{1j}^{+} - \left(C_{c_1} + C_{p_1}\right) \frac{1}{m} \sum_{j=1}^{m} d_{1j}^{-} + \sum_{i=2}^{n} \left(C_{s_i} d_i^{+} - \left(C_{c_i} + C_{p_i}\right) d_i^{-}\right)$$

Subject to

$$G_{1j} - X_1^I + X_1^O + d_{1j}^{-} - d_{1j}^{+} = Y_1 \quad \mathrm{j} = 1, \dots, \mathrm{m} \qquad (1)$$
$$T_1 + efI \; X_1^I - efO^{-1} X_1^O = T_2 \quad \mathrm{j} = 1, \dots, \mathrm{m} \qquad (2)$$
$$G_{ij} - X_{ij}^I + X_{ij}^O = Z_{ij} \quad \mathrm{i} = 2, \dots, \mathrm{n}, \; \mathrm{j} = 1 \dots, \mathrm{m} \qquad (3)$$
$$T_{ij} + efI \; X_{ij}^I - efO^{-1} X_{ij}^O = T_{i+1\,j} \quad \mathrm{i} = 2, \dots, \mathrm{n}, \; \mathrm{j} = 1 \dots, \mathrm{m} \qquad (4)$$

$$Z_i = (\varphi_t^E)^{W_t} \frac{\sum_{j=1}^{m} Z_{ij}}{m} \quad i = 2, \dots, n, \qquad (5)$$
$$Z_i + d_i^{-} - d_i^{+} = Y_i \quad \mathrm{i} = 2, \dots, \mathrm{n} \qquad (6)$$
$$X_1^I, X_{ij}^I \le Cap_{transf} / efI \quad \mathrm{i} = 2, \dots, \mathrm{n}, \mathrm{j} = 1 \dots, \mathrm{m} \qquad (7)$$
$$X_1^O, \; X_{ij}^O \le Cap_{Recovery} * efO \quad \mathrm{i} = 2, \dots, \mathrm{n}, \mathrm{j} = 1 \dots, \mathrm{m} \qquad (8)$$
$$T_{ij} \le Cap_{Tank} \quad \mathrm{i} = 2, \dots, \mathrm{n}, \mathrm{j} = 1 \dots, \mathrm{m} \qquad (9)$$
$$Z_i, Z_{ij}, \; d_{1j}^{+}, \; d_{1j}^{-}, d_i^{-}, d_i^{+}, X_1^O, X_1^I, X_{ij}^I, X_{ij}^O, T_{ij} \ge 0$$

4. SIMULATION FRAMEWORK

We develop a discrete time simulation model to test the management policies in different environments defined by the electricity prices, by the accuracy of the PWSF and by different reliability goals.

The simulation model includes all of the important equipment that comprises the wind-H2 energy system (wind generators, electrolisers, compressors, H2-tank, fuel cells,...).

The logic of the simulation is described in Figure 1. Before beginning the simulation the energy system is defined by providing value to the parameters that dimension it (transformation curves, efficiencies, capacities,…), a goal of reliability is fixed and the length of the simulation set. Time is initialized at zero.

The clock of the simulation is advanced in steps of one hour. First, the PWSF is generated by simulation by using the method proposed in Mallor et al. (2009): an autoregressive time series model generates autocorrelated errors that modify the true wind speed series. The method uses maximum relative errors that vary in the forecast horizon from an initial value to a final value following different functional patterns. All these parameters can be modified. Following this method *m* wind speed trajectories are generated. From them the probabilistic electricity generation forecast for the next *n* hours are obtained.

First it is check if the current hour is an hour to send the electricity dispatch schedule for the day ahead to the grid regulator. If it is, then the problem OP is solved to get the operational policy, that is, the amount of electricity that either has to be stored in the next hour or has to be released from the storage. Then, the energy system is updated taking into account the electricity production simulated at that hour: level of energy in the storage, economic profit from the selling of electricity and reliability of the energy systems regarding the commitments.

If it is the hour to send the grid operator the electricity dispatch schedule then the problem TP is solved to obtain the commitments for the 24 hours of the day ahead. Then, the OP problem is solved for that hour.

After updating the statistical counters, the clock of the simulation is advanced one hour and the previous procedure is repeated again. This simulation framework is useful to test different values for the memory parameter λ used in the definition of the local indices of reliability and the extra penalty parameter $\mathrm{C_R}$ used to favor the reliability goal in the objective function.

The simulation model has been implemented in Java and the optimization problems are solved by using the CPLEX solver. The size of the optimization problems allows to obtaining the optimal solution very quickly and as a consequence the simulation of one year of this energy system only takes less than one minute with a computer with an i7 processor.

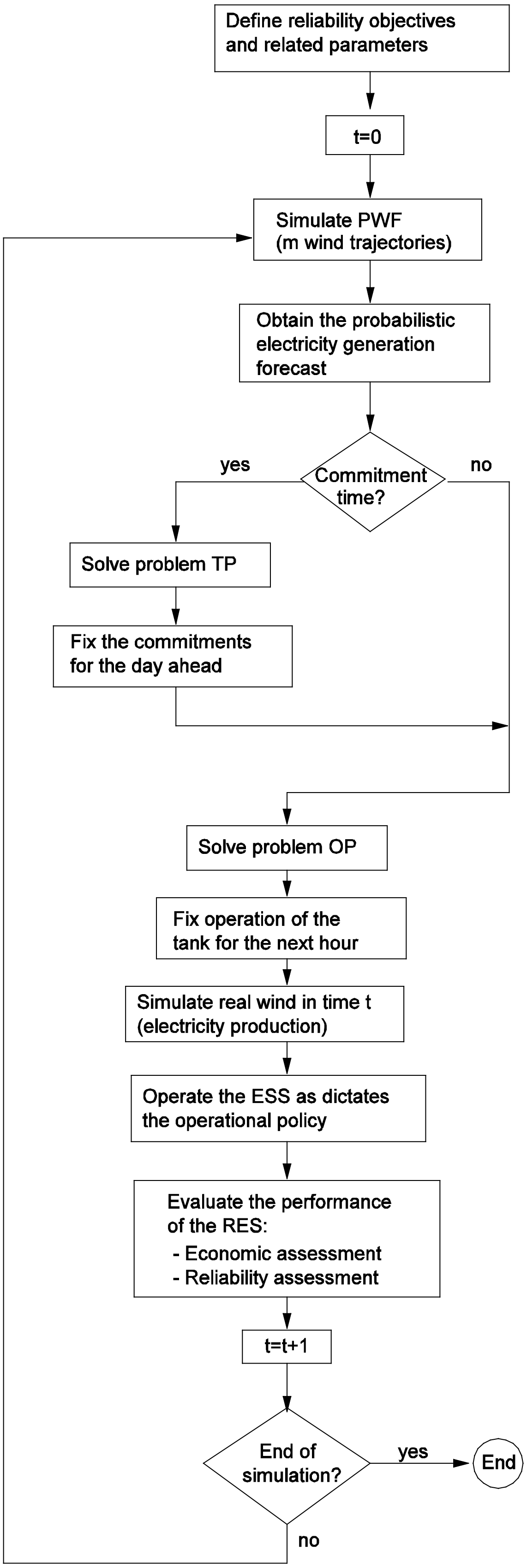

Figure 1: Organigram of the simulation framework.

5. RESULTS AND CONCLUSIONS

In this section in order to illustrate the methodology proposed in this research work to obtain both tactical and operational management policies of an energy system with ESS, we consider a renewable wind-farm system with H2-based storage inspired by a real system that the authors studied in a previous paper (see Aguado et al. (2009)). We present graphically (Figures 2 and 3) ten days of simulation results, although the system has been simulated for a whole year. Figure 2 shows the electricity production during these ten days. We use real wind speed data as the true wind speed data during the simulation, and from it we simulate the PWSF and its associated electricity production.

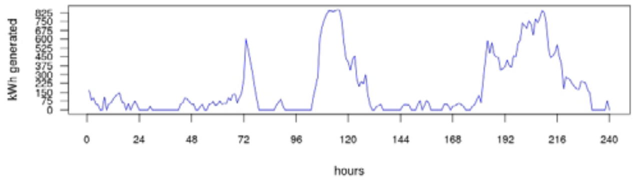

Figure 2: Electricity production of the wind farm.

The simulation experiments are designed to show the effect of introducing the reliability goal in the management of the system, in terms of both economic cost and reliability improvement. Figure 3 shows these results when the objective for the reliability is set to 0,98. In the top graphic of Figure 3 we see that the management including the reliability goal is able to improve it when the local reliability measure decays below the fixed threshold. Furthermore, the biggest differences in the reliability achieved by the two management policies are observed at short periods of maximum electricity production. The reliability of the energy system during the whole year is 92.7% without reliability goal, but if this reliability goal is considered then the reliability increases over 97%. However this improvement has a counterpart in economic terms. The down graphic of Figure 3 shows the revenue obtained from the electricity selling in both cases, and their difference. This difference is not always in favor of one of the management policies but in the long term it is necessary to pay a price for the reliability improvement. Our simulation results provide a decrement of the revenue over 7,5%. The improvement of 4,3% in reliability and 7,5% of worsening in revenue depend on the goal set for the reliability but also of the memory and extra-penalty parameters used to model the reliability in the optimization problems. These parameters could be optimized for a specific application (specific energy system in a specific site) by combining simulation with optimization. As result a Pareto frontier reliability/revenue would be obtained to select from it the best management policy according to the wishes of the energy system manager.

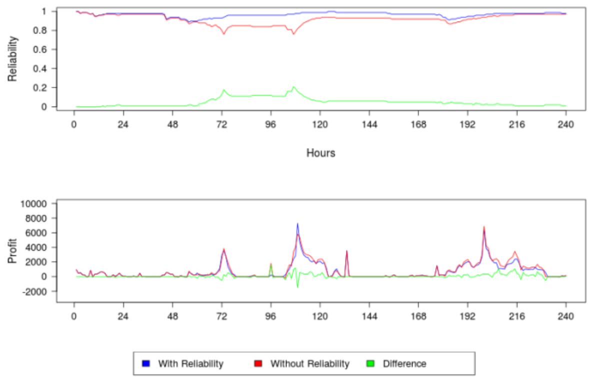

Figure 3: Comparison in terms of reliability and economic revenue of managing the energy system with and without reliability goal.

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APPENDIX A. List of Symbols, Abbreviations, Parameters and Variables

C_{c_i}: unit price of committed energy at hour i

C_{p_i}: unit penalty cost of not supplying committed energy at hour i

C_{s_i}: unit price of surplus energy at hour i

C_R: additional unit penalty cost of not supplying committed energy to achieve reliability goal

$Cap_{Recovery}$: maximum capacity of the recovery process (H2 → kWh)

Cap_{Tank} : maximum storage capacity of the tank

Cap_{transf}: maximum capacity of the transformation process (kWh → H2)

d_i^-: negative deviation of the supplied energy with regard to the commitments

d_i^+: positive deviation of the supplied energy with regard to the commitments

d_{ij}^-: negative deviation of the supplied energy with regard to the commitments associated with the j-th predicted wind speed curve

d_{ij}^+: positive deviation of the supplied energy with regard to the commitments associated with the j-th predicted wind speed curve

EfI : efficiency rates of the transformation process

EfO : efficiency rates of the recovery process

G_i : kWh generated at hour i

G_{ij} : kWh generated at hour i associated with the j-th predicted wind speed curve

m: number of wind speed trajectories in the PWSF

n: planning horizon, measured in hours

PWSF : probabilistic wind speed forecast

T_i : kWh stored in the tank at hour i

T_{ij} : kWh stored in the tank at hour i associated with the j-th predicted curve

X_i^I : kWh transformed into H2 and stored in the tank

X_i^I : kWh transformed into H2 and stored in the tank, at time i, associated with the j-th predicted wind speed curve

X_i^O : kWh obtained transforming H2 from the tank, at time i, into electricity (recovery process)

X_i^O : kWh recovered from the tank, at time i, associated with the j-th predicted wind speed curve

Y_i : kWh committed for selling at hour i

Z_i : kWh sold at hour i

Z_{ij} : kWh sold at hour i associated with the j-th wind speed predicted curve

φ_t^E : reliability ratio at time t

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