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Reducing CO_2 emissions on the electric grid through a carbon disincentive policy

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HIGHLIGHTS

- We study the tradeoff between CO_2 emissions and generation cost on an electric grid.
- The tradeoff was shown by Pareto fronts obtained from optimizations.
- Pareto fronts shows that a carbon disincentive is effective in reducing emissions.
- Controlling both supply and demand on the grid is necessary to reduce CO_2 and costs.

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ABSTRACT

This paper studies the operation of an electric grid with renewable wind generation and plug-in electric vehicles (PEVs). In particular, PEVs will be the controllable demand that can mitigate the intermittency in wind generation and improve the capacity factors of the non-renewable generation assets on the grid. Optimization problems are formulated to minimize the costs of electricity generation, and two approaches are proposed to address the grid CO_2 emission in the optimization. The first approach directly penalizes CO_2 in the objective function, and the second approach adopts a carbon disincentive policy to alter the dispatch order of power plants, so that expensive low-CO_2 plants can replace cheap high-CO_2 plants. These two approaches result in very different outcomes: the first approach affects only the PEV charging demand on the grid and does not result in significant CO_2 reduction, whereas the second approach controls *both* the generation and load, and CO_2 can be reduced substantially. In addition, the carbon disincentive policy, unlike a carbon tax, does not collect any revenue; therefore, the increase in electricity cost is minimal. The effect of the proposed algorithms on the grid electricity cost and carbon emission is analyzed in details and reported.

1. Introduction

The electric grid and the ground transportation are two major sectors producing greenhouse gas emissions (Energy Information Administration, 2011b). Significant research and development works in these two sectors are being pursued to improve sustainability, most notably through the deployment of renewable power sources and plug-in electric vehicles (PEVs). Integration of high volumes of renewable power into the grid has been attempted in several Nordic countries; for example, Denmark uses hydropower to smooth variations in wind generation (Garcia-Gonzalez et al., 2008; Holttinen et al., 2007; Smith, 2010). Various market mechanisms are also proposed to facilitate imports and exports of wind generation when surplus or deficit happens (Ummels et al., 2006). Control algorithms for PEV charging to alleviate impacts of the PEV charging demand on the power grid have been reported in several studies (Hadley and Tsvetkova, 2009; Lemoine et al., 2008; Ma et al., 2010). In addition, some studies discussed the economic potentials or feasibility of controlling PEV charging to provide ancillary services to the grid (Dallinger et al., 2011; Han et al., 2010; Kempton and Tomic, 2005a; Kempton and Tomic, 2005b). The integration of renewable power sources and PEV through smart grids is also being actively studied (Caramanis and Foster, 2009; Ekman, 2011; Galus et al., 2010; Yingzhong and Le, 2010). Our previous study showed that the cost of electricity generation can be significantly reduced by coordinating PEV charging and wind power scheduling (Li et al., 2012, accepted). This paper will extend our previous work and discuss the implication of optimizing the generation cost and CO_2 emissions on an electric grid.

A complete greenhouse gases (GHG) emission analysis on an energy technology should cover all stages of the technology and its fuel life cycle. To date, a great variety of life-cycle emission assessments of electricity generation have been conducted, and

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a comprehensive summary can be found in (Weisser, 2007). Furthermore, the CO_2 emissions created by electricity generation are crucial in assessing the life-cycle emissions for PEVs. Since PEVs will have relatively lower tank-to-wheel emissions due to the better fuel economy granted by powertrain hybridization, the well-to-tank emissions will play a dominant role to determine the lifecycle emissions of PEVs. The literature has several studies focusing on CO_2 emissions on the well-to-tank stage for PEVs (Bandivadekar et al., 2008; Baptista et al., 2010; Electric Power Research Institute, 2007; Kintner-Meyer et al., 2007; Lane, 2006; Samaras and Meisterling, 2008; Sioshansi et al., 2010). Furthermore, CO_2 emissions on the well-to-tank stage can be reduced by integrating renewable generation to the grid, and this will be the focus of discussion in this study.

Reducing CO_2 emissions and electricity generation costs are often conflicting goals because low-cost power plants, such as coal power plants, often produce higher CO_2 than high-cost power plants, such as natural gas plants. However, there was an exception in 2010–2012 in the U.S.: the natural gas reached record-low prices, and more natural gas was used for electricity production as it was more cost-competitive than coal in that period (Energy Information Administration, 2013). The price dips in natural gas therefore helped to reduce the grid CO_2 emissions, but the price dips are usually temporary. The U.S. Energy Information Administration predicts that the natural gas price will gradually rise and reach the level before 2010 in the next few years (Energy Information Administration, 2011a).

Because the low-CO_2 generating technologies often are not favored in the open market due to their higher prices, non-market-driven means are needed to reduce the CO_2 emissions. Carbon taxation has been proposed in a number of EU countries since the 1990s (Bosquet, 2000; Ekins, 1999). The literature has extensively discussed the effectiveness of carbon tax in reducing CO_2 emissions and its impact on economic activities (Ekins and Baker, 2001; Scrimgeour et al., 2005; Wier et al., 2005). There also have been many discussions on the design of tax policies; for example, how to return or distribute the tax revenues (Metcalf, 2007, 2009). It was found that the macroeconomic costs (e.g., losses in GDP) can be reduced if tax revenues are effectively returned (Ekins et al., 2012). However, because it is difficult to quantify the societal cost of pollutants (Metcalf, 2009), the literature does not provide a consensus view on how high the tax rate should be (Bovenberg and Goulder, 1996; Nordhaus, 1992; Ulph and Ulph, 1994). The tax rate varies between \$4 and \$185/ton CO_2, although \$15–30/ton CO_2 are more commonly seen (Ekins et al., 2012; Hogue, 2012; International Energy Agency (IEA)/OECD Nuclear Energy Agency (NEA), 2010; Metcalf, 2009; Scrimgeour et al., 2005).

In this study, instead of suggesting an arbitrary carbon tax rate to suppress the use of high-carbon power plants, the optimal Pareto front will be used to show the trade-off between CO_2 emissions and electricity generation costs. Two approaches are adopted to include the grid CO_2 emissions into the cost optimization scheme. The first approach directly penalizes the CO_2 emissions in the objective function, and the second approach uses a carbon disincentive to alter the dispatch order of power plants so that some expensive, low-CO_2 plants can replace cheap, high-CO_2 plants. In addition, PEVs and wind power sources are assumed to be present on the grid. The PEV charging is controlled to eliminate the intermittency of wind power, and the wind power provides low-carbon electricity to charge PEVs. The implications of these two approaches are different and are discussed in detailed in this study.

The remainder of this paper is organized as follows: Section 2 describes the grid model, including the load, the generation cost, CO_2 emissions, wind power, and the PEV fleet; Section 3 presents the optimization formulation to minimize the electricity generation cost and CO_2 emission; Section 4 discusses the optimal solutions and the tradeoff between CO_2 and cost; and Section 5 provides concluding remarks.

2. System models

The target system is a hypothetical future electric grid in the State of Michigan, and all data/information were collected accordingly. Both wind power and PEVs are assumed to have sizable market penetrations, so they have significant influence on the supply and demand of the electric grid. The models and model parameters are described in the following.

2.1. The electric grid

The grid model describes the grid load, generation costs, and CO_2 emissions.

2.1.1. Grid load

The non-PEV grid load is shown in Fig. 1, which is extracted from the annual load data in the service area served by Detroit Edison (Federal Energy Regulatory Commission (FERC), 2009). The non-PEV grid load is assumed to be price-inelastic, and the grid operator schedules the conventional generation and/or wind power to satisfy this demand.

On top of the non-PEV load, the PEV charging will add to the grid demand. However, the PEV charging is assumed to be controllable (can be throttled back and forth or delayed to some extent), and the charging rate and timing are to be solved through the optimization in Section 3.

Furthermore, the grid operator schedules reserves for uncertainties in the supply and demand. The reserve requirement for the grid load is assumed to be 5% of the load magnitude, according to Doherty and O'Malley (2005). The reserve requirement for wind energy is discussed in Section 2.2.

2.1.2. Generation cost

The cost of electricity generation is based on operation costs of power plants in Michigan, and the data in the Oak Ridge Competitive Electricity Dispatch Model (Hadley, 2008) are used. Fig. 2 shows the extracted costs sorted in the ascending order to be consistent with the assumption that the grid operator dispatches power plant according to the merit order, i.e., cheaper plants will be deployed before more expensive ones.

Notice that the cost curve in Fig. 2 increases in a staircase fashion with the power generation because the cost jumps when additional (more expensive) power plant is dispatched. Renewable capacities, such as wind power, are not shown in the cost curve because they do not have a fixed sorting position in the merit order. Wind power is assumed to have very low operation costs,

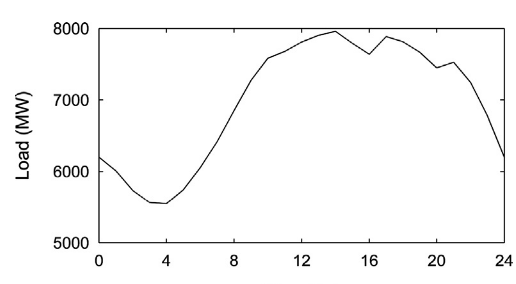

Fig. 1. The hourly grid load (extracted from Federal Energy Regulatory Commission (FERC), 2009; the PEV charging load is not included).

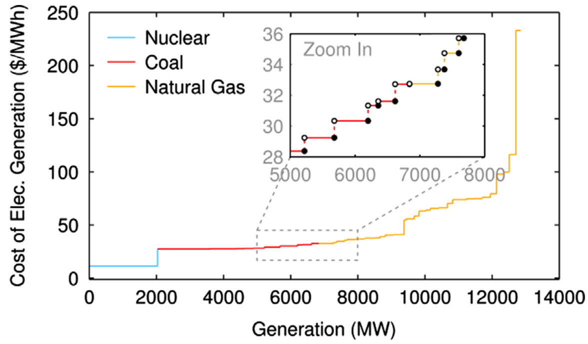

Fig. 2. The cost of electricity generation (extracted from Hadley (2008)). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

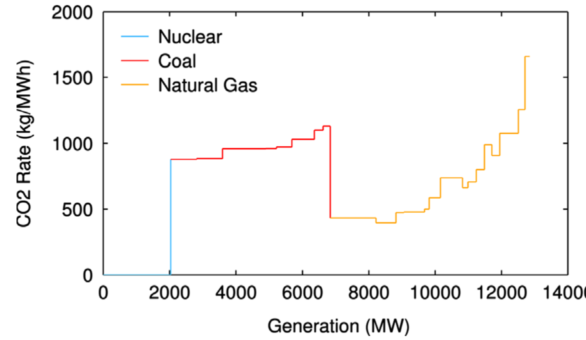

Fig. 3. CO_2 emission rate of grid electricity (Kelly et al. 2011)—the generation is shown in ascending order of cost given in Fig. 2. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

but have relatively high costs associated with reserves, if they are provided by non-renewable sources. Thus, the wind power may not always be the cheapest to dispatch when the reserve costs are considered. The reserve requirement for wind power will be discussed in Section 2.2, and the scheduling of wind power will be discussed in Section 3. Physical limitations, such as ramp rates or transmission line limits, are not considered in the grid modeling. To make the optimization problem in Section 3 numerically tractable, several simplifications were made, for example, plants with very small capacity were combined with adjacent plants, and outliers (e.g., very expensive peak-load plants) were removed.

In addition to electricity generation, the grid operator schedules reserves to cover uncertainties on the power grid, and there are two costs associated with reserves: (1) the reserve scheduling cost is assumed to be 3% more expensive than the electricity generation cost based on the statistics reported by the Potomac Economics (2011); and, (2) the reserve dispatch cost is assumed to be the same as the electricity generation cost and is paid by consumers only if the reserve is dispatched.

2.1.3. CO_2 emissions of electricity generation

The CO_2 emission rate of power plants in Michigan is acquired from Kelly et al. and shown in Fig. 3, in which the order of power plants is arranged to match the dispatch order in Fig. 2. Wind power is assumed to have zero CO_2 emission, but, again, is not shown in the CO_2 curve as its sorting position in the merit order is yet to be determined. In addition, the data shown in Fig. 3 only cover CO_2 emissions during the operation phase of a power plant and exclude emissions in the upstream during fuel mining/transportation and downstream during plant decommissioning.

The color scheme in Figs. 2 and 3 shows different types of power plants, and it is seen that Michigan has significant amounts of coal generation. Among the several types of generation capacities, nuclear power has the lowest price and CO_2 emissions. Coal-fired generation, in general, is cheaper than natural gas, but has higher CO_2 emissions; thus, it can be expected that, without the carbon disincentive, the grid operator will have to dispatch all coal plants before natural gas plants according to the merit order dispatch.

2.2. Wind power

The wind power capacity is assumed to be lumped together and modeled as a single wind farm with an 800 MW nameplate capacity, which can support up to 10% of the peak load on the hypothetical Michigan grid. The intermittency of wind power can be described by the probability distribution, $\mathbf{P}(w_a|w_f)$, which is extracted from the Eastern Wind Dataset from the NREL (2010)

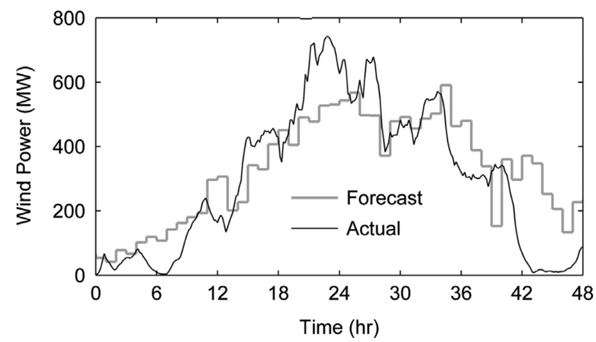

Fig. 4. A 48-h snapshot of hourly wind forecasts, w_f, and actual wind generation, w_a (extracted from the NREL Eastern Wind Dataset (2010)).

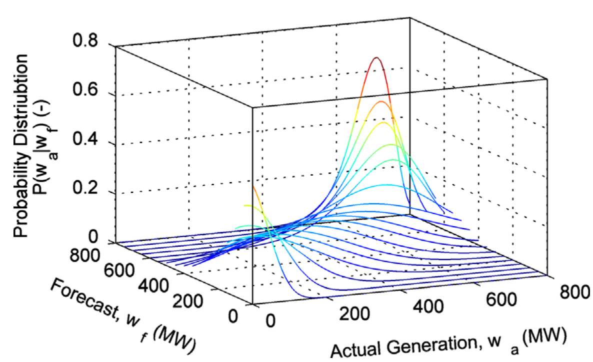

Fig. 5. The conditional probability distributions, $\mathbf{P}(w_a|w_f)$.

and represents the (stochastic) actual wind generation (w_a) under a given forecast (w_f). In other words, $\mathbf{P}(w_a|w_f)$ represents the uncertainty in wind power at various wind prediction levels and will be used to derive the reserve requirement and estimate the expected shortfall of wind power. Fig. 4 shows a representative 48-h snapshot of the NREL dataset, and Fig. 5 shows the conditional probability distribution extracted from the dataset. The peak value of each probability distribution in Fig. 5 is close to the forecast value, w_f, implying that the forecast is generally good.

To use the probability distributions to derive the reserve requirement of wind power, it is assumed that over-production in wind power can always be curtailed, and then only the up-regulation reserve is needed for under-production. Curtailing surplus wind outputs has been seen in real-world practices for stability-related reasons (Rogers et al., 2010), and it is likely to become a norm for the wind farm owner or grid operator to avoid risks in the market when the wind penetration level is high in the future. A further assumption is that the reserve is acquired to

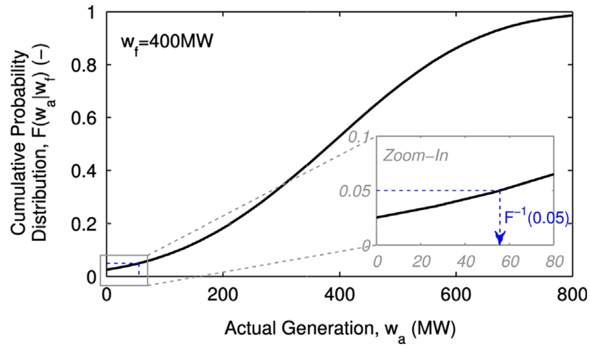

Fig. 6. The cumulative probability distribution, $\mathbf{F}(w_a|w_f)$, at w_f=400 MW.

cover 95% of the under-production, and the reserve requirement, $R_{w,rqd}$, can be computed using Eq. (1). In addition, the expected wind deficit, w_d, found using Eq. (2) must be made up by dispatching the reserve or throttling back PEV charging.

$$R_{w,rqd}(w_f, w_s) = [w_s - \mathbf{F}^{-1}(0.05)]^+ \tag{1}$$

$$w_d(w_f, w_s) = \mathbf{E}\{[w_s - w_a]^+\} \tag{2}$$

where both $R_{w,rqd}$ and w_d are functions of w_f and w_s. w_s is the scheduling of wind power, which is a control variable to be detailed in Section 3. $\mathbf{F}$ is the cumulative probability distribution function of $\mathbf{P}(w_a|w_f)$, and $\mathbf{F}^{-1}$ is the inverse of $\mathbf{F}$. Then, $\mathbf{F}^{-1}(0.05)$ is the guaranteed wind power generation for 95% of the time. Fig. 6 shows the example of $\mathbf{F}$ at w_f=400 MW, and its inverse is found to be 58 MW. This can be interpreted as follows: when the forecast is at 50% of the nameplate capacity, the actual wind output will be at least 7.25% of the nameplate capacity for 95% of time; then, Eq. (1) quantifies how much reserves need to be *scheduled* when the wind farm owner decides to schedule wind power higher than 7.25% of the nameplate capacity, and Eq. (2) quantifies how much reserve is expected to be *dispatched*. Both the reserve scheduling and reserve dispatch matter because they induce costs to the wind farm owner. The plus sign (+) in both Eqs. (1) and (2) indicates the truncation of negative values, and the expectation (the operation imposed by $\mathbf{E}$) in Eq. (2) is taken with respect to w_a. This approach of modeling wind power uncertainty is similar to that in Li et al. (2012, accepted.

2.3. Plug-in vehicle fleet

The number of PEVs is assumed to be two million, which represents a 25% market penetration in the Michigan ground transportation. All PEVs are assumed to use programmable chargers to control the charging level, but we do not consider the V2G power flow (battery discharge). The maximum charging power is 1440 W, according to the power limit of Level-I charger (SAE, 2012), and only night charging at home is allowed.

The trip length statistics reported in Lee et al. (2011), shown in Fig. 7, is used to derive the state of charge (SOC) of the battery at plug-in using Eq. (3), which then is used to find the total energy requirement to charge the PEV fleet using Eq. (4).

$$SOC_{ini} = \begin{cases} 0.8-(0.8-0.3)\cdot\frac{L}{\mathrm{AER}} & \text{if} L < \mathrm{AER} \\ 0.3 & \text{otherwise} \end{cases} \tag{3}$$

$$K = \sum_{i=1}^{N} (0.8 - SOC_{ini})_i \cdot Q \tag{4}$$

where L is the trip length and AER is the all-electric range of the PEV. The battery SOC is assumed to be limited to the window between 30% and 80% (GM-Volt Website, 2007). K is the energy required to charge the whole PEV fleet, and Q is the battery

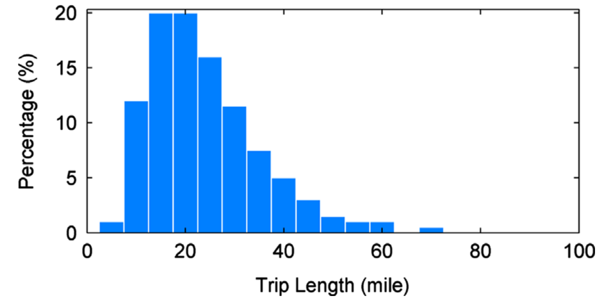

Fig. 7. The trip length distribution of two million PEVs (Lee et al., 2011).

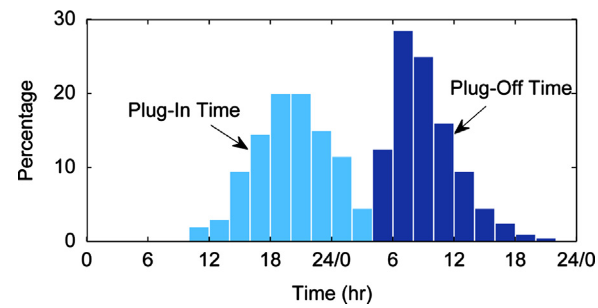

Fig. 8. Plug-in time and plug-off time distributions of two million PEVs Lee et al., 2011.

capacity. With the assumption that all PEVs have a 40-mile AER and a 16 kWh battery, K was found to be 7.38 GWh.

The data in Lee et al. (2011) also provide information on distributions of the plug-in time and plug-off time of PEVs, which are shown in Fig. 8. Notice that these two distributions are shown in a 48-hr long window, instead of a 24-hr long window, to illustrate that many PEVs' plug-off times will be in the early morning of the *next day*.

Three pieces of information, the SOC, plug-in time, and plug-off time, are inputs to the PEV charging algorithm for determining which vehicle receives immediate or delayed charging services. Our prior study proposes a control algorithm, which allocates a higher charging power to the PEV with a low SOC or an early plug-off time using strategies similar to the concept of proportional sharing, and the result has shown that the grid has adequate capacity to charge all PEVs in the valley hours (11PM to 8AM). Implementing a demand-side management system for PEV charging is not trivial, as poorly coordinated charging may lead to degraded power quality or oscillations on the grid, but those problems are not within the scope of this paper. In this paper, it is assumed that a perfect demand-side management system is in place to control the PEV charging, and the allocation of PEV charging power will follow the strategy shown in Li et al. (2011) and will not be repeated in this paper. The optimization in the following sections will demonstrate the best-case scenario that can be achieved if the grid operator can utilize the PEV fleet, wind generation, and existing generation assets to improve the grid operation.

3. Optimizations of CO_2 emission and electricity generation cost

We formulate three optimization problems to investigate the tradeoff between the electricity generation cost and CO_2 emissions on the grid. The first problem only minimizes the electricity generation and serves as the baseline case. The other two problems consider the CO_2 emissions; one penalizes CO_2 directly in the objective function, and the other uses a carbon disincentive to alter the dispatch order of power plants. These three optimization problems are described in the following.

3.1. *Scheduling for minimum electricity cost*

The baseline case minimizes only the electricity generation cost with no consideration of CO_2 emissions. This is similar to current practices in the US market: power plants submit their bidding prices to the wholesale market, which presumably will cover their operating costs, and the grid operator sorts these bids and creates the merit order. Then, in each operating hour, the grid operator tries to minimize the overall electricity price for consumers by deploying power plants according to the merit order. The optimization problem is stated in Eqs. (5)–(15). Eq. (5) is the objective function, including costs of non-renewable electricity generation (C_g), reserve scheduling (C_{Rs}), and expected reserve dispatch (C_{Rd}), which will be the total price consumers pay to power plants (with the assumption that the grid operator is a profit-neutral entity in the market). As explained earlier, wind power does not have steady outputs and its intermittency induces costs because of reserve scheduling and dispatch; therefore, the costs of scheduling wind power will implicitly show up in the second (C_{Rs}) and third term (C_{Rd}) in the objective function. The objective function is minimized by two control variables, u_1 and u_2, to address the scheduling of the non-renewable generation and wind power (w_s) separately. The state, x, is the *remaining* PEV energy demand; its dynamics and constraints are detailed below.

$$\min_{u_1,u_2} : J = \sum_{t=1}^{T} [C_g(u_1(t)) + C_{Rs}(R_s(t)) + C_{Rd}(R_d(t))] \tag{5}$$

subject to

$$u_1(t) + u_2(t) - P_L(t) = P_{PEV}(t),\ \forall t \tag{6}$$

$$\sum_{t=1}^{T} P_{PEV}(t) \cdot \Delta t = K \tag{7}$$

$$0 \le P_{PEV}(t) \le \min\{x(t), U_{PEV}\},\ \forall t \tag{8}$$

$$x(t+1) = x(t) - P_{PEV}(t) \cdot \Delta t,\ \forall t \tag{9}$$

$$x(0) = K \tag{10}$$

$$R_{L,rqd}(t) = 0.05 \cdot P_L(t),\ \forall t \tag{11}$$

$$R_{w,rqd}(t) = [u_2(t) - \mathbf{F}^{-1}(0.05)]^+,\ \forall t \tag{12}$$

$$R_s(t) + P_{PEV}(t) \ge R_{L,rqd}(t) + R_{w,rqd}(t),\ \forall t \tag{13}$$

$$w_d(t) = \mathbf{E}\{[u_2(t) - w_a(t)]^+\},\ \forall t \tag{14}$$

$$R_d(t) = [w_d(t) - P_{PEV}(t)]^+,\ \forall t \tag{15}$$

where,

P_L: non-PEV load (MW)
P_{PEV}: aggregate PEV charging load (MW)
U_{PEV}: charging limit (MW)
K: total PEV energy demand (MW)
$R_{L,wqd}$: reserve requirement for grid load (MW)
$R_{w,rqd}$: reserve requirement for wind power (MW)
R_s: scheduling of conventional reserve (MW)
W_d: expected deficit of wind power (MW)
R_d: expected dispatch of conventional reserve (MW)

Eqs. (6)–(10) are constraints related to electricity generation: Eq. (6) states the balance between supply and demand (i.e. scheduled generation and loads); Eq. (7) ensures that the total PEV charging demand is satisfied; Eq. (8) states that the PEV load is bounded from below by zero to prevent the V2G power and bounded from above by the Level-I charger limit (the upper bound, U_{PEV}, is calculated by multiplying the power limit of a single charger with the total number of PEV); Eq. (9) describes the state dynamics; and, Eq. (10) is the constraint on the initial state.

Eqs. (11)–(15) are related to reserves: Eq. (11) states the reserve requirement for the grid load; Eq. (12) describes the reserve requirement for wind power as derived in Eq. (1); Eq. (13) states that the total reserve requirement must be met by either the controllable PEV load or the scheduling of conventional reserves; Eq. (14) states the expected deficit of wind power as derived in Eq. (2); and Eq. (15) states the expected dispatch of conventional reserves if wind deficit exceeds the magnitude of the controllable PEV load. Notice that Eq. (13) counts the PEV load as reserves because it can be throttled back if wind power drops unexpectedly. Finally, Eq. (15) implies that throttling back PEV load is preferred to dispatching the conventional reserves because the former is free.

The scheduling optimization is solved assuming that the following information is known: the generation costs (shown in Fig. 2), the grid load (shown in Fig. 1), and wind forecasts (the gray line in Fig. 4). However, the actual wind outputs are not known. This optimization problem is solved using the Dynamic Programming (DP) technique, which is a gradient-free technique that can suitable to handle the discontinuity in the cost function and the constraints. In addition, DP guarantees global optimality. The optimization horizon is from 11PM to 8AM, which are the valley hours of the Michigan grid when the grid load is low and most PEVs are plugged onto the grid to recharge.

Fig. 9 shows the optimal solution of the baseline case, and the non-renewable generation is marked using the color scheme consistent with those in Figs. 2 and 3. The optimal scheduling of non-renewable generation is consistent with the merit order shown in Fig. 2, in that the generation above 6840 MW is produced by natural gas while between 6840 and 2040 MW is by coal. The generation below 2040 MW is produced by nuclear power, although not shown in the figure. The four arrows marked at 2AM illustrate that the supply and demand are balanced. Also, it can be seen that DP strategically schedules the non-renewable generation and plans the PEV charging to exploit the staircase changes in the cost curve of electricity generation. In addition, wind power is scheduled meticulously to avoid paying for conventional reserves. In terms of the CO_2 emission, the optimal solution shows that the grid load and PEVs almost use up the generation capacity of coal power plants, and few natural gas power plants are dispatched during the valley hours.

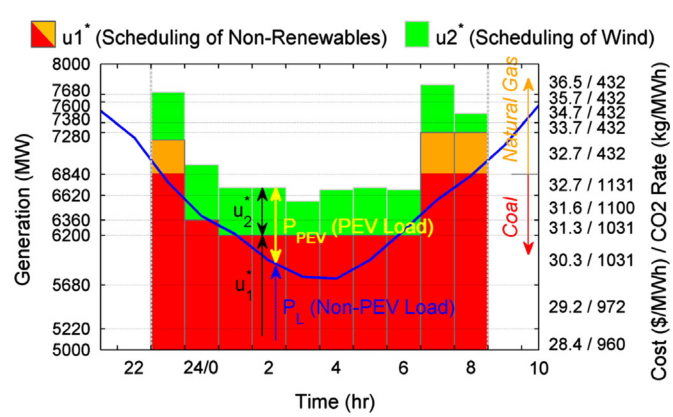

Fig. 9. Optimal generation scheduling of the baseline case. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

3.2. Scheduling optimization with direct penalty on CO_2

To reflect the importance of CO_2 emissions, a penalty on CO_2 is included in the objective function, as shown in Eq. (16).

$$\min_{u_1,u_2} : J_\alpha = \sum_{t=1}^{T} [C_g(u_1(t)) + C_{Rs}(R_s(t)) + C_{Rd}(R_d(t)) + \alpha \cdot CO_2(u_1(t))] \tag{16}$$

where α is a weighting coefficient.

Fig. 10 shows the optimal solution with $\alpha = 10$, which is the smallest weight that produces control signals different from the baseline case. Specifically, some non-renewable generation was shifted from Hour 24 to Hour 23. The non-renewable generation in Hour 23 increases from 7200 MW to 7280 MW, whereas the non-renewable generation in Hour 24 decreases from 6360 MW to 6280 MW. The shift allows more electricity to be generated by the natural gas power plant with a CO_2 rate of 432 kg/MWh rather than by the coal power plant with a CO_2 rate of 1131 kg/MWh. The shift of the non-renewable generation means that some of the controllable PEV load will be served at different times.

Fig. 11 shows the optimal solution with $\alpha = 55$, which is much larger than the previous value. As expected, more non-renewable generation is relocated to times when the low-CO_2 natural gas capacities are available, which creates undesired peaks at the beginning and the end of valley hours. Although this solution is mathematically correct, the undesired peaks make this approach impractical. Thus, a different means, more than relocating the PEV load, needs to be developed to reduce the carbon emissions.

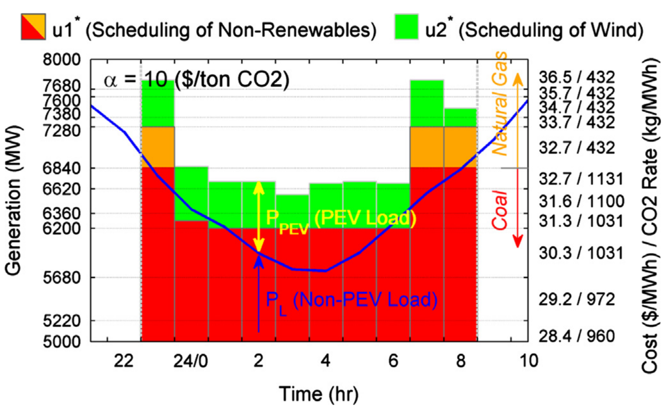

Fig. 10. Optimal generation scheduling with a direct penalty on CO_2 emissions.

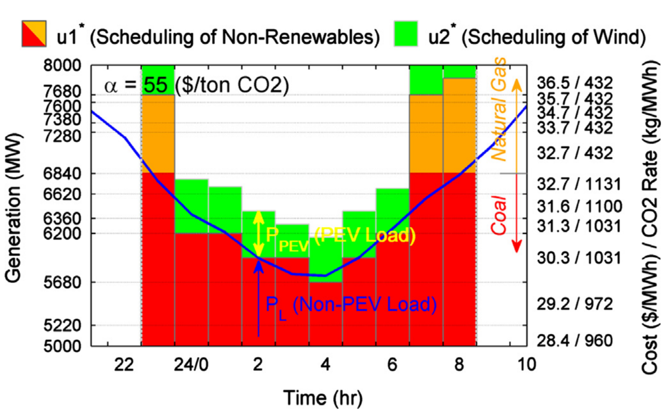

Fig. 11. Optimal scheduling with a large direct penalty on CO_2 emissions.

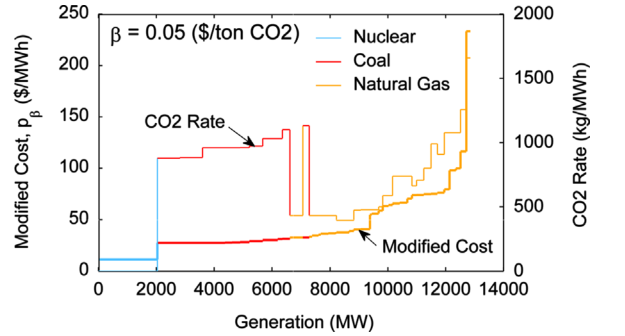

Fig. 12. The modified cost curve and CO_2 rate with a carbon disincentive of $\beta =$ \$0.05/ton CO_2.

3.3. Scheduling optimization with CO_2 disincentive

The solutions in the previous section show that controlling the demand on the grid (by controlling the PEV charging) can only achieve limited reduction in the grid CO_2 emissions. Therefore, in addition to the demand-side control, a new approach to manipulate the supply is proposed. The idea is to alter the dispatch order of power plants, so that expensive low-CO_2 plants can be dispatched before cheap high-CO_2 plants. A carbon disincentive, denoted as β, is introduced for this purpose. The generation cost of each power plant is modified by adding a carbon disincentive based on plant emission levels, as shown in Eq. (17), and a new dispatch order is determined based on this modified cost.

$$p_\beta = p + \beta \cdot (CO_2 \text{ rate}) \tag{17}$$

where p is the original unit cost shown in Fig. 2, and CO_2 rate is shown in Fig. 3. Since coal-fired power plants generally have much higher CO_2 rates than natural gas power plants, it does not require a large β to swap the dispatch order of the most expensive coal-fired plant with the least-expensive natural gas plant. Fig. 12 shows the new dispatch order with $\beta =$ \$0.05/ton CO_2, the smallest disincentive rate to change the dispatch order. Therefore, by varying β, the grid operator has a means to alter the generation mix and to dispatch low-CO_2 power plants.

The modified cost curve and new dispatch order, such as the one shown in Fig. 12, are then used in the optimization, and the objective function is revised from Eq. (5) to Eq. (18). Notice that this objective function does not contain any explicit penalty on CO_2 emissions; however, due to the new dispatch order, more low-CO_2 generation capacities will be dispatched and the grid CO_2 emissions will be reduced.

$$\min_{u_1,u_2} : J_\beta = \sum_{t=1}^{T} [C_{g,\beta}(u_1(t)) + C_{Rs,\beta}(R_s(t)) + C_{Rd,\beta}(R_d(t))] \tag{18}$$

The consequence of imposing the carbon disincentive is that the objective function, J_β, will increase substantially, because the optimization is based on the higher modified cost defined in Eq. (17) and J_β includes the carbon tax revenue. More specifically, the carbon revenue will be the quantity shown in Eq. (19), which is correlated to the CO_2 produced by dispatched power plants. However, if this extra revenue due to the carbon disincentive is not collected (or collected and later returned to consumers), consumers will need to pay only the modified costs shown in Eq. (20).

$$\gamma = \sum_{t=1}^{T} \beta \cdot CO_2(u_1^*(t)) \tag{19}$$

$$J'_\beta = \sum_{t=1}^{T} [C_{g,\beta}(u_1^*(t)) + C_{Rs,\beta}(R_s(t)) + C_{Rd,\beta}(R_d(t))] - \gamma \tag{20}$$

with the "revenue return mechanism", this carbon disincentive policy is revenue-neutral to the grid operator and is less burdensome to consumers. Again it should be emphasized that the carbon disincentive policy suggested above is not taxation, but a mechanism used by the grid operator to alter the dispatch order of power plants for CO_2 reduction.

Fig. 13 shows the optimal solution when β=0.05/ton CO_2. The CO_2 emission is reduced by 0.13% at the expense of the cost increased by 0.04% after the carbon revenue is returned to consumers.

Fig. 14 shows the modified cost curve and the new dispatch order when the carbon disincentive is more aggressive (β=20/ton CO_2), in that about 25% of the coal-fired plants in the generation mix are replaced by natural gas plants. The optimal solution is shown in Fig. 15. Notice that no spikes were created at the beginning or end of the valley hours. Compared to the baseline case, the CO_2 emission is reduced by 24.5% and the cost increased by 19.5%.

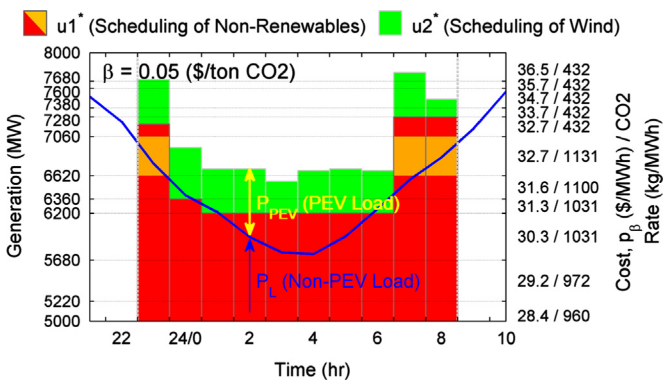

Fig. 13. The optimal scheduling with a carbon disincentive of β=\$0.05/ton CO_2.

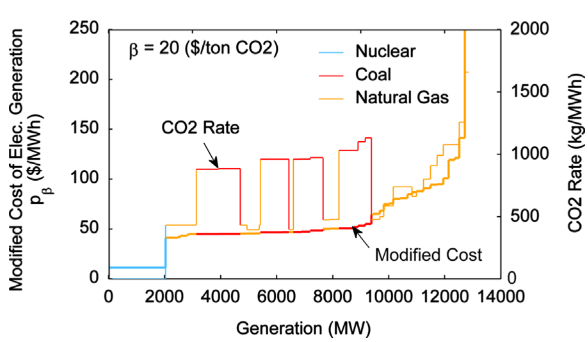

Fig. 14. The modified cost curve and CO_2 rate with a carbon disincentive of β=\$20/ton CO_2.

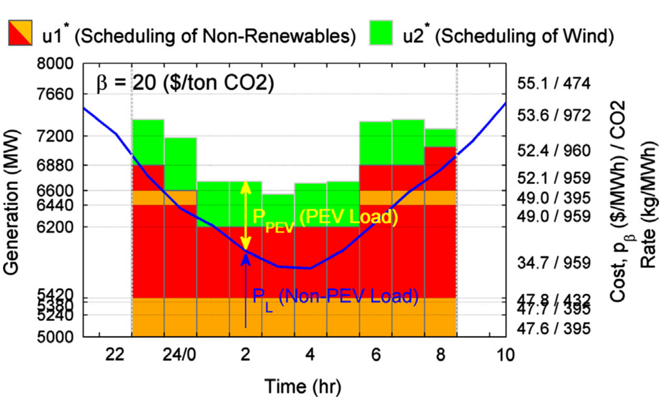

Fig. 15. The optimal scheduling with a carbon disincentive of β=\$20/ton CO_2.

Besides better utilizing the generation capacities in the middle of the valley hours, this optimization formulation is more effective in reducing the CO_2 emission. The solution in Fig. 15 achieves a 24.5% CO_2 reduction, better than the 9.8% reduction achieved in Fig. 11. In this optimization formulation, *both* the supply and demand are manipulated, rather than only the demand, which is the key for achieving reduction in both CO2 emissions and costs of electricity generation.

4. Impacts of the carbon disincentive

As mentioned earlier, the grid operator can view the parameter β as a tuning knob to weigh the electricity generation costs and the grid CO_2 emissions. The optimal Pareto fronts are used to show the tradeoff between the CO_2 emissions and cost of electricity generation when the carbon disincentive varies. Impacts of the carbon disincentive on the mix of electricity generation and the profits to power plants are also discussed.

4.1. Tradeoff between electricity generation costs and CO_2 emission

Fig. 16 shows the optimal Pareto fronts with the carbon disincentive, β, varying from zero to \$20/ton CO_2. It is clear that, to reduce the CO_2 emissions, the cost of electricity generation has to increase because the low-CO_2 natural gas power plants are more expensive. As stated in the previous section, the emission-conscientious instance (β=20) has 24.5% less CO_2 emissions but 19.5% higher costs than the cost-conscientious instance (β=0).

Fig. 17 further shows that, when the carbon disincentive is imposed, significant amounts of electricity generation are shifted

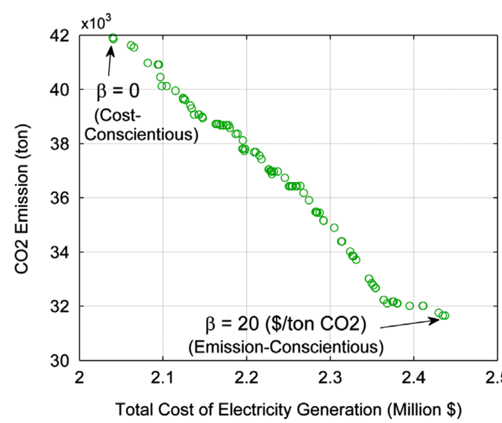

Fig. 16. Optimal Pareto Front with β varying from 0 to \$20/ton CO_2.

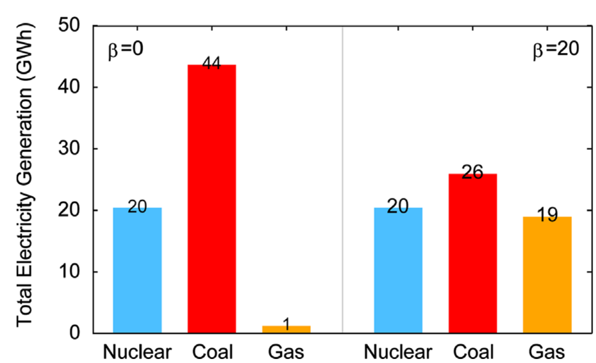

Fig. 17. Electricity generation by different types of power plants.

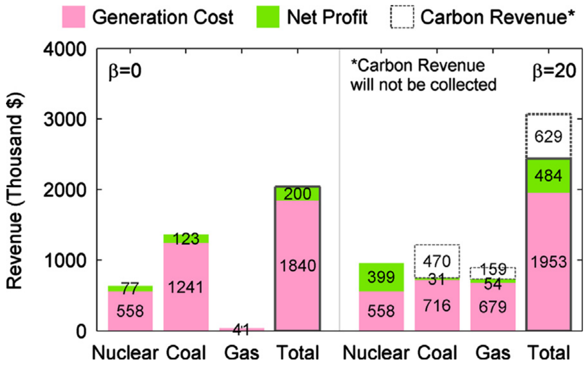

Fig. 18. Revenue distributions of different types of power plants.

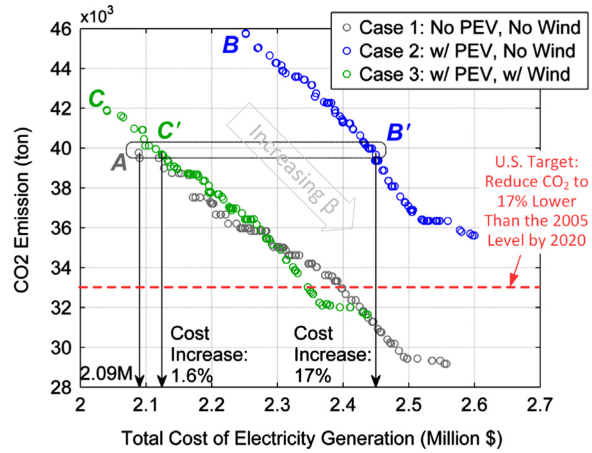

Fig. 19. Pareto fronts of three different scenarios.

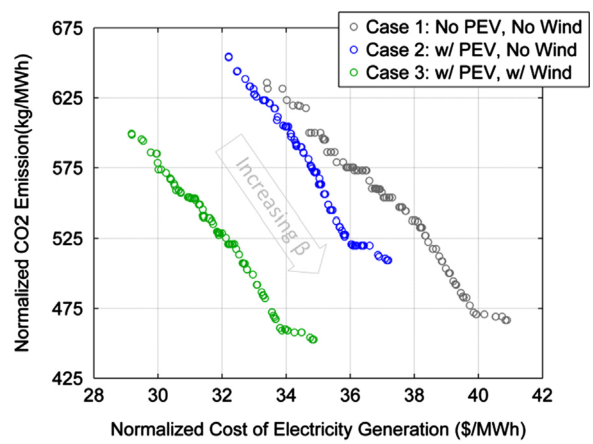

Fig. 20. Normalized Pareto fronts.

from high-CO_2 coal power plants to low-CO_2 natural gas power plants. However, the amount of electricity generated by nuclear plants is not affected. This is because nuclear power is assumed to produce no emissions; therefore, nuclear power is still the cheapest capacity after the carbon disincentive policy is imposed and will be dispatched first by the grid operator.

Furthermore, the carbon disincentive policy, although not intentionally planned, impacts profit distributions of the power plants: profits to high-CO_2 power plants are reduced and profits to low-CO_2 power plants are increased. The changes in the net profits among different types of power plants are shown in Fig. 18. Notice that the carbon revenue is only shown for the sake of completeness but is not actually charged to the consumers. The profit changes in different types of power plants can be explained by Eq. (21).

$$q = MC - p - \beta \cdot (CO_2 \text{ rate}) \tag{21}$$

where q is the net profit to a power plant, MC is the market clearing price, p is generation cost, and $\beta \cdot (CO_2$ rate) is the (virtual) carbon revenue. The presence of β increases MC, but the increased MC may not guarantee a higher net profit to high-CO_2 power plants because β also increases the carbon revenue that has to be returned to consumers. The total revenue received by all power plants is also shown in Fig. 18, which will be the total costs paid by consumers.

4.2. *Optimal Pareto fronts of various scenarios*

The Pareto front can further provide insights into how aggressive a carbon disincentive should be to achieve a certain CO_2 reduction target. Three scenarios were investigated: Case 1 has only the non-PEV grid load and has no wind power; Case 2 has the non-PEV grid load and two million PEVs but no wind power; and, Case 3 is the case reported in the previous sub-sections with the grid load, PEVs, and wind power. These three scenarios are set up to have PEVs and wind power included onto the electric grid progressively. Therefore, the comparison on their CO_2 emissions and costs will allow us to understand, not only the effectiveness of imposing the carbon disincentive policy, but also the effectiveness of introducing PEVs and wind power on the electric grid. Fig. 19 shows the Pareto fronts of these three scenarios.

The instances in the three cases with $\beta=0$ are marked as A, B, and C, among which B has the highest cost and CO_2 emissions because it has more load due to the PEV charging but no wind power. However, it is unclear if C is better or worse than A because the former has lower CO_2 emissions but higher costs. In fact, it is more meaningful to compare A, B', and C' because they all have the same level of CO_2 emissions. Case B' has $\beta=12.62$ and a cost 17% higher than A, whereas C' has $\beta=5.38$ and a cost only 1.6% higher than A. The lower cost increase in Case C' is attributed to replacing non-renewable generation with wind energy. Note that the cost assessment is based on the assumption that the wind generation is free, although the wind generation may incur reserve costs if the reserves to cover wind intermittency are provided by non-renewable sources. Furthermore, the red dashed line in Fig. 19 marks the U.S. target to reduce the greenhouse gas emissions to 17% lower than the 2005 level by 2020 (The White House, 2009). For a grid with no PEVs and no wind power (Case 1), a carbon disincentive of \$15.36/ton CO_2 needs to be imposed and the electricity generation costs will increase by 15.3%. In contrast, with PEVs and wind on the grid (Case 3), a carbon disincentive of \$17.16/ton CO_2 should be imposed and the electricity generation costs will increase only by 12.8%. For Case 2, the carbon disincentive needs to be higher than \$20/ton CO_2.

Fig. 20 shows the three Pareto fronts in normalized units; the normalized units provide a more fair comparison. The comparison in Fig. 19 is not entirely fair because the demands in the three scenarios are not identical; two of the three scenarios have the additional demand due to PEV charging and require more electricity generation. The normalized units render the CO_2 emissions and costs of electricity generation with the total demand served, and eliminate the inconsistency among the three scenarios. Therefore, the fact that Case 2 has higher total emissions and total costs in Fig. 19 does not mean it is worse than Case 1. In the normalized units, Case 2 has lower per unit costs of electricity generation than Case 1 because the controllable PEV load helps to reduce the costs associated with conventional reserves and the charging is done strategically when cheap generation is available. However, given the same carbon disincentive, Case 2 still has higher per unit CO_2 emissions because this scenario dispatches relatively more coal generation in order to fulfill the PEV load. Furthermore, the fact that Case 3 outperforms

Case 2 in both emissions and costs suggests that PEVs and wind power should be deployed simultaneously.

Notice that the above results are based on the data specific to the Michigan grid; in particular, the generation mix is coal-dominant. However, the same analysis can be applied to other power systems with different generation mix, grid load, and wind conditions. For example, a gas-dominant grid, such as the Texas grid, will have a Pareto front with a flat slope (i.e. lower sensitivity) because the merit order of the power plants will not change much even if the carbon disincentive varies. A much higher load profile will also make the Pareto Front has a flat slope because, when the load is high, most generation capacity will be dispatched no matter which dispatch order is in use. Imposing a carbon disincentive policy in this situation will not change the CO_2 emissions.

5. Conclusion

This study investigates the tradeoff between the costs of electricity generation and CO_2 emissions of an electric grid with substantial amounts of PEVs and wind power. An optimization problem for generation scheduling is formulated to minimize the costs of electricity generation, and two approaches are adopted to include the grid CO_2 emissions into the cost optimization scheme. The first approach directly penalizes the CO_2 emissions in the objective function, and the second approach introduces a carbon disincentive to alter the dispatch order of power plants. The difference between these two approaches is that the first approach only manipulates the demand, whereas the second approach controls both supply and demand and achieves more CO_2 reduction. The key findings are summarized below.

1. The proposed carbon disincentive policy provides a tuning knob to the grid operator to weigh the importance between the electricity generation costs and grid CO_2 emissions. The carbon disincentive policy is designed to have a revenue return mechanism, so that it is less costly to consumers.
2. The optimal Pareto fronts confirm that the costs of electricity generation and the CO_2 emissions are competing objectives on the Michigan grid: the generation mix has significant coal capacities that are cheaper but produces more emissions than natural gas capacities.
3. Furthermore, our investigation shows that having both PEVs and wind power on the grid is helpful, in that CO_2 can be reduced with minimum increase in the costs of electricity generation. This finding implies that PEVs and wind power should be deployed *simultaneously*, so that the synergy between them can be fully utilized. More importantly, the grid operator should control *both* supply and demand; controlling only the demand cannot adequately address both costs and emissions on the electric grid.

Our discussion focuses on the grid operation and does not include costs or emissions during vehicle operation. A possible extension of this work is to consider aspects in both the grid and transportation sector, which should provide more insights into the tradeoff of CO_2 and cost in both sectors.

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References

Bandivadekar, A., Bodek, K., Cheah, L., Evans, C., Groode, T., Heywood, J., Kasseris, E., Kromer, M., Weiss, M., 2008. On the Road in 2035. Report #LFEE 2008-05 RP. Laboratory for Energy and the Environment, Massachusetts Institute of Technology.
Baptista, P., Tomás, M., Silva, C., 2010. Plug-in hybrid fuel cell vehicles market penetration scenarios. International Journal of Hydrogen Energy 35, 10024–10030.
Bosquet, B., 2000. Environmental tax reform: does it work? A survey of the empirical evidence. Ecological Economics 34, 19–32.
Bovenberg, A., Goulder, L., 1996. Optimal environmental taxation in the presence of other taxes: general- equilibrium analyses. The American Economic Review 86, 985–1000.
Caramanis, M., Foster, J.M., 2009. Management of electric vehicle charging to mitigate renewable generation intermittency and distribution network congestion, 48th IEEE Conference on Decision and Control, Shanghai, China, pp. 4717–4722.
Dallinger, D., Krampe, D., Wietschel, M., 2011. Vehicle-to-grid regulation reserves based on a dynamic simulation of mobility behavior. IEEE Transactions on Smart Grid 2, 302–313.
Doherty, R., O'Malley, M., 2005. A new approach to quantify reserve demand in systems with significant installed wind capacity. IEEE Transactions on Power Systems 20, 587–595.
Ekins, P., 1999. European environmental taxes and charges: recent experience, issues and trends. Ecological Economics 31, 39–62.
Ekins, P., Baker, T., 2001. Carbon taxes and carbon emissions trading. Journal of Economic Surveys 15, 325–376.
Ekins, P., Pollitt, H., Summerton, P., Chewpreecha, U., 2012. Increasing carbon and material productivity through environmental tax reform. Energy Policy 42, 365–376.
Ekman, C.K., 2011. On the synergy between large electric vehicle fleet and high wind penetration – an analysis of the Danish case. Renewable Energy 36, 546–553.
Electric Power Research Institute, 2007. Environmental Assessment of Plug-In Hybrid Electric Vehicles, Vol. 1. Nationwide Greenhouse Gas Emissions. Report #1015325.
Federal Energy Regulatory Commission (FERC). Form 714-Annual Electric Control and Planning Area Report [Online]. Available: 〈http://www.ferc.gov/docs-filing/ferconline.asp〉 (accessed 3.11.2011).
Galus, M.D., La Fauci, R., Andersson, G., 2010. Investigating PHEV wind balancing capabilities using heuristics and model predictive control, IEEE Power and Energy Society General Meeting, Minneapolis, MN, pp. 1–8.
Garcia-Gonzalez, J., de la Muela, R.M.R., Santos, L.M., Gonzalez, A.M., 2008. Stochastic joint optimization of wind generation and pumped-storage units in an electricity market. IEEE Transactions on Power Systems 23, 460–468.
GM-Volt Website. Latest Chevy Volt Battery Pack and Generator Details and Clarifications [Online]. Available: 〈http://gm-volt.com/2007/08/29/latest-chevy-volt-battery-pack-and-generator-details-and-clarifications〉 (accessed 5.13.2010).
Hadley, S., 2008. The Oak Ridge Competitive Electricity Dispatch (ORCED) Model. Report #ORNL/TM-2007/230. Oak Ridge National Laboratory.
Hadley, S., Tsvetkova, A., 2009. Potential impacts of plug-in hybrid electric vehicles on regional power generation. The Electricity Journal 22, 56–68.
Han, S., Han, S., Sezaki, K., 2010. Development of an optimal vehicle-to-grid aggregator for frequency regulation. IEEE Transactions on Smart Grid 1, 65–72.
Hogue, M.T., 2012. A Review of the Costs of Nuclear Power Generation. Report. Bureau of Economic and Business Research, University of Utah.
Holttinen, H., Lemström, B., Meibom, P., Bindner, H., Orths, A., Hulle, F.v., Ensslin, C., Hofmann, L., Winter, W., Tuohy, A., O'Malley, M., Smith, P., Pierik, J., Tande, J., Estanqueiro, A., Ricardo, J., Gomez, E., Söder, L., Strbac, G., Shakoor, A., Smith, J., Parsons, B., Milligan, M., Wan, Y.-H., 2007. Design and operation of power systems with large amounts of wind power. VTT Working Papers 82. International Energy Agency (IEA).
International Energy Agency (IEA)/OECD Nuclear Energy Agency (NEA), 2010. Projected Costs of Generating Electricity – 2010 Edition. Report.
Keoleian, G.A., Kelly, J., MacDonald, J., Camere, A., Monasterio, C.D., Schafer, A., 2011. Environmental Assessment of Plug-In Hybrid Electric Vehicles in Michigan: Greenhouse Gas Emissions, Criteria Air Pollutants, and Petroleum Displacement. Report #CSS11-01. Center for Sustainable Systems, University of Michigan.
Kempton, W., Tomic, J., 2005a. Vehicle-to-grid power fundamentals: calculating capacity and net revenue. Journal of Power Sources 144, 268–279.
Kempton, W., Tomic, J., 2005b. Vehicle-to-grid power implementation: from stabilizing the grid to supporting large-scale renewable energy. Journal of Power Sources 144, 280–294.
Kintner-Meyer, M., Schneider, K., Pratt, R., 2007. Impacts Assessment of Plug-In Hybrid Vehicles on Electric Utilities and Regional U.S. Power Grids—Part 1: Technical Analysis. Report. Pacific Northwest National Laboratory (PNNL).
Lane, B., 2006. Life Cycle Assessment of Vehicle Fuels and Technologies. Report. Ecolane Transport Consultancy.
Lee, T.-K., Baraket, Z., Gordon, T., Filipi, Z., 2011. Stochastic modeling for studies of real-world PHEV usage: driving schedules and daily temporal distributions. IEEE Transactions on Vehicular Technology 61, 1493–1502.
Lemoine, D., Kammen, D., Farrell, A., 2008. An innovation and policy agenda for commercially competitive plug-in hybrid electric vehicles. Environmental Research Letters 3, 14003–14013.

Li, C.-T., Ahn, C., Peng, H., Sun, J., 2011. Decentralized charging of plug-in electric vehicles, Dynamic System and Control Conference, Arlington, VA.
Li, C.-T., Ahn, C., Peng, H., Sun, J., 2012. accepted. Synergistic control of plug-in vehicle charging and wind power scheduling. IEEE Transactions on Power Systems..
Ma, Z., Callaway, D., Hiskens, I., 2010. Decentralized charging control for large populations of plug-in electric vehicles: application of the nash certainty equivalence principle, IEEE International Conference on Control Applications, Yokohama, Japan, pp. 191-195.
Metcalf, G., 2007. A Proposal for a U.S. Carbon Tax Swap: An Equitable Tax Reform to Address Global Climate Change. Discussion Paper 2007-12. Hamilton Project, Brookings Institute,.
Metcalf, G., 2009. Designing a carbon tax to reduce U.S. greenhouse gas emissions. Review of Environmental Economics and Policy 3, 63–83.
National Renewable Energy Laboratory (NREL). Eastern Wind Dataset [Online]. Available: 〈http://www.nrel.gov/wind/integrationdatasets/eastern/methodology.html〉 (accessed 9.15.2010).
Nordhaus, W., 1992. An optimal transition path for controlling greenhouse gases. Science 258, 1315–1319.
Potomac Economics, 2011. 2010 State of the Market Report for the MISO Electricity Markets. Report.
Rogers, J., Fink, S., Porter, K., 2010. Examples of Wind Energy Curtailment Practices. Subcontract Report #NREL/SR-550-48737. National Renewable Energy Laboratory.
SAE Electric Vehicle and Plug in Hybrid Electric Vehicle Conductive Charge Coupler, SAE Standard J1772, 2012.
Samaras, C., Meisterling, K., 2008. Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: implications for policy. Environmental Science & Technology 42, 3170–3176.
Scrimgeour, F., Oxley, L., Fatai, K., 2005. Reducing carbon emissions? The relative effectiveness of different types of environmental tax: the case of New Zealand. Environmental Modelling & Software 20, 1439–1448.
Sioshansi, R., Fagiani, R., Marano, V., 2010. Cost and emissions impacts of plug-in hybrid vehicles on the Ohio power system. Energy Policy 38, 6703–6712.
Smith, A., 2010. Quantifying exports and minimising curtailment: from 20% to 50% wind penetration in Denmark, BIEE Conference, Oxford, UK.
The White House. Administration Announces U.S. Emission Target for Copenhagen [Online]. Available: 〈http://www.whitehouse.gov/the-press-office/president-attend-copenhagen-climate-talks〉 (accessed 1.4.2012).
U.S. Energy Information Administration, 2011a. Annual Energy Outlook 2011. Report #DOE/EIA-0383.
U.S. Energy Information Administration, 2011b. Emissions of Greenhouse Gases in the United States 2009. Report.
U.S. Energy Information Administration. Market Trends – Natural Gas [Online]. Available: 〈http://www.eia.gov/forecasts/aeo/MT_naturalgas.cfm#natgas_prices〉 (accessed: 4. 23./2013).
Ulph, A., Ulph, D., 1994. The optimal time path of a carbon tax. Oxford Economic Papers 46, 857–868.
Ummels, B.C., Gibescu, M., Kling, W.L., Paap, G.C., 2006. Integration of wind power in the liberalized Dutch electricity market. Wind Energy 9, 579–590.
Weisser, D., 2007. A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. Energy 32, 1543–1559.
Wier, M., Birr-Pedersen, K., Jacobsen, H.K., Klok, J., 2005. Are CO_2 taxes regressive? Evidence from the Danish experience. Ecological Economics 52, 239–251.
Yingzhong, G., Le, X., 2010. Look-ahead coordination of wind energy and electric vehicles: a market-based approach, North American Power Symposium (NAPS), 2010, pp. 1–8.