Digital Object Identifier: 10.1109/TPWRS.2011.2129542

Efficient Coordination of Wind Power and Price-Responsive Demand—Part I: Theoretical Foundations

Marija D. Ilić, *Fellow, IEEE*, Le Xie, *Member, IEEE*, and Jhi-Young Joo, *Student Member, IEEE*

***Abstract*—In Part I of this two-part paper, we introduce several possible methods for integrating wind power, price-responsive demand and other distributed energy resources (DERs). These methods differ with respect to information exchange requirements, computational complexity, and physical implementability. A novel look-ahead interactive dispatch that internalizes inter-temporal constraints at the DERs level, and dispatches the results of distributed decisions subject to spatial security constraints, is proposed as a possible effective algorithm. This method requires only the use of today's static security-constrained economic dispatch (SCED) by the system operators. The optimization accounting for inter-temporal constraints, and ramping rates in particular, is done by the DERs while they create their own supply and demand functions. To implement this method, today's supervisory control and data acquisition (SCADA) needs to be transformed into a multi-directional, multi-layered information exchange system.**

***Index Terms*—Advanced metering infrastructure (AMI), congestion-constrained look-ahead dispatch, dynamic monitoring and decision-making systems (DYMONDS), intermittent resources, look-ahead economic dispatch, model predictive control (MPC), price-responsive demand, security-constrained economic dispatch (SCED), security-constrained unit commitment (SCUC), supervisory control and data acquisition (SCADA).**

I. Introduction

THIS paper is motivated by the need for better algorithms to compensate for highly variable power imbalances through the scheduling of conventional resources as well as through price-responsive demand. The first contribution concerns several new problem formulations which explicitly include wind power. Notably, some of the formulations are the first to consider wind power as an explicit decision variable. Not surprisingly, these formulations show that the challenge of efficient and reliable integration of intermittent resources and price-responsive demand is closely related to the technical problem of dispatching diverse power plants with vastly different ramping rates connected to a potentially congested nonlinear transmission and distribution (T&D) system. Depending on the assumptions made, and on how the inter-temporal constraints are managed and by whom (the system operator or the users), seemingly indistinguishable formulations lead to qualitatively different algorithmic challenges. At present, a centralized security-constrained look-ahead dispatch relies on wind forecast and requires a complex unit commitment across all the power plants. It is much harder to solve than our novel interactive look-ahead dispatch based on distributed unit commitment by the system users and the static security-constrained economic dispatch by the system operator. In Part II of this paper, we compare the several methods formulated in Part I. The recommendation is, at least in the near term, to select the interactive look-ahead dispatch because, in addition to its computational efficiency, it does not require in-depth knowledge of the different users' abilities to respond. The supply and demand functions are strictly static after internalizing the unique temporal constraints by the system users themselves.

In this paper, we take a step back to assess the feasibility of accounting for wind power efficiently. Of particular interest is the inter-dependence of information technology (IT) and the ability to make the most out of distributed energy resources. In what follows, we describe several qualitatively different algorithmic approaches to integrating renewable resources. The taxonomy introduced in Section II differentiates methods based on: 1) the required spatial information flow between the end users and the system operator; 2) the required temporal information flow (static versus predictive); and 3) the required type of information to be exchanged (bid functions versus specific (power-price pointwise) specifications).

We introduce these algorithms in increasing order of complexity. We first provide, in Section III, a mathematical formulation of the static economic dispatch which treats wind power as a negative load. The least generation cost problem is stated, and this is followed by a generalized formulation which includes demand-side management to optimize total surplus. This is done for completeness and a consistent assessment of newly introduced possible solutions in the remainder of this paper. In most of the published literature, the solution to least-cost dispatch is used as the benchmark for assessing the potential cost-benefit analysis from wind power deployment [8], [9]. However, the results of these least-cost dispatch algorithms are not physically implementable since the least-cost method does not take into consideration the effects of ramping rates. To introduce a more realistic benchmark, we formulate in Section IV a multi-temporal static economic dispatch that is physically implementable.

Manuscript received December 09, 2009; revised March 30, 2010, July 22, 2010, October 26, 2010, and February 26, 2011; accepted March 03, 2011. Date of publication May 05, 2011; date of current version October 21, 2011. Acknowledgements are included in Part II of this paper. Paper no. TPWRS-00953–2009.

M. D. Ilic is with Carnegie Mellon University, Pittsburgh, PA 15213 USA and also with the Delft University of Technology, Delft, The Netherlands (e-mail: milic@ece.cmu.edu).

L. Xie is with the Texas A&M University, College Station, TX 77843 USA (e-mail: lxie@ece.tamu.edu).

J. Y. Joo is with Carnegie Mellon University, Pittsburgh, PA 15213 USA (e-mail: jjoo@andrew.cmu.edu).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TPWRS.2011.2129542

To ensure physical implementability, power plants are grouped into slow- and fast-responding ones. The slow and fast plants are dispatched each hour ahead statically since their dispatch is feasible at this rate. The fast-responding plants are re-dispatched every 10 min to compensate for load and wind power deviations from their hourly forecast.

In addition to the least generation cost algorithm, the total market surplus maximization version of the algorithm is formulated to enable the inclusion of price-responsive demand. In Section V, we formulate a centralized model predictive control (MPC) look-ahead dispatch that optimizes system operation over the following 6 hours. The purpose of this look-ahead 6-hour optimization is to utilize the potential of slow-response units for balancing short-term demand and wind power fluctuations. Another lesser advantage of the look-ahead methods is the ability to decide which portion of the predicted available wind power should be sent to the grid in order to minimize the total generation cost, while taking into account the ramping rates of all units. The centralized MPC-based predictive dispatch is generalized in the same section to include price-responsive demand. To overcome inherent computational complexity, we consider next two other types of candidate methods. The first dispatch uses a fully-distributed architecture introduced in Section VI. This is an algorithm which lets DERs make their own decisions locally on how much power to schedule without system-level coordination.

Overcoming the dimensionality problem ingrained in the centralized MPC-based dispatch or similar dynamic programming (DP)-based economic dispatch approaches proposed in the past is very difficult [15], [16], and a fully distributed decision-making algorithm is fundamentally complex [17]. Therefore, we propose, in Section VII, a novel multi-directional interactive dynamic monitoring and decision-making systems (DYMONDS) [29] algorithm to implement near-optimal predictive dispatch. We differentiate between the static DYMONDS and the MPC-based DYMONDS algorithms. The proposed approach requires information exchange in the function spaces, instead of point-wise (quantity, price) information exchange. These two are qualitatively different methods since the coordination is much more straightforward and non-iterative at any point in time since the functions are used to communicate users' characteristics to the system operator [18] instead of only communicating (quantity, price) data points [19]. We close in Section VIII with a summary of recommendations for methods capable of integrating large amounts of intermittent resources and adaptive loads efficiently. Open questions are stated.

II. Possible Taxonomy of Scheduling Methods

The following notation is used throughout the paper. The variables with a hat are expected values, used typically as parameters. The variables with an underscore sign are vectors.

G	Set of all available generators.
$G_f,\ G_s$	Set of fast and slow conventional generators.
G_r	Set of intermittent energy generators.
Z	Set of load zones.
$\hat{L}_z(k)$	Expected demand at load zone z time step k.
$C_i(P_{G_i})$	Cost function of generator i.
$S_i(P_{G_i}(k))$	Supply bid function of unit i.
$B_z(L_z(k))$	Benefit function of load z consuming $L_z(k)$.
$P_{G_i}^{\min}, P_{G_i}^{\max}$	Minimum and maximum generation output.
$\hat{P}_{G_j}^{\min}, \hat{P}_{G_j}^{\max}$	Expected minimum and maximum wind generation output at time step $k,\ j \in G_r$.
$f_z(L_z)$	Forecast of demand in zone z.
$g_j(\hat{P}_{G_j})$	Forecast of available generation for generator j.
$h(\Delta P_{SD}(k))$	Forecast of price in iteration stage k.
R_i	Ramping rate of generator $i,\ i \in G$.
K	Number of samples in the optimization period.
$P_i(k)$	Demand quantity of an individual end user i at time step k.
$x_i(k)$	Temperature of the premise of an user i.
$\lambda(k)$	Price of electricity at time step k.
$x_i^{\min}, x_i^{\max}$	Minimum and maximum temperature setpoint.
$T_o(k)$	Outdoor weather temperature at time step k.
$\varepsilon,\ \gamma$	Factor of AIR inertia and thermal conversion efficiency.
$F,\ F^{\max}$	Vector of line flows and their limits.

In this section, we provide a classification of possible methods for scheduling existing power plants, wind power, and demand side response together. As discussed in the introduction, this problem is fundamentally the same as the problem of coming up with computationally efficient algorithms that take into consideration the ramping rates while accounting for nonlinear real and reactive power network constraints. This problem has remained a computational grand challenge [1]–[3]. A security-constrained economic dispatch (SCED) that accounts for ramping rates differs from a security-constrained unit commitment (SCUC) because it only schedules units that are already on, and it typically neglects start-up and shut-down costs as well as the must-run times of the different units. The full-blown SCUC that also decides on turning units on and off is fundamentally a mixed-integer programming (MIP) problem. The unit commitment problem was originally solved by Lagrangian relaxation (LR) approaches which effectively solve SCED that consider the ramping rates of the power plants [4]. Recent advances in optimization and computing capabilities have made solutions of branch and bound-based MIP computationally tractable [5]. Many of the independent system operators (ISOs) have begun to deploy MIP-based tools [2].

TABLE I
TAXONOMY OF METHODS FOR INTEGRATING INTERMITTENT RESOURCES AND PRICE-RESPONSIVE DEMAND

	Static Dispatch	Look-ahead Dispatch
Centralized	Problems 1 and 2	Problem 3
Fully-distributed	Problem 4	Problem 5
DYMONDS-based	Problem 6	Problem 7

In parallel with these new efforts, a majority of the industry has continued to rely on SCUC that iteratively solves: 1) unit commitment, or economic dispatch subject to ramping rates, without considering network constraints; and 2) DC power flow equations to ensure that the power flows are within the thermal line limits. It is often the case that a system operator must modify the results from step 1) to ensure that there is no transmission congestion in the system. Once a modified combination of units is found which meets step 2), step 1) can be repeated to improve the solution suggested by the operator. This process is prone to convergence problems, and the results are hard to justify to the market participants. Moreover, such solutions also result in voltage violations and difficulties in balancing reactive power [2], [3].

For several reasons, these inherent challenges to SCED and SCUC software are likely to become even more complex with the high penetration of unconventional resources for the following reasons: 1) the inter-temporal variations of the power output are significant, not known ahead of time, and their power output is not directly dispatchable; 2) the number of new small resources is likely to be very large; 3) their characteristics are not standardized, and system operators do not have ready-to-use models and parameters; and 4) the large-scale deployment of wind could create qualitatively different T&D line flow patterns. This, altogether, requires very careful dispatch management of 1) the conventional plants by taking into account their ramping rate constraints and utilizing the new DERs, and 2) different congestion management approaches than the ones used today.

As the interest in deploying more wind power has rapidly grown, many studies have been put forward concerning the potential benefits from these new resources, and also possible congestion problems and the need for transmission investments to support wind power integration into the existing systems [8]. This study deploys a highly simplified model of a power grid, and it therefore does not account for realistic network power flow constraints. This is yet another reflection of the lack of large-scale software that would account for ramping rates and the nonlinear real and reactive power flow constraints. Of course, only physically implementable solutions, which take into account the inter-temporal ramping constraints as well as nonlinear power flow constraints, are realistic ones.

In this section, we introduce a possible taxonomy of the candidate algorithms in increasing order of complexity, as shown in Table I. It can be seen that the methods are qualitatively different with respect to how they account for temporal and spatial interdependencies within a complex power grid. For example, there are qualitative differences between the so-called static dispatch methods which only rely on single snapshot optimization at a time stamp (column 1 in the table). Similarly, recently considered multi-temporal look-ahead optimization by the leading ISOs [3], [7] as well as our mathematical formulations of Problems 3, 5, and 7 require forecasts and computing of data over multiple future time horizons (column 2 in the table). Similarly, there are qualitative differences between fully centralized, fully-distributed and multi-layered interactive algorithms with respect to their spatial complexity. In the following, mathematical formulations of the different algorithms shown in Table I are introduced.

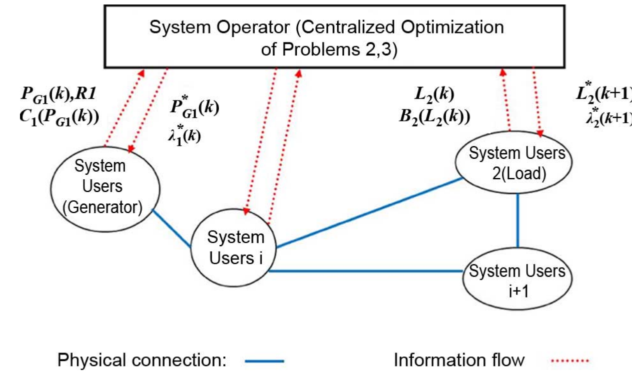

Fig. 1. Required information exchange for centralized dispatch.

Finally, the type of information exchange required for implementing the considered methods is sketched in Figs. 1–3. It can be seen in Fig. 1, which depicts the required information exchange for centralized dispatch, that the system users must provide their cost $C_i(P_{Gi})$ and/or benefit functions $B_j(L_j)$, as well as their ramping rates R_i. The system operator implements a centralized economic dispatch subject to the given ramping rates and sends back the information on optimal dispatch quantities $P^*_{Gi}(k)$ and cleared prices $\lambda^*_i(k)$. Similarly, Fig. 2 is the information flow typical of fully-distributed static dispatch. System users optimize their own objectives for projected prices $\lambda_i(k)$; the projected price is best given by the system operator. System users are not required to give information about their dispatch; the operator, based on supervisory control and data acquisition (SCADA), detects the total power imbalance $\Delta P_{SD}(k-1)$ defined as $\Delta P_{SD}(k-1) = \Sigma_i P_{G_i}(k-1) - \Sigma_z L_z(k-1)$ and posts new prices $\lambda_i(k)$ to give incentives to system users to balance the system.[1] Two types of rules could be defined: first, the adjustments are done until equilibrium is reached or second, the adjustments are implemented sequentially over time, creating power imbalances. Finally, shown in Fig. 3 is our proposed multi-layered interactive information exchange in support of implementing DYMONDS. Based on the projected look-ahead prices $\lambda_i(k)$, $k = 1, \ldots, K$ by the system operator, each (group of) system users performs its look-ahead optimization to create static supply $S_i(P_{Gi})$ and demand $B_i(L_i)$ functions for $k = 1, \ldots, K$. The system operator, in turn, performs a static SCED for each k as information from the users becomes available. The system operator returns the results of the system-level optimization P^*_{Gi}, ${L_i}^*$, and λ^*_i.

[1] A particular case of this approach would require only a technical information update about the system-wide power imbalance $\Delta P_{SD}(k-1)$ by the system operator. In this case, additional rules concerning the responsibilities of system users need to be defined in order to allocate responsibilities for contributing to $\Delta P_{SD}(k-1)$ on the part of individual users.

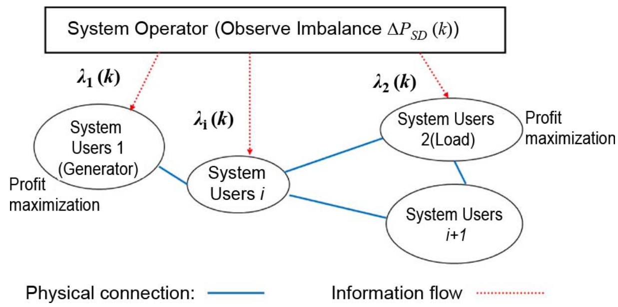

Fig. 2. Required information exchange for fully-distributed dispatch.

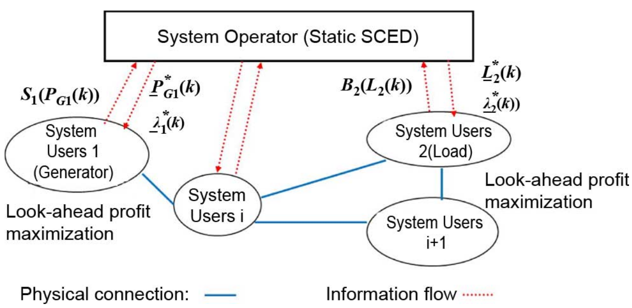

Fig. 3. Required information exchange for DYMONDS-based dispatch.

III. Centralized Static SCED With DERs Included

In this section, we extend the formulation of the currently implemented static SCED without accounting for the ramping rates of power plants to include the effects of DERs and price-responsive demand.[2] The least generation cost problem is formulated as Problem 1A by simply representing wind power as a negative demand assuming wind predictions in a 10-min interval known[13] in much the same way as the 10-min load predictions are assumed to be known.

1) Problem 1A: The least generation cost centralized SCED which includes wind power as negative loads:

$$\text{Solve: } \min_{P_G} \sum_{i\in G\backslash G_r} (C_i(P_{G_i}(k))) \tag{1}$$

$$s.t. \sum_{i\in G\backslash G_r} P_{G_i}(k) = \sum_{z\in Z} \hat{L}_z(k) - \sum_{j\in G_r} \hat{P_{G_j}}(k) \tag{2}$$

$$P_{G_i}^{\min} \le P_{G_i}(k) \le P_{G_i}^{\max}, i \in G\backslash G_r \tag{3}$$

$$\hat{L}_z(k) = f_z(L_z(k-1)), z \in Z \tag{4}$$

$$\hat{P}_{G_r}(k) = g_j(\hat{P}_{G_j}(k-1)), j \in G_r \tag{5}$$

$$|F(k,P,L)| \le F^{\max}. \tag{6}$$

The wind forecast function $g_j(\cdot)$ can be based on a finite impulse response filter-based discrete Markov model introduced in [13] or other appropriate methods. The load forecast functions $f_z(\cdot)$ can be obtained from much load forecast literature, e.g., [21]. The inclusion of price-responsive demand is a straightforward extension of the Problem 1A formulation.

2) Problem 1B: The maximum total market surplus centralized SCED that includes wind power as negative loads. This formulation assumes that static demand functions are given instead of specifying the load [22]. Instead of minimizing total generation cost, the total surplus is maximized subject to both generation and load dispatch, as follows:

$$\text{Solve: } \min_{P_G,L} \sum_{i\in G\backslash G_r} (C_i(P_{G_i}(k))) - \sum_{z\in Z}(B_z(L_z(k))) \tag{7}$$

$$s.t. \sum_{i\in G\backslash G_r} P_{G_i}(k) = \sum_{z\in Z} L_z(k) - \sum_{j\in G_r} \hat{P_{G_j}}(k) \tag{8}$$

$$P_{G_i}^{\min} \le P_{G_i}(k) \le P_{G_i}^{\max}, i \in G\backslash G_r \tag{9}$$

$$0 \le L_z(k), z \in Z \tag{10}$$

$$\hat{P}_{G_r}(k) = g_j(\hat{P}_{G_j}(k-1)) \text{ and} \tag{11}$$

$$|F(k,P,L)| \le F^{\max}. \tag{12}$$

The result of solving Problem 1A is the optimized power generation $P^*_{G_i}(k)$ of each dispatchable generation unit $i \in G\backslash G_r$ and the locational marginal prices (LMPs). This is similar to the results of the static SCED currently used in control centers. Also, the results of solving Problem 1B are the optimized power generation $P^*_{G_i}(k)$ of a dispatchable generation unit $i \in G\backslash G_r$ and the dispatchable load $L^*_z(k)$, as well as the LMPs at all system nodes. However, as pointed out in our introductory remarks, the dispatch obtained by solving Problems 1A or 1B is not physically implementable since it disregards the ramping rates of all units. Nevertheless, the solutions to Problems 1A and 1B are generally used as the theoretical benchmarks when assessing the potential of wind power and price-responsive demand. For consistency, we will compare the results of physically implementable algorithms we obtain in this paper to this theoretical benchmark.

The remainder of this paper concerns only physically implementable algorithms. The complexity of the introduced algorithms greatly depends on how the ramping rate-related intertemporal dependencies are accounted for.

IV. Multi-Temporal Static Dispatch

In this section, a simple static dispatch problem that is physically implementable is formulated as Problem 2. This algorithm reflects the present practice that treats intermittent resources as negative loads. Slow dispatchable power plants such as large coal and nuclear units are dispatched hour-ahead for the predicted load and wind generation. This way, no explicit ramping rate exists and only SCED is carried out. Consequently, within an hour, it becomes necessary to re-dispatch only fast-responding conventional units (oil and gas, typically) in order to balance supply and demand in response to temporal deviations in wind and load. This requires expensive fuel-consumption and sometimes the turning off of power plants that are hard to re-start, or the spilling of hydro resources. Moreover, the wind

[2] We use the word "static" to stress that the optimization is done statically for each given time k. This is different from the "dynamic" algorithms which are of the look-ahead nature and are capable of correlating actions in time.

and load prediction accuracy will determine the amount of regulation reserve needed to balance the supply and demand deviations from the predicted values. The mathematical formulation of Problem 2 is as follows.

1) Problem 2A: Physically implementable static dispatch with inelastic demand: At each hour H, solve the problem stated in (1)–(6). The result of this optimization is $P_G^*(H) = \left[P_{G_s}^*(H) \quad P_{G_f}^*(H)\right]^T$.

Then at each 10-min interval k, the ISO updates the wind power forecast and re-runs optimizations (1)–(6) assuming the slow generator units' output will stay the same within that hour.

2) Problem 2B: Physically implementable static dispatch with elastic demand

At each hour H, solve the problem stated in (7)–(12). The result of this optimization is $[P_G^*(H) \quad L_Z^*(H)]^T = \left[P_{G_s(H)}^* \quad P_{G_F(H,P,L)}^* \quad L_Z^*(H)\right]^T$.

Then at each 10-min interval k, the ISO updates the wind power forecast and solves (7)–(12) assuming the slow units' outputs stay unchanged within that hour H. This approach to economic dispatch is suboptimal relative to a full-blown SCUC because it somewhat arbitrarily decomposes a single problem into two subproblems. In the remainder of this paper, we introduce MPC-based methods which optimize over the entire look-ahead time horizon in order to better account for the ramping rate constraints. The MPC-based calculations are repeated at each stage k by optimizing over all stages K, given the best information about the future. It will be shown in this paper that the MPC-based approach greatly contributes to smoother generation scheduling and lower overall generation costs.

V. Centralized MPC-Based Dispatch

In this section, we introduce an MPC-based economic dispatch that takes into consideration the ramping rates of dispatchable power plants by optimizing the total cost over the look-ahead time horizon; this method is a further extension of the work in [10]. A Markov model from [13] is used to represent a 10-min wind prediction of minimum and maximum wind power output. A similar model is used for the 10-min load prediction. Based on these models, a mathematical formulation of the MPC-based economic dispatch from [10] is restated here for completeness as follows.

1) Problem 3A: Centralized MPC-based dispatch with inelastic demand:

$$\text{Solve: } \min_{P_G} \quad \sum_{k=1}^{K}\sum_{i\in G}(C_i(P_{G_i}(k))), i \in G \tag{13}$$

$$s.t. \quad \sum_i P_{G_i}(k) = \sum_z \hat{L}_z(k), i \in G, z \in Z; \tag{14}$$

$$\hat{L}_z(k) = f_z(L_z(k-1)), z \in Z \tag{15}$$

$$\hat{P}_{G_j}^{\max}(k) = g_j(\hat{P}_{G_j}^{\max}(k-1)) \tag{16}$$

$$\hat{P}_{G_j}^{\min}(k) = h_j(\hat{P}_{G_j}^{\min}(k-1)) \tag{17}$$

$$\hat{P}_{G_j}^{\min}(k) \le P_{G_j}(k) \le \hat{P}_{G_j}^{\max}(k), j \in G_r \tag{18}$$

$$P_{G_i}^{\min}(k) \le P_{G_i}(k) \le P_{G_i}^{\max}(k), i \in G \setminus G_r \tag{19}$$

$$|P_{G_i}(k+1) - P_{G_i}(k)| \le R_i, i \in G \text{ and} \tag{20}$$

$$|F(k,P,L)| \le F^{\max} \; \forall k. \tag{21}$$

Here, instead of representing wind generation outputs as negative loads, the wind generation outputs $P_{G_r}(k)$ are considered as decision variables. A look-ahead moving horizon consisting of K samples is chosen over which all generation outputs are optimized. Inter-temporal constraints such as ramping rates are explicitly modeled in this formulation, therefore eliminating the need for the two-step optimization stated above in Problem 2. Similarly, with price-responsive demand, the generation cost minimization problem becomes a market surplus maximization problem. This is stated as Problem 3B next.

2) Problem 3B: Centralized MPC-based dispatch with elastic load:

$$\text{Solve: } \min_{P_G,L} \quad \sum_{k=1}^{K}\left(\sum_{i\in G}(C_i(P_{G_i}(k))) - \sum_{z\in Z}(B_z(L_z(k)))\right) \tag{22}$$

$$s.t. \quad \sum_{i\in G} P_{G_i}(k) = \sum_{z\in Z} L_z(k) \tag{23}$$

$$\hat{P}_{G_j}^{\max}(k) = g_j(\hat{P}_{G_j}^{\max}(k-1)), j \in G_r \tag{24}$$

$$\hat{P}_{G_j}^{\min}(k) = h_j(\hat{P}_{G_j}^{\min}(k-1)), j \in G_r \tag{25}$$

$$\hat{P}_{G_j}^{\min}(k) \le P_{G_j}(k) \le \hat{P}_{G_j}^{\max}(k), j \in G_r \tag{26}$$

$$0 \le L_z(k), z \in Z \tag{27}$$

$$P_{G_i}^{\min}(k) \le P_{G_i}(k) \le P_{G_i}^{\max}(k), i \in G \setminus G_r \tag{28}$$

$$|P_{G_i}(k+1) - P_{G_i}(k)| \le R_i, i \in G \text{ and} \tag{29}$$

$$|F(k,P,L)| \le F^{\max} \; \forall k. \tag{30}$$

This problem formulation is a quadratic programming (QP) problem and not a mixed-integer programming problem of a full-blown unit commitment. As such, its computational complexity is of the order $K^3(4N)^3$, where K is the number of decision stages on a selected look-ahead horizon, and N is the number of decision variables per stage [11]. The QP problem (22)–(30) without wind included has $P_Gj, \ j \in G \setminus G_r$ number of generators over which the decisions are being made. In this formulation, the decision variables are $P_Gi(k), \ i \in G$, $L_z(k), \ z \in Z$. This increases the complexity accordingly. It is important to recognize that a full-blown unit commitment has a combinatorial search space $O(N^K)$ over discrete variables [12]. This is a huge combinatorial problem typically solved by using approximate methods only.[3] When N increases due to the presence of dispatchable wind, this complexity increases significantly.

Even greater computational complexity arises when the network flow constraints are taken into account. This must be done

[3]We note that now the system operators solve this problem using mixed-integer linear programming (MILP), usually having a finite duality gap.

in order to compute a dispatch that is within the transmission congestion limits. Unfortunately, even in the case of relatively small systems, the computing time becomes prohibitively long when attempting to arrive at a centralized MPC-based economic dispatch that accounts for the line flow constraints. This clearly stresses the fundamental complexity of centralized optimization which must account for both inter-temporal and spatial constraints when attempting to integrate new resources. Such centralized network optimization will present a major challenge in the years to come in the design of large-scale computing algorithms necessary for optimizing dispatch with a high penetration of intermittent resources in spatially vast electric power grids. Given this major roadblock to computing optimal centralized dispatch, we assess in the next section another extreme: fully-distributed dispatch by the power plants themselves.

VI. Fully Distributed Economic Dispatch

In what follows, we provide a mathematical formulation for self-dispatch. The only coupling variable is the electricity market price estimate, which is used by both power producers and consumers when deciding how much to commit to sell and/or purchase and at which price. The distributed system users (power plants, demand) optimize their own sub-objectives given the market price estimate, and self-dispatch. There is neither centralized market clearing mechanism nor direct interaction with the system operator. This method rests on the idea of the invisible hand in markets, and it is known to have the same equilibrium as the centralized market assuming convex costs, no ramping rates, no system congestion, and no delivery losses [22]. Most of the general literature does not concern the dynamics of arriving at this equilibrium. However, in electric power systems without storage, the time needed for decisions to converge to a system-wide equilibrium is important since the system must balance almost instantaneously.[4] Here we consider particularly the effect of ramping rates on the time needed for self-dispatch to settle a market equilibrium in an entirely distributed way by adjusting to changes in the market price in a manner that reflects the system-wide supply- demand imbalance. More recently, this self-dispatch has been referred to as a plug-and-play interpretation of distributed power producers and end users.

Consider first the decision-making in a system without congestion. Self-dispatch can be posed as either a static optimization problem or a look-ahead distributed optimization problem by each power plant and/or end user. Problems 4 and 5 are formulations of these two approaches, respectively.

1) Problem 4A: Fully-distributed static self-dispatch with inelastic demand

At time k, the system operator provides price forecast $\hat{\lambda}(k)$ to the distributed decision makers (generators).[5] Each generator $i \in G$ solves the following distributed optimization problem:

$$\text{Solve: } \max_{P_{G_i}(k)} \quad \lambda(\hat{k})(P_{G_i(k)}) - (C_i(P_{G_i}(k))) \tag{31}$$

$$\text{s.t.} \quad P_{G_i}^{\min} \leq P_{G_i}(k) \leq P_{G_i}^{\max}. \tag{32}$$

[4]If storage is taken into account, the system equilibrium may not have to be calculated instantaneously because storage can compensate for small imbalances of the system. However, how storage should automatically respond to system imbalances still remains an open question.

[5]This information could be also based on historic prices.

Each generator maximizes its expected profit given a price prediction $\hat{\lambda}(k)$. The optimization results obtained by generator i are therefore the output levels $P_{G_i}^*(k)$. It is important to observe that the system supply-demand energy balance equation is not an explicit constraint in this problem formulation. Therefore, the self-dispatch of individual generators generally results in system supply-demand imbalance.

Similarly, when both generators and end users self-dispatch, the system imbalance is a result of not explicitly imposing the supply-demand constraint. The decisions of both generators and end users are formulated as follows.

2) Problem 4B: Fully-distributed static self-dispatch with elastic demand

At time k, the system operator provides price forecast $\hat{\lambda}(k)$ and this information is used by all distributed decision makers (generators and loads). Each generator $i \in G$ solves the distributed decision-making problem as formulated in Problem 4A. Similarly, each load $z \in Z$ solves the following distributed optimization problem:

$$\text{Solve: } \max_{L_z(k)} \quad (-\lambda(\hat{k})L_z(k) + (B_z(L_z(k)))) \tag{33}$$

$$\text{s.t.} \quad 0 \leq L_z(k) \leq L_z^{\max}(k). \tag{34}$$

The process repeats at time $(k+1)$, and with this new information, the self-dispatch is recomputed. The imbalance of generation and demand at time k

$$\Delta P_{SD}(k) = \Sigma_i P_{G_i}(k) - \Sigma_z L_z(k) \tag{35}$$

is generally non-zero and it takes several iterations for the decision makers to converge to an equilibrium in which $\Delta P_{SD}(k) = 0$.

Shown in Fig. 4 is a typical iterative process based on top-down price information by the system operator to the system users. At step $k = 1$, the announced price is 50 $/MWh; optimizations in (31)–(32) by the generator, and (33)–(34) by the load zones, lead to a power shortage of approximately 2000 MW. At time step $k = 2$, the system operator, not knowing what individual system users have scheduled, observes this shortage and increases the price to give incentive to generators to produce more. System users, in turn, respond to this new price and adjust according to their own optimization goals. This process ultimately converges to $(P_G^*, L_Z^*, \lambda^*)$, which is the true market equilibrium. The sequential balancing of supply and demand becomes much more complex when suppliers and users are asked to trade within the system congestion limits. For a more detailed example of these iterative distributed adjustments within the system congestion constraints, see [23].

There are at least two possible ways to deal with the time needed to converge. First, the price resulting from the dispatched resources is posted, and the decision makers adjust to it until no further changes in price are observed; only then is the self-dispatch implemented. Second, power plants and loads respond locally to frequency deviations seen at their location and increase their output as frequency decreases, and vice versa. This is effectively the idea of homeostatic control [14]. Both approaches require time for the adjustments to settle and one may run the risk of cumulatively increasing supply and

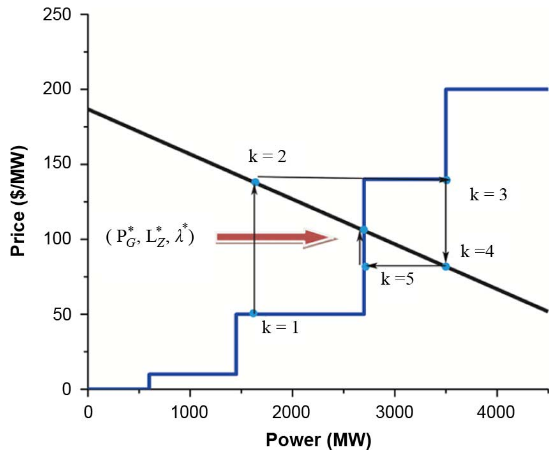

Fig. 4. Conceptual comparison of point-wise self-dispatch and DYMONDS-based dispatch.

demand imbalances as the power generated by the intermittent resources gets intertwined with the imbalances due to lack of coordination [24].

A more realistic approach is based on the observation that the distributed decision makers would optimize their expected profit not in a static way but in some look-ahead manner. A mathematical formulation of such self-dispatch is as follows.

3) Problem 5A: MPC-based self-dispatch with inelastic demand

For a given vector of prices $\underline{\hat{\lambda}(k)}$ defined as $[\,\hat{\lambda}(k+1) \quad \cdots \quad \hat{\lambda}(k+K)\,]$

$$\text{Solve: } \max_{P_{G_i}(k)} \sum_{k+1}^{k+K} \hat{\lambda}(k)(P_{G_i}(k)) - (C_i(P_{G_i}(k))) \quad (36)$$

$$\text{s.t. } \hat{P}_{G_i}^{\max}(k) = g_i(\hat{P}_{G_i}^{\max}(k-1)) \quad (37)$$

$$\hat{P}_{G_i}^{\min}(k) = h_i(\hat{P}_{G_i}^{\min}(k-1)) \quad (38)$$

$$|P_{G_i}(k+1) - P_{G_i}(k)| \le R_i \text{ and} \quad (39)$$

$$\hat{P}_{G_i}^{\min} \le P_{G_i}(k) \le \hat{P}_{G_i}^{\max}. \quad (40)$$

The outcome of the above optimization procedure is a vector of quantities scheduled $\underline{P_{G_i}^*(k)}$ defined as $[\,P_{G_i}^*(k+1) \quad P_{G_i}^*(k+2) \quad \cdots \quad P_{G_i}^*(k+K)\,]$.

4) Problem 5B: MPC-based self-dispatch with elastic demand

Generators dispatch by solving Problem 5A. Similarly, when loads self-dispatch, they must consider their internal dynamics. This can be done by introducing an equivalent to the rate-of-response limit for loads. This rate-of-response limit is a consequence of internal load characteristics and dynamics. To illustrate this, consider a thermal load whose temperature must be maintained within the thermal limits. We model the thermodynamics of an end-user's premise [28] and relate it to the electric energy consumption for each hour. The objective of an end-user is to minimize energy cost given the expected set of prices $[\,\hat{\lambda}(k+1) \quad \cdots \quad \hat{\lambda}(k+K)\,]$ for the next 24 h without violating the temperature comfort level. This comfort level is preset by each end-user as the lower and upper temperature limits $x_i^{\min}$ and $x_i^{\max}$ allowed. Therefore, this decision-making process will take the different needs of each end-user into account and dispatch accordingly. Ideally, this is done according to the following optimization:

$$\min_{P_i(k)} \sum_{k=1}^{24} [P_i(k) \cdot \hat{\lambda}(k) + \{(x_i(k) - x_i^{\max})^2 + (x_i(k) - x_i^{\min})^2\}] \quad (41)$$

$$\text{s.t. } x_i(k+1) = \varepsilon x_i(k) + (1-\varepsilon)(T_o(k) - \gamma P_i(k)) \quad (42)$$

$$x_i^{\min} \le x_i(k) \le x_i^{\max} \text{ forall } k. \quad (43)$$

The MPC-based self-dispatch is computationally simple when compared to the centralized MPC-based dispatch, if one assumes price predictions to be given. The MPC-based method generally results in less volatile prices and fewer system imbalances (even without any additional price updates) when compared with fully-distributed self-dispatch.[6]

Related proposed approaches require a pointwise information exchange between the distributed decision makers and a transmission provider concerning distribution factors, congestion charges μ, or the proximity to line limit information by the transmission providers [22], [25]. Again as in the case of any pointwise information exchange in the supply-demand balancing processes, instabilities may occur and/or the time required to settle may be longer than the rate at which the output of intermittent resources vary. Also, the duality gap between the solution of Problem 5B and Problem 1B may be significant; this reflects the cost of decentralization.

In closing, fully-distributed pointwise self-dispatch is prone to slow settling times and/or genuine instabilities. These are two major issues which require further investigation before seriously considering self-dispatch as an option in the changing energy industry.[7] The role and value of storage become essential if such a method is to be adapted. Important open questions concern the tradeoff between information complexity and the cost of storage.

VII. DYMONDS-BASED ECONOMIC DISPATCH

Keeping in mind the subtle differences between the methods assessed above, we propose a new method for economic dispatch that: 1) is computationally feasible at the 10-min rate even for very large power systems; 2) generally comes very close to the efficiency (the values of the objective functions) of centralized MPC-based economic dispatch (theoretically the most efficient physically implementable dispatch); 3) allows for autonomous adaptation by the generators and loads to changing system conditions; and 4) empowers the system operator with the ability to balance the system almost instantaneously within the system congestion limits. We refer to this economic dispatch as DYMONDS-based, since it requires a more interactive multi-layered IT architecture than today's SCADA. We think

[6]Only risk-free dispatch is considered here. There are methods for accounting for the tradeoff between the expected profit and value, but this becomes computationally more challenging even at the distributed level [24].

[7]The adjustment process by a typical number of power plants is a very different process from the one of many small actors adjusting at the distributed level within the distribution network, where the law of large numbers may ensure more stable processes.

of it as the next generation of SCADA. The DYMONDS-based economic dispatch requires specific information to be given by the distributed decision makers to the system operators in terms of bid and demand functions. These are created by each distributed decision maker as a result of its own objective optimization function in an MPC look-ahead manner. For the predicted price and the range of price variations, the distributed decision maker (generator or load) provides a sensitivity function of price with respect to the quantity at which it is willing to sell or purchase. The demand and supply functions are simply sensitivities of the Lagrangian coefficients associated with $\Delta P_{SD}(k)$ around prices given by the operator.

We stress that the DYMONDS approach requires information exchange in a function space. Shown in Fig. 4 is a sketch of the conceptual advantage provided by supply and demand sensitivity functions as opposed to pointwise single (price, quantity) point data. It can be seen that, for given supply and demand functions, an equilibrium $(P_G^*, L_Z^*, \lambda^*)$ is found in one step, not iteratively. This is in contrast to the point-wise information discovery through iterations which leads to equilibrium. The iterations can be very time-consuming and unacceptable in power systems without storage. Ensuring that system feasibility can be maintained is simply a matter of finding a solution to a static optimal power flow for which supply and demand functions are given. In the case of DC OPF, it is known that a solution exists if the total benefit and total cost functions are concave and convex, respectively.

Given this observation, we propose a DYMONDS-based multi-directional multi-layered information exchange in which distributed decision makers are required to provide their bids in the function space. These are in turn optimized non-iteratively by the entity in charge of balancing supply and demand-the system operator in particular. Moreover, inter-temporal complexity is managed in the look-ahead MPC-based distributed decision-making process over a finite time horizon by the system users themselves, resulting in a set of static bid functions for the entire look-ahead interval. These are in turn communicated to the balancing authority, which carries out a static optimization only. This way the computational complexity at the system level is overcome.

1) Problem 6A: DYMONDS-based static dispatch with inelastic demand

Given the price vector $\underline{\hat{\lambda}(k)}$, each generator solves the problem posed in 5A above to obtain optimum power $P_{G_i}^*$. Then, by varying the price uniformly up and down by $x\%$ the generator obtains a set of optimal points corresponding to these perturbed prices by re-solving the same problem 5A. These solutions are used to create a price sensitivity-based supply vector function $\underline{S}_i(\underline{P}_{G_i}(k))$ around the assumed electricity price. All generators are required to submit their supply functions to the system operator and the market clears the bids, which are the lowest generation cost bids needed to balance supply and demand at time k. Problem formulation 6A resembles the basic day-ahead spot market clearing process. It is known to work well, except for not being able to account for the ramping rates-related inter-temporal dependencies between clearing times k. Variations of this approach can be found in literature related to multilateral energy markets [18], [25].

2) Problem 6B: DYMONDS-based static dispatch with elastic demand

In addition to generators creating their own supply functions as described in 6A, groups of end users optimize their own benefits for given $\lambda(k)$ by solving Problem 5B above to obtain optimal $L_z^*(k)$. Next they create sensitivity-based demand functions by varying the given price by $x\%$ up and down and finding the corresponding optimal demand. The proof-of-concept for such static dispatch that relies on the exchange of bids in a function space subject to congestion limits can be found in [18].

For the purposes of this paper, it is important to assess the duality gap between the results obtainable using centralized MPC-based economic dispatch and the results obtainable using the DYMONDS-based approach. There are several reasons for this gap and the resulting sub-optimality. The main causes are: 1) the non-convexity of the cost functions; 2) the non-concavity of the benefit functions; 3) temporal inter-dependencies; and 4) interactive information exchange-related uncertainties. It has been shown that under certain convexity conditions and assuming no inter-temporal dependencies (no ramping rate-related constraints), there exists a unique equilibrium which can be reached interactively using a static DYMONDS-based economic dispatch [26]. However, given the significant inter-temporal dependencies related with the ramping rates on the power producers' side, and the load dynamics and uncertainties at the end users' level, it is no longer sufficient to rely on static equilibrium thinking. Instead, it becomes essential to introduce a DYMONDS-based MPC interactive dispatch capable of managing the inter-temporal dependencies more efficiently than the DYMONDS-based static dispatch. A mathematical formulation of this approach is introduced next.

3) Problem 7A: DYMONDS-based MPC dispatch with inelastic demand

In the DYMONDS-based MPC dispatch formulation, a two-layer[8] information exchange scheme provides an interactive optimization procedure between the system operator, on the one hand, and an individual power producer and the consumer layers, on the other. For expected power price vector $\underline{\hat{\lambda}(k)}$, each power producer maximizes its expected profits by internalizing the rate of response of the available generation, as well as the inter-temporal ramping constraints. One vector of expected price $\underline{\hat{\lambda}(k)}$ corresponds to one vector of optimum vector generation outputs $\underline{P}_{G_i}^*(k)$. By perturbing the price vector around the nominal value, power producers are able to generate a set of optimum generation output vectors. The pairs of price and optimum generation output vectors are submitted to the system operator as the supply functions for the next 24 h, for example. The calculation of the generator's supply function that accounts for temporal interdependencies

[8]Depending on the granularity of aggregation, there may be multiple layers. For example, the lowest layer will be a single power producer, the secondary layer is a portfolio manager, and the third layer is a system operator. Similarly, for managing loads adaptively, the primary level is comprised of individual end users, the secondary layer of load serving entities, and the tertiary level is the system operator [27].

can be obtained in the following way. For a given vector of $[\,\hat{\lambda}(k+1) \quad \hat{\lambda}(k+2) \quad \cdots \quad \hat{\lambda}(k+K)\,]$

$$\text{Solve: } \max_{P_{G_i}(k)} \sum_{k+1}^{k+K} \lambda\hat{(k)}(P_{G_i}(k)) - (C_i(P_{G_i}(k))) \quad (44)$$

$$\text{s.t. } \hat{P}_{G_i}^{\max}(k) = g_i(\hat{P}_{G_i}^{\max}(k-1)) \quad (45)$$

$$\hat{P}_{G_i}^{\min}(k) = h_i(\hat{P}_{G_i}^{\min}(k-1)) \quad (46)$$

$$|P_{G_i}(k+1) - P_{G_i}(k)| \leq R_i \text{ and} \quad (47)$$

$$\hat{P}_{G_i}^{\min} \leq P_{G_i}(k) \leq \hat{P}_{G_i}^{\max}. \quad (48)$$

For generator $i \in G \backslash G_r$, there are no (45) and (46) constraints.

The outcome of the above optimization is a vector of power quantities $\underline{P}_{G_i}^*(k)$. By varying the price vector uniformly up and down $x\%$, one obtains a desired power output and price pairs shown as

$$\underline{P}_{G_i}^{*+x\%}(k),\ \underline{\lambda}^{*+x\%}(k) \quad (49)$$

$$\underline{P}_{G_i}^{*-x\%}(k),\ \underline{\lambda}^{*-x\%}(k). \quad (50)$$

One then constructs the vector supply function for generator i at time k, $\underline{S}(P_{G_i})(k)$, using the results of (49) and (50). The reason for perturbing up and down uniformly on the price vector is that the search space is reduced from $\Re^K$ to $\Re^1$. Given that the MPC is a moving horizon optimization, the uniform search will result in much faster computation.[9]

At the system operator level, only static SCED is performed, formulated as Problem 1A. Therefore, the computational burden compared with that of fully-centralized MPC dispatch is significantly reduced. At the system level, the ISO simply solves Problem 1A by replacing $C(P_{G_i})$ with $S(P_{G_i})(k)$.

4) Problem 7B: DYMONDS-based MPC dispatch with elastic demand

Similarly, by introducing price-responsive demand, the DYMONDS-based MPC dispatch can be formulated as a total market surplus maximization problem at the system operator level. For a given price vector $\underline{\hat{\lambda}(k)}$

Solve:

$$\max_{L_z(k)} \sum_{k+1}^{k+K} [\hat{\lambda}(k)L_z(k) + \{(x_z(k) - x_z^{\min})^2 + (x_z(k) - x_z^{\max})^2\}] \quad (51)$$

$$\text{s.t. } x_z(k+1) = \varepsilon x_z(k) + (1-\varepsilon)(T_o(k) - \gamma L_z(k)) \quad (52)$$

$$x_z^{\min} \leq x_z(k) \leq x_z^{\max} \text{ for all } k. \quad (53)$$

Then the demand function is obtained by perturbing the price vector around the price vector originally anticipated by the system prediction. The demand functions are obtained by curve-fitting different prices for each hour and the corresponding optimal energy usages. Linear least squares estimation is used to calculate the demand curve and obtain the slopes and y-axis intercepts of the hourly demand functions. These demand functions are expected to show a certain level of price elasticity during some hours each day. Some more insights concerning the benefit and demand functions can be found in the Appendix of Part II of this paper.

The outcome of the above optimization procedure is a demand vector $\underline{L_z^*}(k)$ defined as $[\,L_z^*(k+1) \quad \cdots \quad L_z^*(k+K)\,]$. After calculating these optimal demands at each time step, we perturb the expected price vector (e.g., by $\pm 20, 30\%$) to obtain optimal energy consuming points for a different price vector, as at the individual end-users' level. At each time step, these different price and optimal demand vectors are curve-fitted to form system demand functions. These demand functions carry information about the end-users' economic value of electricity. Together with the supply functions, the demand functions are collected by the system operator, and cleared by solving Problem 1B for each time step.

VIII. Conclusions

In this paper, we present several possible approaches to integrating wind power and assess their strengths and weaknesses. We conclude that the three key factors to successful wind integration are: 1) demand response, 2) the use of predictive wind power models, and 3) the use of a physically implementable dynamic model-predictive dispatch of responsive demand, wind power, and conventional power plants. A physically implementable dispatch takes into consideration the ramping rates of equipment and at the same time ensures that the power can be delivered by the grid within its congestion limits. We first formulate a centralized model-predictive dispatch, and we argue that it is the most efficient physically implementable solution possible. However, we suggest that such a solution would require major breakthroughs to go beyond the computing algorithms currently used for SCED. Such algorithms present a grand challenge in computer science and are not likely to be available any time soon for use in electric power systems. Given this, we next formulate a computationally manageable alternative, which is referred to as DYMONDS. An implementation of DYMONDS-based dispatch will require transforming today's SCADA system to enable online multi-directional, multi-layered information exchange between the centralized scheduler and the energy resources. Based on the algorithmic formulation, we conclude that DYMONDS protocols must provide certain online information exchanges: 1) demand and supply functions from the energy resources ahead of time to the scheduler; and 2) statically optimized schedules and electricity prices using today's SCED from the central dispatcher back to the resources.

[9]Based on the experiments in Part II of this paper, searching the price vector in $\Re^1$ does not yield too much optimality degradation compared to searching in $\Re^K$. Analysis of the suboptimality of uniformly perturbing the price vector is an open research problem.

References

[1] U.S. Department of Energy, Mathematical Research Challenges in Optimization of Complex Systems, 2006.

[2] A. Cohen and C.-N. Yu, "Unit commitment in energy markets: Recent experience and future directions," in *Proc. FERC Technical Conf. Increasing Market and Planning Efficiency Through Improved Software and Hardware*, Washington, DC, Jun. 2010.

[3] A. Ott, "Unit commitment in the PJM day-ahead and real-time markets," in *Proc. FERC Technical Conf. Increasing Market and Planning Efficiency Through Improved Software and Hardware*, Washington, DC, Jun. 2010.

[4] F. Zhuang and F. D. Galiana, "Towards a more rigorous and practical unit commitment by Lagrangian relaxation," *IEEE Trans. Power Syst.*, vol. 3, no. 2, pp. 763–773, May 1988.

[5] R. Sioshansi, R. O'Neill, and S. S. Oren, "Economic consequences of alternative solution methods for centralized unit commitment in day-ahead electricity markets," *IEEE Trans. Power Syst.*, vol. 23, no. 2, pp. 342–344, May 2008.
[6] H. Ma and S. M. Shahidehpour, "Unit commitment with transmission security and voltage constraints," *IEEE Trans. Power Syst.*, vol. 14, no. 2, pp. 757–762, May 1999.
[7] P. Gribik and L. Zhang, "Extended locational marginal pricing (convex hull pricing)," in *Proc. FERC Technical Conf. Unit Commitment Software*, Washington, DC, Jun. 2010.
[8] U.S. National Renewable Energy Laboratory, Eastern Wind Integration and Transmission Study. [Online]. Available: http://wind.nrel.gov/public/EWITS/.
[9] P. Meibom, C. Weber, R. Barth, and H. Brand, "Operational costs induced by fluctuating wind power production in Germany and Scandinavia," *Proc. IET Renew. Power Gen.*, pp. 133–156, 2009.
[10] L. Xie and M. D. Ilic, "Model predictive economic/environmental dispatch of power systems with intermittent resources," in *Proc. IEEE Power and Energy Society General Meeting*, Calgary, AB, Canada, Jul. 2009.
[11] S. J. Wright, "Applying new optimization algorithms to model predictive control," *Chem. Process Control-V*, vol. 93, no. 316, pp. 147–155, 1997.
[12] A. Wright and P. Sandrin, "A new method for unit commitment at Electricite de France," *IEEE Trans. Power App. Syst.*, vol. PAS-102, no. 5, pp. 1218–1225, May 1983.
[13] N. Abdel-Karim and M. D. Ilic, "Short term wind speed prediction by finite and infinite impulse response filters: A state space model representation using discrete Markov process," in *Proc. IEEE PowerTech Conf.*, Bucharest, Romania, Jun. 2009.
[14] F. C. Schweppe, R. D. Tabors, J. L. Kirtley, H. R. Outhred, F. H. Pickel, and A. J. Cox, "Homeostatic utility control," *IEEE Trans. Power App. Syst.*, vol. PAS-99, no. 3, pp. 1151–1163, May 1980.
[15] D. W. Ross and S. Kim, "Dynamic economic dispatch of generation," *IEEE Trans. Power App. Syst.*, vol. PAS-99, no. 6, pp. 2060–2068, Nov./Dec. 1980.
[16] X. S. Han, H. B. Gooi, and D. S. Kirschen, "Dynamic economic dispatch: Feasible and optimal solutions," *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 22–28, Feb. 2001.
[17] J. Tsitsiklis and M. Athans, "On the complexity of decentralized decision making and detection problems," *IEEE Trans. Autom. Control*, vol. 30, no. 5, pp. 440–446, May 1985.
[18] H. Wang, M. D. Ilic, and I. Vogelsang, "Multi-layered unbundled delivery of electricity service to customers under normal conditions," in *Proc. IEEE PES General Meeting*, Jun. 2004.
[19] M. Ilic, E. Hsieh, and P. Ramanan, "Transmission pricing of distributed multilateral energy transactions to ensure system security and guide economic dispatch," *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 428–434, May 2003.
[20] A. I. Cohen, V. Brandwajn, and S. Chang, "Security constrained unit commitment for open markets," in *Proc. IEEE Int. Conf. Power Industry Computer Applications*, Jul. 1999.
[21] G. Gross and F. D. Galiana, "Short-term load forecasting," *Proc. IEEE*, vol. 75, no. 12, pp. 1558–1573, Dec. 1987.
[22] *Electric Power Systems Restructuring: Engineering and Economics*, M. D. Ilic, F. D. Galiana, and L. Fink, Eds. Norwell, MA: Kluwer, 1998, ch. 2.
[23] E. Allen, M. D. Ilic, and Z. Younes, "Providing for transmission in times of scarcity: an ISO cannot do it all," *Int. J. Elect. Power Energy Syst.*, vol. 21, no. 2, pp. 147–163, Feb. 1999.
[24] A. Berger, "Pricing mechanisms in coupled dynamic systems," Ph.D. dissertation, Harvard Univ., Cambridge, MA, 1983.
[25] F. Wu and P. Varaiya, "Coordinated multilateral trades for electric power networks: Theory and implementation," *Working Paper of the Program on Workable Energy Regulation,* University of California Energy Institute, 1995.
[26] Lecture Notes, Engineering and Economics of Electric Power Systems,. Pittsburgh, PA, Carnegie Mellon Univ.
[27] J. Y. Joo and M. D. Ilic, "A multi-layered adaptive load management (ALM) system: Information exchange between market participants for efficient and reliable energy use," in *Proc. 2010 IEEE PES Transmission and Distribution Conf.*.
[28] P. Constantopoulos, F. C. Schweppe, and R. C. Larson, "ESTIA: A real-time consumer control scheme for space conditioning usage under spot electricity pricing," *Comput. Oper. Res.*, vol. 18, no. 8, pp. 751–756, 1991.
[29] M. Ilić, "Dynamic monitoring and decision systems for enabling sustainable energy services," *Proc. IEEE*, vol. 99, no. 1, pp. 58–79, Jan. 2011.

Marija D. Ilić (M'80–SM'86–F'99) is currently a Professor at Carnegie Mellon University, Pittsburgh, PA, with a joint appointment in the Electrical and Computer Engineering and Engineering and Public Policy Departments. She is also the Honorary Chaired Professor for Control of Future Electricity Network Operations at Delft University of Technology in Delft, The Netherlands. Her main interest is in the systems aspects of operations, planning, and economics of the electric power industry. Most recently, she became the Director of the Electric Energy Systems Group at Carnegie Mellon University (http://www.eesg.ece.cmu.edu); the group does extensive research on mathematical modeling, analysis, and decision-making algorithms for future energy systems. She is leading the quest for transforming today's electric power grid into an enabler of efficient, reliable, secure, and sustainable integration of many novel energy resources. She has co-authored several books in her field of interest.

Prof. Ilić is an IEEE Distinguished Lecturer.

Le Xie (S'05–M'10) received the B.E. degree in electrical engineering from Tsinghua University, Beijing, China, in 2004, the M.Sc. degree in engineering sciences from Harvard University, Cambridge, MA, in 2005, and the Ph.D. degree in the Department of Electrical and Computer Engineering at Carnegie Mellon University, Pittsburgh, PA, in 2009.

He is an Assistant Professor in the Department of Electrical and Computer Engineering at Texas A&M University, College Station. His industry experience includes an internship at ISO-New England and an internship at Edison Mission Energy Marketing and Trading. His research interest is the modeling and control of large-scale power systems with renewable energy resources, and electricity markets.

Jhi-Young Joo (S'07) received the B.Eng. and M.Eng. degrees from the School of Electrical and Computer Engineering at Seoul National University, Seoul, Korea, in 2005 and 2007, respectively. She is pursuing the Ph.D. degree in the Department of Electrical and Computer Engineering at Carnegie Mellon University, Pittsburgh, PA.

Her fields of research interest include the modeling and implementation of demand response programs, financial risk management of utilities, and the dynamic pricing of electric energy.