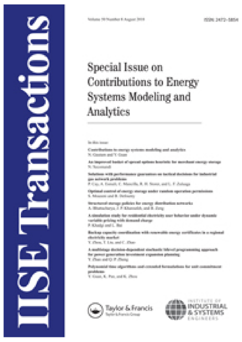

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Backup capacity coordination with renewable energy certificates in a regional electricity market

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ABSTRACT
This article studies a coordination mechanism between a renewable energy supplier and a conventional supplier in a regional electricity market. The intermittent nature of the renewable supplier results in random power shortages. Though the renewable supplier can buy backup power from a conventional supplier who prepares backup capacity to cover the shortage, there is no commitment that enough backup capacity will be prepared without any incentives to the conventional supplier. We design a coordination mechanism where the renewable supplier offers the conventional supplier Renewable Energy Certificates (RECs) proportional to the backup capacity committed. We prove that this mechanism coordinates the conventional supplier's decision on backup capacity and can arbitrarily split the system profit between the two suppliers. Our analytical results show that when the shortage cost increases, the backup capacity increases, the REC offering rate increases, the total profit decreases, and the renewable supplier's profit decreases but the conventional supplier's profit increases. We also show analytically that the social welfare under this mechanism is higher than in the decentralized case unless the regional environment is extremely sensitive to conventional power's carbon footprint, and the benefit of buffering power shortage cannot compensate for the damage to the environment.

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KEYWORDS
Renewable portfolio standard; renewable energy certificate; regional electricity market; game theory; coordination contract

1. Introduction

Renewable energy, typically wind power or solar power, has become an important source in electricity markets (Hammons, 2008). To promote the growth of renewable energy generation, many countries in Europe and more than 30 states in the United States have established the Renewable Portfolio Standard (RPS) regulations in their electricity markets. The RPS regulation requires that a certain percentage of the supplied electricity must be from renewable sources, and the RPS percentage increases gradually per year. For example, the European Union is aiming to generate 20% of its electricity from renewable sources by 2020 and 27% by 2030. In the United States, Illinois has set a 25% target with mandatory RPS regulation to be reached by 2025; California has set mandatory RPS targets of 33% by 2020, 40% by 2024, 45% by 2027, and 50% by 2030; New York's RPS targets are 29% by 2015 and 50% by 2030 (Durkay, 2017). Under the RPS framework, the markets of renewable energy certificates (RECs) have been established, which allow renewable suppliers to sell their surplus RECs to other suppliers who do not meet the RPS requirements.

A critical problem for renewable electricity suppliers is the intermittent nature of the renewable energy sources. Wind and solar power are not as stable and controllable as conventional sources (Sovacool, 2009). Power shortages may occur in a regional electricity market that heavily relies on renewable suppliers, when the renewable power outputs cannot meet the customers' demand.

There are several options for renewable suppliers to cover the shortage and to mitigate the intermittence issue. The first option is to prepare energy storage capacities, such as pumped storage units (Garcia-Gonzalez *et al.*, 2008), compressed air storage (Daneshi and Srivastava, 2012), or batteries (Jiang and Wang, 2013), to absorb extra power during low-demand periods and release power during peak-demand periods (Sovacool, 2009). Unfortunately, although energy storage capacities are generally readily available from ancillary service providers, their high costs hinder large-volume installations. According to Beaudin *et al.* (2010), current energy storage technologies, including pumped hydro storage, compressed air storage, batteries, superconducting magnetic energy storage, hydrogen storage, flywheels, capacitors, and supercapacitors, are still expensive. With the high penetration of renewable power, it will be too costly to solely rely on energy storage capacity to cover the shortage.

Another viable option for renewable suppliers is to purchase reserve power from balancing markets moderated by regional Independent System Operators (ISOs; Vandezande *et al.* (2010)). In a balancing market, a renewable supplier predicts and proposes its demand (power shortage) for a future time period. Suppliers' biddings in the balancing market form a stairwise supply–price curve as shown in Figure 1. The suppliers asking the lowest prices win the bids and provide power up to their respective capacities. Although capacity auctions provide a certain level of protection, challenges still remain in implementing

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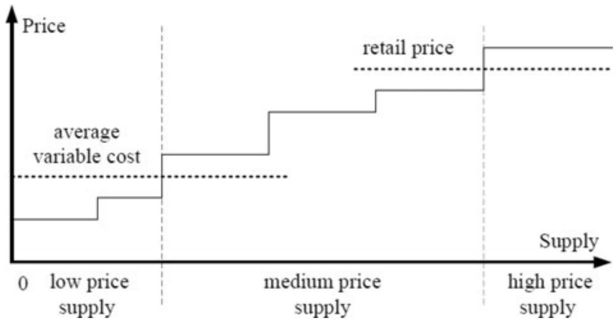

Figure 1. The stairwise supply–price curve in the balancing market.

capacity markets under high-volatility renewable energy penetrations (Jenkin *et al.*, 2016). Due to the long lead time of capacity delivery and the high uncertainties on both the supply and the demand sides, without necessary incentives, it is difficult for balancing markets to guarantee enough reserve power to meet a renewable supplier's need at an acceptable price all the time.

The third option for renewable suppliers is to directly purchase backup capacity (Sovacool, 2009) from other suppliers. Backup capacity is a dispatchable energy source that can be turned on and off in a short time, and its power output is easy to adjust. Among dispatchable renewable power sources, hydropower generation is limited by geographical locations that may not be near the renewable power suppliers (Yang *et al.*, 2012), and biomass generation has a limited capacity (Steinke *et al.*, 2013). Although wind and solar energy may serve as reserves when demand surges, they are not very reliable as backups due to their high uncertainties. Particularly, if the shortage is caused by low outputs from renewable sources, the wind or solar outputs in the surrounding regions are also likely to be low. Thus, the majority of backup power is still generated from conventional power sources, including natural gas, coal, and oil, because they are easier to access than other dispatchable sources (Andersen and Lund, 2007). Among conventional sources, gas-fired generators are a popular choice to serve as backup capacity, as they can quickly respond to demand changes (Lee *et al.*, 2012). For example, the South Texas Electric Cooperative built the gas-fired Pearsall Power Plant (202.5 MW) to provide backup power for their customers in 65 counties where an increasing penetration of wind power brought challenges to the grid stability.[1] Conventional electricity generators are interested in selling backup capacity to renewable suppliers, as in this way, they directly obtain the demands from the renewable suppliers. Therefore, in this article, we only consider conventional suppliers as backup power providers.

Most renewable suppliers outsource backup power capacities from conventional suppliers (Vandezande *et al.*, 2010) due to the difference in the generation technologies. However, when a renewable supplier and a conventional supplier operate independently, there is no economic incentive for the latter to build enough backup capacity for the former (Yang *et al.*, 2012). Due to high variability, backup power suppliers cannot always operate at their optimal points where the generation efficiency is maximal. Thus, backup suppliers' profits will be negatively affected. Therefore, incentives are needed to encourage conventional suppliers to build up more backup capacity to buffer the uncertainty of renewable power output.

In this article, we propose a coordination mechanism based on an REC offering from a renewable supplier to a conventional supplier. In this mechanism, the renewable supplier offers RECs to the conventional supplier, which then prepares backup capacity dedicated to cover the renewable supplier's shortage. The quantity of RECs is proportional to the backup capacity committed by the conventional supplier. The REC offering mechanism is in fact an options contract. It gives the renewable supplier the option to buy up to a certain amount of backup power at a given price from the conventional supplier. The renewable supplier may buy reserve power from the balancing market if the price there is lower. After satisfying the renewable supplier's request, the conventional supplier may sell the remaining capacity on the balancing market.

Compared with a monetary payment for the backup capacity, offering RECs has the following advantages. First, given the RPS regulation and the national REC market, RECs are a reliable and convenient asset for trading between power suppliers. Second, transferring REC is more secure than monetary payment for both suppliers. For renewable suppliers, an REC is a by-product of its daily operation and the supply is reliable, and its impact on the cash flow is smaller than preparing a monetary payment for the backup capacity. For conventional suppliers, having a stable supply of RECs from a coordination contract reduces the risk from both price uncertainty and supply uncertainty of the national REC market (Klessmann *et al.*, 2010). Third, by directly offering RECs, both parties save a transaction cost charged by a third-party broker (3% typically) when they buy or sell RECs in the national market.

We establish a game theory framework to model the market structure with a renewable supplier and a conventional supplier. We show that the coordination mechanism leads to system-optimal investment of backup power and system-optimal profit, and the profit can be arbitrarily allocated between the two parties by adjusting the wholesale price of the backup power. The coordination mechanism achieves Pareto improvement for both parties compared with the decentralized case. The social welfare in the coordination case is higher than that in the decentralized case, unless the regional environment is extremely sensitive to conventional power's carbon footprint, and the benefit of buffering power shortage cannot compensate for the damage to the environment.

The rest of this article is organized as follows. In Section 2, we provide a brief literature review. In Section 3, the models for the decentralized case and the coordinated case are provided. In Section 4, we analyze the coordination contract and discuss its properties. A sensitivity analysis and a social welfare analysis are also performed analytically in Section 4. In Section 5, we summarize our findings and discuss future research directions.

2. Literature review

Our research is related to the impacts of RPS regulation on the electricity market and the coordination between power

[1] http://www.wartsila.com/en/gas-power-plant-to-south-texas-electric-cooperative

suppliers. In this section, we provide a brief literature review in these two streams.

Recently, the impacts of RPS regulations and REC markets on energy firms' decisions have received increasing attention. Kydes (2007) analyzes the impacts of imposing a 20% federal RPS requirement on the U.S. energy markets by 2020 and shows that it will be effective in promoting renewable generation technologies and reducing emissions. Tamas *et al.* (2010) compare decisions made by firms in an oligopoly market under the feed-in-tariff policy and the RPS regulation and perform numerical analysis using data from the UK. Zhou and Tamas (2010) show that the RPS regulation may induce mergers of conventional and renewable generators, which will enable the integrated firms to extend their market power from the REC market to the electricity market. Fischer (2010) analyzes price-taking firms' decisions in electricity and REC markets under perfect competition. Tanaka and Chen (2013) build a Stackelberg game model with a renewable supplier and a conventional supplier to examine the impact of market power on both the electricity and REC markets. Zhou and Liu (2014) find that in a regional power market with access to the national REC market, higher REC price promotes the local renewable power output, but higher regional RPS percentages do not. The above papers focus on the impacts of RPS regulations on firms' competition behaviors, whereas this article studies the collaborations between conventional and renewable suppliers facing the RPS regulation in a regional market. Instead of the mergers suggested by Zhou and Tamas (2010), we design a coordination mechanism to achieve system-optimal backup capacity investment while keeping conventional and renewable suppliers independent.

Coordination in electricity markets has been studied for a long time. The recent rise of renewable power motivates more research in this area, due to the intermittent nature of renewable energy sources requiring more coordination between power suppliers. Andersen and Lund (2007) study how to integrate fluctuating renewable power supplies into power systems by using combined heat and power plants as backups. They focus on the methodologies and computer tools necessary to optimize the participants' market decisions. Klessmann *et al.* (2010) discuss three coordination mechanisms, including transferring RECs between regions, to assist European countries to achieve the RPS target of reaching 20% in 2020. Milligan *et al.* (2010) evaluate important factors to improve electricity systems' ability to absorb renewable power. By studying the Eastern Interconnection electricity markets of the United States, they show how large and responsive energy markets can help the integration of renewable electricity. Vandezande *et al.* (2010) discuss the market structure for backup power. They suggest that a two-part tariff payment, one for backup capacity and one for backup power, is appropriate to build a well-functioning market. Lee *et al.* (2012) explore potential synergies of natural gas and renewable energy in the U.S. power sector and discuss how to design the market mechanism to benefit from collaborative engagement. Although the above literature discusses many aspects of coordination between power suppliers, none of them provide mathematical analysis to support their conclusions. Particularly, the potential of coordination mechanisms based on offering RECs has not yet been fully discussed. In this article, we fill these voids by mathematically analyzing the coordination mechanism between renewable suppliers and conventional suppliers based on offering RECs. This coordination model mathematically validates and also provides an innovative approach to implement the two-part tariff payment coordination mechanism suggested by Vandezande *et al.* (2010).

3. Models

In this section, we first introduce our major assumptions and notations used in this article and then we present the decentralized model (baseline case) and the coordination model.

3.1. Assumptions and notations

We study a regional electricity market served by a renewable supplier (G), who sells power to local customers at a regulated retail price r. G utilizes intermittent energy sources, which may cause a random power shortage, incurring a unit shortage cost c_u to G. Let a series of random variables, $x_t \geq 0, t = 1, \ldots, m$, and denote the shortage faced by G at period t. The probability density function of x_t is $f_t(\cdot)$. When a power shortage occurs, G may seek backup power from an electricity balancing market agency (E), where multiple power suppliers in surrounding regions sell their power. Notice that we focus on a retail renewable supplier but not on large-scale renewable power farms whose major business is selling power to the inter-regional electricity market. We assume the power supply from E to G is unidirectional, because G only serves the local retail market and it is uneconomic to invest in expensive equipment (for voltage-increasing and high-voltage transmission, etc.) to enable inter-regional sales.

As E may not always have enough backup power to cover G's shortage at low prices, G may request an adjacent conventional supplier (B) to prepare backup capacity to buffer its shortage, and B decides the backup capacity units, S. Notice that the entity of B can be a single supplier or a coalition of suppliers acting as a single decision maker (Andersen and Lund, 2007). For simplicity, we treat the latter case also as a single supplier. B makes the capacity investment and accepts the risk if demand for the backup capacity is low. Thus, B may not build enough capacity to satisfy G's needs.

In the proposed coordination mechanism, to encourage B to build enough capacity, G offers B a number of RECs that is proportional to the amount of committed backup capacity. The coordination mechanism is in fact an options contract, which gives G the option to buy up to a certain amount of backup power at a given price from the conventional supplier. G may choose to buy reserve power from the balancing market if the price there is lower. After fulfilling G's request, B may sell any remaining capacity on the balancing market. If B cannot satisfy all of G's requirement, G will buy the rest from E at a high price or choose not to buy.

We assume that B incurs a one-time capacity cost $c_f S$ for the whole m-period planning horizon. We assume that the variable cost of B is c_v, which is at the average level among peers. We assume that B has necessary electrical equipment for inter-regional sales on E when it is profitable. To avoid the trivial case that the average cost is too high and B cannot make any profit, we assume $c_f/m + c_v < r$.

We simplify the stairwise supply–price curve of E into three pricing scenarios $\{H, M, L\}$ (see Figure 1), each with a respective probability $\{p_H, p_M, p_L\}$, and $p_H + p_M + p_L = 1$. We use these three scenarios to approximate most of the prices on the balancing market. The complexity of the model increases if more scenarios are included, however, the structure of the major results remains similar. We assume that there is a non-negligible difference between buying price and selling price in E, because the ISOs need to cover their maintenance costs (Bona *et al.*, 2017). In the medium-price scenario (M), the suppliers sell backup power at price c_v, which is near their average variable cost, and those who need power buy at rate r. In the high-price scenario (H) where the backup power supply is not enough, E purchases backup power at price r and sells at a premium greater than or equal to $r + c_u$. Only key customers whose shortage penalty is higher than that will buy at this price. In the low-price scenario (L) where the amount of backup power is ample, E will sell power at c_v and purchase at a price lower than c_v. Only the most cost-effective backup power suppliers (variable cost less than c_v) can earn a profit in this scenario. Lastly, we assume that the random variables x_t (describing the status of a local market) are independent of the probability distribution of $\{p_H, p_M, p_L\}$ (describing the status of the balancing market connecting many states).

3.2. The decentralized model

The decentralized model (shown in Fig. 2) is the baseline case where B agrees to sell backup capacity to G without REC incentives. B and G need to come to some agreement before the backup capacity is built. When backup power is needed, G will try to buy at the lowest price available to maintain its efficiency. However, G agrees to buy from B first if B's price equals E's price. In return, G requests to set a ceiling price of the backup power to make sure that it will not be unprofitable to purchase from B. In this model, we assume that the ceiling price equals the retail price, r. Please note that an alternative approach is to make the ceiling price a decision variable. In that case, the decentralized model, (D), will become a special case of the later coordination model by setting the number of offered RECs to zero.

In scenarios H and M, B can sell backup power to G at the ceiling price r because E sells at r or higher; in scenario L, B can only sell at c_v because E sells at c_v. We use $\{u_k, v_k, w_k\}$, where $k = H, M, L$, to denote prices between parties in the three scenarios, and their values are summarized in Table 1.

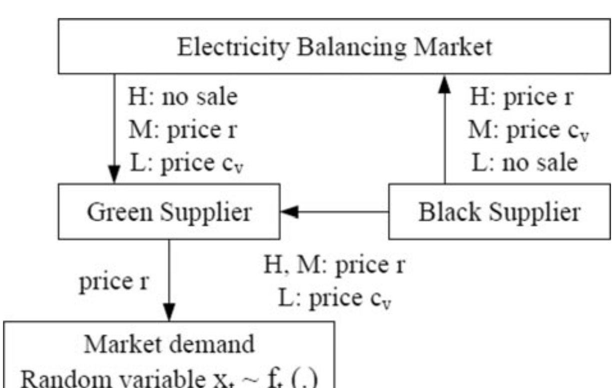

Figure 2. The market structure of the decentralized model.

Table 1. Prices between parties in different scenarios.

	$k = H$	$k = M$	$k = L$
B → E u_k	r	c_v	No purchase
B → G v_k	r	r	c_v
E → G w_k	No purchase	r	c_v

To simplify the notation, let $Y_t(S) = E[Min(x_t, S)] = E[\int_0^S x_t f_t(x_t)dx_t + \int_S^{+\infty} S f_t(x_t)dx_t]$, which is the expected amount of power from B to G at period t. $Y(S) = \sum_{t=1}^m Y_t(S)$ is the summation of the expected amount of backup power delivered to G, which is a monotonically increasing function of S. $\bar{D} = \sum_{t=1}^m \int_0^\infty x_t f_t(x_t)dx_t$ is a constant denoting the expected demand (shortage). It is easy to see $Y(s) \le \bar{D}$.

With the notation defined above, the profit function of G is

$$\Pi_G^D = \sum_{t=1}^m \left\{ \sum_{k=H,M,L} p_k Y_t(S)(r - v_k) + \sum_{k=M,L} p_k(x_t - Y_t(S))(r - w_k) - p_H(x_t - Y_t(S))c_u \right\}$$
$$= p_L(r - c_v)\bar{D} - p_H c_u(\bar{D} - Y(S)).$$

B makes the backup capacity decision S to maximize its profit:

$$\Pi_B^D = \sum_{t=1}^m \left\{ \sum_{k=H,M,L} p_k Y_t(S)(v_k - c_v) + \sum_{k=H,M} p_k(S - Y_t(S))(u_k - c_v) \right\} - c_f S$$
$$= p_M Y(S)(r - c_v) - [c_f - p_H(r - c_v)m]S. \qquad (1)$$

Notice that in scenario M, B can only sell to E at c_v. In scenario L, since the selling price to E is lower than c_v, it is uneconomic for B to generate the power. Setting $\partial \Pi_B^D / \partial S = 0$, we can find B's optimal capacity that satisfies the following condition:

$$\bar{F}(S_D) = m - \frac{c_f'}{p_M(r - c_v)}, \qquad (2)$$

where $\bar{F}(\cdot) = \sum_{t=1}^m F_t(\cdot)$ is the sum of the cumulative distribution functions (cdfs) of the random demands in m periods, and $c_f' = c_f - p_H(r - c_v)m$ is the modified capacity cost.

It is easy to see that the backup capacity investment in the decentralized case is less than the global optimum in the centralized case.

Proposition 1. *The decentralized model leads to underinvestment of backup capacity:*

$$S_D < S_C,$$

where S_C is the optimum in the centralized case and

$$\bar{F}(S_C) = m - \frac{c_f'}{p_M(r - c_v) + p_H c_u}. \qquad (3)$$

Please refer to the online Appendix for all of the proofs. Intuitively, this is true because in the decentralized case B is only

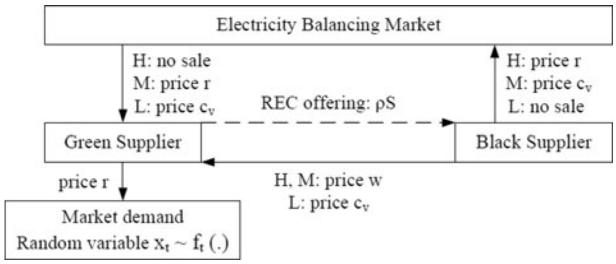

Figure 3. The market structure of the coordination model.

concerned with its own profit without considering G's shortage cost. On the other hand, G does not offer any incentive to B and does not share the risk of investing in the backup capacity, which leads to underinvestment in backup capacity.

3.3. The coordination model

In this section, we design a coordination mechanism (shown in Fig. 3) to encourage B to prepare backup capacity up to the global optimal quantity. In this contract, G first offers B RECs in proportion to the amount of the committed backup capacity, S. Then in each period, G has the option to buy up to S units of backup power at a wholesale price w. The wholesale price w is G's decision variable and we assume $r \geq w \geq c_v$ such that both parties' unit profits are non-negative. We assume that G generates sufficient RECs to cover the offering and sells the rest in the national REC market.

In scenarios M and H, G buys up to S units of backup power from B at w to cover its shortage. The amount of revenue B gains from selling backup power is $(w - c_v)Y(S)$ and G's revenue is $(r - w)Y(S)$. In scenario L, B still sells at $v_k = c_v$ because E sells at c_v. Again, we assume G will buy from B first if B offers the same price as E, due to their long-term collaboration, and also because B is a local supplier; thus, transmitting power with B is more efficient than other options.

The contract defines a Stackelberg game as follows:

Stage 1: G decides the REC offering rate ρ and the wholesale price w.
Stage 2: B decides the backup capacity S.

The profit functions of the two suppliers in the coordination model (P) are as follows:

$$\Pi_G^P = \sum_{t=1}^{m} \left\{ \sum_{k=H,M,L} p_k Y_t(S)(r - v_k) + \sum_{k=M,L} p_k (x_t - Y_t(S))(r - w_k) - p_H (x_t - Y_t(S)) c_u \right\} - \rho S,$$

$$\Pi_B^P = \sum_{t=1}^{m} \left\{ \sum_{k=H,M,L} p_k Y_t(S)(v_k - c_v) + \sum_{k=H,M} p_k (S - Y_t(S))(u_k - c_v) \right\} - (c_f - \rho)S,$$

or in the concise form:

$$\begin{cases} \Pi_G^P(\rho, w) = [p_H(r - w + c_u) + p_M(r - w)]Y(S) \\ +[p_L(r - c_v) - p_H c_u]\bar{D} - \rho S, \\ \Pi_B^P(S) = [p_M(w - c_v) - p_H(r - w)]Y(S) - (c_f' - \rho)S. \end{cases} \tag{4}$$

4. Analytical results

In this section, we first show the properties of the coordination contract. Then we specify the conditions where the contract achieves Pareto improvements compared with the decentralized case. Lastly, we perform sensitivity analysis and social welfare analysis to reveal more properties of the contract.

4.1. Coordination analysis

Theorem 1. *The coordination model has the following properties:*

- *The system achieves coordination when the two parameters (ρ, w) satisfy the following condition:*

$$\rho = \frac{p_H(r - w + c_u) + p_M(r - w)}{p_H c_u + p_M(r - c_v)} c_f'. \tag{5}$$

- *When the system is coordinated, there exists a unique global optimal solution of backup capacity S_P that simultaneously maximizes the total profit and both suppliers' profits:*

$$\bar{F}(S_P) = m - \frac{c_f'}{p_M(r - c_v) + p_H c_u}, \tag{6}$$

where $\bar{F}(\cdot) = \sum_{t=1}^{m} F_t(\cdot)$ is the sum of the cdfs of the random demands in m periods.
- *By adjusting the wholesale price w, the system profit can be arbitrarily allocated between the two suppliers.*

Through a numerical analysis, we find that the performance of the coordination model is robust; e.g., when ρ deviates from the optimal point by ±15%, the total profit loss of the coordination model is less than 6% (see details in the online Appendix).

The coordination is achieved because G compensates for B's capacity risk by offering RECs, which encourages B to invest in the backup capacity at the global optimal level. To intuitively explain the coordination condition specified in Theorem 1, let us compare Equation (4) with the total profit of the centralized model. When (ρ, w) meets the coordination condition as shown in Equation (5), we have

$$\begin{cases} \Pi_G^P(S) = a\Pi_C(S) + b, \\ \Pi_B^P(S) = (1 - a)\Pi_C(S) - b, \end{cases}$$

where $\{a, b\}$ are parameters indicating the allocation of system profit between the two suppliers:

$$\begin{cases} a = \rho / c_f', \\ b = (1 - \rho / c_f')[p_L(r - c_v) - p_H c_u]\bar{D}. \end{cases}$$

Thus, there exists a global optimal S to maximize $\{\Pi_C(S), \Pi_G(S), \Pi_B(S)\}$ simultaneously, and the optimal capacity in the coordination model reaches the global optimum as shown in the centralized model (Equation (3)), $S_P = S_C$. It also shows that w is a lever to arbitrarily split the total profit between G and B.

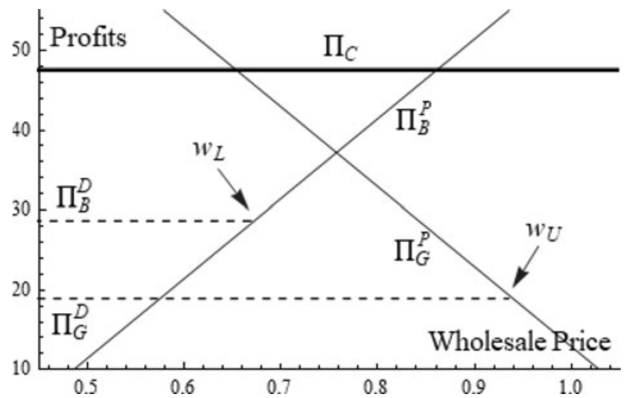

Figure 4. Impacts of the wholesale price on profits.

4.2. Pareto improvements

Under the coordination contract, the wholesale price w serves as a lever to allocate the system profit between the two parties. When w increases, the renewable supplier's profit $\Pi_G^P(w)$ decreases and the conventional supplier's profit $\Pi_B^P(w)$ increases. The total profit can be arbitrarily allocated between the two parties.

To ensure that the coordination contract achieves Pareto improvements for both suppliers compared with the decentralized case, the wholesale price must be appropriately decided. Noticing that the system profit in the coordination structure is more than in the decentralized structure, we can find the range of w where both suppliers have higher profits than in the decentralized case. Derived from $\Pi_G^P(w) \geq \Pi_G^D$, $\Pi_B^P(w) \geq \Pi_B^D$ and Equation (4), we have the closed form of w's lower bound and upper bound as follows:

$$\begin{cases} w_L = \dfrac{\Pi_B^D + (p_H r + p_M c_v)Y(S) - (c_f' - \rho)S}{(p_H + p_M)Y(S)}, \\ w_U = \dfrac{(p_H(r + c_u) + p_M r)Y(S) + (p_L(r - c_v) - p_H c_u)\bar{D} - \rho S - \Pi_G^D}{(p_H + p_M)Y(S)}. \end{cases}$$

Following the numerical setting in the online Appendix, we have $\Pi_G^D = 18.41$ and $\Pi_B^D = 29.21$. From the above equations, we can calculate that $w_L = 0.677$ and $w_U = 0.945$. As shown in Figure 4, when $0.677 < w < 0.945$, the coordination contract achieves Pareto improvements compared with the decentralized case.

4.3. Sensitivity analysis

Here we examine the impacts of market conditions on the suppliers' decisions and their profits in the coordination model. We consider the following market conditions: the fixed cost (c_f), the electricity price (r), the variable cost (c_v), and the shortage cost (c_u). We summarize the results in Table 2.

Table 2. Summary of the sensitivity analyses.

	S_P	ρ	Π_C	Π_G	Π_B
$c_f \uparrow$	↓	↑	↓	↓	↓
$c_v \uparrow$	↓	↑	↓	↓	↓
$r \uparrow$	↑	↑	↑	↑	↑
$c_u \uparrow$	↑	↑	↓	↓	↑

4.3.1. Impacts on the two suppliers' decisions: Backup capacity and REC rate

According to Equation (5), the REC rate (ρ) is a linear function of the wholesale price (w) when the system is coordinated. Since we are more interested in ρ, we fix w to focus on the impacts on ρ.

Proposition 2. *When the wholesale price (w) is unchanged, the impacts of market conditions on the backup capacity (S_P) and the rate of offering RECs (ρ) are as follows:*

- *When the fixed cost (c_f) increases or the variable cost (c_v) increases, the backup capacity (S_P) decreases and the rate of offering RECs (ρ) increases.*
- *When the electricity price (r) increases or the shortage cost (c_u) increases, the backup capacity (S_P) increases and the rate of offering RECs (ρ) increases.*

The first result reveals that a higher fixed cost or a higher variable cost pushes up B's cost burden and B's investment in backup capacity decreases. Facing this change, G will increase the rate of offering RECs to encourage B's investment. The second result reveals that when the backup power becomes more valuable, G offers more RECs to encourage B to invest more in the backup capacity.

4.3.2. Impacts on the profits

Proposition 3. *The impacts of market conditions on the total profit and the two suppliers' profits are as follows:*

- *When the fixed cost (c_f) increases, the total profit (Π_C) decreases. Both the renewable supplier's profit (Π_G) and the conventional supplier's profit (Π_B) decrease.*
- *When the electricity price (r) increases or the variable cost (c_v) decreases, the total profit (Π_C) increases. Both the renewable supplier's profit (Π_G) and the conventional supplier's profit (Π_B) increase.*
- *When the shortage cost (c_u) increases, the total profit (Π_C) decreases, the renewable supplier's profit (Π_G) decreases, but the conventional supplier's profit (Π_B) increases.*

The first result reveals that when the fixed cost is higher, the system-wide cost increases and the total profit decreases. It is a direct cost burden on B and its profit decreases. G shares this burden by offering more RECs (Proposition 2), and its profit also decreases. The second result reveals that when the margin of selling electricity is higher, the total profit increases. If r increases, G directly gains more profit and it offers more RECs to B (Proposition 2). If c_v decreases, B directly gains more profit and G reduces its REC offering to B (Proposition 2). In both conditions the two suppliers share the profit gain and their profits increase. The third result reveals that when the shortage cost is higher, the system-wide cost increases and the total profit decreases. In this case, G needs more backup capacity to cover the electricity shortage, so G offers more RECs to B (Proposition 2), which leads to a decrease in G's profit and an increase in B's profit.

The sensitivity analysis results are summarized in Table 2.

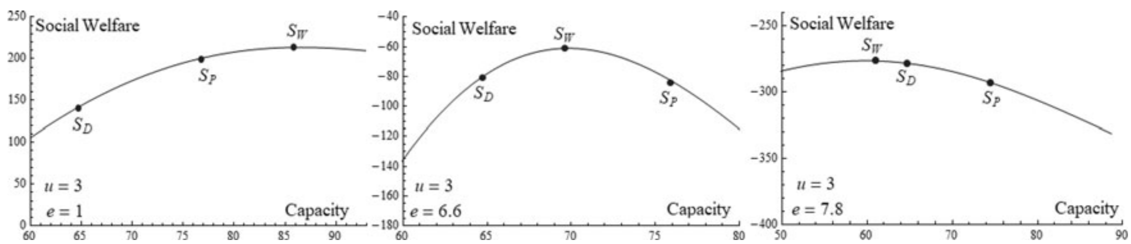

Figure 5. Social welfare under different values of environmental damage.

4.4. Social welfare analysis

An important purpose for promoting renewable energy is to increase the social welfare, defined in Microeconomics as follows (Tamas *et al.*, 2010):

$$\text{social welfare} = \text{customer utility} - \text{production cost} \\ - environmental\ damage$$

To quantitatively measure the social welfare (W) in the regional market considered in this article, we adopt the following form:

$$W = Y(S)U - c_u(\bar{D} - Y(S)) - c_f S.$$

The first term represents the net utility of generated electricity, where $U = u - e - c_v$ is the per unit utility of backup power. u is the utility of consuming electricity, e is the environmental damage of conventional power production, and c_v is the variable cost. The second term measures society's disutility due to power shortage. Being the only power supplier in the regional market, G takes all of the reputation loss due to the inconvenience caused by power shortage. Thus, we assume that the disutility to society is close to G's shortage cost, and use the same c_u here. The third term is the fixed cost to build the backup capacity.

Proposition 4. *There exists a unique optimal capacity of S_W to maximize the social welfare in the regional market in the following form:*

$$S_W = F^{-1}\left(m - \frac{c_f}{U + c_u}\right) = F^{-1}\left(m - \frac{c_f}{u - e - c_v + c_u}\right).$$

By comparison of S_W with the optimal capacity in the coordination structure (S_P) and in the decentralized structure (S_D), we find that their relationships depend on the environmental damage (e) as follows.

Proposition 5. *S_W decreases with the environmental damage e. To compare with S_P and S_D we have*

- *when e is low such that $e \le u - c_v + c_u - p_M(r - c_v) - p_H c_u$, $S_D < S_P \le S_W$;*
- *when e is high such that $e \ge u - c_v + c_u - p_M(r - c_v)$, $S_W \le S_D < S_P$;*
- *when e is medium such that $u - c_v + c_u - p_M(r - c_v) - p_H c_u < e < u - c_v + c_u - p_M(r - c_v)$, $S_D < S_W < S_P$.*

To interpret the results, first we note that S_D is always lower than S_P, since the decentralized structure leads to underinvestment compared with the coordination structure. Second, if the environmental damage e is low, building more backup capacity leads to higher power output without major environmental damage, which makes S_W larger; if e is high, the trend reverses and S_W becomes smaller. Please see Figure 5, which illustrates the social welfare under different values of e, using the previous numerical setting.

5. Conclusions and future research directions

The intermittent energy sources of a supplier of renewable energy can result in random power shortages. ISOs need online reserves to prepare to prepare for any shortage caused by lower-than-predicted renewable energy output. The increase in backup capacity will help improve the system reliability and economic efficiency of energy interchange.

To encourage the conventional supplier to build backup capacity to cover the shortage, we design a coordination mechanism where the renewable supplier offers the conventional supplier RECs in proportion to the committed backup capacity in a regional market. The renewable supplier decides on the rate of offering RECs and the wholesale price of the backup power and then the conventional supplier decides the amount of backup capacity. With the closed-form solution of this coordination model, we prove that the contract achieves system coordination. The system's profit can be arbitrarily allocated between the two suppliers by adjusting the wholesale price. By comparing with the decentralized case, we find that the coordination mechanism can achieve Pareto improvement for both suppliers.

Sensitivity analyses are conducted on the impacts of the following market conditions. First, when the fixed cost increases, the backup capacity decreases and the rate of offering RECs increases. Both suppliers' profits decrease and the total profit decreases. Second, when the electricity price increases or the variable cost decreases, the backup capacity increases and the rate at which RECs are offered decreases. Both suppliers' profits increase and the total profit increases. Lastly, when the shortage cost increases, the backup capacity increases and the rate at which RECs are offered increases. The total profit decreases, the renewable supplier's profit decreases, but the conventional supplier's profit increases.

A social welfare analysis is conducted, and we find that the social welfare of the coordination structure is greater than that of the baseline case unless the regional environment is extremely sensitive to conventional power's carbon footprint, and the benefit of buffering power shortage cannot compensate that the damage experienced by the environment.

To obtain tractable results, we simplify the prices on the balancing market and the wholesale price of the backup power into three scenarios, and we also assume that the prices and the shortages of different periods are independent. To implement the coordination mechanism, more sophisticated models and algorithms need to be developed to capture the dynamics and uncertainties from both the renewable sources and the balancing markets.

Most of the existing models on optimal bidding strategies for renewable energy suppliers are based on a two-stage stochastic programming approach (e.g., Morales *et al.* (2010), Pousinho *et al.* (2011), Dai and Qiao (2013), de la Nieta *et al.* (2013), and Khodayar and Shahidehpour (2013)). In the first stage, the renewable supplier submits its bids in the Day-Ahead (DA) market. In the second stage, it makes its bids in the Real-Time (RT) market after the DA price is known. It is assumed that the bids for all hours of the operating day are made simultaneously at the beginning of the day on the RT market. Hence, this two-stage approach does not capture the flexibility in RT decisions after revealing the uncertain parameters during each time period. Moreover, the above papers did not capture the correlations among consecutive periods of renewable energy outputs. Baringo and Conejo (2016) improve the two-stage approach by allowing suppliers to make their bids in the RT market for each hour of the day separately and adjust their decisions after new information becomes available. However, it does not consider the impact of hourly based RT market bidding on the DA market bidding.

A future research direction would be to develop stochastic programming models to study the backup power capacity coordination problem with more realistic price and shortage scenarios of different periods. Both the conventional and renewable suppliers need to make strategic plans to participate in the DA and RT markets. The model should consider the output correlations and allow the suppliers to decide their RT bidding for each period sequentially and adjust the decisions as new information becomes available. The model should also consider the impacts of backup capacity on RT and DA bidding and *vice versa*. To achieve coordination, we will design the model in the game theory framework and achieve win win situations for the conventional and renewable suppliers. Newly developed game-theoretic models for electricity bidding strategies (e.g., Chattopadhyay and Alpcan (2014), Wu *et al.* (2016), and Xu *et al.* (2016)) do not consider the backup agreements between conventional and renewable suppliers. We will fill this void in our future research.

Another future research direction will be to design the coordination mechanism with multiple conventional energy suppliers and multiple renewable suppliers in different regions. The multi-region coordination problem brings both opportunities and challenges. On the one hand, the risk-pooling effect across different regions can help renewable energy suppliers to reduce the intermittency in their power outputs. If the power shortage in one region cannot be fully covered by the local backup capacity, other regions' power suppliers may send their extra backup power through the grid. All of the interconnected regions can benefit from such a resource-pooling practice. On the other hand, the coordination problem itself becomes much more complicated, as we need to consider how to allocate the profit among multiple suppliers, while facing both the intermittent supplies and the transmission loss across different regions.

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References

Andersen, A.N. and Lund, H. (2007) New CHP partnerships offering balancing of fluctuating renewable electricity productions. *Journal of Cleaner Production*, **15**(3), 288–293.

Baringo, L. and Conejo, A.J. (2016) Offering strategy of wind-power producer: A multi-stage risk-constrained approach. *IEEE Transactions on Power Systems*, **31**(2), 1420–1429.

Beaudin, M., Zareipour, H., Schellenberglabe, A. and Rosehart, W. (2010) Energy storage for mitigating the variability of renewable electricity sources: An updated review. *Energy for Sustainable Development*, **14**(4), 302–314.

Bona, F., Gast, N., Le Boudec, J.-Y., Pinson, P. and Tomozei, D.-C. (2017) Attribution mechanisms for ancillary service costs induced by variability in power delivery. *IEEE Transactions on Power Systems*, **32**(3), 1891–1901.

Chattopadhyay, D. and Alpcan, T. (2014) A game-theoretic analysis of wind generation variability on electricity markets. *IEEE Transactions on Power Systems*, **29**(5), 2069–2077.

Dai, Q. and Qiao, W. (2013) Trading wind power in a competitive electricity market using stochastic programing and game theory. *IEEE Transactions on Sustainable Energy*, **4**(3), 805–815.

Daneshi, H. and Srivastava, A. (2012) Security-constrained unit commitment with wind generation and compressed air energy storage. *IET Generation, Transmission & Distribution*, **6**(2), 167–175.

De la Nieta, A.A.S., Contreras, J. and Munoz, J.I. (2013) Optimal coordinated wind-hydro bidding strategies in day-ahead markets. *IEEE Transactions on Power Systems*, **28**(2), 798–809.

Durkay, J. (2017) State renewable portfolio standards and goals, *National Conference of State Legislatures*. Available at http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx

Fischer, C. (2010) Renewable portfolio standards: When do they lower energy prices? *The Energy Journal*, **31**(1), 101–120.

Garcia-Gonzalez, J., de la Muela, R.M.R., Santos, L.M. and Gonzalez, A.M. (2008) Stochastic joint optimization of wind generation and pumped-storage units in an electricity market. *IEEE Transactions on Power Systems*, **23**(2), 460–468.

Hammons, T.J. (2008) Integrating renewable energy sources into European grids. *International Journal of Electrical Power & Energy Systems*, **30**(8), 462–475.

Jenkin, T., Beiter, P. and Margolis, R. (2016) Capacity payments in restructured markets under low and high penetration levels of renewable energy. Technical Report, National Renewable Energy Laboratory, Golden, CO.

Jiang, Q. and Wang, H. (2013) Two-time-scale coordination control for a battery energy storage system to mitigate wind power fluctuations. *IEEE Transactions on Energy Conversion*, **28**(1), 52–61.

Khodayar, M.E. and Shahidehpour, M. (2013) Stochastic price-based coordination of intrahour wind energy and storage in a generation company. *IEEE Transactions on Sustainable Energy*, **4**(3), 554–562.

Klessmann, C., Lamers, P., Ragwitz, M. and Resch, G. (2010) Design options for cooperation mechanisms under the new European renewable energy directive. *Energy Policy*, **38**(8), 4679–4691.

Kydes, A.S. (2007) Impacts of a renewable portfolio generation standard on U.S. energy markets. *Energy Policy*, **35**(2), 809–814.

Lee, A., Zinaman, O. and Logan, J. (2012) Opportunities for synergy between natural gas and renewable energy in the electric power and transportation sectors. Technical Report, National Renewable Energy Laboratory.

Milligan, M., Kirby, B. and Beuning, S. (2010) Potential reductions in variability with alternative approaches to balancing area cooperation with high penetrations of variable generation. Technical Report, National Renewable Energy Laboratory, Golden, CO.

Morales, J.M., Conejo, A.J. and Pérez-Ruiz, J. (2010) Short-term trading for a wind power producer. *IEEE Transactions on Power Systems*, **25**(1), 554–564.

Pousinho, H.M.I., Mendes, V.M.F. and Catalão, J.P.S. (2011) A risk-averse optimization model for trading wind energy in a market environment under uncertainty. *Energy*, **36**(8), 4935–4942.

Sovacool, B.K. (2009) The intermittency of wind, solar, and renewable electricity generators: Technical barrier or rhetorical excuse? *Utilities Policy*, **17**(3-4), 288–296.

Steinke, F., Wolfrum, P. and Hoffmann, C. (2013) Grid vs. storage in a 100% renewable Europe. *Renewable Energy*, **50**(C), 826–832.

Tamas, M.M., Bade Shrestha, S.O. and Zhou, H. (2010) Feed-in tariff and tradable green certificate in oligopoly. *Energy Policy*, **38**(8), 4040–4047.

Tanaka, M. and Chen, Y. (2013) Market power in renewable portfolio standards. *Energy Economics*, **39**, 187–196.

Vandezande, L., Meeus, L., Belmans, R., Saguan, M. and Glachant, J.M. (2010) Well-functioning balancing markets: A prerequisite for wind power integration. *Energy Policy*, **38**(7), 3146–3154.

Wu, H., Shahidehpour, M., Alabdulwahab, A. and Abusorrah, A. (2016) A game theoretic approach to risk-based optimal bidding strategies for electric vehicle aggregators in electricity markets with variable wind energy resources. *IEEE Transactions on Sustainable Energy*, **7**(1), 374–385.

Xu, Q., Zhang, N., Kang, C., Xia, Q., He, D., Liu, C., Huang, Y., Cheng, L. and Bai, J. (2016) A game theoretical pricing mechanism for multi-area spinning reserve trading considering wind power uncertainty. *IEEE Transactions on Power Systems*, **31**(2), 1084–1095.

Yang, M., Patino-Echeverri, D. and Yang, F. (2012) Wind power generation in China: Understanding the mismatch between capacity and generation. *Renewable Energy*, **41**(2012), 145–151. Available at https://cedmcenter.org/wp-content/uploads/2017/10/Wind-power-generation-in-China-Understanding-the-mismatch-between-capacity-and-generation.pdf

Zhou, H. and Tamas, M.M. (2010) Impacts of integration of production of black and green energy. *Energy Economics*, **32**(1), 220–226.

Zhou, Y. and Liu, T. (2014) Impacts of the renewable portfolio standard on regional electricity markets. *Journal of Energy Engineering*, **141**(1), B4014009. Available at https://ascelibrary.org/doi/pdf/10.1061/%28ASCE%29EY.1943-7897.0000202