Stochastic optimization techniques for the optimal combination of wind power generation and energy storage in a market environment

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Stochastic Optimization Techniques for the Optimal Combination of Wind Power Generation and Energy Storage in a Market Environment

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Abstract

This paper proposes a new method, based on stochastic optimization, for managing the operation of a wind farm in conjunction with energy storage. The main objective is to maximize the benefit of the joint operation of wind generators and energy storage devices, while considering the stochastic nature of wind power production and electricity market prices. The paper presents results of the application of the methodology in decision-making processes related to wind power management.

I. Introduction

DECISION-MAKERS may be faced with many different decision-making problems comprising a wide variety of alternatives. In general, such problems require some decision process to be followed for the decision-maker to achieve good compromise decisions. When the possible consequences of the available alternatives are taken into account in the decision process, the outcomes associated to each alternative become subject of some randomness, which renders them *stochastic* in nature. Decision-making problems incorporating stochastic outcomes are usually referred to as problems of decision-making under uncertainty [1].

In that later case, the decision-maker has to choose among available alternatives under *imperfect* knowledge of what the future outcome of each alternative will be. In other words, some process for making decisions having *imperfect* information as inputs [2] has often to be followed , which implies some amount of *uncertainty* to be associated to decision outcomes. Such uncertainty of the outcomes should therefore be taken into account in the decision process.

Much work has been devoted to problems of decision-making under uncertainty which are often modeled as optimization problems [1], [3]. The extensive state of the art of optimization under uncertainty methods and applications supplied in [4] provides a basis for the development of the present work. The proposed approach was developed bearing in mind the uncertainty modeling possibilities and the decision under risk paradigms presented in [5]. Our technique is also inspired by rule-based models representing the interaction of preferences of the decision-maker as the one proposed in [6].

This paper focuses on the particular problem of *sequential* decision-making under uncertainty, in which, as the name states, decisions have to be made sequentially. For tackling problems of the kind, we propose a decision-making model based on a stochastic dynamic programming approach.

The application concerns the scheduling of a virtual power plant comprising a wind farm and an energy storage device and operating under a day-ahead electricity market. More particularly, hydro storage is considered. The interconnection of the virtual power plant with the main electricity grid is made *via* a single point of common coupling (PCC) as depicted by Figure 1.

While participating on the day-ahead market (i.e.: usually referred to as *spot* market or forward day-ahead market [7], [8]), the wind-hydro power plant owner has to make a decision on what should be the level of energy bids and when to place them on the *spot* market. In this paper, the energy bids on the day-ahead market are determined using the proposed scheduling algorithm, which takes into account the available day-ahead wind power forecasts and the uncertainties associated to such forecasts. Due to the uncertainties associated to the power output of the wind farm, differences between scheduled energy production and *actual* energy production occur, which are usually named *energy imbalances*. Such imbalances are filtered *as much as possible* by the energy storage device on the operation phase. This is done while taking into account the physical limitations of the energy storage device. Finally, remaining imbalances are penalized according to the electricity market regulation prices.

The proposed approach aims at reducing the energy imbalances generated by the wind farm while keeping the profit of the wind farm operator as high as possible. This is achieved by integrating the uncertainty associated to wind power predictions in the decision process. The use of the energy storage

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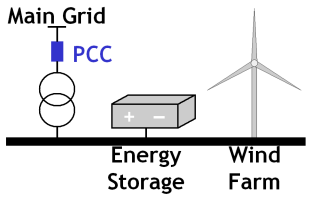

Fig. 1: Wind-hydro power plant model used in this work.

for increasing the controllability of the whole is also evaluated. In short, the proposed approach seeks to maximize the expected revenues associated to the scheduling decisions in the long run while minimizing imbalance risks.

II. State of the Art on Risk-Based Decision-making Approaches

Several risk definitions may be found in the literature. As an example, in [9], risk is defined as the hazard to which a utility is exposed because of uncertainty. In the same reference, risk is defined as a bi-dimensional characteristic of decisions having the following dimensions:

- the likelihood of making a regrettable decision;
- the amount by which the decision is regrettable.

In the presence of uncertainty, one needs to quantify the risk associated to a given decision by using an appropriate risk measure. Many risk measures exist in the literature. Different classes of such measures are presented and reviewed in [10], [3]. However, in the context of decision-making under uncertainty, defining a risk measure is somewhat insufficient. Indeed, one needs to define an appropriate risk-based decision model. In [3] three basic risk-based approaches are resumed. These consist of:

- Expected-Utility Approach: tries to describe the decision maker's attitude towards risk *per se* (i.e.: without reference to any particular situation);
- Mean-Variance Approach: assumes that the best decisions are those with greater expected values and smaller variances (or standard-deviations) of their outcomes;
- Stochastic Dominance Approach: assumes that only limited information on the decision maker's utility function is available and ranks decision preferences through the employment of stochastic dominance theorems based on the cumulative distribution of estimated decision outcomes.*

Here, we do not present an exhaustive state of the art on risk-based approaches. For that purpose, the interested reader may refer to [5]. Moreover, a state of art on optimization under uncertainty may be found in [4]. In this work, an approach based on a stochastic dynamic programming approach using a spot-risk model as the objective function of the single-stage sub-problems is proposed, tested and discussed. The proposed approach follows the same principles of the risk-based approaches used in [12], [13], [14], [15], [16], [17].

III. General Description of the Problem

The problem of operating the wind-hydro power plant depicted in Figure 1 under both day-ahead and regulating market conditions, was subdivided in two main phases. The first one focuses on the production of the day-ahead operation schedule, based on the characteristics of the wind-hydro plant and on the day-ahead forecasts of the hourly *spot* prices for energy and for wind farm output. Concerning wind power forecasts, both the expected value and associated variance are considered. The second phase focuses on the short-term intraday operation of the plant.

A. Market Models

Each electricity market has its own rules, defining the way electricity is to be sold or purchased, how electricity prices are settled, and the obligations with which market participants are committed. Different European electricity markets exist [18]. Most of them include a day-ahead market, also named spot market, and a regulation market:

*It is out of the scope of this paper to analyze such theorems in detail. The interested reader may refer to [3], [1], [11] for more information on the matter.

1) Day-Ahead Market: Day-ahead electricity market rules impose the use of forecasts having a time horizon that depends on the time-lag between the day-ahead market clearance (usually referred to a *gate closure time*) and the start of energy production. In general, power producers have to place their production bids on day d till noon, but will only start generating the corresponding power on the first hour of day $d+1$. This results on a time-lag of 12 h. Moreover, this time-lag corresponds to the best-case as, in fact, the wind power producer will continue generating till the end of day $d+1$, which gives a total time-lag of 36 h. This time-lag range specifies the horizon needed for the forecasts.

2) Imbalance Market: The transmission system operator (TSO) is responsible for maintaining the physical balance between production and consumption. Power producers interacting directly with the electricity market have to help the TSO to maintain power balance at all time by participating in the market balancing mechanisms. Such imbalance mechanisms imply power producers to pay a market imbalance price for their respective power imbalances. Consequently, positive or negative imbalances, in general, lead to the payment of regulation costs by the producers decreasing their individual market incomes. In this work, an imbalance market model is used, based on the studies [19] and [20].

The determination of regulation prices varies according to the considered market. In our case, we consider it is the result of the regulation market, where actors with power reserves place bids for fast production increase or decrease. This is for example the case of NordPool, balance responsible actors are penalized for their imbalance only if they are opposite to the regulation measure taken by the TSO. The interested reader may refer to [21] for obtaining further information on NordPool market rules.

B. Optimal Scheduling of the Virtual Power Plant

In a market context, we consider that the wind-hydro power plant owner or aggregator seeks to maximize the profit generated by the plant. In the scheduling phase, this is achieved by a dispatch function that has the objective of finding the operating set-points of the energy storage that maximize the total profit of the wind-hydro power plant throughout the scheduling horizon (e.g.: 24 h). This function uses forecast of wind generation.

The output of the optimization process supplies the set-points of the energy storage device and the day-ahead contracted power at the point of common coupling (PCC), depending on the wind farm output and *spot* price forecasts. The interested reader may refer to [22], [23] for further details on the followed approach.

C. Simulation of the Operation of the Virtual Power Plant

In this work, the model for representing the hourly operation of the plant is similar to the one presented by the authors in [23]. During each day, the operation model follows as closely as possible the previously decided day-ahead contracted power to the day-ahead market. For achieving this, the model uses the energy storage device for compensating, whenever possible, the power imbalances that occurred due to the wind power forecasts errors. The ability of the storage to filter the imbalance depends both on its power rating and its actual state-of-charge. These physical limitations determine whether the storage device is able to deliver or absorb the required amount of power in order to filter imbalances. The charging and discharging efficiencies of the device are also considered in the operation.

IV. Proposed Scheduling Approach

The wind-hydro power plant scheduling decisions are coupled in time, essentially due to the energy storage ramp-rate constraints. This means that the possible scheduling decisions associated to a given point in time depend on the previous ones and condition later ones. Therefore, the wind-hydro power plant scheduling problem corresponds to an optimization problem belonging to the class of serial multistage sequential decision problems [24]. Several methods can be found in the literature for tackling problems of the kind [25], [26].

In this work we have used a scheduling approach based on a stochastic dynamic programming algorithm similar to the one presented by the authors in [22]. Such algorithm is based on a deterministic dynamic programming algorithm to which we coupled the spot-risk model proposed in this paper. The spot-risk model integrates the uncertainty associated to single-stage decisions in the decision-making process. A short description of the dynamic programming formulation is given in subsection IV-A. The description of the proposed spot-risk model is given in subsection IV-B.

A. Dynamic Programming Model

We developed a dynamic programming approach in which the energy storage state-of-charge (SOC) describes the state of the wind-hydro power plant at a given time-step. State transition costs are given by the state transition cost function $\mathcal{T}$, which, in our case, is given by the energy storage operating cost function. The dynamic programming recursive function $\mathcal{F}$ used in this work may be represented by the Bellman equation:

$$\mathcal{F}(s,t) = \pi_{s,t} + \mathcal{T}(x_{s,t}, x_{k,t+1}) + \mathcal{F}(k,t+1) \tag{1}$$

where:

- $\mathcal{S}$ is the set of system states;
- $s, k \in \mathcal{S}$;
- $x_{s,t}$ represents the system being in state s at time t;
- $\pi_{s,t}$ is the profit associated to $x_{s,t}$;
- $\mathcal{T}(x_{s,t}, x_{k,t+1})$ represents the cost-to-go from state $x_{s,t}$ to state $x_{k,t+1}$;
- $\mathcal{F}(k,t+1)$ represents the cumulated cost associated to state $x_{k,t+1}$.

We have formulated the dynamic programming problem as a *Boundary Value Problem* [24]. This means that both the initial and the final stored energy contained in the energy storage device of the dynamic programming recursion have to be specified *prior* to running the scheduling tool. For doing this, we have proceeded in the following manner:

- we assumed that the energy storage device at the beginning of the simulation period is found at 50% of its maximum storage capacity;
- we have assumed the energy storage device to always reach a final state of 50% of its maximum storage capacity at the end of each scheduling period of 24 hours.
- from the second day till the end of the simulations the energy storage device is initialized at the final SOC that was obtained after the previous day operation takes place. Therefore, the dependency between the scheduling and the operation phases was established.

B. Spot-Risk Model

Electricity market regulation prices are highly variable and hardly predictable [27]. Therefore, producing sufficiently good forecasts of such imbalance prices *prior* to deciding which bids to place on the day-ahead market is very difficult to achieve. This means that, in our case, estimating the expected *recourse* (or penalization) costs associated to every feasible decision (i.e.: hourly energy bid) is hardly feasible in itself. Thus, we have developed an approach that takes into account the wind power forecast uncertainty for minimizing the risks of imbalances associated to the scheduling of the wind-hydro power plant.

For dealing with the uncertainties associated to wind power forecasts, we have opted to use a model based on the same principles as those of the mean-variance approach described in section II. However we call such model a Spot-Risk model because we think that this is a more generic term in the sense that it allows the use of *spot* values other than the mean (e.g: median) and whatever risk measure one thinks to fit the decision-maker's requirements (as opposed to only using the variance).

Spot-risk-based models have been widely used in decision-making processes [15], [28], [29]. One of the main reasons for this is that these models permit the decision-maker to integrate the uncertainty associated to a given random variable χ based on a function f of only two criteria:

1) a *spot* prediction of the random variable outcome $\hat{\chi}$ (e.g.: its expected return $E(\chi)$);
2) the amount of risk associated to such prediction, which is hereby given by $\mathcal{R}(\hat{\chi})$.

The small number of criteria required by mean-risk models makes them quite appealing. Equation 2 defines the Spot-Risk model, where, the β parameter represents the risk attitude of the operator.

$$f(\hat{\chi}, \mathcal{R}(\hat{\chi})) = \hat{\chi} - \beta \cdot \mathcal{R}(\hat{\chi}) \tag{2}$$

In this work, we use a Spot-Risk model similar to the one described by Equation 2 for incorporating the uncertainty associated to wind power predictions in the scheduling decision process. Such uncertainties are associated to the wind power production forecasts for every hour of the scheduling horizon. Hence, the wind power production uncertainty is independent from any variable other than its corresponding wind power forecast. This means that the uncertainty information is independent of the wind-hydro power plant state (SOC). Therefore, using the uncertainty information *as is*, would render the stochastic problem a

purely deterministic one (i.e.: every state transition would be penalized in the same way). This would be equivalent to disregarding the uncertainty information associated to wind power forecasts.

To overcome this design problem, we complemented the uncertainty information associated to wind power forecasts with a preference indicator depending on the state-of-charge states of the energy storage device. Such preference indicator has the role of differentiating the state-transitions evaluated by the dynamic programming recursion described in subsection IV-A according to the operator's preferences. We have defined such preferences following a *Risk Perception* philosophy as such perception has an important role on how risks should be managed [2]. In [30], risk perception is defined as an *intuitive risk judgment*. In other words, risk perception can be viewed as the sensitivity of the decision-maker to estimated risks.

In our case, the risk perception may be seen as a tri-dimensional surface having as dimensions the energy storage state-of-charge, the time axis and the perceived risk value associated with a given state-of-charge at a given moment of the scheduling horizon. Such perception is hereby given by $\mathcal{P}(t+1,k)$, where $\mathcal{P}$ stands for the risk perception, $t+1$ and k represent, respectively, the *"next time-step"* and the *"next state"*.

C. The Proposed Stochastic Dynamic Programming Approach

Due to the sequential nature of the wind-hydro power plant scheduling problem, in this work the evaluations of the risk perception are made dynamically in time. Accordingly, we adopted Equation 3. This equation couples the principles of Equation 1 with those of Equation 2, while permitting decisions under uncertainty to be taken sequentially in time.

In Equation 3, P_{WF_t} and $V(P_{WF_t})$ represent, respectively, the forecast of wind farm power output and the variance associated to such forecast at time t.

$$f(s,k,t,V(P_{WF_t})) = \pi_{s,t} - \beta \cdot \mathcal{P}(t+1,k) \cdot V(P_{WF_t}) \tag{3}$$

For integrating Equation 3, we have replaced Equation 1 by Equation 4 in the scheduling problem formulation.

$$\mathcal{F}(s,t) = f(s,k,t,V(P_{WF_t})) + \mathcal{T}(x_{s,t}, x_{k,t+1}) + \mathcal{F}(k,t+1) \tag{4}$$

For minimizing the risk of obtaining imbalances at the point of common coupling (PCC) between the wind-hydro power plant and the main grid we created the risk perception surface $\mathcal{P}$ following two main rules:

A) the degree of risk perception of the wind-hydro power plant operator was assumed to be proportional to the average *spot* price curve;
B) we assumed the plant operator prefers to maintain the storage as close as possible of a given state s^{spec}, which means that the risk perception of the operator is minimized when the *the next* storage state k equals s^{spec} (in the scope of this paper, we have further assumed such state to be of 50%, as this state-of-charge assures equal slack exists for charging and discharging energy).

Following the previous considerations, the risk perception surface $\mathcal{P}$ is calculated as follows:

1) normalize the average *spot* price curve by its maximum throughout the day obtaining a normalized average *spot* price vector $\mathcal{V}_{p_{spot,N}}$ comprising elements $\{p^1_{spot,N}; p^2_{spot,N}; \ldots; p^T_{spot,N}\}$, where T corresponds to the number of time-steps of the scheduling horizon;
2) considering that the risk aversion of the operator increases according to a quadratic function g of the difference between the *next state* k and the preferred state s^{spec}, calculate for every time-step t the value of $g(k - s^{spec}, d) \cdot p^{t+1}_{spot,N}$, thus obtaining $\mathcal{P}(t+1,k,d)$, where $d \in [0;1]$ is a *depth* parameter that influences the depth of the risk perception surface $\mathcal{P}$;

A value of $d = 0$ implies risk indifference, which is equivalent to say that the scheduling method becomes purely deterministic. Higher values of d increase the *depth* of the risk perception surface. This increases the importance of risk forcing the optimization algorithm maintain the energy storage state-of-charge equal or as close as possible to s^{spec}. Under such behavior, the optimization algorithm ceases to work properly in the sense that it overreacts to risks neglecting scheduling outcomes. Hence, it is advisable to find some satisfactory compromise between these two extreme situations. In this paper we present a series of simulations in which two values of d are used ($0,01$ and $0,05$), as described in subsection V-B.

D. Forecasting Models

Forecasts of *spot* prices and wind power are used as input to the scheduling process. The *spot* price forecasts are computed using a simple method, which consists in taking the last available measured price for a given hour (i.e. the value 48 hours before). The wind power forecasts were obtained with a state-of-the-art *statistical* model based on kernel density estimators [31], [32]. Such model provides predictions in the form of probability density functions, which can be used as such or transformed into different subproducts depending on the application (e.g. single production value, variance, prediction intervals or quantiles). In this paper two subproducts of the predicted wind power distribution have been considered, the mean and the variance.

V. Case-Study

The wind-hydro power plant management strategy has been applied in a case study containing real-world data. subsection V-A describes the case-study selected for this paper. In subsection V-C, the results from the simulation runs presented in subsection V-B are analyzed.

A. Case-Study Description

In this study, we have considered a 21 MW wind farm located in the North West of Denmark, for which power production data was available for the years 2000, 2001 and 2002. Meteorological data, including wind speed and direction numerical weather prediction (NWP) for different heights corresponding to same time and area were also used.

We have used historical prices from the NordPool electricity market [21], which is divided in several market areas. We have used data from the market area corresponding to the location of the wind farm used in this study (West Denmark).

In NordPool, contracts covering each hour of the coming day are traded on the day-ahead market, which is named Elspot. The Elspot gate closure time is at 12:00 pm (local time) of the preceding day. Hence, we used the last available NWP data (06:00 am of the same day) as inputs to the wind power forecasting tool and forecast horizons were selected in order to get the predictions for the next day. The wind power forecasts were then used to calculate the bids. During the delivery day, the storage was operated as described in subsection III-C. The learning and testing of the wind power forecasting model were performed with the data corresponding to the years 2000 and 2001, respectively. The simulations were performed with the data and forecasts corresponding to 2002.

B. Evaluated Simulation Scenarios

In this work, 30 scenarios were simulated. Two of them are deterministic (realistic) reference scenarios using *spot* price and wind power forecasts. The remaining 28 scenarios take into account uncertainties by using the proposed Spot-Risk model.

The two deterministic reference scenarios comprise a base scenario (D) that uses all of the available energy capacity of the energy storage and a *bounded* base scenario (DB) where the energy storage is considered smaller than it actually is (i.e.: the storage energy capacity (SOC) boundaries are narrowed).

In the base deterministic simulation (D), the energy storage device is operated with its energy capacity limits equal to those defined by the energy storage specifications. However, in the *bounded* deterministic simulation (DB) from the literature [33], [34], the storage energy capacity limits are reduced artificially in the scheduling phase (but not in the operation phase). The DB simulation constitutes a rule-of-thumb approach for decreasing the imbalances caused by the wind-hydro power plant.

The remaining 28 simulations may be separated into two main approaches:

- the ones tagged as SR in which the proposed Spot-Risk model was used *as is*;
- the ones tagged as SRB in which the proposed Spot-Risk was used in parallel with the same bounding strategy that was used in the DB base simulation described above.

Each of the two main stochastic approaches (SR and SRB) aggregates 14 different simulations. These simulations were obtained by varying the d and the β parameters. The d parameter (referring to *depth* of the risk perception surface) was allowed to take two values. The β parameter (referring to the risk attitude of the wind-hydro power plant operator) was allowed to take seven different values. Two of the β values are negative, corresponding to risk-prone attitudes of the plant operator. The remaining five β values are positive, representing risk-averse attitudes of the plant operator.

For facilitating the analysis of the results, the different types of stochastic simulations (those with TYPE = SR or SRB) are named as $TYPE\acute{d}_i, \beta_j$, where $i \in \{1, 2\}$ and $j \in \{1, 2, \ldots, 7\}$. So, for instance, the case in which TYPE = SR, $\acute{d}_i = 2$ and $\beta_j = 4$ (i.e.: $SR2, 4$) corresponds to a case using the simple Spot-Risk model (i.e.: without *bounding*) with $\acute{d}$ equaling $0,01$ and β equaling 0.4. Table I summarizes all the simulations that were performed containing the indexes that correspond to the different $\acute{d}$ and β parameters that were used in the simulations.

TYPE	**D**	**DB**	**SR**	**SRB**	$\acute{d}$		
Bounding	No	Yes	No	Yes	$\acute{d}_i$	1	2
Stochastic	No	No	Yes	Yes	**Value**	$0,05$	$0,01$

β							
Risk Attitude	Prone		Averse				
β_j	1	2	3	4	5	6	7
Value	-0.2	-0.1	0.2	0.4	0.6	0.8	1.0

TABLE I: Summary of the simulations performed.

C. Results & Analysis

Figure 2 summarizes the total imbalance and revenue results obtained for the 30 simulations normalized by the base deterministic case (D) that was described above. We can see that imbalance energy improvements were attained in almost every simulation. The only exceptions to this rule were the eight simulations corresponding to the risk prone attitudes (bounded in Figure 2 by the green-dashed rectangles) because these reward risky situations. The base deterministic case corresponding to the rule-of-thumb for reducing imbalances (DB) also led to an imbalance reduction. All the risk averse simulations reduced the imbalances in different amounts. As for the Revenue, Figure 2 shows that the reference revenue (D) was never surpassed (not even by the risk prone simulations). However, such revenue was always quite close to its reference value.

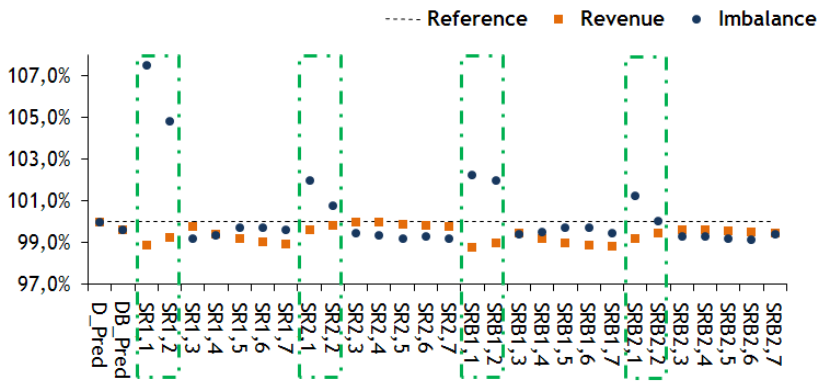

Fig. 2: Total imbalance and revenue obtained for all the simulations performed. The reference simulation is the one denoted by D (deterministic simulation).

The correlation coefficient between the obtained revenues and the obtained values of imbalance energy for every simulation is weak. This is also the case for the correlations between the revenue and the surplus energy and between the revenue and the improvement (i.e.: decrease) of energy imbalance. The correlation between the obtained revenue and the shortage energy takes the highest value. Table II summarizes the correlation results obtained.

The correlation results shown above say that there is a weak link between the imbalance reduction and the obtained revenue. The relatively high dispersion depicted in Figure 3 clearly confirms this result. The same figure also highlights the Pareto-optimal solutions that were obtained. We can see that some improvement of the imbalance was obtained without significantly reducing the revenue. The cases in which imbalances worsen with the use of the proposed method correspond to risk prone attitudes as described above.

We will now analyze the general behavior of the stochastic results in more detail. For this we shall divide such results according to the $\acute{d}$ parameter, thus obtaining four major groups of cases: SR1, SR2, SRB1 and SRB2. In these cases, the number index corresponds to the defined value of $\acute{d}$ in Table I.

Correlation between:	Value
Revenue & Imbalance	$0,402$
Revenue & Shortage	$0,651$
Revenue & Surplus	$0,137$
Revenue & Imbalance Improvement	$0,493$

TABLE II: Summary of the different correlation results obtained.

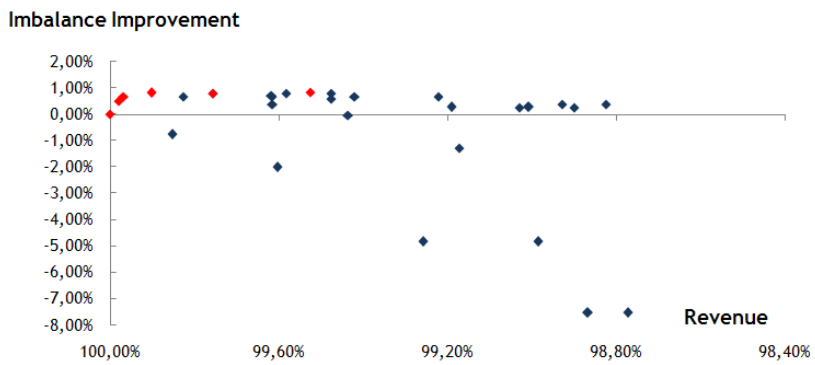

Fig. 3: Imbalance improvement *versus* obtained revenue for every simulation. The points in red represent the Pareto-Optimal solutions obtained.

The imbalance improvement results obtained with the proposed tool are detailed in Figure 4. In that figure we can see that the imbalances between the simulations corresponding to the proposed Spot-Risk method (SR) are approximately superposed with those obtained with the alternative Spot-Risk method (SRB) for the same values of d. In the SRB method, aiming to further reduce imbalances, the Spot-Risk model was submitted to narrower storage energy capacity boundaries. Although such narrower bounds seem to work well when wind power forecast uncertainties are disregarded Figure 4, they do not influence the imbalance results in the presence of such uncertainties.

In Figure 4 we can also verify that using lower values of d (i.e.: $d_i = 2$) allows to obtain better energy imbalance results in the sense that such imbalances are always lower than in both the deterministic simulations and the stochastic simulations using higher values of d (i.e.: $d_i = 1$). This is expected because lower values of d imply the risk perception surface $\mathcal{P}$ to be less *deep*, which helps to reduce the difference between possible decisions in the scheduling phase because the dynamic programming routine becomes less sensitive to the variance associated to wind power forecasts.

Still in Figure 4, under risk averse attitudes, we can verify that the imbalance improvement obtained with the proposed method was always slightly better than the one obtained *via* the DB reference method. Finally, in the same Figure we can see that risk averse attitudes always lead to energy imbalance reductions as opposite to the risk prone attitudes.

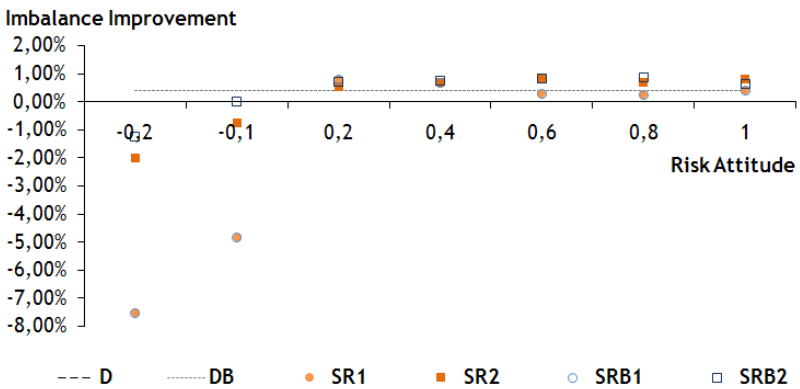

Fig. 4: Energy imbalance improvement for different risk attitudes.

Regarding revenue, in Figure 5 we can see the detailed results that were obtained. The figure shows

that the revenues obtained with the SRB simulations are always lower than the revenues of the *equivalent* SR simulations. Keeping in mind that SR and SRB *equivalent* simulations lead to almost superposed imbalance results (*vide* Figure 4), we can conclude that the SRB approach can be disregarded. Furthermore, the revenue obtained with the SRB approach seems to be limited to that obtained with the simpler DB deterministic approach. However, things seem to be a bit different in what regards the SR approach. In fact, this approach may or not lead to revenue improvements relatively to the DB reference approach. In the case where the $\acute{d}$ is equal to $0,01$ (i.e.: $\acute{d}_i = 2$), the revenue never attains the base reference revenue given by the D simulation, but almost always surpasses the revenue obtained with the reference DB approach. Thus, the SR2 approach permitted to simultaneously obtain the best energy imbalance improvements (*vide* Figure 4) and the best revenue results relatively to the cases aiming to reduce energy imbalances (DB, SR and SRB). Finally, the SR2 approach permitted in some cases to almost attain the reference revenue (D) while improving the energy imbalance of the system.

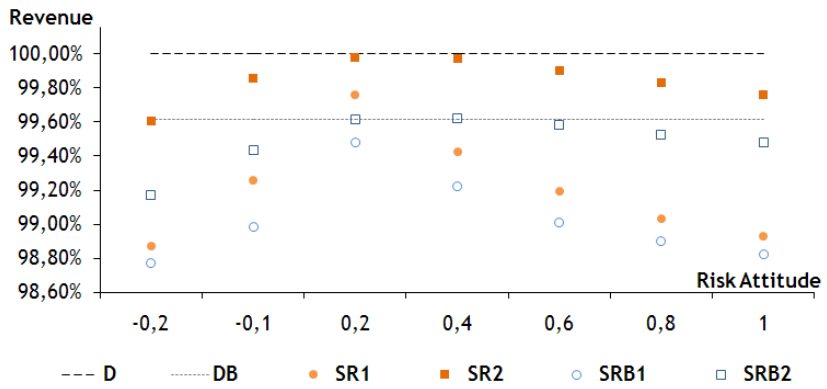

Fig. 5: Revenue loss for different risk attitudes.

Summarizing, the results show that the proposed approach (SR) is able to reduce energy imbalances. However, the imbalance reduction remains quite small, which leads us to believe that further improvement of the approach is possible. Still, with the proposed approach such reduction can be higher than the one obtained with the rule-of-thumb deterministic reference approach (DB). Nevertheless, the revenue losses obtained with the proposed approach (SR) are lower than the ones obtained with the reference deterministic approach (DB). However, in this case-study the proposed approach did not improve the revenue obtained with the base deterministic approach (D). This may be due to the market structure that only penalizes operator imbalances if these are opposite to those occurring in the main grid.

VI. Conclusions

In this paper a novel approach was proposed for dealing with problems of decision-making under uncertainty by building a risk metric based on risk perception and variance and was applied to the case of a wind-hydro power plant comprising energy storage and operating under a day-ahead market. Using simple risk perception rules, we demonstrated that we can obtain an improvement of the energy imbalance, when compared to a reference imbalance reduction method taken from the literature. Furthermore, such energy imbalance reduction is achieved while maintaining the revenue of the plant operator similar to the one obtained in the reference deterministic case, which yields the highest revenue. These results indicate that the joint operation of wind-hydro plant comprising energy storage possibilities enabled the wind farm to behave as a "well-behaved citizen" whilst its operator still maximized the generated profit. However, the defined rules are simplistic and more improvements can be made in the future for further improving these results.

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