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Coupling Wind Generators with Deferrable Loads

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***Abstract*-- We explore the possibility of directly coupling deferrable loads with wind generators in order to mitigate the variability and randomness of wind power generation. Loads engage in a contractual agreement of deferring their demand for power by a fixed amount of time and wind generators optimally allocate available wind power with the objective of minimizing the cost of unscheduled and variable supply. We simulate the performance of the proposed coupling in a market environment and we demonstrate its compatibility with existing technology, grid operations and economic incentives. The results indicate that the combination of existing deregulated power markets and demand side flexibility could support large scale integration of wind power without significant impacts on grid operations and without the requirement for prohibitive investments in backup generation.**

I. Introduction

It is a well known fact that wind power has undergone massive growth during the past 20 years, to the point that large scale integration of wind in power systems is technically and economically conceivable. Nevertheless, the random and variable nature of wind power supply imposes severe limits to the integration of wind power in power systems.

The unpredictable and variable supply of wind power may result in balancing actions that range from ramping other generators, load following, primary and secondary control actions, to the upset of hour-ahead and day-ahead schedules. These balancing actions are costly, lead to air pollution, cause wear and tear to machinery and require significant investments in system backup. Empirical and academic studies have placed an estimate on the costs resulting from wind variability at a range of 0 to 7 $/MWh [1]-[3]. In addition, wind is often adversely correlated with system supply and demand patterns, and may be discarded even when it is abundantly available [4].

The burden that wind power imposes on grid operations is likely to increase in the future due to regulatory commitments for increased integration of wind power. In the meantime, the exploitation of demand flexibility as an ancillary resource for power system operations is evolving rapidly. Time of use pricing, demand response programs [5] and interruptible service contracts [6], [7] are already in place, and the utilization of demand in load following markets is considered as a viable possibility [8]. It is therefore natural to consider the potential of flexible loads fluctuating according to the supply of renewable and non-dispatchable energy sources such as wind power.

In order to reap the greatest benefits from demand flexibility, this flexibility should be explicitly modeled in system operator dispatch algorithms and remunerated in the hour-ahead and real-time markets. Certain market regulations such as the California market redesign (MRTU) aim at incorporating demand resources in market operations, nevertheless demand flexibility is presently far from fully utilized [9]. In the meantime, this paper presents an approach for coupling wind power supply with flexible demand which is compatible with current grid and power market operations, existing technological infrastructure and existing economic incentives. In section II we discuss the operational challenges that result from wind power integration. In section III we present the architecture of the proposed coupling and in section IV we evaluate its performance. Finally, we summarize our conclusions in section V.

II. Impacts of Wind Power on Grid Operations

There are two characteristics of wind power supply which present significant obstacles to large scale wind power integration. Wind power supply is random and cannot be forecast accurately. In addition, it is variable; even if perfect forecasts were available, wind would be a problematic power source because it varies beyond human control.

The unpredictability of wind power supply may cause deviations from hour-ahead dispatch schedules. Starting up units to compensate for a sudden shortage in wind power supply may take hours, lead to additional air pollution, result in wear and the need for frequent maintenance of startup units, and upset system dispatch due to the minimum capacity constraints of startup units. Similar problems are caused by shutting down units to balance an unanticipated increase in wind power supply.

The minute-by-minute and intra-hour variability of wind power generation may also cause system imbalances. This variability imposes a requirement for capacity investments in primary control (spinning reserve), secondary control (non-spinning reserve), load following and regulation units. The inability to perfectly forecast wind exacerbates this problem. Since wind also tends to vary rapidly and in great magnitude, generators with sufficient ramping capabilities are required. The California ISO (CAISO) has estimated that meeting the 20% renewable energy integration target in California will increase the regulation ramping requirement of the system by ±10 to ±25 MW/min, the maximum load following ramping requirement by ±30 to ±40 MW/min, the 3-hour morning ramping requirement by 926 to 1529 MW, and the 3-hour evening ramping requirement by 427 to 984 MW depending on the season [4].

Wind power may also cause oversupply problems in systems which absorb large amounts of hydroelectric power, or in systems where wind patterns are negatively correlated with electricity consumption. Intermittency in the presence of high winds is also a significant drawback of wind power supply. Since wind generators supply a significant amount of power to a system during periods of high winds, there is an increased risk of substantial supply shortage during storms.

The end effects of the problems listed above which originate from the erratic nature of wind power supply are high integration costs and the discarding of wind power. Both of these effects limit our ability to increase our reliance on wind power supply.

The costs of wind integration are captured by market tariffs and may be allocated to the whole market or directly to wind generators, depending on market regulations. Studies have placed an estimate of these costs between 0 and 7 \$/MWh for integration levels between 2.4% to 20%.

Wind energy may be discarded during hours of excess wind power supply if power systems cannot reliably absorb this supply [1], [3]. During early spring the California system operator either spills water supplies from hydroelectric dams or discards wind power [4]. Wind power is also discarded under normal operating conditions in California whenever forecasting underestimates the amount of wind power supply to the system and the excess power cannot be sold in the market. In Texas the system operator limits wind output during load pick-up for reliability reasons. In Denmark, wind power is not consumed during windy and cold evenings when combined heat and power thermal units need to operate [10].

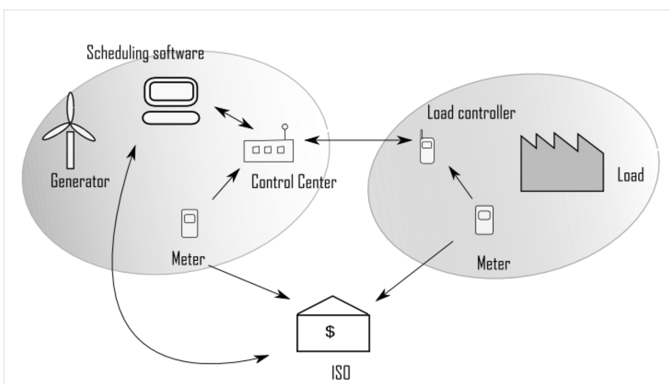

Fig. 1. Data flow of the proposed implementation.

III. NETWORK CONFIGURATION AND MODEL

The proposed coupling of wind generators with flexible loads is presented in Fig. 1. Loads program tasks to be completed within a deadline (e.g. a few hours) and a wind generator control center which controls the output of a large number of wind generators switches these loads remotely and supplies power to loads within the deadline. Duties aggregating from different loads are scheduled according to the availability of wind power.

Meters are installed at every load site and at the wind power plant. The meters monitor the output of wind power and the power consumption of each load. This information is reported to the ISO and to the power plant control center. A central scheduling controller uses all available data (metered data, market prices, load demand, weather forecasts) in order to optimally schedule the allocation of available wind power for satisfying incoming duties. The scheduling controller can also place bids in the power market. The control center collects metered and load demand data and feeds it to the scheduler. After the scheduling algorithm determines which loads can consume power in the following interval, the control center communicates these instructions to each load controller. Load controllers are installed at each load site. These devices collect metered and power demand data, communicate this information to the control center and switch loads.

Apart from load flexibility, wind generators can utilize an additional degree of freedom, the hour-ahead market of electricity. In case forecast wind power supply exceeds the aggregate demand of flexible loads, the excess wind can be sold in the hour-ahead market. Similarly, if aggregate demand is in excess of wind power supply and wind suppliers risk missing load deadlines, their short position can be covered in the market.

Since loads can be switched to vary according to the supply of wind, the net power supply of the network of wind generators and flexible loads to the grid remains near zero constantly, thus resulting in minimal impacts of wind power generation on grid operations. Moreover, by appropriately combining supply and demand bids in the market, wind generators and flexible loads can override the market price and effectively trade the bulk of available wind power bilaterally, using the market solely for the purpose of resolving unscheduled deviations and supplying excessive amounts of wind power. The welfare increase resulting from the proposed coupling can be allocated among wind generators and deferrable loads through the design of an appropriate contractual agreement.

The aforementioned joint decision process of allocating available wind power and participating in the market is formulated as an optimization problem in (1)-(8).

$$\max_{c_{t,i}, w_{t,i}, r_t, B_T} E\left\{ \sum_{t=1}^{N} f \sum_{i \in I} c_{t,i} + \sum_{t \in H_T} \lambda_T B_T - 2 \right.$$

$$\left. - \sum_{t \in H_T} \lambda_D D_T - \sum_{t=2}^{N} \lambda_R \left| s_{t+1} - s_t \right| \right\} \quad (1)$$

s.t

$$R_{t+1,i} = R_{t,i} - c_{t,i} \qquad t \in \{1..N\}, i \in I \quad (2)$$

$$R_{T_i^d} = 0 \qquad i \in I \quad (3)$$

$$\sum_{i \in I} w_{t,i} + r_t \le W_t \qquad t \in \{1..N\} \quad (4)$$

$$c_{t,i} \le C_i \qquad i \in I, t \in \{1..N\} \quad (5)$$

$$c_{t,i} = 0 \qquad i \in I, t \leq T_i^a - 1 \qquad (6)$$

$$w_{t,i}, c_{t,i} \geq 0 \qquad i \in I, t \in \{1..N\} \qquad (7)$$

$$r_t \geq 0 \qquad t \in \{1..N\} \qquad (8)$$

Wind generators supply power to a set of flexible consumers I over a set of ten-minute time intervals $t \in \{1..N\}$. The set H_T consists of those ten-minute intervals belonging to the T-th hour. Wind generators agree to supply power to deferrable loads at a fixed price f. This fixed price should only be a fraction of the hour-ahead market price of electricity λ_T in order to be attractive to flexible. Generators incur an hourly deviation penalty λ_D for deviating from their market bid, and a ten-minute ramping penalty λ_R for variations of their net supply to the market.

At each ten-minute interval t generators determine the amount of power $c_{t,i}$ supplied to user i; the amount of wind power $w_{t,i}$ allocated to user i; and the amount of wind power r_t supplied to the market. At each hourly interval T generators bid a quantity B_T of power to the hour-ahead market. It is assumed that bids are placed two hours in advance of the actual operating interval. Hence the bid at hour T commits the supplier for period $T+2$ and is rewarded the price λ_{T+2}.

The terms in the objective function of (1) include revenues for supplying power to deferrable loads, revenues for energy bids in the hour-ahead market, deviation penalties and ramping penalties. The generator net supply to the market at each ten-minute interval t is $s_t = r_t - \sum_{i \in I}(c_{t,i} - w_{t,i})$. Hence $D_T = \max_{t \in H_T} |s_t - B_{T-2}|$ is the maximum deviation of the net supply to the market from the scheduled quantity B_{T-2} over the course of hour T. Expectation in the objective function is taken over the joint distribution of the wind power supply and price processes.

The remaining energy required to complete the request of user i is $R_{t,i}$ in period t and evolves according to (2). Equation (3) imposes the constraint that the request of user i must be completed by the deadline T_i^d. According to (4) the total amount of wind power supplied to flexible consumers and the spot market cannot exceed the amount of available wind power W_t. Equation (5) models the capacity constraint C_i of user i and according to (6) power cannot be supplied to the task of user i prior to the arrival time T_i^a.

The deviation penalty term in (1) is intended to model the costs associated with the unpredictability of wind power supply, while the ramping penalty term is intended to model variability costs. Apart from their modeling interpretation, these terms also have an economic meaning in the context of power markets. The deviation penalty term can be interpreted as a capacity cost resulting from the required investment in load following generation which can neutralize wind generator deviations from their scheduled outputs in the intra-hour time scale. Likewise, the ramping penalty term can be interpreted as a capacity cost resulting from required upgrades in the ramping requirements of load following units. These investment costs are discussed in section II.

It should be noted that the model in (1)-(8) does not account for transmission constraints. As such, it is a best-case scenario for exploiting demand-side flexibility, since the presence of transmission constraints will both limit and complicate the solution to the problem.

The hardware infrastructure required for implementing the architecture of Fig. 1 is limited to one-way metering devices, communication links and load controllers which are used extensively in power system operations. Instead, it is the availability of flexible power consumers which is in question. There is a variety of large scale industrial and commercial loads which are promising candidates for the proposed coupling. Such loads include industrial electric heaters, thermal storage, HVACs, pumps, agitators, smelters, refrigerators, and potentially programmable thermostats and data centers. An emerging source of flexibility which will probably revolutionize our ability to incorporate wind power in power systems are plug-in electric vehicles. Using wind power supply to power electric vehicles is in the process of implementation in Denmark, and a pilot program in California is also being considered.

The coupling which is advocated in this paper can equally well be applied to mitigate the variability and randomness of any renewable energy source which is beyond human control. In particular, solar power is a promising area of application for this concept, especially in California where solar power supply is complementary to wind power. The reason that we have decided to focus on wind power in the present paper is that wind power is currently the primary renewable energy source in California, and we have access to a more detailed database for our simulation model.

It could be argued that the proposed coupling is redundant in the presence of an ancillary services market, where the price signal would be sufficient to activate the necessary responses which would balance the impact of wind power variations on system reliability. However, designing a market which is fast and accurate enough to ensure grid reliability is a challenging task. Hence, an a priori contractual agreement of the sort described in this paper may be an attractive alternative to ensuring reliability in the presence of large amounts of wind power.

In order to demonstrate the incentive compatibility of the proposed coupling for both wind power suppliers and flexible consumers, the proposal must be compared to a benchmark of existing practices. We will consider a baseline scenario in which wind generators bid the forecast wind supply in the hour-ahead market, and supply all wind power as it becomes available. Hence wind generators receive the market price for the full amount of available wind power, however they incur significant deviation and ramping charges.

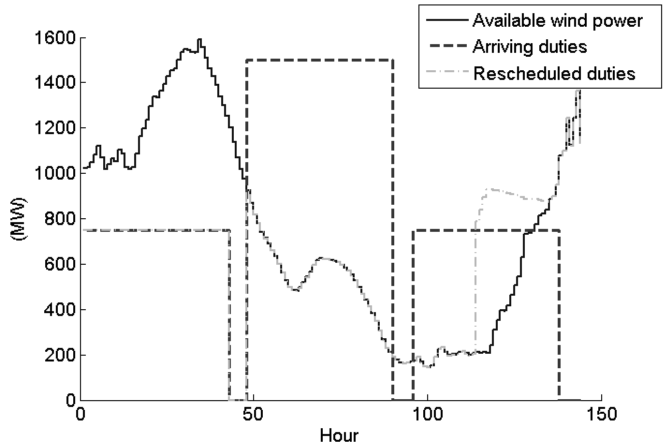

Fig. 2. A snapshot of load scheduling for 1500 users and 18 hours of available time for processing jobs.

To argue that deferrable loads have an incentive to couple, we will content ourselves to demonstrating that wind power suppliers are able to provide power to flexible consumers below the average market price. We will therefore refrain from explicitly modeling consumer utility functions, and the resulting discomfort of postponing electricity consumption. To demonstrate that suppliers have an incentive to couple, we will show that it is possible to use the flexibility of deferrable users in combination with market bidding to mitigate both ramping and deviation penalties. The savings in deviation and ramping penalties, as compared to the baseline case, will exceed the revenue losses resulting from selling power at a discounted price to deferrable loads instead of the hour-ahead market.

IV. Simulation Results

Rather than providing an exact assessment of the integration costs of wind power in the presence of demand-side flexibility, the simulations presented in this section aim at estimating at what point this proposal becomes an economically viable alternative to existing practices. In addition, the simulations analyze the sensitivity of the proposed coupling to certain significant problem parameters, such as the number of available deferrable loads and the deadlines of the deferrable tasks. Such an analysis is intimately related to the question of how much flexibility is inherent in our consumption patterns: if indeed a significant proportion of the power we consume can be deferred for only a few hours at a minimal impact, and if these few hours of flexibility can be optimally rescheduled so as to mitigate the costs of wind power integration, then there is good reason to pursue the route of demand-side management as an avenue of addressing our dependence on fossil fuels and mitigating the environmental impacts of electricity generation.

The assumptions that are employed in the simulations are listed in appendix A. The algorithm that is used for scheduling loads and participating in the hour-ahead market is described in appendix B.

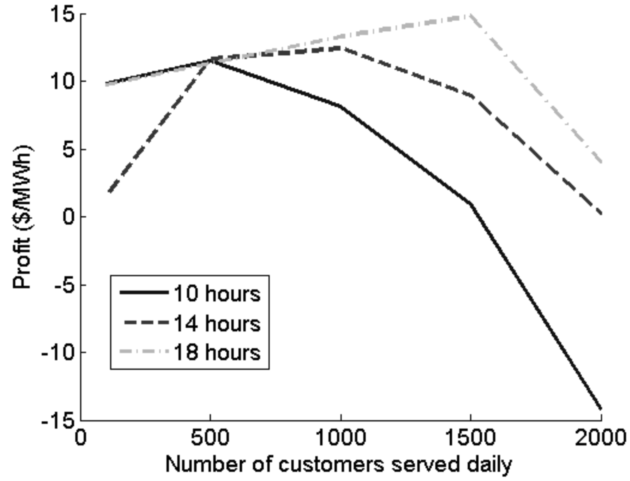

Fig. 3. Profitability of the proposed coupling as a function of the number of deferrable loads for various levels of consumer flexibility.

A. An Example Run

Fig. 2 is a 24-hour snapshot of the load scheduling for the case of 1500 users, each of which provides an 18-hour time window for processing a task which would normally require 7 hours (see appendix A). The solid line is the total amount of available wind energy, and the broken dark line represents the consumption profile of incoming blocks of perfectly inflexible loads. The broken light line is the power consumption of these loads, as adjusted by the scheduling algorithm. The first block of incoming duties is satisfied upon arrival, as plentiful wind power is available in the night time. At approximately 6 a.m., wind power supply drops sharply, at the same time when the second block of loads arrives. If these loads were rigid, the power supplier would face a severe deficit from 8 a.m. up until 10 p.m. in the evening of the same day. However, the supplier is able to postpone the power consumption of the second block of loads until about 8 p.m., by which time the supplier needs to start feeding power to the loads from the market in order to satisfy the 18-hour deadline.

B. Optimal Choice of Consumers

Fig. 3 demonstrates the performance of the proposed coupling as a function of the number of deferrable loads, for various levels of consumer flexibility (measured in terms of the available time window to satisfy the tasks at hand). The parameters used to derive these results were $f = 30\$/\mathrm{MWh}$, $\lambda_D = 100\$/\mathrm{MWh}$, and $\lambda_R = 100\$/\mathrm{MWh}$. We conclude that the optimal choice of contracted deferrable loads depends on the processing time that these loads offer to wind power suppliers. The longer the time window, the greater the number of loads which suppliers can accommodate, and the greater the profitability of the suppliers. For a 10-hour time window, it is optimal for suppliers to contract with 500 users per day, for a 14-hour window with 1000 users per day and for an 18-hour window with 1500 users. Moreover, the profitability is sensitive to the number of served loads, therefore the decision of an optimal mix of flexible consumers is critical to the performance of the proposed coupling. Wind power supply patterns can vary from season to season, which imposes a challenge of dynamically adjusting the mix of flexible consumers and/or the quality of service to deferrable loads so as to accommodate these seasonal variations.

C. Economic Performance

In order to assess the economic performance of the coupling, it is necessary to compare the costs under the coupling with the baseline integration scenario described in section III. However, assessing the costs of wind power variability is a challenging task, since the result depends on numerous factors which are unique to each system under consideration, such as the supply mix, the consumption patterns, the transmission constraints and other factors which are independent from wind power supply. Therefore, a model such as the one described in (1)–(8) which considers the system of wind generators and deferrable loads in isolation from the remaining power system cannot be used to accurately assess the costs of wind power variability. A proper assessment of the cost implications would require simulating the performance of the coupling in a unit commitment model in order to evaluate the resulting savings in ancillary services requirements. This is a direction which will be pursued by the authors in future work. Instead, in the present paper we make a preliminary assessment by employing an inverse approach to the one outlined above: instead of assessing costs and determining whether the coupling outperforms current practice, we will inquire what level of capacity charges would justify the utilization of this coupling. If these prices are sufficiently lower than the existing capacity charges for load following reserves and ramping upgrades, then this is an indication that coupling is justifiable in economic grounds.

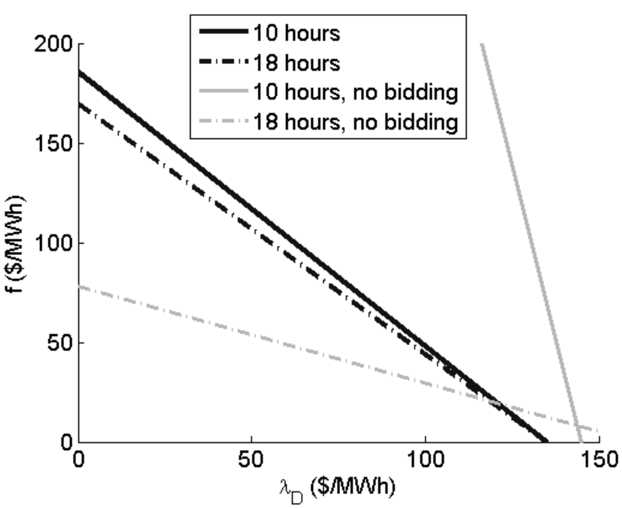

Fig. 4. Performance of coupling compared to the baseline case for a fixed capacity charge of ramping reserve $\lambda_R = 100\$/\mathrm{MW}$.

This approach is adopted in Fig. 4. The graphs in Fig. 4 plot combinations of capacity charge λ_D and discounted energy price f which yield the same profits as the baseline case for a fixed ramping capacity charge of $\lambda_R = 100\$/\mathrm{MW}$. These graphs are drawn for four separate cases. The bold solid line refers to the case of 500 users with a 10-hour time window and the bold broken line refers to the case of 1500 users with an 18-hour time window. In order to evaluate the contribution of bidding in the hour-ahead market to the performance of the coupling, the counterparts of the two cases above are drawn in light solid and light broken lines respectively.

The further left that the graphs lie in the plane, the better the performance of the corresponding case. Therefore, Fig. 4 confirms the conclusion drawn from Fig. 3 that the profitability of the coupling increases as time windows increase. However, performance is not significantly better, which is fairly surprising given that consumers are offering an extra 8 hours of flexibility to complete tasks. On the other hand, bidding in the hour-ahead market can lead to significant gains for the case of a 10-hour time window, but to significant losses for the case of an 18-hour window, which implies that the employed bidding strategy performs poorly in terms of mitigating deviations. Taking into account the fact that the average spot price of electricity for these simulations is 83.4 $/MWh, all cases but one are competitive to existing practices. This can be deduced from Fig. 4. For example, in the case of the 10-hour time window with bidding (bold solid line), if capacity charges for load following capacity are as high as $\lambda_D = 100\$/\mathrm{MW}$ generators can afford to charge flexible consumers $f = 50\$/\mathrm{MWh}$ (a significant discount compared to the average 83.4 $/MWh) and perform as well as in the baseline scenario.

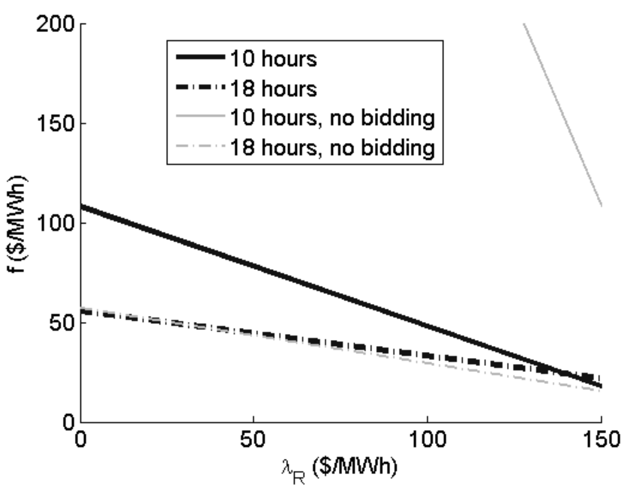

Fig. 5. Performance of proposal compared to the baseline case, for a fxed capacity price of load following reserve $\lambda_D = 100\$/\mathrm{MW}$.

Fig. 5 is the counterpart of Fig. 4 for the case where $\lambda_D = 100\$/\mathrm{MWh}$ and λ_R varies. In this case, the incremental benefits from an additional 8 hours of flexibility are greater, and bidding in the hour-ahead market is beneficial.

Again, with the exception of one case the proposal is competitive to current practice, but now to a greater extent since the coupling can be justified at a discount of $f = 50\$/\mathrm{MWh}$ for capacity charges as low as $\lambda_R = 40\$/\mathrm{MW}$.

D. Other Performance Metrics

Table 1 presents the dependence of some additional performance metrics of the proposed coupling on the degree of consumer flexibility. The first row of the table refers to the fraction of wind power supply that was actually used, rather than discarded. This power may have been allocated either to deferrable loads or to the market. Ideally, this value would be close to unity. The amount of power which is utilized increases with flexibility, however significant portions of power are discarded even in the case of very flexible consumers. The second row refers to the fraction of utilized wind power which was allocated to deferrable loads, rather than to the market. As loads offer greater time windows, the scheduling algorithm can incorporate a greater number of users (Fig. 3), resulting in an increased allocation of wind power to users rather than the market. In contrast to the case of 10-hour windows where comparable quantities of wind power are supplied to users and the market, in the case of 18-hour windows the bulk of the power is supplied to users and only a small fraction is supplied to the market when available wind supply is excessively high. The last row of the table refers to the fraction of deferrable consumption which is actually deferred, as measured in MWh. Ideally, this figure too would be close to unity, since it would not be desirable to have consumers commit to a delay in their power consumption without the need to do so. With greater time windows more energy is deferrable, but at the same time a relatively higher quantity of this flexibility is utilized. Therefore, this figure also increases with consumer flexibility but never approaches unity.

TABLE I
PERFORMANCE OF THE SCHEDULING ALGORITHM AS A FUNCTION OF AVAILABLE PROCESSING TIME

Processing time (hrs)	**10**	**14**	**18**
Wind power utilization (%)	40.1	59.5	73.1
Fraction of wind power supplied to deferrable loads (%)	64	84.5	92.3
Fraction of deferrable consumption which was actually deferred (%)	8.2	26.5	55.2

V. CONCLUSIONS

In this paper we propose a direct coupling between wind generators and deferrable loads, in order to mitigate the variability and randomness of wind power supply. We argue that by utilizing load flexibility and simultaneously bidding in the electricity market, wind generators can significantly mitigate capacity costs resulting from the variable and random nature of wind power supply. The proposal is compatible with existing technology, grid operations and market operations, and is also justifiable on economic grounds. We have developed a heuristic approach for achieving this coupling which confirms that the economic incentives for coupling wind suppliers with flexible consumers exist. In future work we will work on improving the performance of the algorithm which we have developed and on accurately estimating the economic savings of the proposed coupling.

VI. APPENDIX

A. Simulation Assumptions and Data

The simulations were performed on a 5-day horizon. Hour-ahead energy price data were obtained from the CAISO Oasis database (http://oasis.caiso.com/) for the period from 4/2/2007 to 4/6/2007.

We used wind speed data which is publicly available by NREL at http://wind.nrel.gov/public/WWIS/Wind_Data/Terms_of_use.htm. We assumed a total of 1200 generators dispersed in the six locations within California for which the NREL database contains data [11]. As prescribed in [11], we used the power curve characteristics of Vestas V90 3 MW generators with a cut-in speed of 4 m/s, a cut-off speed of 25 m/s, and a speed of 15 m/s for maximal output. Generators located in the same site were assumed to have identical outputs. We used data for the time interval from 4/2/2004 to 4/6/2004, that is, for an identical season as the price data. Unfortunately we could not find data at the CAISO and NREL databases which overlapped. We believe this to be of no significance to our study, since the NREL database is itself a model output, and in addition the impact of wind power generation on California market prices in 2007 was not significant since the integration level in California at the time was still fairly low.

Incoming loads were assumed to arrive according to the same pattern each day. A quarter of the daily loads arrived in the beginning of the day (midnight), half of the loads arrived in the eighth hour of the day (8 a.m.) and the remaining quarter of the loads arrived in the sixteenth hour (4 p.m.). Loads were assumed to be identical, with a power rating of 2 MW and an energy demand of 14 MWh. Hence, the task of each load requires 7 hours to be completed. It is worth noting that the assumption on the power rating of the loads can be relaxed to include smaller ratings, resulting in a better objective function value for the solution but a slower running time for the algorithm. The number of loads arriving each day, as well as the time windows offered by the loads, was varied in order to investigate the impact of these factors on algorithm performance. The number of daily loads varied between 100 and 2000 loads, while the available time window for completing each task varied between 10 and 18 hours.

Wind forecasts were based on a very simple forecasting model: $F_t = \left(W_t + 2\left(W_t - W_{t-6}\right)\right)^+$ where F_t is the forecast wind power supply made in interval t for two hours ahead. The forecast is simply a linear extrapolation of an hourly sample of wind power generation. The forecast is 12% (standard deviation as a fraction of total installed wind capacity), which is not significantly worse than the expected forecasting error of 7-9% in the CAISO large scale integration study [4].

B. Scheduling and Bidding Algorithm

The problem posed in (1)-(8) can be interpreted as an optimal inventory control problem and various techniques can be used to solve it, including dynamic programming, model predictive control or various scheduling heuristics. In the simulations, we have attained a suboptimal solution to the problem by breaking it in two components, load scheduling, and optimal bidding, which are solved sequentially.

The scheduling sub-problem is solved first by use of the earliest deadline algorithm. Subsequently, bidding in the market is determined by a very simple heuristic: at each period, the bid quantity is 20% of the excess forecast supply: $B_T = 0.2 \cdot (F_{6(T-1)+1} - \sum_{i \in I} c_{6(T-1)+1,i})^+$. $F(6(T-1)+1)$ is the wind forecast in the first interval of the T-th hour and $\sum_{i \in I} c_{6(T-1)+1,i}$ is the aggregate supply of power to deferrable loads in the first interval of the T-th hour. The amount of wind power supplied to the market in interval t is then the minimum of the market commitment and the actually available wind $r_t = \min(W_t, B_{T-2})$.

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VII. BIOGRAPHIES

Anthony Papavasiliou is a third year PhD student in the department of Industrial Engineering and Operations Research at UC Berkeley. He has received a Bachelor's degree in Electrical Engineering and Computer Science from the National Technical University of Athens, Greece.

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