Optimal Bidding Strategy of Battery Storage in Power Markets Considering Performance-Based Regulation and Battery Cycle Life

Guannan He, Qixin Chen, *Member, IEEE*, Chongqing Kang, *Senior Member, IEEE*, Pierre Pinson, *Senior Member, IEEE*, and Qing Xia, *Senior Member, IEEE*

Abstract—Large-scale battery storage will become an essential part of the future smart grid. This paper investigates the optimal bidding strategy for battery storage in power markets. Battery storage could increase its profitability by providing fast regulation service under a performance-based regulation mechanism, which better exploits a battery's fast ramping capability. However, battery life might be decreased by frequent charge–discharge cycling, especially when providing fast regulation service. It is profitable for battery storage to extend its service life by limiting its operational strategy to some degree. Thus, we incorporate a battery cycle life model into a profit maximization model to determine the optimal bids in day-ahead energy, spinning reserve, and regulation markets. Then a decomposed online calculation method to compute cycle life under different operational strategies is proposed to reduce the complexity of the model. This novel bidding model would help investor-owned battery storages better decide their bidding and operational schedules and investors to estimate the battery storage's economic viability. The validity of the proposed model is proven by case study results.

Index Terms—Battery cycle life, battery storage, optimal bidding strategy, performance-based regulation (PBR), power markets.

Nomenclature

Indices and Sets

t	Time index.
s	Scenario index.
k	Half cycle index.
H	Set of time.
S	Set of scenarios.
C	Set of half cycles.
e	Superscript for energy market.
res	Superscript for spinning reserve market.
reg	Superscript for regulation market.
cap	Superscript for regulation capability.
perf	Superscript for regulation performance.
day	Superscript for daily variables.

Parameters and Constants

R^{mileage}	Mileage ratio for regulation resource.
$P_{\max}$	Rated power capacity of battery storage, MW.
$E_{\max}$	Rated energy capacity of battery storage, MWh.
c_m	Daily maintenance cost per unit power capacity, \$/MW.
c_{op}	Operational cost per unit energy, \$/MWh.
$P_{s,t}^{(\cdot)}$	Market price at time t in scenario s, \$/MWh or \$/MW.
γ^{res}	Probability of spinning reserve deployment.
α	Self-discharge rate of battery storage.
η_0	Charging/discharging efficiency of battery.
T_{float}	Float life of battery storage, year.

Variables

$\text{Cap}_t^{(\cdot)}$	Capacity bid in market at time t, MW.
$\text{Pay}_{(\cdot),(\cdot)}^{\text{reg},(\cdot)}$	Payment for regulation service, \$.
T_{service}	Service life of battery storage, year.
T_{cycle}	Cycle life of battery storage, year.
$\text{Cost}_t^{\text{op}}$	Operational cost of battery storage at time t, \$.
Cost^m	Daily maintenance cost of battery storage, \$.
d	Depth of discharge (DOD).
N_d^{fail}	Maximum number of charge–discharge cycles at a DOD of d before the battery's failure.
n_d	Number of cycles at a DOD of d.
E_t	Battery's energy stored level at time t, MWh.
ΔE_t	Battery's energy level change at time t, MWh.
g_t^{res}	Spinning reserve deployment at time t, MW.

I. Introduction

BATTERY storage will play a critical role along the entire value chain of the future smart grid [1]. The largest obstacle that prevents large-scale battery storage from commercial operation is the relatively high-investment cost and revenue risk. Thus, how to explore the best cost-benefit results and more precisely evaluate the economics of battery storage in power markets have become significant issues.

One major application for battery storage is to provide regulation service. Compared with traditional generators, battery storage could ramp much more rapidly and respond faster with better performance. However, for most of the existing regulation markets, regulation resources are only compensated based on the committed capacity, with no regard for its actual performance. Therefore, battery storages' potential to provide flexibility is not fully exploited, and the revenue from regulation markets might be underestimated.

Federal Energy Regulatory Commission (FERC) Order 755 [2], issued on October 20, 2011, started to address this problem. It requires market operators to develop pay-for-performance protocols and tariffs, which compensate regulation providers according to their actual performance to remedy undue discrimination [3], [4]. This order has already been implemented in most independent system operator/regional transmission organization under FERC. For example, in PJM, a new performance-based regulation (PBR) mechanism is instituted in which regulation service providers receive a two-part payment consisting of a capability payment and a performance payment. A new fast regulation signal is introduced that brings approximately three times the performance revenue of a traditional signal for eligible resources.

A few papers have evaluated the economics of energy storage considering their participation in power markets. Some of them only consider participation in energy markets, leaving out the possible revenues from providing ancillary services. Though the others well formulate energy storage's participation in both energy and ancillary service markets, the PBR mechanism is not considered. The economic viability and potential of energy storages' arbitraging in power markets is researched in [5]. Storages' self-scheduling in energy and ancillary service markets is researched in [6]–[10], some of which also consider joint operation with wind farms.

Another problem missed by the literature above is that battery storages' frequent charge–discharge cycling incurs an extra cost as it accelerates depreciation. This extra cost of depreciation might be significant when the regulation signal is extraordinarily fast. Thus, it is essential to introduce formulations accounting for battery life into an optimal bidding model in joint energy and ancillary service markets.

Some papers have studied the relations between the battery's life and its operation including providing regulation services. However, none of them introduce formulations accounting for battery life into the battery's optimal bidding model. Thus, the battery life's impact on the battery's economic viability has not been totally revealed. A few papers [11]–[21] have provided some data on different batteries' cycle lives at different DOD. In [11], the data are used to calculate the cost per cycle of primary frequency regulation for the purpose of selecting the cheapest battery technology. Reference [15] presents a short-term battery storage scheduling model in conjunction with traditional generators considering battery cycle life. Reference [16] applies the battery life model to better manage an energy storage system in microgrids. In [20], battery lifetime is calculated to assess the battery and ultracapacitor ratings in electric vehicles.

Reference [22] calculates a battery's capacity reduction from its cycles. Some papers derive formulations on the relation between battery cycle life and DOD using different fitting techniques. Reference [20] uses a fourth-order polynomial function, whereas [21] and [22] used an exponential function. Another widely used function is the power function [14]–[16], which also fits the data in [12] and [13] very well.

Regardless of the specific cycle life models, a rainflow counting algorithm is commonly used to calculate a battery's lifetime, as referenced in [13], [14], [22], and [23]. Most papers above apply this algorithm for static evaluation with fixed operating strategies. However, because a battery's cycle life is affected by its cycling strategy, it is necessary to incorporate cycle life calculation into dynamic strategy optimization. Moreover, as the calculation algorithm of cycles includes some discrete logical judgment and cannot be analytically expressed with respect to the operation strategies, it is difficult to embed the calculation algorithm into an analytical programming model that can be solved by a commercial optimization solver.

To solve the problems addressed above, this paper proposes a model that decides the optimal joint bidding strategy of battery storage in joint day-ahead energy, reserve, and regulation markets with multi-scenario settings to consider price uncertainty. The PBR mechanism is included in this model. A battery cycle life model is embedded into the optimization scheme to calculate the cycle life under different operational strategies. Additionally, a decomposition method is introduced to simplify the battery life calculation with little loss of accuracy while largely reducing the complexity of modeling and computation. By applying the proposed model, investors could obtain more accurate and realistic economic evaluation results of battery storage, and storage owners could make better day-ahead bidding decisions. Case study results prove a significant impact through considering the PBR mechanism and cycle life on a battery's bidding strategy and overall profits.

This paper is organized as follows. Section II introduces the market mechanisms with PBR settings. Section III presents the battery life model and calculation method. Section IV formulates the optimal bidding strategy decision-making model. Case study results are discussed in Section V. Section VI draws the conclusion.

II. MARKET FRAMEWORK

A. Basic Market Mechanism

Without loss of generality, common settings of power market mechanisms are implemented in this paper, which include day-ahead energy, spinning reserve, and regulation markets [7], [9].

We assume that battery storage simultaneously bids in the three day-ahead markets, treated as a normal market participant like traditional generators. Considering its relatively small capacity, battery storage is reasonably assumed to be price-taker. Multi-scenario settings are established to consider price uncertainty. As a price-taker, the storage has to make an optimal allocation of its resources in the three markets based on price prediction to maximize the expected total profit while
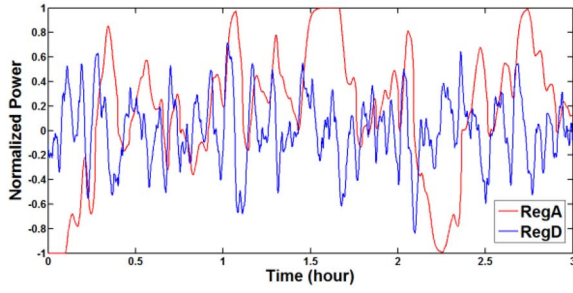
This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

HE *et al.*: OPTIMAL BIDDING STRATEGY OF BATTERY STORAGE IN POWER MARKETS 3

Fig. 1.   3-h sample profiles of RegA and RegD.

Fig. 2.   Curves of cycle life versus DOD with different k_P values.

ensuring all operational constraints are satisfied. The bidding strategy has to be decided every day before the closure of the day-ahead market for the next day.

B. Performance-Based Regulation

The PBR mechanism is included in this model, typically referenced from the PJM [24]. This mechanism provides incentives for high-performing regulation resources and reduces the overall regulation capacity requirement in PJM [3].

Under PBR, a dynamic regulation signal (RegD) is added as a supplement to the traditional regulation signal (RegA). Derived from the area control error with a low-pass filter, RegA is used for resources with a limited ramp rate, whereas RegD, derived with a high-pass filter, results in much faster movement, as shown in Fig. 1. Regulation resources receive a two-part payment that consists of capability payment and performance payment. The system operator calculates the two payments based on the regulation market capability clearing price $P^{\text{reg,cap}}$ and the regulation market performance clearing price $P^{\text{reg,perf}}$, respectively, as in the following [25]:

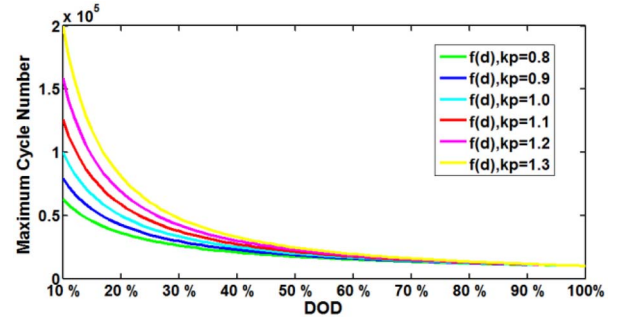$$\text{Pay}^{\text{reg,cap}} = P^{\text{reg,cap}}\text{Cap}^{\text{reg}}\text{Score}^{\text{perf}} \tag{1}$$

$$\text{Pay}^{\text{reg,perf}} = P^{\text{reg,perf}}\text{Cap}^{\text{reg}}R^{\text{mileage}}\text{Score}^{\text{perf}}. \tag{2}$$

Cap^{reg} is the hourly committed regulation capacity. The performance score $\text{Score}^{\text{perf}}$ reflects the accuracy of a regulation resource's response to PJM's regulation signal [26]. The mileage ratio R^{mileage} is the ratio between the requested mileage (absolute summation of movement) of one signal to that of RegA. Because RegD's mileage is approximately three times that of RegA, the mileage ratio of RegD is approximately three times larger as well. Thus, qualified resources following RegD would earn three times the performance revenue.

Most battery storages are capable of ramping from zero power output to full capacity within seconds or even milliseconds, such as the vanadium redox flow battery, and thus could provide fast regulation service following RegD. RegD's other favorable characteristic for battery storage is that it requires net zero energy over a 15-min time period [4], which reduces the amount of obligated reserved energy.

III. Battery Life Model and Calculation Method

In this section, a battery life model is introduced and a reasonably simplified online calculation method is proposed to compute a battery's service life based on its cycling strategy.

A. Life Model

A battery's service life (calendar life) T_{service} is determined by its cycle life T_{cycle} or float life T_{float}, whichever is shorter [19].

The battery's cycle life is related to the cycling aging and dependent on its cycling behavior. Frequent and deep cycles accelerate cyclic aging and reduce the cycle life. It can be derived as

$$T_{\text{cycle}} = \frac{N_d^{\text{fail}}}{W \cdot n_d^{\text{day}}} \tag{3}$$

where N_d^{fail} is the maximum number of charge–discharge cycles at a specific DOD before the battery's failure, n_d^{day} is the number of daily cycles at the DOD, and W denotes the average number of operating days in one year for battery storage, considering 20% time allotted for necessary maintenance.

The battery's float life corresponds to the normal corrosion processes. It is independent of its cycling behavior, and thus regarded as a constant. Temperature's impact on battery life is assumed to be under consideration and beyond the scope of this paper.

For any type of battery, N_d^{fail} is a function of DOD (%), as

$$N_d^{\text{fail}} = f(d). \tag{4}$$

$f(d)$ can be obtained by a fitting technique using detailed experimental data provided by manufacturers. The cycle life loss $\text{Loss}_{\text{cycle}}$ for n_d cycles at d DOD is calculated as

$$\text{Loss}_{\text{cycle}}(\%) = \frac{n_d}{f(d)} \times 100\%. \tag{5}$$

In this paper, $f(d)$ is adopted to be a power function for its good applicability in different kinds of batteries, as

$$f(d) = N_{100}^{\text{fail}} \cdot d^{-k_P} \tag{6}$$

where k_P is a constant ranging from 0.8 to 2.1 [12]–[16] and N_{100}^{fail} is the number of cycles to failure at 100% DOD. Fig. 2 shows the curves of cycle life versus DOD with different k_P, assuming the N_{100}^{fail} to be 10 000. In practice, k_P can be obtained by a fitting technique using detailed experimental data provided by battery manufacturers.

By keeping the loss of cycle life a constant, the equivalent 100%-DOD cycle number n_{100}^{eq} of n_d cycles at d DOD is derived as

$$n_{100}^{\text{eq}} = n_d \cdot d^{k_P}. \tag{7}$$

A larger k_P means fewer equivalent 100%-DOD cycles for n_d cycles at d DOD, as d is always no more than 100%.

Taking a vanadium redox flow battery as an example, the cell stack's float life T_{float} can be expected to last more than ten years [27], and its number of 100%-DOD cycles to failure N_{100}^{fail} usually exceeds 10 000 [1]. After replacing some components such as the cell stack and pumps, the vanadium redox flow battery storage station can operate another T_{service} years, totaling $2T_{\text{service}}$ years.

B. Battery Cycle Life Calculation Method

For a given bidding strategy and regulation signal, there exists a corresponding energy changing curve of battery storage. The first step of cycle life calculation is to identify each half cycle by picking out every local extreme point on the curve with corresponding energy level E_k^m, as in Fig. 3.

The battery storage completes a half cycle between every two adjacent local extreme points. E_k^m is just the energy level at the end of the kth half cycle. Then, the DOD of every half cycle d_k^{half} is calculated as

$$d_k^{\text{half}} = \left| \frac{E_k^m - E_{k-1}^m}{E_{\max}} \right|. \tag{8}$$

According to (3) and (7), a battery's daily equivalent 100%-DOD cycle number and cycle life are derived, respectively

$$n_{100}^{\text{eq,day}} = \sum_{k \in C} 0.5 \cdot \left(d_k^{\text{half}} \right)^{k_P} \tag{9}$$

$$T_{\text{cycle}} = \frac{N_{100}^{\text{fail}}}{W \cdot n_{100}^{\text{eq,day}}}. \tag{10}$$

This DOD calculating approach is similar to the rainflow counting algorithm [23]. However, as the decision variables would affect the local extreme points on the energy curve and then the identification of the half cycle, extreme point picking should be conducted for each feasible bidding strategy to calculate the battery cycle life. The relation between the decision variables and the local extreme points can be only analytically expressed in a very complicated form, so it is difficult to embed the identification of the half cycle into a model that can be solved by a commercial optimization solver. Thus, a decomposition calculation method is proposed to separate the decision variables from the identification of the half cycle, while precisely approximating the cycle life.

For a battery storage participating in joint energy, spinning reserve, and regulation markets, its total energy changing process, as shown in Fig. 3, can be decomposed into two parts, as shown in Fig. 4(a) and (b). The time range in Fig. 4(a) is 24 h, whereas it is 1 h in Fig. 4(b).

The first part is related to the bids in markets in each time period, typically 1 h, denoted by ΔE_t, as shown in Fig. 4(a). The causes of this part of the energy change include charging and discharging in the energy market, reserve deployment, and energy loss in providing regulation service.

The other part of energy changing is caused by regulation up and down, according to the RegD with 4-s resolution.
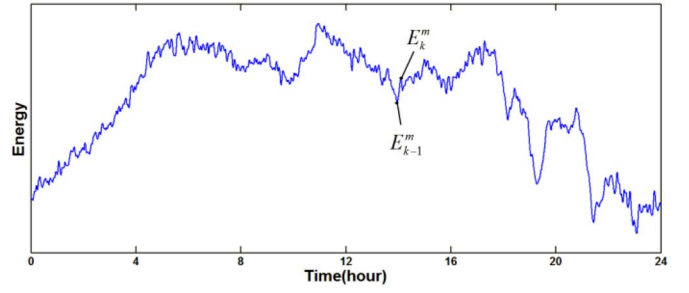

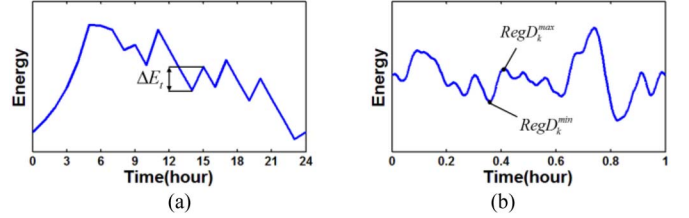Fig. 3. Energy curve of battery storage's operation.

Fig. 4. Decomposition of the energy changing process. (a) Energy change between hours. (b) Intra-hour energy change.

It is reasonable to simulate the real up-coming day's regulation signal based on the historical regulation signal when making day-ahead decisions. The simulated signal serves as a parameter in optimization, and its local extreme points could be picked out in advance, as shown in Fig. 4(b). $\text{RegD}_k^{\min}$ and $\text{RegD}_k^{\max}$ denote the energy levels of the kth local minimum and maximum points on the energy curve of RegD signal, respectively. $t_k^{\min}$ and $t_k^{\max}$ denote the corresponding time of $\text{RegD}_k^{\min}$ and $\text{RegD}_k^{\max}$.

When the capacity bid in the regulation market is much larger than that in the energy and spinning reserve markets, the second part of the energy change is usually larger than the first part, as is the corresponding impact on cycle life calculation. Then, for most adjacent local extreme points in the same hour that satisfy $t-1 < t_k^{\min} < t_k^{\max} < t$, the DOD of corresponding half cycles can be simplified as

$$d_k^{\text{up}} = \frac{\Delta E_t \left(t_k^{\max} - t_k^{\min} \right) / h + \text{Cap}_t^{\text{reg}} \left(\text{RegD}_k^{\max} - \text{RegD}_k^{\min} \right)}{E_{\max}} \tag{11}$$

$$d_k^{\text{down}} = \frac{-\Delta E_t \left(t_k^{\max} - t_k^{\min} \right) / h + \text{Cap}_t^{\text{reg}} \left(\text{RegD}_k^{\max} - \text{RegD}_{k+1}^{\min} \right)}{E_{\max}} \tag{12}$$

where d_k^{up} denotes the DOD of the kth regulation-up movement; d_k^{down} denotes the DOD of the kth regulation-down movement; $\text{Cap}_t^{\text{reg}}$ denotes the capacity bid in the regulation market at time t; h denotes the time interval, which is equal to 1 h in this paper. In (11) and (12), the two parts of the energy change are arrayed in order. For the remaining adjacent local extreme points at different hours, $\text{Cap}_t^{\text{reg}}$ and ΔE_t should be adjusted to be hourly weighted averages. Then, the battery's daily equivalent 100%-DOD cycle

number can be derived as

$$n_{100}^{\text{eq,day}} = \sum_{k \in C} 0.5 \cdot \left[\left(\left| d_k^{\text{up}} \right| \right)^{k_P} + \left(\left| d_k^{\text{down}} \right| \right)^{k_P} \right]. \quad (13)$$

The proposed algorithm using the decomposition method, described in (11)–(13), separates decision variables from extreme point picking, and thus we do not have to pick again when decision variables change. This simplifies the cycle life calculation with little loss of accuracy and enables the model to be solved by commercial solvers because the local extreme points only serve as parameters.

To guarantee the rigorousness of the above proposed method, we could re-identify the half cycles on the total energy curve of the optimal result and compute the cycle life again using the original calculation method without decomposition. If the first part of the energy change exceeds the second part in some time intervals, there will be a slight difference between the local extreme points picked in advance and those re-picked. Then, an iteration process could be implemented by re-optimize the bidding strategy using the re-picked local extreme points to get a more accurate result. As tested, this iteration could be usually skipped because the results are very close.

IV. MODEL FORMULATION

In this section, the proposed model of battery storage bidding in the joint power markets is presented in detail. The decision variables are Cap_t^{e}, $\text{Cap}_t^{\text{res}}$, and $\text{Cap}_t^{\text{reg}}$, the optimal capacity bids in the energy, reserve, and regulation markets for each hour in the next day. We assume the storage to be a price-taker and to play no tricks to seize profit.

A. Objective Function

The bidding model is an income maximizing problem, as described in (14). It is nonlinear because the cycle life calculation is embedded.

$$\max \ \text{Income}^{\text{total}} = \min(T_{\text{cycle}}, T_{\text{float}}) \cdot W \cdot \text{Income}^{\text{day}}. \quad (14)$$

The battery storage's total income $\text{Income}^{\text{total}}$ is dependent on the daily income $\text{Income}^{\text{day}}$ and cycle life T_{cycle}. T_{cycle} is calculated using (10)–(13). The daily income is equal to the sum of the revenues from each market minus the operational and maintenance costs. To take price uncertainty into account, we generate some scenarios based on historical price data. Then, the expected value of the daily income is calculated as

$$\text{Income}^{\text{day}} = \sum_{s \in S} \gamma_s \left[\sum_{t \in H} (\text{Income}_{s,t}^{\text{e}} + \text{Income}_{s,t}^{\text{res}} \right. $$
$$\left. + \ \text{Income}_{s,t}^{\text{reg}} - \text{Cost}_t^{\text{op}}) \right] - \text{Cost}^m. \quad (15)$$

The energy market income comes from two parts, the day-ahead energy bid and the real-time spinning reserve deployment

$$\text{Income}_{s,t}^{\text{e}} = P_{s,t}^{\text{e}} \text{Cap}_t^{\text{e}} h + P_{s,t}^{\text{e}} g_t^{\text{res}} h. \quad (16)$$

In (16), $P_{s,t}^{\text{e}}$ is the energy price at time t in scenario s. The spinning reserve deployment g_t^{res} is calculated by assuming a probability γ^{res} of its occurrence [9] as

$$g_t^{\text{res}} = \gamma^{\text{res}} \text{Cap}_t^{\text{res}}. \quad (17)$$

The reserve market income is determined by the spinning reserve capacity price $P_{s,t}^{\text{res}}$ and the capacity bid $\text{Cap}_t^{\text{res}}$

$$\text{Income}_{s,t}^{\text{res}} = P_{s,t}^{\text{res}} \text{Cap}_t^{\text{res}}. \quad (18)$$

In (19), the regulation market income consists of the capability payment and the performance payment, calculated in (20) and (21), respectively.

$$\text{Income}_{s,t}^{\text{reg}} = \text{Pay}_{s,t}^{\text{reg,cap}} + \text{Pay}_{s,t}^{\text{reg,perf}} \quad (19)$$
$$\text{Pay}_{s,t}^{\text{reg,cap}} = P_{s,t}^{\text{reg,cap}} \text{Cap}_t^{\text{reg}} \text{Score}^{\text{perf}} \quad (20)$$
$$\text{Pay}_{s,t}^{\text{reg,perf}} = P_{s,t}^{\text{reg,perf}} \text{Cap}_t^{\text{reg}} R_{s,t}^{\text{mileage}} \text{Score}^{\text{perf}}. \quad (21)$$

The operational cost is proportional to the amount of energy change in storage, as derived in (22). β_t indicates the average energy consumed in regulation up or down within hour t for 1-MW committed regulation capacity, as determined by the generated RegD signal.

$$\text{Cost}_t^{\text{op}} = c_{\text{op}} \left[\left(\text{Cap}_t^{\text{e,sell}} + \text{Cap}_t^{\text{e,buy}} \right) h + 2\beta_t \text{Cap}_t^{\text{reg}} + g_t^{\text{res}} h \right] \quad (22)$$

$$\text{Cap}_t^{\text{e}} = \text{Cap}_t^{\text{e,sell}} - \text{Cap}_t^{\text{e,buy}} \quad (23)$$
$$0 \leq \text{Cap}_t^{\text{e,sell}} \leq P_{\max} \quad (24)$$
$$0 \leq \text{Cap}_t^{\text{e,buy}} \leq P_{\max}. \quad (25)$$

The capacity bid in the energy market is split into the selling part $\text{Cap}_t^{\text{e,sell}}$ and the buying part $\text{Cap}_t^{\text{e,buy}}$, as described in (23). A positive Cap_t^{e} indicates the storage selling energy to the market, and a negative value indicates purchasing. Equations (24) and (25) set bounds for bidding capacities in the energy market.

The maintenance cost Cost^m is proportional to the rated power capacity of the battery as

$$\text{Cost}^m = c_m P_{\max}. \quad (26)$$

B. Constraints

Equations (27)–(34) model the operational constraints of the battery storage.

1) Capacity Constraints: The sum of the capacity bids of battery storage must be kept within its upper and lower limits

$$\text{Cap}_t^{\text{e}} - \sigma \text{Cap}_t^{\text{reg}} \geq -P_{\max} \quad (27)$$
$$\text{Cap}_t^{\text{e}} + \text{Cap}_t^{\text{res}} + \sigma \text{Cap}_t^{\text{reg}} \leq P_{\max}. \quad (28)$$

For 1-unit capacity committed in the regulation market, storage should hold capacity of σ unit for both regulation up and down. Since the battery's full power response time is several milliseconds, which is much shorter than the RegD signal's 4-s resolution, there is no ramping rate constraint.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

6   IEEE TRANSACTIONS ON SMART GRID

2) Energy Constraints: Battery storage is also required to hold energy to provide ancillary service in response to the system operator's order

$$E_t \geq \left(\text{Cap}_t^e h + \text{Cap}_t^{\text{res}} h + \text{Cap}_t^{\text{reg}} h^{\text{reg}}\right) / \eta_0 \tag{29}$$

$$E_t \leq E_{\max} + \left(\text{Cap}_t^e h - \text{Cap}_t^{\text{reg}} h^{\text{reg}}\right) \eta_0. \tag{30}$$

A battery must be able to maintain the fully-deployed output level for at least h (typically 1 h) for spinning reserve service and h^{reg} (typically 15 min) for regulation service [4], considering the energy loss.

3) State of Charge Constraints: E_{t+1}, the state of charge (SOC) at hour $t + 1$, depends on the SOC at hour t and the charge–discharge behavior during hour t

$$E_{t+1} = (1 - \alpha) E_t + \Delta E_t. \tag{31}$$

ΔE_t represents the amount of energy change due to energy selling and purchasing, reserve deployment, and energy loss in providing regulation service L_t^{reg}, as

$$\Delta E_t = -\frac{1}{\eta_0} \text{Cap}_t^{e,\text{sell}} h + \eta_0 \text{Cap}_t^{e,\text{buy}} h - \frac{1}{\eta_0} g_t^{\text{res}} h - L_t^{\text{reg}} \tag{32}$$

$$L_t^{\text{reg}} = \frac{\beta_t \text{Cap}_t^{\text{reg}}}{\eta_0} - \beta_t \text{Cap}_t^{\text{reg}} \eta_0. \tag{33}$$

Despite the energy-neutral characteristic of the RegD signal, there exists energy loss in the battery providing regulation service, resulted from the battery's energy loss in both charging and discharging. As in (33), this energy loss in providing regulation service, L_t^{reg}, depends on the average energy consumed in regulation up or down per unit committed capacity, the committed regulation capacity and energy efficiency. The first part on the right side of (33) represents the energy discharged from the battery during regulation up in hour t, while the second part represents the energy charged to the battery during regulation down in hour t.

$$E_0 = E_{t_{\max}}. \tag{34}$$

The initial and final SOC are set to be equal during the optimization period, as described in (34). $t_{\max}$ represents the end of the day.

V. CASE STUDY

We used GAMS and MATLAB to solve the model on a PC with an Intel Core 7 CPU (2.4 GHz) and 8.0 GB RAM.

A. Basic Data

We used historical market data in May 2014 from PJM and Electric Reliability Council of Texas (ERCOT) to generate scenarios. Day-ahead prices for energy and spinning reserve were obtained from ERCOT and regulation market data from PJM. The reason that we used the spinning reserve price from ERCOT rather than PJM is that PJM's price of spinning reserve is very low because it has a capacity market to compensate, which is beyond the scope of this paper. The probability of reserve deployment γ^{res} is chosen to be 5% [9]. σ is set to be 1. A 4-s simulated RegD signal was generated based on real RegD signal data in May 4–10, 2014. As tested, the

TABLE I
AVERAGE PRICE AND REGD PARAMETERS

$P_{s,t}^e$ ($/MWh)	$P_{s,t}^{res}$ ($/MW)	$P_{s,t}^{reg,cap}$ ($/MW)	$P_{s,t}^{reg,perf}$ ($/MW)	$R_{s,t}^{mileage}$	β_t (MWh/MW)
35.90	10.72	30.73	3.31	2.87	0.13

Fig. 5.   Average generated hourly market prices.

TABLE II
BATTERY STORAGE PARAMETERS

P_{max}	E_{max}	η_0^2	α	$Score^{perf}$	T_{float}	N_{100}^{fail}	k_P
30 MW	30 MWh	70%	0	0.9	10 years	10,000	0.85

TABLE III
COST PARAMETERS

μ	IC_P ($/kW)	IC_E ($/kWh)	IC_F ($)	c_{op} ($/MWh)	c_m ($/MW)
15%	2300	300	250,000	0.5	15.4

cycle life calculation result of the simulated signal was very close to that of the real signal. Table I summarizes the price data and the RegD's parameters, averaged across all scenarios and hours. Fig. 5 shows the hourly prices in energy, spinning reserve, and regulation markets, averaged over all generated scenarios.

A 30-MW, 1-h vanadium flow battery with 70% round trip efficiency was considered in the base case. k_P is fitted to 0.85, based on the cycle life data of the vanadium flow battery from [13]. Table II summarizes the battery's parameters.

A vanadium redox flow battery's cost is introduced in [27] based on investigation. The total investment cost is derived as

$$\text{Cost}_{\text{invest}} = (1 + \mu) \cdot (IC_P \cdot P_{\max} + IC_E \cdot E_{\max} + IC_F) \tag{35}$$

where μ denotes the component replacement cost as a proportion of initial investment cost, IC_P and IC_E are the unit costs related to power and energy capacity, respectively, and IC_F is the fixed cost part. All cost parameters are summarized in Table III [27].

B. Results and Comparisons

Fig. 6 shows the optimal bidding strategies and energy curves of battery storage in different cases. The optimal

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

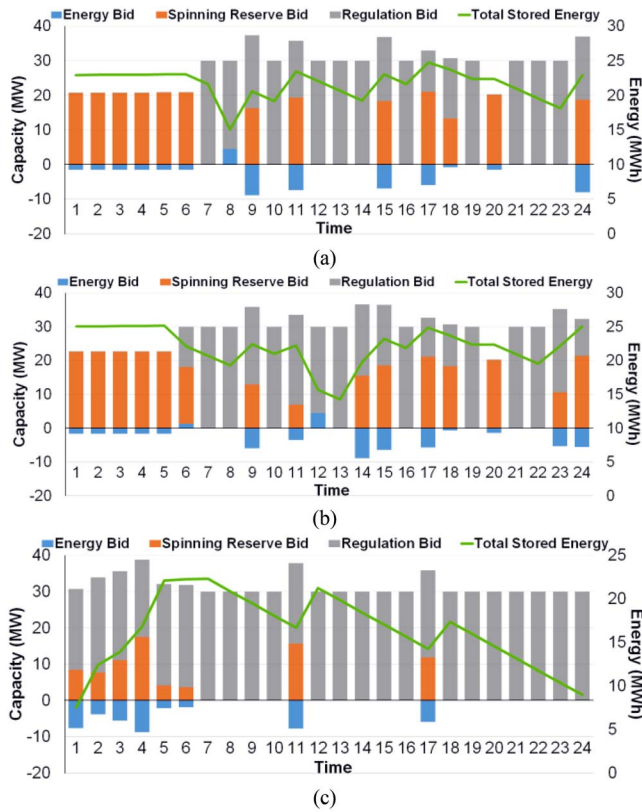HE *et al.*: OPTIMAL BIDDING STRATEGY OF BATTERY STORAGE IN POWER MARKETS 7

Fig. 6. Optimal bidding strategies and energy curves of battery storage. (a) Base case considering PBR payment and cycle life. (b) Case without considering PBR payment. (c) Case without considering cycle life.

bidding strategy and corresponding energy curve of battery storage in the base case are shown in Fig. 6(a). The results in the other cases when PBR payment or battery cycle life is not considered are shown in Fig. 6(b) and (c), respectively. The blue, orange, and gray bars represent energy, spinning reserve, and regulation bids, respectively. The length of bar denotes the amount of bid. The green curves represent the energy levels in storage at different hours.

In all three cases, regulation capacity dominates most of the day. When regulation prices are comparatively low, battery storages purchase in the energy market to balance the energy loss, which can be observed by comparing Figs. 5 and 6. The regulation capacity bids must be reduced at that time to make charging possible, and the spinning reserve can be supplied then.

The impact of considering PBR payment on battery storage's optimal bidding strategy can be observed by comparing Fig. 6(b) with Fig. 6(a). There are more spinning reserve bids and fewer regulation bids in Fig. 6(b) compared with those in Fig. 6(a) during some hours. This is because the income from the regulation market is comparatively lower without considering PBR payment, making increasing of the spinning reserve bids profitable.

Embedding battery cycle life into bidding strategy optimization has a significant impact on the optimal bidding strategy of battery storage, which can be clearly observed by comparing Fig. 6(c) with Fig. 6(a). It is beneficial for the battery to

TABLE IV
DEVIATIONS IN BIDDING STRATEGY

	Energy	Reserve	Regulation
Average Hourly Deviation (MW)	2.15	7.14	10.28
Average Hourly Bid (MW)	2.20	10.47	17.91
Percentage	97.6%	68.2%	57.4%

TABLE V
BASE CASE RESULTS

	Income ($)	Percentage
Energy	-1221	-6.3%
Reserve	2731	14.0%
Regulation Capability	14,676	75.4%
Regulation Performance	3827	19.7%
Operational Cost	-551	-2.8%
Daily Income ($)	19,462	
Gross Income (mil. $)	114	
Total Investment Cost (mil. $)	90	
Profit Rate	26.3%	
Daily Equivalent 100%-DOD Cycle Number	3.42	
Cycle Life (year)	10.0	

TABLE VI
RESULTS OF A COMPARISON BETWEEN THE BASE CASE AND CASES
NOT CONSIDERING PBR PAYMENT OR BATTERY CYCLE LIFE

		Base case	No PBR payment	No cycle life
Daily Income ($)		19,462	15,591	23,790
Gross Income (mil. $)		114	91	88
Profit Rate		26.3%	1.2%	-2.2%
Daily Equivalent 100%-DOD Cycle Number	Decomposition Method	3.42	3.42	5.41
	Original Method	3.58	3.55	5.55
	Deviation Ratio	4.47%	3.52%	2.55%
Cycle Life (year)		10.0	10.0	6.3

slow degradation by not providing regulation service in some periods such as hours 1–6 and 20 in the base case as compared to the case of not considering battery cycle life in optimization. We summarize the hourly deviations in the optimal bidding strategy in Table IV, averaged across all 24 h in the day. The relative deviations of energy, spinning reserve, and regulation bids are 97.6%, 68.2%, and 57.4%, respectively.

Table V summarizes the cost-benefit analysis results of the base case. We can see that the income from the PBR market is the major income of battery storage. Income from providing the spinning reserve also contributes over 10%. Income from the energy market is negative, as the battery has to purchase electricity to balance energy consumption and loss. This indicates that in a market with a PBR mechanism, battery storage would be deeply involved in ancillary service markets, especially the regulation market, while taking advantage of the comparatively low price in off-peak periods to compensate for the energy loss in providing ancillary services. Under the optimal bidding strategy, the battery could make a 26.3% profit in total, and the daily equivalent 100%-DOD cycle number is limited to 3.42 to keep cycle life no less than ten years.

Table VI compares the profit and cycle life results of the three cases. The results indicate that considering PBR payment

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

8   IEEE TRANSACTIONS ON SMART GRID
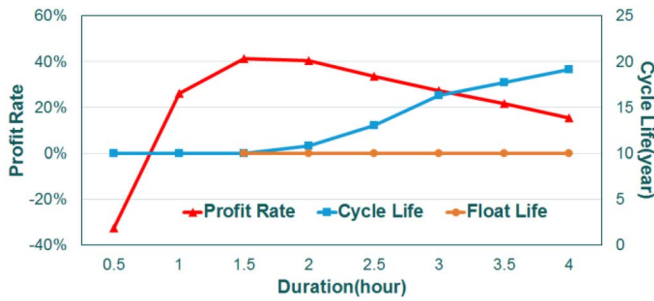

Fig. 7.   Sensitivity analysis on cases with different battery durations.

increases the battery storage's gross income and profit rate by approximately 25%. As for considering battery cycle life, though the daily income is lower, the profit rate is improved by nearly 30% because the battery's life is extended by limiting battery's cycling strategy. This improvement might be even more significant when the battery has a smaller k_P or number of 100%-DOD cycles to failure.

The accuracy of the proposed decomposition method is validated by comparing the daily equivalent 100%-DOD cycle numbers calculated using the simplified decomposition method and the original method, summarized in Table VI. In all the three cases, the deviation ratios in the cycle number are below 5%. Most of the deviations come from the hours when the capacity bid in the regulation market is not much larger than that in the other markets, such as hours 8, 9, 11, 15, 17, 18, 20, and 24.

The comparison results above prove that the proposed model considering the PBR mechanism and battery cycle life provides a different but more effective bidding strategy for storage owners, as well as a more realistic and accurate cost-benefit result for investors.

C. Sensitivity Analysis

The energy capacity of battery storage has an impact on its total profit. We examine cases with different battery durations, as shown in Fig. 7.

The result indicates that the optimal battery duration is approximately 1.5 h, with the largest profit rate. For batteries with a duration of less than 1.5 h, the profit rate increases as the duration increases, as shown by the red line in Fig. 7. This is because the energy constraints' limitations on the profit are relaxed when the storage has a longer duration. Additionally, the DOD of a certain bidding strategy is smaller for a battery with larger energy capacity, which allows for a wilder cycling strategy and thereby a higher daily income, while maintaining the same battery cycle life as the blue line in Fig. 7. These two factors that contribute to total profit are less significant for batteries with durations of more than 1.5 h. The cycle life has become even larger than the float life and thus has no impact on total profit. When we continue to raise the energy capacity, the increase of the investment cost dominates and causes the decrease in the profit rate.

The battery storage parameters concerning cycle life also have significant impact on its profit. Fig. 8 presents how the profit rate changes with variations in k_P and the
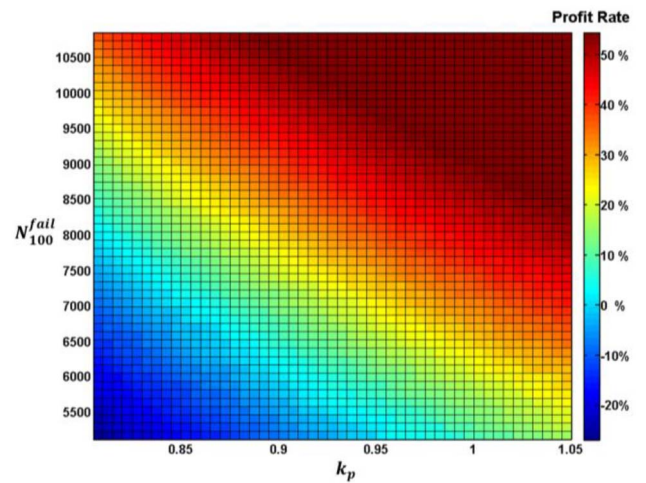

Fig. 8.   Sensitivity analysis of profit rate with different k_P and N_{100}^{fail}.

number of 100%-DOD cycles to failure N_{100}^{fail}, assuming the same investment cost. A larger k_P or N_{100}^{fail} means a higher tolerance in frequent and shallow cycles for fast regulation service and usually brings higher profit. For the same battery technology, a larger k_P or N_{100}^{fail} requires more investment cost, so that investors need to consider the tradeoff between the extra profit and investment cost. In the deep red area of Fig. 8, improvement of battery cycle life performance is unnecessary, as it brings no additional profit.

VI. Conclusion

Better bidding and operating strategies in power markets could remarkably improve the prospects and economic viability of battery storage. This paper proposes a model for investor-owned battery storage to optimally bid in power markets implementing a PBR mechanism. Considering providing fast regulation service largely affects battery life, a battery life model and a simplified battery cycle life calculation method are incorporated into the profit maximization model to take into account the battery life's impact on the total profit. Numerical results suggest that considering the PBR mechanism and battery cycle life could significantly improve battery storage's overall economics. Batteries with different durations and cycle life parameters are compared in sensitivity analyses, which could help decide its optimal configuration.

The regulation market is small compared to the energy and reserve markets. One remaining issue for future research is how to decide a battery storage's bidding strategy when it is no longer a price-taker in the regulation market.

References

[1] D. Rastler, "Electricity energy storage technology options: A white paper primer on applications, costs, and benefits," Elect. Power Res. Inst., Palo Alto, CA, USA, Tech. Rep. 1020676, 2010.

[2] Frequency Regulation Compensation in the Organized Wholesale Power Markets, Dockets RM11-7-000 and AD10-11-000, U.S. Fed. Energy Reg. Comm., Washington, DC, USA, Oct. 2011. [Online]. Available: http://www.ferc.gov/whats-new/comm-meet/2011/102011/E-28.pdf

[3] M. Kintner-Meyer, "Regulatory policy and markets for energy storage in North America," Proc. IEEE, vol. 102, no. 7, pp. 1065–1072, Jul. 2014.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

HE *et al.*: OPTIMAL BIDDING STRATEGY OF BATTERY STORAGE IN POWER MARKETS 9

[4] R. D. Masiello, B. Roberts, and T. Sloan, "Business models for deploying and operating energy storage and risk mitigation aspects," *Proc. IEEE*, vol. 102, no. 7, pp. 1052–1064, Jul. 2014.

[5] K. Bradbury, L. Pratson, and D. Patiño-Echeverri, "Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets," *Appl. Energy*, vol. 114, pp. 512–519, Feb. 2014.

[6] H. Akhavan-Hejazi and H. Mohsenian-Rad, "Optimal operation of independent storage systems in energy and reserve markets with high wind penetration," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1088–1097, Mar. 2014.

[7] S. J. Kazempour, M. Hosseinpour, and M. P. Moghaddam, "Self-scheduling of a joint hydro and pumped-storage plants in energy, spinning reserve and regulation markets," in *Proc. IEEE PES Gen. Meeting*, Calgary, AB, Canada, Jul. 2009, pp. 1–8.

[8] I. G. Moghaddam and A. Saeidian, "Self scheduling program for a VRB energy storage in a competitive electricity market," in *Proc. Int. Conf. Power Syst. Technol. (POWERCON)*, Hangzhou, China, Oct. 2010, pp. 1–6.

[9] A. K. Varkani, A. Daraeepour, and H. Monsef, "A new self-scheduling strategy for integrated operation of wind and pumped-storage power plants in power markets," *Appl. Energy*, vol. 88, no. 12, pp. 5002–5012, 2011.

[10] S. Tewari and N. Mohan, "Value of NAS energy storage toward integrating wind: Results from the wind to battery project," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 532–541, Feb. 2013.

[11] M. Swierczynski, D. I. Stroe, A.-I. Stan, R. Teodorescu, and D. U. Sauer, "Selection and performance-degradation modeling of $LiMO_2/Li_2Ti_5O_{12}$ and $LiFePO_4/C$ battery cells as suitable energy storage systems for grid integration with wind power plants: An example for the primary frequency regulation service," *IEEE Trans. Sustain. Energy*, vol. 5, no. 1, pp. 90–101, Jan. 2014.

[12] B. Yang *et al.*, "On the use of energy storage technologies for regulation services in electric power systems with significant penetration of wind energy," in *Proc. 5th Int. Conf. Eur. Elect. Market*, Lisbon, Portugal, pp. 1–6.

[13] R. Dufo-Lopez, J. L. Bernal-Agustin, and J. A. Dominguez-Navarro, "Generation management using batteries in wind farms: Economical and technical analysis for Spain," *Energy Policy*, vol. 37, pp. 126–139, Jan. 2009.

[14] S. You and C. N. Rasmussen, "Generic modelling framework for economic analysis of battery systems," in *Proc. IET Conf. Renew. Power Gener. (RPG)*, Edinburgh, U.K., Sep. 2011, pp. 1–6.

[15] I. Duggal and B. Venkatesh, "Short-term scheduling of thermal generators and battery storage with depth of discharge-based cost model," *IEEE Trans. Power Syst.*, in press.

[16] D. Tran and A. M. Khambadkone, "Energy management for lifetime extension of energy storage system in micro-grid applications," *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1289–1296, Sep. 2013.

[17] M. C. W. Kintner-Meyer *et al.*, "Energy storage for power systems applications: A regional assessment for the northwest power pool (NWPP)," Pac. Northwest Nat. Lab., Richland, WA, USA, Tech. Rep. PNNL-19300, 2010.

[18] C. J. Barnhart and S. M. Benson, "On the importance of reducing the energetic and material demands of electrical energy storage," *Energy Environ. Sci.*, vol. 6, no. 4, pp. 1083–1092, 2013.

[19] C. J. Rydh and B. A. Sandén, "Energy analysis of batteries in photovoltaic systems. Part I: Performance and energy requirements," *Energy Convers. Manage.*, vol. 46, nos. 11–12, pp. 1957–1979, Jul. 2005.

[20] E. Schaltz, A. Khaligh, and P. O. Rasmussen, "Influence of battery/ultracapacitor energy-storage sizing on battery lifetime in a fuel cell hybrid electric vehicle," *IEEE Trans. Veh. Technol.*, vol. 58, no. 8, pp. 3882–3891, Oct. 2009.

[21] L. H. Thaller, "Expected cycle life vs. depth of discharge relationships of well behaved single cells and cell strings," Lewis Res. Center, Nat. Aeronaut. Space Admin., Washington, DC, USA, Tech. Rep. 82597, 1982.

[22] T. Dragicevic *et al.*, "Capacity optimization of renewable energy sources and battery storage in an autonomous telecommunication facility," *IEEE Trans. Sustain. Energy*, vol. 5, no. 4, pp. 1367–1378, Oct. 2014.

[23] M. Musallam and C. Johnson, "An efficient implementation of the rain-flow counting algorithm for life consumption estimation," *IEEE Trans. Rel.*, vol. 61, no. 4, pp. 978–986, Dec. 2012.

[24] *Performance Based Regulation: Year One Analysis*, PJM, Valley Forge, PA, USA, 2013.

[25] *PJM Manual 28: Operating Agreement Accounting*, PJM, Valley Forge, PA, USA, 2014.

[26] *PJM Manual. 12: Balancing Operations*, PJM, Valley Forge, PA, USA, 2014.

[27] S. Eckroad, "Vanadium redox flow batteries: An in-depth analysis," Elect. Power Res. Inst., Palo Alto, CA, USA, Tech. Rep. 1014836, Mar. 2007.

Guannan He received the Bachelor's degree in electrical engineering from Tsinghua University, Beijing, China, in 2014, where he is currently pursuing the post-graduate degree.

His current research interests include energy storage economics, power system economics, power markets, and smart grid.

Qixin Chen (M'10) received the Ph.D. degree in electrical engineering from Tsinghua University, Beijing, China, in 2010.

He is currently an Associate Professor with Tsinghua University. His current research interests include low-carbon electricity, power system economics and optimization, power markets, and power generation expansion planning.

Chongqing Kang (M'01–SM'07) received the Ph.D. degree in electrical engineering from Tsinghua University, Beijing, China, in 1997.

He is currently a Professor with Tsinghua University. His current research interests include renewable energy, power system planning and operation, low-carbon electricity, electricity marketing, and load forecasting.

Pierre Pinson (M'11–SM'13) received the M.Sc. degree in applied mathematics from the National Institute for Applied Sciences (INSA) ,Toulouse, France, in 2002, and the Ph.D. degree in energetics from Ecole des Mines de Paris, Paris, France, in 2006.

He is a Professor with the Department of Electrical Engineering, Centre for Electric Power and Energy, Technical University of Denmark, Lyngby, Denmark, also heading a group focusing on Energy Analytics & Markets. His research interests include, among others, forecasting, uncertainty estimation, optimization under uncertainty, decision sciences, and renewable energies.

Prof. Pinson acts as an Editor for the IEEE TRANSACTIONS ON POWER SYSTEMS, the *International Journal of Forecasting, and Wind Energy*.

Qing Xia (M'01–SM'08) received the Ph.D. degree in electrical engineering from Tsinghua University, Beijing, China, in 1989.

He is currently a Professor with Tsinghua University. His current research interests include power economics, power markets, generation scheduling optimization, power system planning, and load forecasting.