Simulation Of Energy Storage In A System With Integrated Wind Resources

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Abstract – Utility-scale storage is key to providing the means of better harnessing wind energy potential. This paper proposes a probabilistic simulation approach capable of assessing - over longer time periods - the impacts of a utility scale storage unit on the economics and reliability of power systems with integrated wind resources. We deploy a snapshot-based simulation approach to account for the time dependencies of the load, wind power outputs and storage operation as well as their impacts on the utilization of the transmission resources as prescribed by the clearing mechanism of the hourly transmission-constrained day-ahead markets. We run Monte Carlo simulations in order to capture the uncertainty in thermal unit availabilities, the load and the wind power outputs. The methodology is able to represent the seasonal effects in loads and wind speeds, the impacts of maintenance scheduling and the ramifications of new policy initiatives. We illustrate the benefits of storage exploitation with several application studies run on the IEEE 118 test system. Results show that storage can effectively help reduce the overall buyer payments and improve system reliability by storing energy in the low load hours and discharging at peak hours, thereby displacing more expensive units.

***Keywords* – Utility-Scale Storage Integration, Wind Resources Integration, Transmission-constrained Day Ahead Markets, Probabilistic Simulations, Locational Marginal Prices, Reliability.**

I. Introduction

Wind is a clean and renewable source of energy with zero fuel costs. However, wind generation outputs are highly variable, intermittent and not fully controllable/ dispatchable by the operator. The wind speed pattern presents a key challenge to integration of wind resources [1] since the wind may not blow during the peak load hours when the system most needs it. The lack of controllability over such wind speed patterns implies that the integration of wind resources into the grid may be unable to realize the full potential of wind resources. Moreover, there are concerns about "spilling" of wind energy at night due to the insufficiency of the load demand, not providing to the system, in such cases, the benefits from this energy to meet the demand. The basic tool operators use to manage the wind variability is the raising of the reserve levels [2], which, typically, results in increasing the overall production costs, notwithstanding the zero fuel costs of the wind resources. Such situations create excellent applications for utility-scale storage [3],[4] to facilitate the improved harnessing of the wind resources by storing wind energy for release during peak-load hours so as to displace the costly energy from polluting generating units. We have worked on the development of a probabilistic simulation approach of systems with integrated wind and storage resources over longer-term periods. The approach is able to evaluate the impacts of storage integration into a grid with wind resources, taking explicitly into account various sources of uncertainty, wind variability and intermittency as well as the impacts of the time varying utilization of transmission resources on the deliverability of the electricity to the loads. The methodology may be used to quantify the variable effects of large-scale power systems with storage and intermittent wind resources operating in a market environment over longer-term periods.

The approach uses an hour as the smallest indecomposable unit of time and deploys a snapshot representation of the resources and the grid. We incorporate into the snapshot-based framework probabilistic regimes [5] for modeling the time-dependent wind resources at various sites and the modeling of the storage operations taking into account arbitrage and storage cycle efficiency and the impacts of transmission constraints. The simulation methodology makes effective use of the widely-used concepts in probabilistic simulation and deploys Monte Carlo Simulation [6] with systematic sampling techniques to represent the various sources of uncertainty considered. The emulation captures effectively the synergies between wind and storage to allow the assessment over the longer term of the impacts on reliability and economics of storage integration into power systems with multi-site wind farms. We represent the economic effects by clearing the 24 hourly transmission-constrained day-ahead markets (DAMs) by determining the solution of an *OPF* problem. From the sampling performed in the framework of the Monte Carlo simulation, we obtain the approximations to the various economic and reliability metrics, including locational marginal prices (*LMP*s), the total buyer payments, carbon emissions and the *LOLP* and the *EUE*. We note that these metrics implicitly account for the effects in the deliverability of the electricity. The methodology is able to capture the seasonal effects in loads and wind speeds, the impacts of maintenance scheduling and the ramifications of new policy initiatives. We ensure the simulation scheme computational tractability for application in large scale systems and/or over long study periods by making use of the Latin Hypercube sampling technique [6] to improve Monte Carlo simulation tractability and by reducing the number of weeks to be simulated to a smaller number of representative weeks.

There are numerous applications of the approach to a broad range of planning, investment, transmission utilization and policy formulation and analysis studies for systems with deepening penetration of wind and storage resources. We illustrate the capabilities of the simulation approach using a modified version of the IEEE 118-bus system model with historical wind data. Our extensive testing indicates that storage effectively displaces peaking units and causes a marked reduction in total buyer payments whereas system reliability is improved. As storage capacity is increased, the synergetic benefits of wind and storage become more pronounced in terms of the better utilization of the wind resources generation, with favorable impacts on system economics and reliability.

The paper contains five additional sections. In section II, we address the modeling of wind resources as well as the process through which we establish an average storage operating policy for use in the simulations. Section III describes the snapshot-based probabilistic simulation approach and the obtaining of realizations of market outcomes of interest and contributions to the reliability metrics. In section IV, we focus on the steps taken to ensure the computational tractability of the simulation approach in practical cases. Section V demonstrates the capabilities of the approach with case studies run on the IEEE 118 bus test system. We conclude with a summary in section VI along with directions for future work.

II. Incorporation of time-dependent resources in probabilistic simulations

We devote this section to the modeling of wind and storage resources in the probabilistic simulation and their integration in the framework of the hourly market clearing mechanism. Load and generator availabilities are modeled accordingly to conventional approaches [7]. As such, the load is modeled as a random variable for which we use the hourly forecasted data to estimate the cumulative distribution function (c.d.f.), whereas thermal generator availabilities are modeled as multistate-multiblock units. Note that our models make the assumption that the wind resources, the thermal generating unit availabilities are statistically independent from each other.

A. Wind Resources

The basic modeling of wind resources at *S* geographically dispersed wind farms is thoroughly described in [5]. System wind speed patterns are essentially modeled by a multivariate random variable for the purpose of capturing wind daily patterns as well as the cross-correlation existing between them. Note that such cross-correlations – which depend on the geographical spread of the wind farms [8] – are of importance since they determine the pattern of wind power injections to the network and therefore impact the utilization of the transmission resources.

We denote the aforementioned multivariate r.v. by “system wind speed daily pattern” and empirically build its probability distribution based on historical data. Realizations of such a r.v. are none other than supervectors of dimension 24*S that capture the simultaneous wind farm wind speeds for each hour of the day.

We go further in the structuration of the probability space by reprising the notion of wind regimes developed in [5]. The basic idea of regimes consists in grouping supervectors of daily wind speed patterns into classes of “look-alike”. The result is an effective partition of the state space of the r.v. “system wind speed daily pattern” into mutually exclusive subsets for which we can define specific random variables descriptive of our so-called regimes.

Also, for the need of the Monte Carlo simulations as presented in section III, the joint probability density function of “system wind speed daily pattern” is smoothed out and made continuous thanks to the application of kernel smoothing techniques [9]. Gaussian kernels are chosen for this purpose and the joint probability density function is effectively turned into a Gaussian mixture from which realizations can easily be sampled. Note that each sample of the wind speed pattern random variable is a 24*S vector that contains the hourly realizations of each wind farm. As such, a particular sample for the wind is drawn only once for 24 hours of simulation.

Wind speeds are converted into corresponding power outputs using well known wind farm characteristic power curves [10]. The latter are non-linear mappings whose characteristics clearly depend on the wind turbine models and number within a given wind farm. It is important to note that wind turbines within the same wind farm are all assumed to experience the same wind speed, i.e. wind turbines do not “cannibalize” each other. This means that two turbines of the same class and within the same site are assumed to yield the exact same power output at all time. Wind power outputs are therefore obtained by feeding wind speeds as inputs to the appropriate wind farm power curve.

B. Storage

In view of carrying out the proposed snapshot-based simulations, we need to gain insight in how a utility scale storage unit may effectively be used economically in a power system with integrated wind resources. To this end, we make use of an algorithm relying on probabilistic production costing methods to derive a near optimal way of deploying the storage unit economically in actual operations [11] – that is, operating the storage unit in such a way that electricity prices are reduced and system reliability improved. The algorithm ignores transmission constraints as it represents the load with its duration curve (LDC). The thermal units are loaded accordingly to a merit (cost-based) order that also accounts for the costs associated with the unit commitment. The algorithm is capable of assessing the expected production costs and delivered energy of each thermal unit based on their respective marginal costs of energy and availabilities. The goal is to provide a list of the thermal units that may be used to charge the storage unit, as well as the economical positioning of the storage unit in the merit order. We account for the time-dependent wind resources by modifying the load accordingly to the wind power output patterns. Such modification is achieved by conceptually subtracting the aggregated wind power output r.v. from the hourly load r.v. for each given hour of the study period. Such operation results in the controllable load, that is the load left to be served by controllable thermal units after deducting the aggregated wind power output. In practice, since the wind and load patterns are assumed to be statistically independent from each other, the operation may easily be performed by convolving the hourly load with the hourly aggregated wind power output. Then, the c.d.f. of the controllable load r.v. can be reconstituted by applying the law of total probability over the set of the hours of the study period. The use of the controllable load allows for the representation of the wind as a time-dependent resource despite the time-abstracted framework. However, such use clearly makes the assumption that wind is the cheapest source of energy available and comes first in the merit order.

In such a framework, the storage unit is to be deployed as a limited energy plant with the following specifics: first, the storage unit must accomplish a full cycle over the study period, that is, all stored energy must be discharged before the end of the period. Taking into account the efficiency η_s of the overall process of storing and discharging energy, we obtain the following formulation

$$\eta_c \xi^c = \frac{\xi^d}{\eta_g} \Leftrightarrow \eta_c \eta_g \xi^c = \xi^d \Leftrightarrow \eta_s \xi^c = \xi^d , \qquad (1)$$

with η_c the efficiency of the storage unit when charging, η_g the efficiency of the storage unit when discharging, ξ^c the excess energy taken from the thermal units to charge the storage unit, ξ^d the energy effectively provided by the storage unit upon discharging.

Second, the storage must be used economically, that is, the cost of storing one MWh must never exceed the cost of producing one MWh with the thermal unit(s) the storage is supposed to displace. Therefore, the storage unit is usually charged by absorbing the excessive energy of otherwise-spilled wind energy or base loaded thermal units that are not dispatched at full capacity to meet the controllable load during low peak hours. As such, the cost of charging the storage unit is always associated with the actual price of electricity (notwithstanding the transmission constraints), i.e. the marginal cost of the last thermal unit dispatched to meet the load. Mathematically, we write such economic criterion as follows:

$$\omega^{\bar{c}} \leq \eta_s \omega^{\bar{d}} \qquad (2)$$

That is, the marginal cost $\omega^{\bar{c}}$ of the most expensive thermal unit used to charge the storage must be less than the marginal cost of the cheapest unit displaced by the storage, taking into account the efficiency η_s of the storage cycle. It is important to note that no unit is dispatched for the specific purpose of charging the storage unit; in other words, the charging of the storage must not increase the marginal cost of energy.

Third, the storage unit must be operated within its own physical limits, i.e. capacity constraint and reservoir constraint.

Given those constraints, the algorithm determines exactly the list I_c of thermal units that should be used for charging the storage unit, the amount of total energy the storage is to store during a full cycle and the position of the storage unit in the merit order list so that as much expensive energy as possible is displaced. For future reference, we denote by I_d the set of thermal units higher in the merit order than the storage unit.

Such scheme therefore provides a good idea of the way the storage unit should be operated despite its non-representation of the transmission constraints and chronology of events. We use such solution as an average operating policy in the emulation of the storage unit in the snapshot-based simulations. However, the consideration of the transmission constraints in each installment of the hourly day-ahead markets may entail the modification of such a schedule so as to ensure that (1) holds in the MCS. We next introduce the market clearing process and describe how storage is integrated into such a framework.

C. *The hourly market clearing mechanism*

We adopt the dispatch mechanism used in homogenous transmission-constrained day-ahead markets [12] for the purpose of emulating system operation in a given hour of the simulation period.

The hourly DAM clearing mechanism is modeled by a DC Optimal Power Flow (DCOPF) whose goal consists in maximizing the social welfare (or minimizing the social costs when the entire load is deemed to be fixed) under a set of DC power flow constraints that model the transmission network. The following model takes into account the wind power injections.

We denote by $\mathscr{B}$ the set of energy buyers and $\mathscr{G}$ the set of controllable generators selling energy in the market. β^b is the price at which buyer b is willing to buy energy; γ^g is defined as the price offer of seller (generator) g .

Matrices $\underline{A}$, $\underline{B}_d$ and $\underline{B}$ respectively designate the reduced branch to node incidence matrix, the branch susceptance matrix and the reduced nodal susceptance matrix whereas $\underline{b}_0$ is the column vector of the augmented susceptance matrix corresponding to the slack node.

$\underline{p}$ designates a vector of power injection. Superscript *s* indicates seller (supply side players), *b* buyers (demand side players), *g* conventional generation (thermal units) and *w* wind power.

$\underline{\theta}$ is the vector of power angles (0 at the slack bus) and

$\underline{f}^{\max}$ is the vector of transmission line thermal rating.

$\underline{\lambda}$ the vector of dual variables associated with the nodal power balance constraints. λ_0 is the dual variable of the power balance constraint of the slack node.

Then the DC OPF formulation for hour *h* (with no reference to *h* for more clarity) is the following linear program $\mathscr{M}(\mathscr{G},\mathscr{S})|_h$:

$$\max_{\underline{p}^b,\underline{p}^s}\left\{\sum_{b\in\mathscr{B}}\beta^b\left(p^b\right)-\sum_{s\in\mathscr{S}}\gamma^s\left(p^s\right)\right\} \tag{3}$$

subject to

$$\underline{p}^s = \underline{p}^g + \underline{p}^w$$
$$\underline{p}^g + \underline{p}^w - \underline{p}^b = \underline{B}\underline{\theta} \leftrightarrow \underline{\lambda}$$
$$p_0^g + p_0^w - p_0^b = \underline{b}_0^T\underline{\theta} \leftrightarrow \lambda_0$$
$$\underline{B}_d\,\underline{A}\underline{\theta} \le \underline{f}^{\max}$$
$$\underline{p}_{\min}^g \le \underline{p}^g \le \underline{p}_{\max}^g$$
$$\underline{p}_{\min}^b \le \underline{p}^b \le \underline{p}_{\max}^b$$

Note that the first equality constraint highlights the fact that sellers in the market are entities such as thermal generating units or wind farms (plus storage unit in the relevant conditions as described in the following paragraph).

The storage is operated based on the knowledge of the resource dispatch provided by the solution to $\mathscr{M}(\mathscr{G},\mathscr{S})|_h$. If the most expensive thermal unit dispatched to serve the load belongs to I_c, then excess capacities from units belonging to I_c are used to charge the storage within its physical limits. On the other hand, if expensive thermal units belonging to I_d are dispatched, then the storage unit must come in and displace, within its physical ratings, as much energy as possible from the more expensive thermal units. In a congested network, the storage unit may be bidded/offered both as a load and generator in view of giving more degrees of freedom to the dispatch process. It can be shown that an optimal solution to the DCOPF determines without ambiguity storage operation in such a mode. The DCOPF formulation is then run a second time to take storage operation into account. For this purpose, storage is bidded/offered at a price consistent with the economic criterion (2).

The next section is devoted to the use we make of those models in the actual simulation process and the obtaining of realizations of market outcomes of interest as well as reliability indices.

III. The proposed simulation approach

The goal of the proposed simulation approach is to emulate power systems with wind and storage resources over longer term periods. We divide the study period into non-overlapping simulation periods – typically weeks – to capture seasonal effects, changes in the resource mix and the transmission grid, maintenance schedules as well as the introduction of new policies. Any system change must therefore entails switching to another simulation period for which system characteristics are required to remain constant. Inside each simulation time period, we employ a snapshot-based approach to accommodate the time varying nature of the load, wind and storage cycle with a time granularity of one hour. Therefore, we view the system to be in steady-state in each hour of the simulation period. The resolution chosen does not allow for the representation of any phenomenon of duration shorter than an hour and, consequently, such phenomena are entirely ignored. The basic simulation process consists in clearing the hourly transmission-constrained markets $\mathscr{M}(\mathscr{G},\mathscr{S})|_h$ for each hour h of the simulation period, so as to obtain the load and generation dispatch from which we derive the economic and reliability effects. However, most inputs to the market are sources of uncertainty; the load, wind power outputs and generator availabilities behave in unpredictable ways we need to account for. We run Monte Carlo simulations for each simulation periods in order to account for the multiple possible (and likely) realizations of the input space - random variables associated with the load, the wind power outputs and the generator availabilities - and obtain, via the solution of the corresponding hourly market clearing processes, representative realizations of the market outcomes. With such realizations, it is possible to approximate the c.d.f.'s of market outcomes of interest as well as some reliability metrics, which provide us with a good picture of power system economics and reliability over longer term periods when deep penetrations of wind power and a utility scale storage unit are integrated to the grid.

In practice, for each hour of the simulation period, the DAM clearing process is fed with deterministic inputs that are particular realizations (samples) of the random variables associated with the wind power outputs, the load and the controllable generating unit availabilities. Other inputs are modeled deterministically from the onset and therefore can be seen as having a unique realization with probability 1. In this regard, note that we assume that sellers (generators) always offer at cost (wind is assumed to be offered at 0$/MWh) and electricity buyers bid in a deterministic (and therefore known) fashion. The solution to $\mathscr{M}(\mathscr{G},\mathscr{S})|_h$ (or rather its solution after consideration of the storage unit as described in the end of section II) yields corresponding realizations of the load and generation dispatch from which we derive the realizations of market outcomes of interest. Failure to solve $\mathscr{M}(\mathscr{G},\mathscr{S})|_h$, that is infeasibility of the linear program, is an occurrence of loss of load that counts towards the evaluation of the reliability metrics *LOLP* and *EUE*. Such event is likely to occur when most of the load is fixed (price insensitive), a situation leading to potential shortfall in the total generation capacity *or* inability of the transmission network to deliver energy at certain nodes of the network.

We compute the economic outcomes of a particular realization of the market for hour h, given the realizations of wind power outputs, load and controllable generator availabilities fed as inputs to $\mathscr{M}\left(\mathscr{G},\mathscr{S}\right)|_h$. We provide the formulas for evaluating some market outcomes and reliability metrics of interest.

The LMPs are given by the dual variables λ associated with the power balances at each node. Therefore, the LMP at node *i* is given by $\lambda_i|_h$.

The total buyer payments are computed as

$$\varpi^{\mathscr{B}}|_h=\sum_{i=0}^{N-1}\left\{\left[\lambda_i\right]^*|_h\times\left[p_i^b\right]^*|_h\right\}, \tag{4}$$

where, *N* is the total number of buses in the network. The total payments to the supply side are given by

$$\varpi^{\mathscr{S}}|_h=\sum_{i=0}^{N-1}\left\{\left[\lambda_i\right]^*|_h\times\left(\left[p_i^g\right]^*|_h+\left[p_i^w\right]^*|_h+\left[p_i^{g_s}\right]^*|_h\right)\right. \tag{5}$$

where $\left[p_i^{g_s}\right]^*|_h$ is the storage power output when used as a generator. The hourly carbon emissions $\varepsilon|_h$ rents are evaluated by

$$\varepsilon|_h=\sum_{g\in\mathscr{G}}\chi_g\times\left[p^g\right]^*|_h, \tag{6}$$

with χ_g the emission factor of unit *g* (*kg/MWh*) and $\mathscr{G}$ the set of thermal units. We assess the unserved load $u_i|_h$ at each node *i* of the network and the total unserved energy due to loss of load in hour *h* as in

$$U|_h=\sum_{i=0}^{N-1}u_i|_h. \tag{7}$$

$U|_h$ is a realization of the unserved energy r.v. $\underset{\sim}{U}$, for which we have $\Pr\left(\underset{\sim}{U}>0\right)=LOLP$ and $EUE=E\left(\underset{\sim}{U}\right)$.

Note that all aforementioned outcomes are merely one realization of the associated random variables conditioned on hour h. Monte Carlo simulations require a reasonable amount of such realizations to approximate the associated random variables. We therefore clear the market for each hour of a simulation period multiple times in order to obtain a sufficient number of realizations. In the end, we quantify the variable effects of the system by evaluating the expected values of the market outcomes r.v.'s and the reliability metrics *LOLP* and *EUE*.

We next discuss some methods for ensuring the computational tractability of our simulation approaches when emulating large scale systems over long term periods.

IV. Implementational aspects

In this section, we discuss implementational aspects of the proposed approach and the steps taken to ensure its computational tractability and applicability to large scale power systems over long study periods. The main concern lies in the computational burden associated with the Monte Carlo simulations of study periods spanning many years. We consider simulation periods defined as 168h weeks and notice the fact that both wind and load patterns have a seasonal nature; the consequence is that weeks within a same season experience comparable wind and load patterns. We effectively take advantage of this fact by simulating only representative weeks of a season in order to reduce the computational burden. However, scheduled maintenance may still differ across weeks with similar patterns, driving us to increase the number of representative weeks to well account for this feature. Eventually, each group of similar weeks effectively ends up being represented by a certain number of representative weeks. The contribution of those representative weeks to the metrics we evaluate over the whole study period is then weighted by the number of weeks they represent. In practice, such scheme can reduce the computational burden by a factor 3, as exemplified in our application studies in which the 52 weeks of the year are reduced to a mere 16 representative weeks.

We can further enhance the overall computational tractability by improving on the MCS sampling scheme used in the emulation of each hour of a given simulation period. We make use of the Latin Hypercube Sampling (LHS) technique to reduce the number of samples necessary to obtain a representative coverage of the input probability space (i.e. representative samples/realizations). LHS is essentially a variance reduction technique that uses stratified sampling [5] to efficiently cover the probability space of r.v.s with known distributions given the user specified number of samples (realizations). Consider the one random variable case: the LHS methodology divides the probability domain of the random variable c.d.f. into a number of intervals – also called strata – equal to the desired number of samples. Then the next step consists in extracting a sample from each stratum by use of schemes such as the inverse transform method. This simple scheme is easily extended to the sampling of multiple r.v.s that are statistically independent from one another, as this is the case - or at least we assume it is in our modeling – with the r.v.s that model the wind, the load and the generator availabilities.

Unlike random sampling, LHS ensures that the entire range of a distribution is sampled, thus making the most out of the user specified number of samples when it comes to providing a representative coverage of the r.v. probability space. We perform a sufficient number of Monte Carlo runs to ascertain convergence. We use a convergence criterion based on the standard error of the sample mean (similar to coefficient of variation/relative standard error as seen in [12]). For the particular case studies presented in Section V, extensive testing shows that 200 hundred runs allow the Monte Carlo simulation to converge for all random variables of interest.

The implementation of both representative week scheme and Latin Hypercube sampling allows for substantial reduction in the computational time required by the simulation approach. We next introduce application studies to illustrate our approach on a number of sensitivity studies of interest.

V. Application studies

We illustrate the application of the proposed simulation approach with some representative results for a large test system. We limit our analysis to a single year in order to gain insights into the nature of the results obtained. We build a base case with integrated wind resources and study the system behavior when a utility-scale storage is incorporated into the grid. We run sensitivity studies to assess the impacts of the storage nominal capacity on various metrics of interest.

Simulations are run on the IEEE 118 bus test system [14] with a load shape based on the 1996 IEEE RTS [15] and scaled so that the annual peak load is 8021MW. The base system sports 99 controllable generators with an aggregated total nameplate capacity of 9914MW. Taking into account the seasonality effects, wind and load patterns as well as maintenance schedules, we select 16 representative weeks out of the 52 weeks of the year in order to improve computational tractability. The unit commitment is performed for every one of the 16 representative weeks so as to maintain a reserve margin of 20%. The wind resources are modeled after 4 wind farms whose wind speed data and wind turbine characteristics (including power curves) are collected from NREL wind integration studies [16]. The aggregated nameplate capacity of wind power amounts to 2584MW (about 30% of the peak load) and is equally distributed between wind farms. Storage nominal capacity is respectively taken as 0, 200, 300 and 400 MW in each case study. Storage reservoir (energy capability) is limited to 5000 MWh, while charge and discharge efficiencies are set to 0.89 in order to simulate higher-end efficient utility-scale storage.

We examine storage behavior under various storage nominal capacities. Fig.1 displays the average charge-discharge cycles of the storage unit for various nominal capacities (200, 300 and 400MW) as well as the load pattern during the so-called "average week of the year".

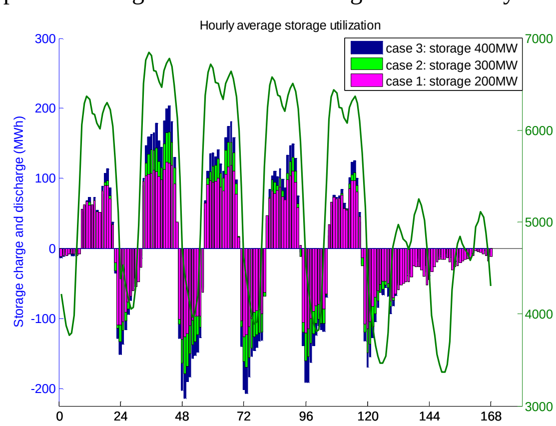

Fig. 1 Average charge-discharge cycles of the storage unit during the "average week of the year"

Note that we construct the 'average week' of the year for a specific metric using the results of the representative weeks in the simulation. For each of the 168 hours of a week, we determine the weighted average of the metric with the weight given by the fraction of the number of weeks in the year that correspond to that representative week. In this way, for each hour of the week, we obtain an estimate of the average value of the metric. Back to Fig.1, it can easily be seen that energy is stored during the low load hours and released at peaking times. Interestingly, week-ends are being used for the sole purpose of charging and in order to meet the high demand of the second day onwards. Also, storage utilization is obviously amplified as the nominal capacity increases. We next look at the expected total buyer payments to determine whether increased storage capacity (that is increased storage utilization as seen in Fig. 1) yield benefits for the buyers. We plot in Fig.2 the duration curves of such expected buyer payments for "the average week of the year" and observe that the integration of the utility-scale storage unit helps reduce the total buyer payments during hours when payments are generally highest. Such hours can be shown to be the peak hours by looking at the same data but keeping the chronological format.

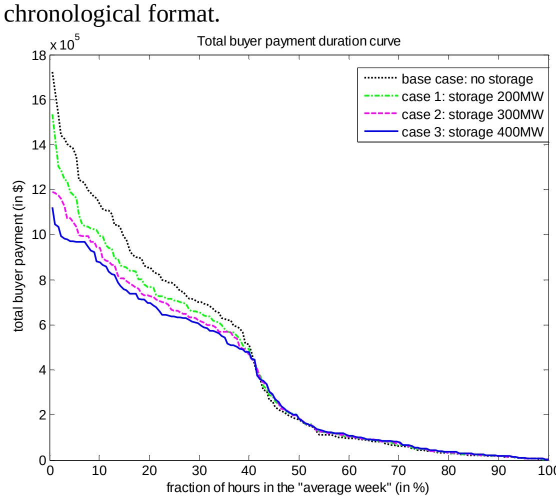

Fig. 2 Total buyer payments duration curve for the "average week of the year". The plot displays all cases.

The reductions in total buyer payments are significant in regard to the yearly-averaged percentage of energy served (and therefore charged) by a 400MW storage unit with respect to the supplied load that amounts to 0.81%. This directly results from the fact that storage is primarily used to displace expensive thermal units, thereby driving down LMPs. Also note that buyers never have to pay more at any time, including for hours during which the storage charges. This is due to the fact that storage is only charged with the excess capacities of the marginal units (those that set the market price). No more expensive unit is dispatched for that sole purpose.

Looking more closely, we also notice that as storage capacity increases, so do the reduction in payments, although the effect becomes less and less pronounced as greater capacities are selected. Such saturation effect may be explained by the fact that the storage displaces more units and therefore comes lower in the cost merit order as storage capacity is increased. However, economic criterion (2) limits the number of base loaded units that can effectively charge the storage, therefore resulting in the impossibility to fully take advantage of its large capacity.

We now present in Table 1 the impacts of storage capacity on the average total buyer payment, average congestion rents, carbon emissions as well as the reliability metrics *LOLP* and *EUE* for the all cases of the sensitivity study.

case	average buyer payment ($)	average congestion rents ($)	average carbon dioxide emissions (kg)	LOLP	EUE (MWh)
base case - no storage	425,830	32,977	89,785	0.0019	3.0311
case 1 - 200MW	389,190	30,565	90,239	0.0014	2.1985
case 2 - 300MW	366,630	28,956	90,174	0.0013	2.1796
case 3 - 400MW	351,100	29,037	90,279	0.0011	1.7841

Table 1. Impacts of storage on various metric of interest

Having discussed the average total buyer payments with Fig. 2, we now examine the impact of the utility-scale storage unit capacity on the average total congestion rents. Total congestion rents are computed as the difference between the total buyer payments and the total seller earnings and may be interpreted as the cost of network congestion. From Table 1, we notice that the integration of a storage unit consistently reduces the total congestion rents. As such, storage tends to relieve network congestion. However it is not exactly clear what role storage capacity plays in this reduction, especially since those results also heavily depend on the storage location in the network.

Carbon dioxide emissions largely depend upon the generation mix of the considered power system. There is always a trade-off between the emission factors of the units used for charging and those of the units displaced by the storage. In the particular case of our study, the charging of the storage unit involves conventional units that turn out to be more polluting than the 'peaking' units the storage displaces during peak hours.

The *LOLP* and *EUE* results from Table 1 show that storage also contributes to system reliability. The latter can be seen to improve as storage capacity increases.

VI. Conclusion

In this paper, we propose a probabilistic simulation approach capable of quantifying over longer term periods the variable effects of wind and storage resources on power system economics, reliability and environmental impacts. The methodology deploys a snapshot-based simulation approach in order to account for the time varying natures of the wind, load and utilization of the transmission network, and make use of Monte Carlo simulation techniques to represent the various sources of uncertainty. As such, the proposed approach allows the comparison of multiple resource mixes and network configurations and is therefore useful in a variety of planning studies or policy analysis. We present results that show that wind and storage resources both contribute to effectively drive buyer's electricity payments and congestion rents significantly, whereas system reliability is improved. Carbon dioxide emissions do not vary significantly due to the particular setup of our generation mix that sports base-loaded units generally more polluting than peaking units.

Future work includes the consideration of multiple storage units, and the integration of wind, storage, demand response resources and solar power altogether.

VII. Acknowledgement

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