Fast MPC-Based Coordination of Wind Power and Battery Energy Storage Systems

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Abstract: In this paper, a model predictive control (MPC)-based coordinated scheduling framework for variable wind generation and battery energy storage systems (BESSs) is presented. On the basis of the short-term forecast of available wind generation and price information, a joint look-ahead optimization is performed by the wind farm and storage system to determine their net power injection to the electric power grid. In conjunction with moderate battery capacity, the excess unpredictable wind generation can be used to charge the battery storage and vice versa. The benefits of the proposed scheduling approach are that (1) the combined profit of wind generation and BESS is increased; (2) the net power injection from the wind farm into the power grid is smoothed out; and (3) the look-ahead optimization updates the price prediction in a moving horizon, which leads to more robust profit for wind farm and BESS against price uncertainties. By formulating the MPC-based coordinated scheduling as a quadratic programming problem, several numerically efficient algorithms to compute the optimal control strategy for wind generation and BESS are proposed. The effectiveness of the proposed algorithm in a modified IEEE 24-bus reliability test system with aggregated plug-in hybrid electric vehicles is demonstrated. It is shown that the proposed algorithm can increase the joint profit of wind farm and BESS while smoothing out the net power injection to the electricity grid. The proposed MPC-based scheduling problem can be solved in approximately 400 ms, which makes the framework implementable in realtime electricity market operations. DOI: 10.1061/(ASCE)EY.1943-7897.0000071. © 2012 American Society of Civil Engineers.

CE Database subject headings: Predictions; Wind power; Energy storage; Vehicles.

Author keywords: Model predictive control; Wind power integration; Battery energy storage systems; Plug-in hybrid electric vehicle; Power system economic dispatch; Electricity market.

Introduction

This paper is motivated by the need for novel operation modeling and computation in support of large-scale variable energy resources integration into the electric power grid (U.S. Dept. of Energy 2008). In particular, the inherent inter temporal variability and limited predictability of wind power generation pose unique challenges to power system operation. Enabled by many recent advances in energy engineering research, the potential of utilizing large-scale wind in a cost-effective and reliable manner becomes not only important, but also achievable. Starting from the work by Illic et al. (2011), a model predictive control (MPC)-based coordinated scheduling framework for wind generation and battery energy storage systems (BESSs) is proposed in this paper.

Current operation by regional transmission organizations (RTOs) typically consider wind generation as nondispatchable (Makarov et al. 2009). In a 10-min-ahead security-constrained economic dispatch (SCED), RTOs treat the predicted wind generation as must-take “negative loads” (Makarov et al. 2009). This leads to two potential causes of inefficiency: (1) the requirement for the backup reserves from conventional generation is high because of the variability of wind fluctuations; and (2) there is little incentive for wind farms to improve their forecast and smooth out their generation. Recently in New York Independent System Operator (NYISO) and Electric Reliability Council of Texas (ERCOT), a penalty was introduced for a large deviation of wind power from the scheduled output level (NYISO 2008; Sioshansi and Hurlbut 2010).

The need for incorporating wind into the dispatch model is discussed by General Electric Energy (2008). In the paper by Xie and Illic (2009), a look-ahead dispatch is formulated to schedule intermittent generation. Look-ahead dispatch is shown to be a more cost-effective approach to utilizing the system generation portfolio. The short-term, e.g., 10-min-ahead, forecast of wind power generation is incorporated in a look-ahead SCED. Rates of response by different generation technologies and the near-term wind generation forecasts are explicitly modeled in the formulation. After the SCED operation, the fluctuations of wind power within 10 min are no longer dispatchable. To account for the intertemporal variations of wind generation within 10 min, a prespecified “buffer zone”, e.g., ±10% of the scheduled output, is typically allowed for wind generation (Sioshansi and Hurlbut 2010).

The potential of utilizing BESS to compensate the deviation of predicted and actual available wind generation is emphasized (GE 2008; Cimuca et al. 2006). Given the high cost of utility-scale storage devices, the questions of how much storage and how to coordinate it need to be studied. Motivated by the increasing concern for high fuel price, the coordination of aggregated small BESSs, such as plug-in hybrid electric vehicles (PHEVs), becomes...
a viable choice (Hajimiragha et al. 2010; Gao and Elsani 2010). However, neither clear formulation nor efficient algorithm for analyzing the coordination has been presented.

The main contribution of this paper is threefold:

- The MPC-based coordinated scheduling of wind generation with BESS, which is implementable in deregulated electricity markets, is formulated;
- Efficient numerical algorithms that allow online implementation of the proposed coordination framework are suggested; and
- The economic benefit of coordinated scheduling is analyzed. In the numerical example, it is shown that the proposed scheduling framework results in overall higher profits for wind and BESS than their joint profit without coordination. The net power injection to the power grid is also smoothed out.

The rest of this paper is organized as follows. In “Related Work”, related work on coordinating wind generation and BESS is reviewed. In “Problem Formulation”, the problem of coordinated scheduling of wind energy and aggregated PHEVs in deregulated electricity markets is formulated. In “Numerical Algorithms”, several fast numerical algorithms tailored for the structured MPC formulation are applied. In “Case Studies”, the potential economic benefits and computational performances of the proposed method in a modified IEEE reliability test system are illustrated. Concluding remarks and future work are discussed in “Concluding Remarks”.

Related Work

The short-term wind power forecast has also been an active field of research in recent years (Hering and Genton 2010; Abdel-Karim et al. 2009). Unlike the difficulty seen in day-ahead or longer-term forecast of wind power, the short-term, e.g., 10-min ahead, forecast of wind power has demonstrated satisfactory accuracy and confidence level. For example, Abdel-Karim et al. (2009) showed that, a Markov-chain-based prediction model has an approximately 85% level of accuracy.

The issues of integrating variable wind generation to the electric power grid have been extensively studied in recent literature (Carrasco et al. 2006; Blaabjerg et al. 2006). The frequency and voltage requirements at the interface between the wind farm and the power grid can be maintained by advanced power electronics—based controllers. However, the inter temporal variability of wind generation at the time scale of 10–15 min, which is the time scale of power system dispatch, could still be a major category source of added cost for the power system operators unless some coordination between wind generation and energy storage systems is implemented (Xie et al. 2011).

Schill and Kemfert (2009) presented a game-theoretic analysis of combining storage and fluctuating wind power in electricity market. On the basis of a German electricity market model, Schill and Kemfert argue that the introduction of storage capacities generally increase social welfare. However, the model does not include the forecast value of near-term wind generation. The potential of reducing the required capacity of storage is therefore not discussed. Khalid and Savkina (2010) presented an MPC approach to smoothing wind power fluctuation with controlled battery storage. The objective of the MPC is to minimize the real power deviation from schedule values. However, the forecast wind generation is not considered as a dispatchable resource. Also, the objective of minimizing the deviation between the actual and desired wind power output does not include the price incentives, which are essential in a deregulated electricity market environment.

A large body of literature discusses the feasibility of controlling battery energy storage systems such as aggregated PHEVs. An overview of the power electronics and motor drive requirements for electric vehicles is presented by Emadi et al. (2008). The high-speed communication architecture for the interface between an individual electric vehicle and a charging/discharging station could be realized in a similar approach discussed by Bueno et al. (2009). In other words, the implementation of coordinating aggregated PHEVs with wind power generation in an electricity market environment is technically feasible.

The general MPC method has been recognized as an effective and practical control strategy that uses a prediction of system evolution to establish an updated control response. A recent study shows that the distributed MPC with cooperation achieves and optimal performance equivalent to centralized MPC if the available computational time allows convergence (Venkat et al. 2008). An efficient MPC algorithm with quadratic cost and linear constraints has been improved significantly by using the approximate primal barrier method (Wang and Boyd 2010). One of the major aspects to improve the computational speed of MPC is to utilize the structural properties of the specific problem. Several numerical algorithms in support of implementing the proposed coordination in real time electricity markets will be presented in “Numerical Algorithms”.

Problem Formulation

In deregulated electric power systems, power generation, e.g., wind farms or conventional units, and power demands, e.g., load serving entities, are regarded as market participants. The RTO collects the supply/demand curves from these participants, clears the market subject to security constraints, and sends the pricing and dispatch signals to both generators and load serving entities. Multiple markets with different timescales and functionalities are established for such purposes. For different timescales, there are forward markets, such as day-ahead markets and hour-ahead markets, and real time markets. For different functionalities, there are energy balancing markets, which primarily maintain the energy balancing in near real time, and ancillary service markets, which primarily ensure the system reliability and security.

The problem to be addressed in this paper is how to coordinate BESS resources with wind generation to maximize the joint profit and reduce the deviation of wind power injection into the power grid because of forecast inaccuracies. Certain types of information are required in the proposed formulation. First, the predicted prices in the energy balancing market and the regulation market are required. As individual participants, wind farms and storage resources are typically considered as market price takers because of their relatively low marginal cost and relatively small sizes. Second, the available wind generation is required, which could be obtained from many wind forecast methods such as the one by Abdel-Karim et al. (2009). Third, the availability of PHEVs is required to estimate the energy capacity and power capacity of the resources. In this paper, a constant level of PHEVs’ availability is assumed. The challenges of this problem come from the uncertainty of price prediction and available wind generation.

The formulations of scheduling of wind and BESS, e.g., PHEVs, without coordination has been discussed by Illic et al. (2011) and Rotering and Ilić (2010). In this paper, the coordinated optimal control of wind generation and BESS can be formulated as follows:
\[ \min J = \sum_{k=1}^{T} \left[ -\lambda_{WG} P_{WG}^k + C_p P_{WG}^k \right] + \sum_{k=1}^{T} C_p \Delta P_{net}^k \]
\[ - \sum_{i=1}^{N} \lambda_{EV} E_i^p + \sum_{i=1}^{N} \sum_{k=1}^{T} -\lambda_i^k \left( P_{VDi} - P_{VCi}^k \right) \]
\[ + \sum_{k=1}^{T} \sum_{i=1}^{N} \left( C_{RUi} - \omega_{RUi}^k \right) P_{RUi}^k \]
\[ + \sum_{k=1}^{T} \sum_{i=1}^{N} \left( C_{RDNi} - \omega_{RDNi}^k \right) P_{RDNi}^k + \sum_{k=1}^{T} \sum_{i=1}^{N} \gamma_i \left( P_{VDi} + P_{VCi}^k \right) \]
\[ + \sum_{k=1}^{T} \sum_{i=1}^{N} \omega_{XUi}^k C_{XUi}^k P_{XUi}^k + \sum_{k=1}^{T} \sum_{i=1}^{N} \omega_{XDNi}^k C_{XDNi}^k P_{XDNi}^k \]

Subject to

\[ E_i^p = E_i^{p-1} - \tau [P_{VDi}^k - P_{VCi}^k] \] for all \( k, i \) (2)

\[ P_{VDi}^k + P_{RUi}^k + P_{XUi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (3)

\[ P_{VCi}^k + P_{RDNi}^k + P_{XDNi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (4)

\[ 0 \leq P_{VDi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (5)

\[ 0 \leq P_{VCi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (6)

\[ E_{\text{min}}^V \leq E_i^p \leq E_{\text{max}}^V \] for all \( k, i \) (7)

\[ 0 \leq P_{RUi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (8)

\[ 0 \leq P_{RDNi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (9)

\[ 0 \leq P_{XUi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (10)

\[ 0 \leq P_{XDNi}^k \leq P_{\text{max}}^V \] for all \( k, i \) (11)

\[ P_{\text{min}}^W \leq P_{WG}^k \leq P_{\text{max}}^W \] for all \( k \) (12)

\[ P_{\text{min}}^W \leq P_{WG}^k \leq P_{\text{max}}^W \] for all \( k \) (13)

\[ -P_{\text{comp}}^W \leq P_{WG}^k - P_{\text{comp}}^W \leq -P_{\text{comp}}^W \] for all \( k \) (14)

Where,

\[ \Delta P_{\text{net}}^k = \| P_{\text{net}}^k \| \approx \Delta P_{\text{net}}^k \] for all \( k, i \) (15)

\[ \Delta P_{\text{net}}^k = \Delta P_{\text{net}}^k + \Delta P_{\text{net}}^k \] (16)

The objective of the coordination is to maximize the joint expected profit of wind generation and BESS over a predefined period of time, e.g., 1 day. The potential benefits and cost on both the wind generation side and BESS side are considered. In the objective function of Eq. (1), \( \sum_{k=1}^{T} \left[ -\lambda_{WG} P_{WG}^k + C_p P_{WG}^k \right] \) is the negative profit of wind generation during the whole period; \( \sum_{k=1}^{T} C_p \Delta P_{\text{net}}^k \) estimates the potential penalty on wind generation because of the output deviation from the dispatch point; the wind generation forecast errors and the exchange capacity of BESS are used to estimate the deviation of wind generation; the value of energy stored in the BESS at the final step of the operating period is used to estimate the deviation of wind generation; the mean value of the energy of the final step, the optimization will always try to empty the battery; \( \sum_{k=1}^{T} \sum_{i=1}^{N} \gamma_i \left( P_{VDi} + P_{VCi}^k \right) \) considers the revenue/cost from the BESS charging/discharging activities in the energy market; and \( \sum_{k=1}^{T} \sum_{i=1}^{N} \left( C_{RUi} - \omega_{RUi}^k \right) P_{RUi}^k \) considers the profit and costs of BESS on regulation-up market. For BESS, the cost of providing frequency regulation services is primarily the battery degradation cost. Because of the requirement of reliability, during a relatively long period (1 h), the mean value of the frequency deviation of the power system is typically zero. Therefore, over a relatively long period the change in the energy because of regulation services is negligible. However, the energy storage level \( E_i^p \) or the state of change (SOC) does affect the decision making in regulation services. For example, if the SOC of BESS is 1.0 (full battery), it is very less likely to participate into the regulation-down market because the BESS cannot be charged anymore. Conversely, if the SOC is 0 or the battery is empty, BESS is less likely to participate into the regulation-up market because the BESS cannot be discharged anymore. A weighted function is introduced as \( \omega_{RUi}^k \), a linear function of SOC which helps to characterize the difficulty to participate in the regulation-up/down market when the SOC is too low/high. Similar terms are introduced in the exchange capacity of BESS for compensating the deviation of wind generation. According to the study of Peterson et al. (2010), the battery degradation cost is a linear function of the cumulative energy processed through the battery. Therefore, the term \( \sum_{k=1}^{T} \sum_{i=1}^{N} \gamma_i \left( P_{VDi} + P_{VCi}^k \right) \) is used to calculate the battery degradation cost because of charging/discharging.
Various constraints are considered from both the BESS side and wind generation side. Eq. (2) is the energy level dynamics of BESS. Depending on the types of BESS, different efficiency rates on charging and discharging are represented. Although there is no hard constraint that the charging power $P_{VC}^k$ and the discharging power $P_{VB}^k$ should not be nonzero at the same time, the optimal solution will guarantee the fact that when one of them is nonzero, the other should be zero. This is because of the fact that both the charging and discharging efficiency is not 100%. Therefore, although it is a feasible solution that the charging and discharging power of BESS can be nonzero at the same time, it will never be an optimal solution. This kind of formulation is also used in previous studies in pumped hydroresourses (Benitez et al. 2008; Castromonov and Lopes 2004). Eq. (3) represents the upward capacity constraint that is composed of the capacity for regulation up, exchange up, and discharging power. Similarly, Eq. (4) is the downward capacity constraint of BESS. Eqs. (5) and (6) are the discharging/charging power constraints of the BESS. The energy limit of the BESS is considered in Eq. (7), in which the upper bound is usually the rated energy capacity and the lower bound is usually zero. However, depending on tasks of the BESS, the lower bound of a specific time step, e.g., before morning rush hours for PHEVs, can be configured for driving purposes. Eqs. (8)–(11) are the power constraints for regulation capacity and exchange capacity between BESS and wind generation. Eq. (12) is the upper and lower bound of wind farm power capacity, whereas Eq. (13) is the wind generation forecast constraint that indicates the available wind generation for dispatch. The ramping constraints of wind turbines are considered in Eq. (14).

The wind generation deviation $\Delta P_{wind}$ in the objective function of Eq. (1) is defined as Eq. (15), which is the function of actual wind generation, actual power exchange between wind farm and BESS, and the dispatch point of wind generation. The norm is defined as 1-norm or absolute value. Before realtime operation, the actual wind generation is not known so Eq. (16) is used to estimate the potential wind generation deviation, which consists of two components: upward estimated net injection Eq. (17) and downward estimated net injection Eq. (17), both of which are linear functions of wind generation, and forecast inaccuracy and the exchange capacity between wind generation and BESS. The wind deviation coefficients $\mathcal{w}_d$ and $\mathcal{w}_u$ estimate the downward and upward wind generation deviation.

In this study, there are several assumptions. First, the randomness of the availability of PHEVs is not considered. It is assumed that during the optimization, the number of available vehicles maintains at a constant level. Second, a hard energy constraint of BESS for frequency regulation is not implemented in the proposed model. During the decision making of BESS charging/discharging, the weighting function of SOC is assumed to ensure enough energy for proving frequency regulation services (Sekyung et al. 2010). The notations are summarized in the notation list.

### Numerical Algorithms

The proposed coordinated scheduling process at the wind generation and BESS layer is a model predictive control problem. For an MPC problem, the control action is obtained by solving a fast look-ahead optimization problem at each time step. Only the optimal control action for the first time step is executed. In the proposed coordinated scheduling framework, the state transition is a linear model and the constraints are polyhedral. With a quadratic objective function, the optimal control problem can be formulated as a quadratic programming (QP) problem. With the development of fast algorithms and powerful solvers, realtime MPC becomes feasible in many large-scale problems (Wang and Boyd 2010; Bieglera 2009). In this section, several efficient algorithms to improve the computational speed of QP are presented. By exploring the structure of the problem formulation, the proposed numerical algorithm can speed up the computation significantly compared with the general purpose QP method.

### Interior Point Method

In this subsection, the primal-dual interior point method (PDIPM) is described. It is commonly used to solve nonlinear programming (NLP) (Irisarri et al. 1997). The proposed model of Eq. (1) can be reformulated in the following way.

First of all, $x$ is defined as the vector of primal variables. Then, objective function Eq. (1) can be written as a typical form of quadratic problems in Eq. (24)

$$
\min : F(x) = x' H x + f' x
$$

The equality constraints of Eq. (2) can be expressed as equality constraints vector $h$

$$
h(x) = 0
$$

Besides, all the inequality constraints of Eqs. (3)–(14) can be rewritten as

$$
g_{\min} \leq g(x) \leq g_{\max}
$$

The preceding two vectors $g_{\min}$ and $g_{\max}$ identify the upper and lower boundaries of these inequality constraints.

Barrier function is introduced to convert those inequality constraints Eq. (25) into equality constraints. Karush-Kuhn-Tucker (KKT) conditions are applied. Therefore, Eq. (25) can be written as

$$
g(x) + u = g_{\max} \quad g(x) - l = g_{\min} \quad u \geq 0; \quad l \geq 0.
$$

Then, logarithmic barrier function can be added into the objective function so as to eliminate inequality constraints in Eq. (25)

$$
\min \frac{f(x) - \mu \sum_{j=1}^{r} \log(l_j) - \mu \sum_{j=1}^{r} \log(u_j)}{2}
$$

Subject to $h(x) = 0$

$$
g(x) + u = g_{\max}
$$

$$
g(x) - l = g_{\min}
$$

where $\mu > 0$ is called the barrier factor. When $l_i$ or $u_i (i = 1, \ldots, r)$ is moving forward to their boundaries, the value of the objective function will go to infinity. Hence, the optimum solution to the objective function, if it exists, cannot be out of the feasible region, which guarantees all the inequality constraints of Eq. (25) satisfied

$$
L = f(x) - y'h(x) - z'[g(x) - l - g_{\min}] - w'[g(x) + u - g_{\max}]
- \mu \sum_{j=1}^{r} \log(l_j) - \mu \sum_{j=1}^{r} \log(u_j)
$$

The Lagrangian function of Eq. (26) can be used to solve this problem. The dual variables $y, z, \text{ and } w$ correspond to Eqs. (27), (29), and (30), respectively. The method of solving $L$ is presented in many papers, such as the one by Wang and Boyd (2010).
Warm Start

Warm start is a technique to exploit the structure of the MPC problem to improve the efficiency of the algorithm. The key idea of warm start is to set the initial points of variables, i.e., state variables and control variables, according to the previous stage. Particularly, at the 4th stage of which the start point is \( t = t_k \), the plan over time window \([t_k + 1, t_k + T + 1]\) is to be solved. However, only the first step of the solved plan will be executed. Then MPC is going to solve the next stage: the \((k + 1)\)th stage, with time window \([t_{k+1} + 1, t_{k+1} + T + 1]\) and start point \( t_{k+1} = t_k + 1 \). At this time, if the results of the rest of the \(T - 1\) steps of the previous solutions, which correspond to the first \(T - 1\) stages of this stage, can be used as the initial points for the following iterations, it will be of great potential to reduce iterations. The disturbances between the two stages determine the effect of the warm start. Generally, the lower the disturbances are, the more iterations can be saved. In the proposed model, warm start technique works for not only those primal variables, i.e., control variables and state variables, but also dual variables, i.e., Lagrangian multipliers and slack variables. It is because all equality and inequality constraints of Eqs. (2)-(14) are closely matched with each stage. At time \( t_{k+1} = t_k + 1 \), the initial points of variables, i.e., primal and dual, of the current stage can be settled according to the previous stage. The primal and dual variables are updated as in Eqs. (31) and (32)

\[
x = [x(t_{k+1} + 1), \cdots, x(t_k + T - 1)]
\]

\[
[y] = [y(t_{k+1} + 1), \cdots, y(t_{k+1} + T - 1)]
\]

\[
[z] = [z(t_{k+1} + 1), \cdots, z(t_k + T - 1)]
\]

\[
w = [w(t_{k+1} + 1), \cdots, w(t_k + T - 1)]
\]

Fixed \( \mu \)

As proposed by Wang and Boyd (2010), instead of solving a decreasing sequence of \( \mu \), one fixed value of \( \mu \) is used so as to improve the efficiency of the algorithm. During the optimization process, the duality gap goes to zero. In every iteration, the duality gap is calculated, which provides a criterion of convergence and gives a solution for \( \mu \) as well

\[
\text{Gap} = z^T I - w^T u
\]

There is a close relationship between the duality gap and \( \mu \) so every iteration \( \mu \) can be solved by solving the duality gap

\[
\mu = \frac{z^T I - w^T u}{2r} = \frac{\text{Gap}}{2r}
\]

Although for general quadratic problems a fixed \( \mu \) may lead to a very poor optimal solution, lots of experiments by Wang and Boyd (2010) show that for MPC problems, a fixed \( \mu \) technique can get a relatively high quality of control.

Early Termination

Generally, PDIPM terminates when either the convergence criteria is satisfied or the maximum iteration steps are reached. The latter one is considered as the failure of the algorithm given that the considerable iterations cannot effectively reduce the duality gap and residue terms to zero. Therefore, the maximum iteration limit is set to be a high value like 200–1,000 times. For the early termination technique, the maximum iteration limit is set to be a small value like 3–15 times and furthermore, reaching that limit is to be regarded as a convergence criterion. In that case, for each MPC stage, iterations will be no more than that fixed limit.

The quality of control might be concerned because a crude optimization can lead to a solution even not feasible to the primal problem. However, extensive numerical experiments show that the resulting control is of very high quality (Wang and Boyd 2010).

Actually, the result does respect the constraints, especially those inequality constraints. On the basis of warm start and a reasonable iteration limit, the beginning several steps are enough for primal variables to provide a high quality control. The rest of that stage is to make those dual variables converge and reduce the duality gap.

For MPC, only the first step of each plan is executed; the rest of the plan provides a reference to avoid a bad effect on future control. If warm start is applied, all of the control and state variables, i.e., \([x(t_0 + T + 1), \cdots, x(t_N + T)\] will undertake at least \((T - 1) \cdot K_{\text{max}}\) iterations in previous stages before they are executed. That is why the early termination technique can be effectively applied for MPC.

Case Studies

This section illustrates the proposed coordinated MPC-based scheduling under an electricity market environment in an IEEE reliability test system, as shown in Fig. 1. Wind farms and PHEV aggregators represent variable wind generation resources and BESS

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**Fig. 1.** Modified IEEE reliability test system
for which the charging/discharging signals will be sent through smart grid communication networks, e.g., advanced metering infrastructures.

In deregulated electricity markets, the security-constrained economic dispatch (SCED) takes place at ISO every 10 to 15 min, with the objective of maximizing the market social welfare to balance the system supply and demand while observing the system security constraints. The results of the SCED include the dispatch signals to all the market participants, including the wind farms and the energy storage systems. The communication between individual market participants and the ISO is through a supervisory control and data acquisition (SCADA) system (Wu et al. 2005). In this paper, we assume the communication delays are assumed to be much smaller than the time scale of interest, which is 10–15 min. As more and more distributed energy resources are integrated to the power grid, the communication burden for the SCADA system will likely increase. Future research will investigate the effect of communication delays and communication channel requirements on the performance of SCED.

A 24-bus ERCOT equivalent system is established in a recent publication (Gu et al. 2011). The simulation in this paper is on the basis of this system. The configuration of the generators is presented in Table 1.

In this study, aggregated PHEVs are employed as the BESS resources. The coordination of the case study is between the wind farm located at bus 15, with a capacity of 160 MW, and seven PHEV aggregators, with a total energy capacity of approximately 7 MW and a total power capacity of 4 MW, shown in Table 2. In Table 2, column “Identity” identifies different PHEV aggregators, column “Bus” shows the buses where PHEV aggregators are located, column “PHEVs” shows the number of PHEVs in each aggregator, columns “Energy” and “Power” show the energy capacity and power capacity of the individual PHEV of each aggregator, columns “Effd” and “Effc” show the discharging and charging efficiency of the individual PHEV of each aggregator, column “Deg” shows the battery degradation coefficient of the individual PHEV of each aggregator, and columns “TE” and “TP” show the total aggregated energy capacity and power capacity of each aggregator. Penalty coefficient $C_p$ for wind generation deviation from the scheduled level is assumed to be 12 dollars/MW. The 15-min-ahead forecast of available wind power forecast is obtained from Abdel-Karim et al. (2009). The optimal power flow formulation is presented in the Appendix.

The regulation price data shown in Fig. 2 are collected from ERCOT (2011). The simulation is conducted on a personal computer (PC) desktop with Intel Core i7–990X 3.46 GHz central processing unit (CPU), 16 GB of memory, and Windows 7 operating system. The proposed scheduling model was implemented in the PDIPM, including extra optional segments of warm start, early termination, and fixed barrier parameter, program coded in MATLAB R2011a, IBM ILOG CPLEX 12.1, and the quadprog module in MATLAB.

### Economic Benefits Analysis for Typical Day

Two cases in a 3-day period was simulated for an economic benefits analysis. Case A represents MPC-based coordinated scheduling of the wind farm and PHEVs. Case B corresponds to scheduling of the wind farms and PHEVs without coordination. Table 3 shows the economic benefits for the wind farm and PHEVs of the two cases in the first 24 h. In this subsection, perfect price prediction is assumed. In Case A, wind farms and aggregated PHEVs coordinate their net power injection to maximize their profits. The PHEVs will allow exchange of power capacity to smooth out the fluctuation of wind output. By paying less penalty because of less variation from the scheduled output, the wind farm will have the economic incentive to coordinate with the PHEVs.

It can be observed that the combined profit of Case A, $35,357.27, is 6.65% higher than the combined profit of Case B. Coordination with PHEV can help the wind farm to reduce the deviation penalty by 28.76%. Conversely, because PHEVs are allowed to participate into both electric energy markets and regulation services markets, they need to reserve power exchange capacity from the regulation market to be charged/discharged against the excess/insufficient wind generation. Therefore, the PHEVs’ own profits will be reduced by $4,855.19 for a 24-h period. However, given that the combined profit from both the wind farm and PHEVs is higher in the coordinated case, contractual agreements can be established between the two entities to make both the wind farm and PHEVs economically better off through coordination.

### Table 1. Generator Parameters

<table>
<thead>
<tr>
<th>Identity</th>
<th>Bus</th>
<th>Type</th>
<th>Capacity (MW)</th>
<th>Cost (dollars/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Coal</td>
<td>360</td>
<td>13</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>Coal</td>
<td>370</td>
<td>15</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>Gas</td>
<td>700</td>
<td>30</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>Gas</td>
<td>600</td>
<td>45</td>
</tr>
<tr>
<td>5</td>
<td>14</td>
<td>Wind</td>
<td>210</td>
<td>3</td>
</tr>
<tr>
<td>6</td>
<td>8</td>
<td>Coal</td>
<td>150</td>
<td>17</td>
</tr>
<tr>
<td>7</td>
<td>15</td>
<td>Wind</td>
<td>160</td>
<td>4</td>
</tr>
<tr>
<td>8</td>
<td>4</td>
<td>Gas</td>
<td>400</td>
<td>50</td>
</tr>
<tr>
<td>9</td>
<td>21</td>
<td>Nuclear</td>
<td>240</td>
<td>12</td>
</tr>
<tr>
<td>10</td>
<td>22</td>
<td>Gas</td>
<td>700</td>
<td>60</td>
</tr>
<tr>
<td>11</td>
<td>23</td>
<td>Wind</td>
<td>110</td>
<td>5</td>
</tr>
</tbody>
</table>

### Table 2. Configuration of PHEV Aggregators

<table>
<thead>
<tr>
<th>Identity</th>
<th>Bus</th>
<th>PHEVs</th>
<th>Energy (kWh)</th>
<th>Power (kW)</th>
<th>Effd</th>
<th>Effc</th>
<th>Deg</th>
<th>TE (kWh)</th>
<th>TP (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>65</td>
<td>16</td>
<td>7.2</td>
<td>0.92</td>
<td>0.92</td>
<td>4.2</td>
<td>1,040</td>
<td>468</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>80</td>
<td>16</td>
<td>7.2</td>
<td>0.91</td>
<td>0.91</td>
<td>4.2</td>
<td>1,280</td>
<td>576</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
<td>150</td>
<td>4.5</td>
<td>4</td>
<td>0.94</td>
<td>0.94</td>
<td>4.2</td>
<td>675</td>
<td>600</td>
</tr>
<tr>
<td>4</td>
<td>7</td>
<td>140</td>
<td>4.5</td>
<td>4</td>
<td>0.87</td>
<td>0.87</td>
<td>4.2</td>
<td>630</td>
<td>560</td>
</tr>
<tr>
<td>5</td>
<td>9</td>
<td>125</td>
<td>4.5</td>
<td>4</td>
<td>0.9</td>
<td>0.9</td>
<td>4.2</td>
<td>562.5</td>
<td>500</td>
</tr>
<tr>
<td>6</td>
<td>13</td>
<td>85</td>
<td>16</td>
<td>7.2</td>
<td>0.89</td>
<td>0.89</td>
<td>4.2</td>
<td>1,360</td>
<td>612</td>
</tr>
<tr>
<td>7</td>
<td>18</td>
<td>95</td>
<td>16</td>
<td>7.2</td>
<td>0.93</td>
<td>0.93</td>
<td>4.2</td>
<td>1,520</td>
<td>684</td>
</tr>
</tbody>
</table>
Fig. 3 shows the scheduled wind power output versus predicted maximum available wind generation. Because of the relatively low marginal cost and penalty level, the wind farm generates power as much as possible to maximize its profit. Therefore, in both Cases A and B, the wind generation is equal to the maximum available wind. Another important aspect of benefits through coordination is the smoothed net power injection of the wind farm and PHEVs to the electric power grid. Fig. 4 shows how PHEVs’ charging and discharging can smooth out the variable wind power output. The wind generation output error from scheduled output has a standard deviation (STD) of 9.4230 MW. The net power injection (the solid curve) from the wind farm and PHEVs to the power grid has a standard deviation of 7.0854 MW, which is 33% lower than the standard deviation of the stand-alone wind power. Coordinated scheduling with PHEVs does not qualitatively change the scheduled wind power while smoothing out actual net power injection to the grid.

Fig. 5 shows the aggregated discharging power and energy level of PHEVs. In the proposed MPC formulation, the energy level of PHEVs is required to be no lower than 60% of the maximum energy level for driving purposes at both 8 a.m. and 4 p.m. The STD of discharging power for Case B is 0.8835, which is comparable with a 0.6816 STD for Case A. The similar value of STD in Cases A and B suggests that coordination does not lead to more frequent battery charging/discharging behaviors in the energy balancing market. Future work could investigate a more detailed analysis of the level and cost of battery degradation because of coordination.

Figs. 6 and 7 show the PHEVs’ capacity allocation for Cases A and B, respectively. Compared with Figs. 2 and 3, it is observed that the allocation of aggregated power exchange capacity between the wind farm and PHEVs is higher when the predicted available wind generation and energy price are higher. When the regulation market

<table>
<thead>
<tr>
<th>Case</th>
<th>Wind farm (dollars)</th>
<th>PHEVs (dollars)</th>
<th>Combined (dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case A</td>
<td>35,186.97</td>
<td>170.30</td>
<td>35,357.27</td>
</tr>
<tr>
<td>Case B</td>
<td>28,127.39</td>
<td>5,025.49</td>
<td>33,152.88</td>
</tr>
<tr>
<td>Difference (B−A)</td>
<td>(7,059.58)</td>
<td>4,855.19</td>
<td>(2,204.39)</td>
</tr>
</tbody>
</table>

Fig. 2. Electricity price in system

Fig. 3. Predicted versus scheduled wind power generation

Fig. 4. Smoothed net wind generation to grid

Fig. 5. Discharging and energy storage level of PHEVs

Table 3. Operating Profits in Two Scenarios

prices are higher, PHEVs will allocate more capacity to participate in the system regulation services rather than providing exchange capacity for the wind farm. Future work could investigate the effects of reducing the wind energy resources’ variability on the pricing of regulation markets.

**Computational Analysis**

Table 4 shows the computational performances among different algorithms described in “Numerical Algorithms”. The benchmarks are the MATLAB R2011a quadprog solver and IBM ILOG CPLEX 12.1. The problem size depends on the look-ahead horizon. In this subsection, a horizon of 48 steps (1 day) is selected and hence the problem has 3,072 decision variables, 3,504 constraints for each step, and 96 steps in all.

Compared with the MATLAB R2011a quadprog solver (benchmark I), the proposed algorithm with fast MPC techniques, e.g., warm start, fixed $\mu$, and early termination, is approximately 400–1,600 times faster. In addition to MATLAB R2011a, the commercial solver IBM ILOG CPLEX 12.1 (benchmark II) was also used. The performance of ILOG CPLEX 12.1 is much better than the MATLAB R2011a quadprog solver but is still slower than the fast MPC algorithm. Furthermore, the computational gain between the fast MPC algorithm and the PDIPM developed by the authors (benchmark III) was compared. Compared with CPLEX, PDIPM without warm start is approximately 48% faster. By utilizing warm start, the computation time can be further reduced by 70%, which effectively reduce the iterations. The performances of PDIPM were also compared by including early termination and fixed $\mu$. For early termination, the average computational time can be reduced by 89.27, and 73.39%, corresponding to $K_{\text{max}} = 4$ and 16, respectively. Neither the control error nor sub optimality is significant. Even for the case with $K_{\text{max}} = 4$, the control error is only 0.7962%. With moderate iteration steps, the MPC can yield to a control strategy without much degradation of the optimality. Similar observations have also been discussed by Wang and Boyd (2010).

For the fixed $\mu$ technique, in which $\mu$ is fixed at 0.1 and 0.01, compared with the ILOG CPLEX 12.1 solver, the computational

![Fig. 6. Regulation capacity provided by PHEVs; no coordination](image_url)

![Fig. 7. Regulation and power exchange capacity provided by PHEVs](image_url)

![Fig. 8. Deviation of net power injection (wind and aggregated PHEVs) from scheduled level](image_url)

**Table 4. Computational Performances of Algorithms**

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Time (s)</th>
<th>Control error (%)</th>
<th>Total profit difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quadprog (MATLAB R2001a)</td>
<td>541.72</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>IBM ILOG CPLEX 12.1</td>
<td>4.7282</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>PDIPM without warm start</td>
<td>3.1842</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>PDIPM with warm start</td>
<td>1.0439</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Early termination ($K_{\text{max}} = 4$)</td>
<td>0.3415</td>
<td>0.7962</td>
<td>-0.5908</td>
</tr>
<tr>
<td>Early termination ($K_{\text{max}} = 16$)</td>
<td>0.8473</td>
<td>0.0081</td>
<td>-0.0201</td>
</tr>
<tr>
<td>Constant $\mu$ ($\mu = 0.1$)</td>
<td>0.8213</td>
<td>0.5036</td>
<td>-0.0201</td>
</tr>
<tr>
<td>Constant $\mu$ ($\mu = 0.01$)</td>
<td>0.9529</td>
<td>0.0667</td>
<td>-0.0017</td>
</tr>
</tbody>
</table>
Table 5. Economic Performance of BESS

<table>
<thead>
<tr>
<th>Without coordination</th>
<th>740 PHEVs</th>
<th>1,480 PHEVs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind generation profit (dollars)</td>
<td>59,726.75</td>
<td>59,726.75</td>
</tr>
<tr>
<td>Wind deviation penalty (dollars)</td>
<td>(31,599.36)</td>
<td>(24,539.78)</td>
</tr>
<tr>
<td>Energy market profit (dollars)</td>
<td>(1,353.97)</td>
<td>(1,991.78)</td>
</tr>
<tr>
<td>Regulation-up profit (dollars)</td>
<td>3,492.00</td>
<td>1,879.99</td>
</tr>
<tr>
<td>Regulation-down profit (dollars)</td>
<td>2,887.78</td>
<td>282.23</td>
</tr>
<tr>
<td>Joint profit (dollars)</td>
<td>33,152.88</td>
<td>35,357.27</td>
</tr>
</tbody>
</table>

Table 6. Benefits Analysis of Market Mechanisms

<table>
<thead>
<tr>
<th>With AS</th>
<th>No AS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind generation profit (dollars)</td>
<td>59,726.75</td>
</tr>
<tr>
<td>Wind deviation penalty (dollars)</td>
<td>(24,539.78)</td>
</tr>
<tr>
<td>Energy market profit (dollars)</td>
<td>(1,991.78)</td>
</tr>
<tr>
<td>Regulation-up profit (dollars)</td>
<td>1,879.99</td>
</tr>
<tr>
<td>Regulation-down profit (dollars)</td>
<td>282.23</td>
</tr>
<tr>
<td>Battery degradation (dollars)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Joint profit (dollars)</td>
<td>35,357.27</td>
</tr>
</tbody>
</table>

time in the proposed approach is reduced by 74.20 and 70.07%, respectively. The control error is also insignificant. With an appropriate choice of $\mu$, the fixed $\mu$ technique can improve the computational speed without sacrificing much optimality. From this case study, it is suggested that fast MPC techniques could be implemented in different solvers fast enough for realtime electricity market operations. Similar results are also obtained in the numerical studies in other publications, such as the one by Wang and Boyd (2010).

Effect of Storage Size on Proposed Optimization

The overall available BESS capacity is an important factor in the proposed MPC-based coordinated scheduling framework. In this subsection, the net power injection and the potential economic benefits with different battery storage capacity from aggregated PHEVs are analyzed.

Fig. 8 shows the deviation of net power injection, both wind and aggregated PHEVs, from the scheduled level. With a higher storage capacity, the net power injection is more smoothed out. Table 5 shows the economic performance of BESS. In the simulation, the total number of the PHEVs doubles from 740 to 1,480, with the total power capacity increasing from 4 to 8 MW. As is observed in Fig. 8, the wind generation deviation is further smoothed out. The STD of the wind generation deviation decreases from 9.423 MW (no PHEVs) to 7.0854 (740 PHEVs) and to 4.8292 MW (1,480 PHEVs). With the increase in the number of PHEVs, the joint profit of wind generation and PHEVs can also increase, as indicated in Table 6, by allowing PHEVs to provide ancillary services (column “Without AS”), the joint profit of wind and PHEVs increase by 1.2%. This also reduces the burden of providing ancillary services from conventional fossil fuel-based units. Therefore, the system operator, the wind farms, and the PHEVs are all better off by allowing the provision of ancillary services from PHEVs.

Concluding Remarks

The formulation and numerical algorithms of fast MPC-based coordination of wind power generation and battery energy storage systems are presented. By allowing the power exchange between wind farms and the energy storage systems in a deregulated electricity market environment, the proposed dispatch method can reduce the variability of net wind power seen from the external power grid, thus reducing the system cost of ancillary services, such as spinning reserve and frequency regulation. Comparative case studies show the potential economic benefits of coordination to wind generation, storage, and the system operator. This suggests that, given the appropriate storage size and market signals, the wind farm could become dispatchable from the system operator’s point of view. By leveraging the fast MPC algorithm against the special structure of the optimization problem, it has been shown that the proposed coordination can be computed in less than a second, which is approximately 400 times faster than MATLAB R2011a quad-quad programming and approximately four times faster than the ILOG CPLEX 12.1 solver.

Future work would investigate a more detailed model of battery energy storage system, including the cost associated with the charging and discharging and the modeling of battery degradation. Although in this paper the physical proximity of wind farms and battery energy storage systems is assumed, future work should investigate the effect of transmission network constraints on the performance of the coordination between wind farms and BESS. Game-theoretical analysis of wind generation, storage, and the system operator would also provide more insights to the market mechanism design in support of cost-effective integration of renewable variable energy resources.

Appendix Optimal Power Flow Formulation

In this Appendix, the formulation of direct current (DC) optimal power flow (DCOPF), which takes place every 10–15 min in...
regional electricity markets. The DCOPF result provides the loca-
tional marginal prices (LMPs) for the wind farm and the PHEV
aggregators in the framework proposed in this paper.

\[
\begin{align*}
\text{min} & : \sum_{i \in G} S_{G_i}(P_{G_i}) + \sum_{i \in W} D_{G_i}(P_{w}) \\
\text{s.t.} & : \sum_{i \in G} P_{G_i} = \sum_{i \in D} P_{w} \\
& |F| = |H \cdot P| \leq F_{\text{max}} \\
& |P_{G_i} - P_{G_i}^0| \leq P_{\text{ramp}} \Delta T, i \in G \cup W \\
& P_{\text{min}} \leq P_{G_i} \leq P_{\text{max}}, i \in G
\end{align*}
\]

(33)

(34)

(35)

(36)

(37)

In this formulation, the objective function of Eq. (33) is to min-
imize the total system operating costs, primarily generation cost.
Constraints of this problem are the operation constraints of the sys-
tem and the individual units for security and reliability purposes.
Eq. (34) is the energy balance equation, which requires the system
wide power generation equal to system wide demand in steady
state. Eq. (35) shows the transmission line capacity constraints,
which contribute to network transmission congestion. Eq. (36)
shows the ramping constraints of the units. Eq. (37) shows the
upper and lower bounds of conventional generators’ output.

Acknowledgments
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Power Systems Engineering Research Center (PSERC). The
authors greatly appreciate the financial help.

Notation

The following symbols are used in this paper:

- \( C_p \) (dollars/MWh) = penalty coefficient of wind generation
deviation;
- \( C_{RU} \) (dollars/MW) = battery cost of regulation up capacity for
BESS \( i \);
- \( C_{RD} \) (dollars/MW) = battery cost of regulation down capacity for
BESS \( i \);
- \( C_w \) (dollars/MWh) = marginal cost of wind generation;
- \( E_{\text{max}}(i) \) (MWh) = energy storage level of BESS \( i \) at time step \( k \);
- \( E_{\text{max}}(i) \) (MWh) = rated energy capacity of BESS \( i \);
- \( E_{\text{min}}(i) \) (MWh) = minimum energy storage requirement for BESS \( i \);
- \( N \) = total number of BESS aggregators;
- \( P_{\text{max}}^{\text{WH}}(k) \) (MW) = actual power exchange at time step \( k \);
- \( P_{\text{max}}^{\text{RU}}(k) \) (MW) = regulation-up capacity of BESS \( i \) to grid at
time step \( k \);
- \( P_{\text{max}}^{\text{RD}}(k) \) (MW) = regulation-down capacity of BESS \( i \) to grid at
time step \( k \);
- \( P_{\text{actual}}^{\text{WH}}(k) \) (MW) = rated power capacity of BESS \( i \);
- \( P_{\text{actual}}^{\text{WH}}(k) \) (MW) = actual wind power output to grid at time step \( k \);
- \( P_{\text{wind}}^{\text{actual}}(k) \) (MW) = wind power forecast at time step \( k \);

\( P_{\text{XDi}}(k) \) (MW) = Downward power exchange capacity of BESS \( i \) at
time step \( k \);
\( P_{\text{XUi}}(k) \) (MW) = Upward power exchange capacity of BESS \( i \) at
time step \( k \);
\( \text{SOC}^i \) = state of charge of BESS \( i \) at time step \( k \);
\( T \) = MPC look-ahead window size;
\( \gamma_i \) (dollars/MWh) = battery degradation cost coefficient for
BESS \( i \);
\( \Delta P_{\text{wind}}^{\text{act}}(k) \) (MW) = deviation of wind generation from dispatch
point at time step \( k \);
\( \eta_{\text{VCi}} \) = charging efficiency of BESS \( i \);
\( \eta_{\text{VDi}} \) = discharging efficiency of BESS \( i \);
\( \lambda_{\text{RD}}(\text{dollars/MW}) \) = expected regulation-down price at time step \( k \);
\( \lambda_{\text{RU}}(\text{dollars/MW}) \) = expected regulation-up price at time step \( k \);
\( \omega_{\text{k}}(\text{kg}) \) (dollars/MWh) = expected LMP at wind farm at time step \( k \);
\( \omega_{\text{RD}} \) = weight function of regulation down capacity for
BESS \( i \);
\( \omega_{\text{RU}} \) = weight function of regulation up capacity for
BESS \( i \);
\( \omega_{\text{RD}} \) = weight function of exchange capacity down for
BESS \( i \) and
\( \omega_{\text{RU}} \) = weight function of exchange capacity up for
BESS \( i \).

References

prediction by finite and infinite impulse response filters: A state space
model representation using discrete Markov process.” PowerTech, 2009

economics of wind power with energy storage.” Energy Econ., 30(4),

optimization.” 10th Int. Symp. on Process Systems Engineering: Part A,
Vol. 27 of Computer Aided Chemical Engineering, R. M. de Brito
Alves, C. A. O. do Nascimento, and E. C. Bisciaia, Jr, eds., Elsevier,
1–6.

“Overview of control and grid synchronization for distributed power

Bueno, E., Hernandez, A., Rodriguez, F., Giron, C., Mateos, R., and
high-speed communication interfaces for grid converters applied to
distributed power generation systems.” IEEE Trans. Ind. Electron.,
56(3), 654–669.

53(4), 1002–1016.

hydro storage sizing of a wind-hydro power plant.” Int. J. Electr. Power

Cimuca, G. O., Saudemont, C., and Robyns, B. (2006). “Control and per-
formance evaluation of a flywheel energy-storage system associated to a
1074–1085.

Electric Reliability Council of Texas (ERCOT), (2011). “Ancillary services

motor drives in electric, hybrid electric, and plug-in hybrid electric

Gao, Y., and Elsani, M. (2010). “Design and control methodology of plug-


ILOG CPLEX 12.1 [Computer software]. IBM, Armonk, NY.


MATLAB R2011a [Computer software]. MathWorks, Natick, MA.


