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Scheduling of wind-battery hybrid system in the electricity market using distributionally robust optimization

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ABSTRACT

With the liberation of the electricity market, a growing number of investors participate in market bidding. However, due to the inaccurate prediction of wind power, the interest of the investors can be damaged. In order to solve such problem, a distributionally robust chance-constrained (DRCC) scheduling for a wind-battery hybrid system in the day-ahead electricity market is developed by considering the uncertain wind power. The overall objectives of this paper contain revenue calculation from the electricity market, curtailment penalty caused by the wind power, and degradation cost of the battery. When selling/buying electricity is to/from the electricity market, the available power is limited by the capacity of the transmission line. This paper develops a chance constraint for the transmission line and introduces the moment ambiguity set to capture the uncertain wind power generation. The chance constraint can be reformulated into a standard second-order conic programming problem (SOCP) via a distributionally robust optimization method. The model is tested with a case study and the results indicate that the battery plays an important role in wind power scheduling in the electricity market. In the end, comparison with the stochastic optimization with normal distribution (SND) is conducted to prove the performance and robustness of the proposed model based on a distributionally robust optimization (DRO) method.

1. Introduction

In recent years, the proportion of wind power has rapidly increased. In Europe, wind power generation is the highest installed capacity for the new installations among other generating technologies [1]. However, the growing penetration of wind power with high uncertainty and randomness may bring large operational challenges to the electricity markets. The market behaviors being influenced by the spatially correlated wind production are analyzed in Ref. [2]. Meanwhile, ref. [3] evaluates the impact of wind power generation on the electricity price behaviors. The long-term impact of wind power with different share on the Iberian day-ahead electricity market price is quantified in Ref. [4]. Besides, short-term forecasting of wind power and market price is considered to dispatch the wind-battery power station for maximizing the revenue [5]. In the electricity market, these inherent natures (such as stochastic and uncertainty) are unfriendly to the wind power producers (WPPs), which can do damage on the WPPs' interest.

In order to address the non-dispatchable wind power generation, integrating energy storage devices in a single wind farm may be a promising way to so forward [6]. In Ref. [7], the wind power plant combines with a pumped hydro storage plant to maximize benefits in the day-ahead and the balancing markets. Due to the investment cost reduction on the battery energy storage system (BESS), it becomes an amiable alternative for different gird-support situations. Ref. [8] assesses the economic feasibility of investing in BESS in the electricity markets. In Ref. [9] is proven the technical feasibility of using a battery storage system to ensure the WPPs' commitment to day-ahead ancillary services market. This paper selects the battery to operate with a wind farm.

To address the inaccurate prediction, many methods are presented to improve the short-term forecasting accuracy of wind power. Existing short-term wind power forecasting methods can be

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Nomenclature

A. ABBREVIATIONS

BESS	Battery Energy Storage System
CC	Chance Constraint
CCP	Chance Constrained Programming
CVaR	Conditional Value-at-Risk
DRO	Distributionally Robust Optimization
DRCC	Distributionally Robust Chance-Constrained
OPF	Optimal Power Flow
PSMTLC	Percentage of the Scenarios that Meet the Transmission Line Constraint
RO	Robust Optimization
SP	Stochastic Programming
SND	Stochastic Optimization with Normal Distribution
SOCP	Second-Order Conic Programming Problem
VaR	Conditional Value-at-Risk
WPPs	Wind Power Producers

B. DECISION VARIABLES

$P_{bat,t}$	Charge/discharge power at time interval t, its charge/discharge behavior is determined by a binary variable (MW)
B_t	Binary variable at time interval t (0, 1)
$P_{cur,t}$	Wind power curtailment at time interval t (MW)

C. PARAMETERS

$C_{bat,t}$	Battery degradation cost at time interval t (DKK)
$E_{bat,t}$	Energy storage of the battery at time interval t (MWh)
$E_{bat,t+1}$	Energy storage of the battery at time interval t+1 (MWh)
E_{bat}^{min}	Minimum energy storage of the battery (MWh)
E_{bat}^{max}	Maximum energy storage of the battery (MWh)
$E_{bat,0}$	Energy storage at beginning the simulation time (MWh)
$E_{bat,T}$	Energy storage at the end of the simulation time (MWh)
EP_t	Electricity price at time interval t (DKK/MWh)
$\mathbb{E}_{\mathbb{P}_t}$	Expectation under distribution $\mathbb{P}_t$
G_t	The distribution space of the random variable
k_{bat}	Battery degradation cost coefficient (DKK/MW)
k_{WF}	Curtailment penalty coefficient (DKK/MW)
P_{bat}^{max}	Maximum charge/discharge power of the battery (MW)
$P_{WF,t}$	Forecasted wind power generation at time interval t (MW)
$PE_{WF,t}$	Wind power curtailment penalty at time interval t (DKK)
P_{line}^{max}	Maximum transmission line capacity (MW)
$\mathbb{P}_t$	Probability distribution of the random variable
$\mathscr{P}_t^0(G_t)$	The set of all the probability distributions supported on G_t
$\mathscr{P}_t$	Ambiguity set of the probability distribution of the uncertain wind power generation
R_{tot}	Total revenue during the simulation time (DKK)
$R_{WF,t}$	Revenue by selling electricity to the electricity market (DKK)
t	Index of time slot
x_t	The general representation of decision variables
$z^0(x_t)$	Auxiliary function of x_t
$z(x_t)$	Auxiliary coefficient function of x_t
η_{dch}	Discharge efficiency of the battery
η_{ch}	Charge efficiency of the battery
ζ_t	Random variable to represent the uncertain wind power generation at time interval t (MW)
ε	Violation probability of the bounds of transmission line
μ_t	Forecasted wind power generation which is the same as $P_{WF,t}$
σ_t^2	Variance of the wind power generation obtained from historical data
Δt	Time constant (1 h)
$\theta, \rho, \varsigma, \nu, \gamma, \xi$	Auxiliary variables in the SOCP constraint formulation

divided into three types [10]: physical models, statistical models and hybrids which combines physical and statistical models. The forecasting error is unavoidable, so the wind power generation was still uncertainty and randomness. To handle the uncertainty caused by renewable energy generation such as wind power, solar power, various methods which are robust optimization (RO), stochastic programming (SP) and chance-constrained programming (CCP) have been analyzed.

Stochastic programming is a popular method to deal with the uncertainties of renewable power generation in the electricity markets [11]. This method uses a determinated distribution like normal distribution to represent the uncertainties caused by the renewable energy generation [12]. Ref. [13] aims to address the problem of joint bidding for a system including photovoltaic power, wind power and BESS in a day-ahead market, a two-stage stochastic programming model is developed, which considers the uncertainty of wind and PV power generation. This model can be also found in Refs. [14,15] to deal with the uncertainties. A novel stochastic programming framework is proposed to schedule a microgrid system in a pool market [16]. However, SP is computationally challenging since it needs to generate a large number of scenarios. Additionally, the probabilistic distribution of the uncertainty variables must be known, which is impractical in the actual situation [11]. In general, RO can be used to deal with similar problems as SP. Compared with SP, RO needs less information on the uncertainty variables and can be solved faster. Ref. [17] gives a detailed description of the RO. [18] investigates the robust optimization to find an optimal bidding strategy in the pool-based electricity market. The study of RO in the unregulated electricity markets can be found in Ref. [19]. However, the conservatism of the RO should be addressed.

The SP needs the exact probability distribution of the random variable [20]. In general, the exact probability distribution cannot be obtained since the distribution itself is uncertain. The deviation between the real distribution and the used distribution may lead to suboptimal results [21]. Although the RO does not need the exact probability distribution [22], it may be excessively conservative because it only considers the maximum forecast error [23]. The distributionally robust optimization (DRO) is an intermediate method between SP and RO, which combines the advantages of the two methods [24]. Unlike SP, an exact probabilistic distribution does not need to obtain, DRO optimizes the expectation of the objective function based on a set of unknown distributions with certain statistical characteristics (such as mean and variance). The

DRO has been applied in the electric power system optimization like scheduling [25], unit commitment [26], energy management [27] and optimal power flow (OPF) [28] problem. Besides, it has been used to planning problems of the wind farm allocation [29], biding problems in the electricity markets [30] and so on. With the consideration of its advantages and wide utilization, the DRO is applied in this paper. Despite the wide investigation of DRO as a hot topic, it is not very abundant in terms of its utilization on chance-constrained problems. For the DRCC model, it is mainly focused on OPF problems [28,31].

The contributions of the study are:

(1) A CC for the transmission line of a wind-battery hybrid system is proposed. It aims to investigate a scheduling problem of the system in the day-ahead electricity market. Most of the existing study concentrates on the strict inequality constraint with limit attention on the CC.
(2) The objective function of this study contains three different aspects. They are revenues obtained from the electricity market, curtailment penalty caused by the wind power, and degradation costs of the battery. The degradation cost is a very important parameter as it may affect the operation of the system. It is, however, not considered in most of the previous literature.
(3) This study adopts DRO method to transform the CC scheduling problem of the wind-battery hybrid system into a standard SOCP problem. To prove the performance of the DRO method, SND is used to conduct the simulation for the purpose of comparison.

The rest of the paper is organized as follows. The problem formulation of wind-battery hybrid system scheduling is presented in Section 2. Section 3 proposes solution method to reformulate the DRCC to be a standard SOCP. Simulation results are given in Section 4, and finally, conclusions can be found in Section 5.

2. Problem formulation

The scheduling problem of a wind-battery hybrid system in the electricity market is formulated in this section. Fig. 1 shows the diagram of the wind-battery hybrid system. The main grid represents the electricity market. In this paper, the transmission lines only support the operation of the wind-battery hybrid system. This setting is supported by the studies with real wind farms as the case. Horns Rev [32] and Anholt [33] are two real offshore wind farms in Denmark which connect to the main grid through the transmission

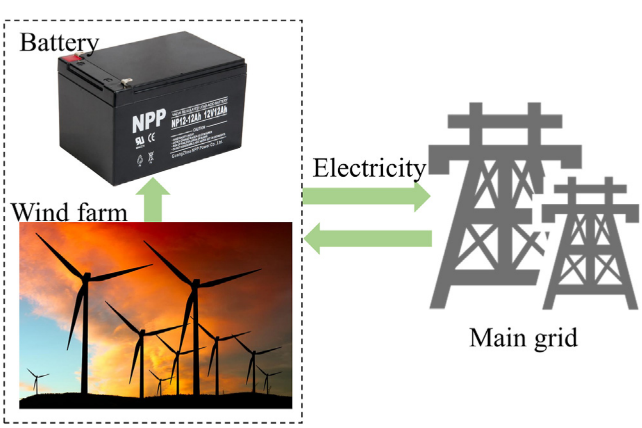

Fig. 1. The diagram of the wind-battery hybrid system.

lines. In order to obtain the complete optimization model, the models of each component and the objectives are presented below.

2.1. Battery

In the day-ahead electricity market, battery shows an excellent performance in terms of getting profits. In this work, under the constraint of transmission line capacity, the batteries operate with a wind farm to improve the revenue obtained from the electricity market and reduce the wind power curtailment with the consideration of the uncertain wind power. The dynamic model and constraints of the battery are given below [34]. Constraint (1) is the dynamic energy model of the battery, which changes if the battery works. Constraint (2) is used to confine the charge/discharge power, its charge/discharge behavior is determined by a binary variable B_t. Constraint (3) limits the stored energy of the battery to avoid over-charge/discharge. Constraint (4) is used to manage the energy change of the battery at the beginning and end of the day in order to extend the battery's lifetime and ensure the discharge/charge ability the next day. In this paper, it is considered that the stored energy at the beginning of the simulation time should be equal to that at the end of the simulation time. (5) is a binary constraint that makes the problem be a mixed-integer linear programming (MILP) problem. When$B_t = 1/B_t = 0$, the battery is in the charging/discharging state.

$$E_{bat,t+1} = E_{bat,t} + \eta_{ch} \cdot B_t \cdot P_{bat,t} \cdot \Delta t - (1 - B_t) \cdot P_{bat,t} \cdot \Delta t / \eta_{dch}, \forall t \tag{1}$$

$$0 \le P_{bat,t} \le P_{bat}^{\max}, \forall t \tag{2}$$

$$E_{bat}^{\min} \le E_{bat,t} \le E_{bat}^{\max}, \forall t \tag{3}$$

$$E_{bat,T} = E_{bat,0} = E_{bat}^{\max}/2, \forall t \tag{4}$$

$$B_t \in (0, 1), \forall t \tag{5}$$

where $E_{bat,t+1}$ and $E_{bat,t}$ are the energy storage of the battery at time interval t+1 and t, respectively. $P_{bat,t}$ is the charge/discharge power at time interval t, its charge/discharge behavior is determined by a binary variable. B_t is the Binary variable at time interval t. η_{ch} and η_{dch} are the charge and discharge efficiency of the battery, respectively. Δt is the time constant. $P_{bat}^{\max}$ is the Maximum charge/discharge power of the battery. $E_{bat}^{\min}$ and $E_{bat}^{\max}$ are the minimum and maximum energy storage of the battery, respectively. $E_{bat,0}$ and $E_{bat,T}$ are the energy storage at the beginning and end of the simulation time, respectively.

Due to the frequent charge and discharge behaviors, the battery will degrade, which may result in a higher cost. Hence, the battery degradation cost is considered in this work. For simplification, a linear model is used to evaluate the battery degradation cost, which is expressed as follows [35]:

$$C_{bat,t} = k_{bat} \left(\eta_{ch} P_{bat,t} B_t + P_{bat,t} (1 - B_t) / \eta_{dch} \right) \Delta t \tag{6}$$

where $C_{bat,t}$ represents the Battery degradation cost at time interval t. k_{bat} is the Battery degradation cost coefficient.

2.2. Wind power curtailment

For the WPPs, they hope all the power generated from the wind farm can be sold. It is difficult to achieve due to the capacity limit of the transmission line between the wind farm and the main grid. In order to improve the utilization of wind power, the wind power curtailment is considered as a penalty term in the complete objective function. The wind power curtailment penalty can be calculated by Equation (7). The constraint of the curtailed wind power is given in Equation (8) which cannot exceed the actual wind power output at time interval t.

$$PE_{WF,t} = k_{WF} P_{cur,t} \tag{7}$$

$$0 \le P_{cur,t} \le P_{WF,t} \tag{8}$$

where $PE_{WF,t}$ is the wind power curtailment penalty at time interval t. k_{WF} is the curtailment penalty coefficient. $P_{cur,t}$ is the forecasted wind power generation at time interval t. $P_{cur,t}$ is the Wind power curtailment at time interval t.

2.3. Revenue

Investors focus on the revenue earned by selling power to the electricity market. When the electricity price is low, the power generated from the wind farm can be stored in the battery or sold to the electricity market directly. When the price is high, the power stored in the battery can be sold. In this way, wind power dispatching is realized via battery. Equation (9) is used to calculate the revenue obtained from the wind-battery hybrid system. It should be noted that the wind-battery hybrid system cannot buy electricity from the electricity market. All the charged power of the battery comes from the wind farm. Therefore, Equation (10) gives the constraint of the charged power of the battery, which means that the charged power cannot exceed the wind power output.

$$R_{WF,t} = EP_t(\zeta_t - P_{bat,t}B_t + P_{bat,t}(1 - B_t) - P_{cur,t}) \tag{9}$$

$$0 \le P_{bat,t}B_t \le P_{WF,t} \tag{10}$$

where $R_{WF,t}$ represents the revenue by selling electricity to the electricity market. EP_t is the electricity price at time interval t. ζ_t is the random variable to represent the uncertain wind power generation at time interval t.

2.4. Chance constraint for transmission line

For the transmission line constraint, most of the existing study concentrates on the strict inequality constraint. Actually, the transmission line has a certain ability to operate overloaded. In this context, CCP is applied to allow the electricity transmitted on the line to violate the maximum transmission line maximum capacity, which should be no more than $1 - \varepsilon$for all the probability distributions of the wind power generation in the ambiguity set. Therefore, this paper proposes a chance constraint for the transmission line, which can be written as follows:

$$Pr\{P_{bat,t}(1 - B_t) - P_{bat,t}B_t - P_{cur,t} + \zeta_t \le P_{line}^{\max}\} \ge 1 - \varepsilon \tag{11}$$

where ε is the violation probability of the bounds of transmission line. $P_{line}^{\max}$ is the Maximum transmission line capacity. It should be noted in Equation (11) that the wind power generation is the random variable which is determined by the ambiguity set, while the wind power curtailment is the decision variable and needs to be optimized. In the next section, the ambiguity set of its probability distribution is presented.

According to the above model, the objective function of the scheduling of the wind-battery hybrid system can be obtained, i.e., the total revenue of the wind-battery hybrid system in the electricity market, which contains the revenue by selling electricity, the wind power curtailment penalty and the battery degradation cost as given below:

$$\max R_{tot} = \max \mathbb{E}\left\{ \sum_{t=1}^{T} [R_{WF,t} - PE_{WF,t} - C_{bat,t}] \right\} \tag{12}$$

where R_{tot} represent total revenue during the simulation time. $\mathbb{E}\{\bullet\}$ is used to calculate the expected value of the objective function. Equation (12) is the objective function of the wind-battery hybrid system which aims to maximize the expected revenue obtained from the electricity market with considering wind power curtailment penalty and the battery degradation cost. The objective function includes the random variable ζ_t. Based on the ambiguity set, it can be known that the expectation of the random variable ζ_t is μ_t. And $P_{WF,t}$ is used to represent μ_t. Therefore, the random variable ζ_t is replaced by $P_{WF,t}$ after finding the expectation of the objective function. The complete optimization model is formulated as follows:

$$\max_{\mathbf{x}}\{(12) : (1) - (11)\} \tag{13}$$

where $\mathbf{x}$ represents a set of decision variables. In (13), constraint (11) is a chance constraint and it cannot be calculated directly. In the next section, constraint (11) is reformulated into a second-order cone programming problem using distributionally robust optimization.

3. Solution methodology

The scheduling problem of the wind-battery hybrid system modelled above is hard to find the results directly because of the proposed chance constraint of the transmission line and the uncertain wind power generation. In order to deal with the problem, an ambiguity set under known moment information is introduced to depict the uncertain probability distribution of the wind power generation. Next, according to the ambiguity set, the DRO method is used to reformulate the CC. In the end, the CC problem is transformed into a SOCP problem.

3.1. An ambiguity set for wind power generation

In the chance constraint of the transmission line, the random variable only considers the uncertain wind power generation. Another random variable such as uncertain electricity price is not considered in this work, which will be conducted in future work. In the previous studies, various methods have been investigated to describe the uncertain renewable energy generation. For RO method [36], uses polyhedral uncertain set to address the stochastic availability of renewable energy generation. The ellipsoid uncertain set is applied for unit commitment problem in Ref. [37]. For SO method, the uncertain parameters are described based on certain distribution functions [38]. Unlike these two methods, the DRO methods process the uncertain parameters based on an ambiguity set. The ambiguity set can represent all the probability distributions of the uncertain parameters. Many types of ambiguity sets have been proposed.

Considering that the moment ambiguity sets are widely investigated and have been used to deal with the uncertain wind power generation [27], this method is selected in this paper. The moment ambiguity set with known mean and variance is given as follows:

$$\mathscr{P}_t = \left\{ \mathbb{P}_t \in \mathscr{P}_t^0(G_t) \middle| \begin{array}{l} \mathbb{P}\{\zeta_t \in G_t\} = 1 \\ \mathbb{E}_{\mathbb{P}_t}\{\zeta_t\} = \mu_t \\ \mathbb{E}_{\mathbb{P}_t}\left\{(\zeta_t - \mu_t)^2\right\} = \sigma_t^2 \end{array} \right\} \tag{14}$$

where $\mathscr{P}_t$ represents the Ambiguity set of the probability distribution of the uncertain wind power generation. μ_t denotes the forecast wind power generation. σ_t^2 denotes the variance of the wind power generation obtained from historical data. $\mathbb{P}_t$ represents the probability distribution of the random variable. $\mathscr{P}_t^0(G_t)$ represents the set of all the probability distributions supported on G_t. $\mathbb{E}_{\mathbb{P}_t}$ is the Expectation under distribution $\mathbb{P}_t$. G_t is the distribution space of the random variable.

According to the moment ambiguity set, the variant of the CC (10) can be obtained as follows:

$$\mathbb{P}_t\{P_{bat,t}(1-B_t) - P_{bat,t}B_t - P_{cur,t} + \zeta_t \le P_{line}^{\max}\} \ge 1-\varepsilon, \ \forall \mathbb{P}_t \in \mathscr{P}_t \tag{15}$$

3.2. Problem reformulation

In this subsection, the distributionally robust chance constraint (DRCC) (15) can be reformulated to be a tractable SOCP problem. Then the scheduling models of the wind-battery hybrid system based on the DRO method can be solved. For convenience, DRCC (15) are presented in a general form.

$$\mathbb{P}_t\left\{z^0(x_t) + z(x_t)\cdot\zeta_t \le 0\right\} \ge 1-\varepsilon \, \forall \mathbb{P}_t \in \mathscr{P}_t \tag{16a}$$

$$z^0(x_t) = P_{bat,t}(1-B_t) - P_{bat,t}B_t - P_{cur,t} - P_{line}^{\max} \tag{16b}$$

$$z(x_t) = 1 \tag{16c}$$

where $z^0(x_t)$ represents the Auxiliary function of x_t. $z(x_t)$ represents the Auxiliary coefficient function of x_t.

The DRCC problem is processed using Conditional Value-at-Risk (CVaR) approximation. It has been proved in Ref. [39] that:

$$\begin{array}{l} \mathbb{P}_t - \mathrm{CVaR}_\varepsilon\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right) \le 0 \\ \Rightarrow \mathbb{P}_t\left\{z^0(x_t) + z(x_t)\cdot\zeta_t \le 0\right\} \ge 1-\varepsilon \end{array} \tag{17}$$

where the CVaR at confidence level ε regarding probability distribution $\mathbb{P}_t$ is presented below:

$$\begin{array}{l} \mathbb{P}_t - \mathrm{CVaR}_\varepsilon\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right) \\ \quad = \inf\limits_{\lambda\in\mathscr{R}}\left\{\lambda + \frac{1}{\varepsilon}\mathbb{E}_{\mathbb{P}_t}\left\{\left(z^0(x_t) + z(x_t)\cdot\zeta_t - \lambda\right)^+\right\}\right\} \end{array} \tag{18}$$

where $(\beta)^+ = \max(0,\beta)$. CVaR is put forward based on the Value-at-Risk (VaR). CVaR is defined as the mean of $z^0(x_t) + z(x_t)\cdot\zeta_t$ on the tail distribution exceeding VaR. The detailed description of VaR and CVaR can be found in Ref. [40]. According to (17) and (18), constraint (16a) is satisfied if

$$\mathbb{P}_t - \mathrm{CVaR}_\varepsilon\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right) \le 0 \, \forall \mathbb{P}_t \in \mathscr{P}_t \tag{19}$$

Theorem 1. *Under the moment ambiguity set $\mathscr{P}_t$, the DRCC (19) can be satisfied if and only if there exist auxiliary variables $\lambda, \theta, \rho, \nu, \varsigma$, such that*

$$\lambda + \frac{1}{\varepsilon}(\theta + \rho) \le 0 \tag{20a}$$

$$\varsigma + \rho \ge \sqrt{\nu^2 + z^2(x_t)\sigma_t^2 + (\varsigma - \rho)^2} \tag{20b}$$

$$\theta - z^0(x_t) + \lambda + \nu - z(x_t)\mu_t - \varsigma > 0 \tag{20c}$$

$$\theta \ge 0, \varsigma > 0 \tag{20d}$$

Note that the constraint (20b) is a tractable standard SOCP constraint [41]. Therefore, the CC problem (11) for the transmission line capacity is reformulated to the SOCP constraints (20).

Next, the DRCC scheduling problem of the wind-battery hybrid system based on the moment ambiguity set can be reformulated as follows (21):

$$\max_{\mathbf{x},\partial}\{(12) : (1) - (10), (20)\} \tag{21}$$

where $\mathbf{x}$ and ∂ represent the set of decision variables and auxiliary variables.

Proof: First, the left side constraint (19) is equivalent to

$$\begin{array}{l} \sup\limits_{\mathbb{P}_t\in\mathscr{P}_t}\inf\limits_{\lambda\in\mathscr{R}}\left\{\lambda + \frac{1}{\varepsilon}\mathbb{E}_{\mathbb{P}_t}\left\{\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right)^+\right\}\right\} \\ \quad = \inf\limits_{\lambda\in\mathscr{R}}\left\{\lambda + \frac{1}{\varepsilon}\sup\limits_{\mathbb{P}_t\in\mathscr{P}_t}\mathbb{E}_{\mathbb{P}_t}\left\{\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right)^+\right\}\right\} \le 0 \end{array} \tag{22}$$

where the sup and inf can be interchanged on the basis of stochastic saddle point theorem [42]. In order to reformulate constraint (22), the inner maximum expectation problem, which is presented in (23) should be processed.

$$\sup_{\mathbb{P}_t\in\mathscr{P}_t}\mathbb{E}_{\mathbb{P}_t}\left\{\left(z^0(x_t) + z(x_t)\cdot\zeta_t\right)^+\right\} \tag{23}$$

It can be observed that the probability distribution of the wind power generation is not known and there are endless possibilities, which constitute an ambiguity set. Then, let $\xi = z(x_t)\cdot\zeta_t$, the mean and variance of ξ are $z(x_t)\mu_t$ and $(z(x_t))^2\sigma_t^2$ based on the moment ambiguity set $\mathscr{P}_t$, respectively. Hence, problem (23) is equivalent to the below integral from:

$$\sup_{\xi\in\mathscr{M}}\int_{\mathbb{R}}\left(\left(z^0(x_t) + c - \lambda\right)^+\right)\gamma(d\xi) \tag{24a}$$

$$\text{s.t.} \int_{\mathbb{R}}\gamma(d\xi) = 1 \tag{24b}$$

$$\int_{\mathbb{R}} c\gamma(d\xi) = z(x_t)\mu_t \tag{24c}$$

$$\int_{\mathbb{R}} c^2\gamma(d\xi) = z^2(x_t)\sigma_t^2 + (z(x_t)\mu_t)^2 \tag{24d}$$

where $\mathscr{M}$ denotes the cone of nonnegative Borel measures on$\mathbb{R}$. By introducing dual variables y_1, y_2, y_3, (24) is reformulated as

$$\inf_{y_1,y_2,y_3} y_1+y_2z(x_t)\mu_t+y_3\left[z^2(x_t)\sigma_t^2+(z(x_t)\mu_t)^2\right] \tag{25a}$$

$$s.t. y_1+y_2c+y_3c^2 \geq z^0(x_t)+c-\lambda \tag{25b}$$

$$y_1+y_2c+y_3c^2 \geq 0 \tag{25c}$$

$$y_3>0 \tag{25d}$$

Since $z^2(x_t)\sigma_t^2>0$, the strong duality satisfies, which is proved in [43]. *Then the constraint* (25*b*) *and* (25*c*) *can be equivalently formulated as*:

$$\inf_{y_1,y_2,y_3} y_1+y_2z(x_t)\mu_t+y_3\left[z^2(x_t)\sigma_t^2+(z(x_t)\mu_t)^2\right] \tag{26a}$$

$$s.t. y_1+\lambda-z^0(x_t)-\frac{(y_2-1)^2}{4y_3} \geq 0 \tag{26b}$$

$$y_1-\frac{y_2^2}{4y_3} \geq 0 \tag{26c}$$

$$y_3>0 \tag{26d}$$

Next, let $y_1=\theta+\frac{(\nu-z(x_t)\mu_t)^2}{4\varsigma}$, $y_2=\frac{\nu-z(x_t)\mu_t}{2\varsigma}$*and* $y_3=\frac{1}{4\varsigma}$ *with the auxiliary variables* θ,ν,ς, *the problem* (24) *can be transformed into* (20) [41].

The flowchart of the whole optimization process is given in Fig. 2. Firstly, the model of the operational problem of the wind-battery hybrid system is modelled. The transmission line constraint is formulated into a chance constraint with the uncertain wind power generation as the consideration. Then the ambiguity set is introduced to depict the random variable. It reformulates the operating problem into a SOCP model. Finally, the optimal operational results containing $P_{bat,t}$, B_t, $P_{cur,t}$ are solved by Gurobi solver using interior point method. It based on the SOCP model and input data including wind power generation and electricity price.

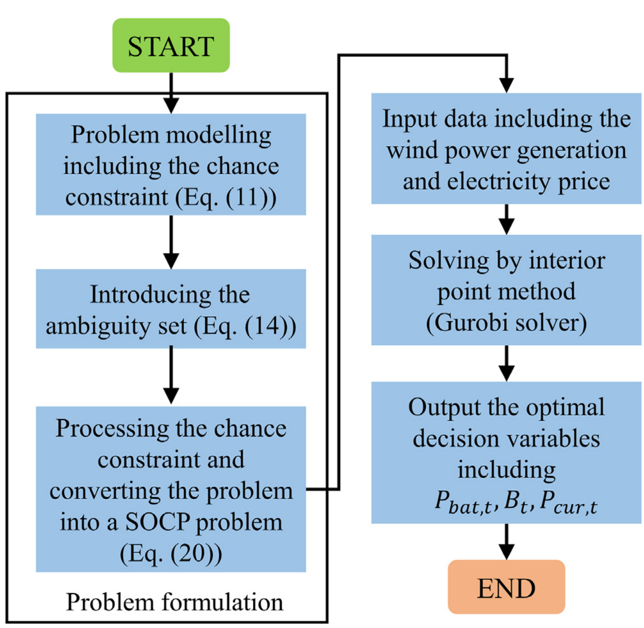

Fig. 2. Optimization process flowchart

4. Case study

This section presents a case study to prove the feasibility of the proposed DRCC scheduling problem of the wind-battery hybrid system in the day-ahead electricity market. Firstly, the description of the wind-battery hybrid system and used datasets and parameters are given. After that, the simulation is conducted and a detailed discussion is given. In this paper, the time simulation period of the scheduling problem is 24 h. All the simulations are implemented in Python with Gurobi 8.1.1 as the solver running on an Intel Core i9-9820X CPU 3.30 GHz and 64 GB of RAM.

4.1. Description of the hybrid system

This paper investigates a scheduling problem of the wind-battery hybrid system in the electricity market with consideration of the uncertain wind power generation. Thus, in order to implement the simulation, the specifications of the battery are given in Table 1 [28]. The energy storage of the battery at the beginning of the day is equal to that at the end of the day. The maximum capacity of the transmission line is set to be 150 MW. The size of the wind farm in this paper is 160 MW, which refers to the Horns Rev I wind farm in Danish waters in the North Sea. The referenced wind farm is composed of 80 2 MW Vestas 2.0-V80 wind turbines [44]. In addition, the degradation cost coefficient and the wind power penalty coefficient are assumed to be the same which are 10 DKK/MWh, the sensitivity analysis of the various degradation cost coefficient and wind power penalty coefficient are investigated in the following section.

Fig. 3 shows the forecasting wind power and the electricity price of the day-ahead market in Denmark during the simulation time. It should be noted that this paper only considers the random wind power generation and the fixed electricity prices. Based on the mean values of wind power, it is assumed that the variance of wind power is equal to 10% of the mean values at each hour. Since the limit of the transmission line capacity is 150 MW, the wind power curtailment may occur when the wind power generation is greater than 100 MW. The chance constraint confidence $1-\varepsilon$is set to be 95%.

4.2. Simulation results

Based on the parameters, specifications, and datasets introduced above, the DRCC scheduling problem of the wind-battery hybrid system in the electricity market is solved in this section, and a detailed description is presented.

Fig. 4 gives the charge/discharge power of the battery during the simulation time. The battery discharges at 2:00 and 3:00 under the relatively high electricity price, it makes more storage space available in order to absorb the wind power generated from 5:00 to 9:00. In this way, the wind power curtailment penalty can be reduced to improve revenue. Further, the battery discharges to earn money at 17:00 and 18:00, since the electricity price is the highest among the 24 h.

Fig. 5 shows the energy storage change of the battery during the simulation time. The curve change in Fig. 5 is determined by the behavior of the battery in Fig. 4. At 10:00, the energy stored in the battery reaches its maximum capacity. Notably, the energy storage

Table 1
Specifications of the battery.

E_{bat}^{min}(MWh)	E_{bat}^{max}(MWh)	P_{bat}^{max}(MW)	η_{ch}	η_{dch}
0	20	5	0.95	0.95

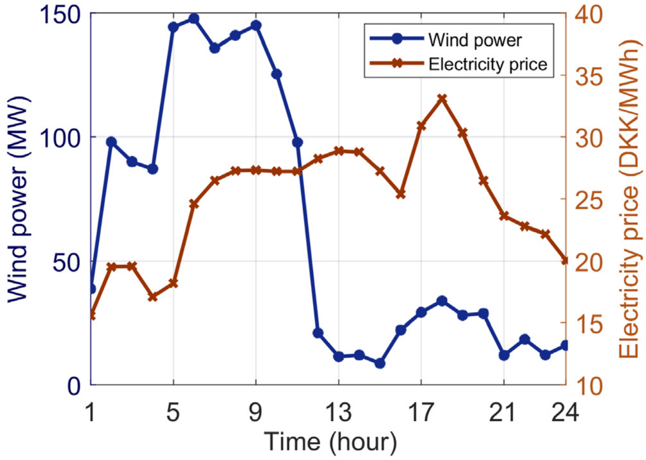

Fig. 3. Wind power and electricity price during the simulation time.

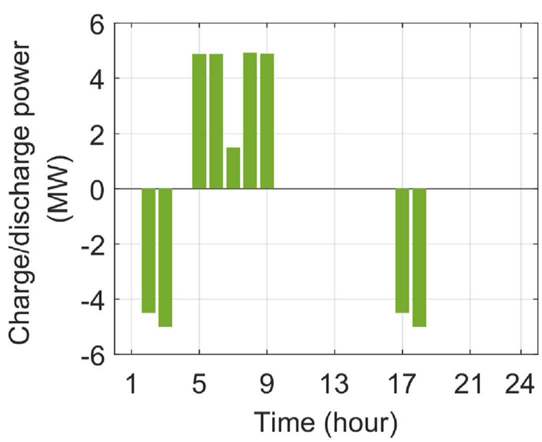

Fig. 4. The charge/discharge power of the battery during the simulation time.

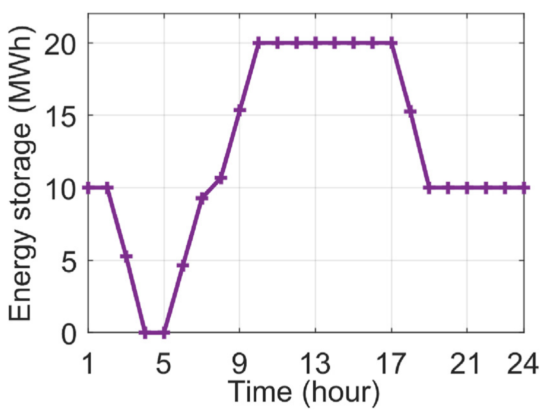

Fig. 5. The change of energy storage of the battery during the simulation time.

of the battery at the beginning of the day is equal to that at the end of the day, which can protect the performance of the battery and ensure that the battery will be available the next day. Battery plays an important role in wind power scheduling in the electricity market. In this work, the battery can not only be used to reduce the wind power curtailment, but it can also participate in market bidding.

Fig. 6 presents the wind power curtailment during the simulation time. The wind power curtailment occurs from 5:00 to 9:00. It can be seen from Fig. 4 that the charge power of the battery reaches its maximum expectation for 7:00. In the worst scenario, the generated wind power may be more than 150 MW which exceeds the maximum capacity of the transmission line, where the battery is not capable of handling this.

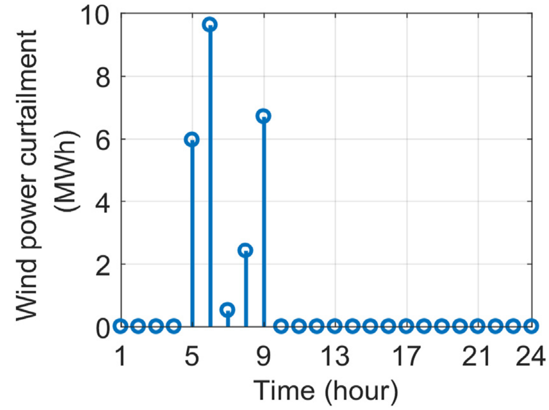

Fig. 6. Wind power curtailment during the simulation time.

The degradation cost and curtailment penalty coefficient of the wind power are also assumed in this paper. Actually, it has a great impact on revenue, which may depend on the real situation, e.g., the types of the battery, the local policy. Fig. 7 shows the revenue of the wind-battery hybrid system where different degradation cost and wind power penalty coefficient is considered. It can be seen that the impact of the degradation cost coefficient is greater than the wind power penalty coefficient. When the degradation cost coefficient decreases from 15 to 5 DKK/MWh under 10 DKK/MW wind power penalty coefficient, the revenue increases by 1.54%. Nevertheless, the revenue only increases by 0.71% when the wind power penalty coefficient decreases from 15 to 5 DKK/MW under 10 DKK/MWh degradation cost coefficient.

The capacity of the transmission line is also an important parameter to determine the revenue. Therefore, the influence of various transmission line capacities is given in Fig. 8. With the increment of the transmission line capacity, the revenue increases significantly and the wind power curtailment decreases. When the transmission line capacity reaches 160 MW, there is no wind power curtailment in the worst-case scenario. Under this condition, the battery can fully deal with the wind power curtailment. To analyze

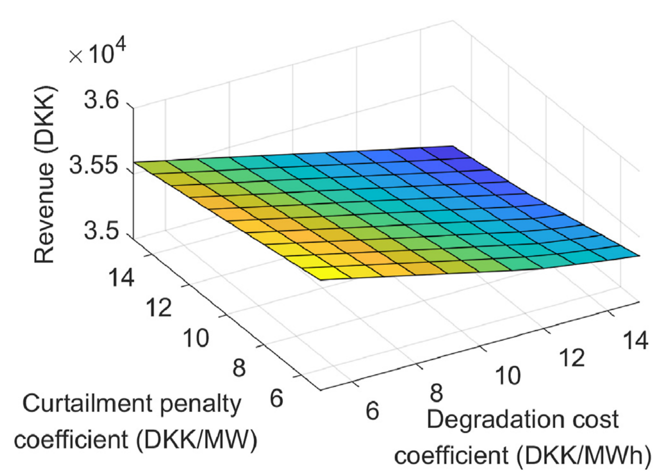

Fig. 7. Wind power and electricity price during the simulation time.

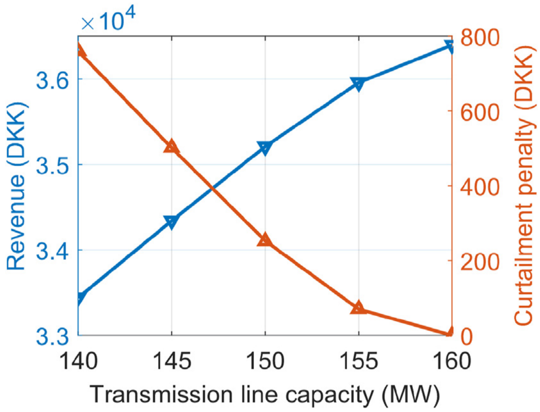

Fig. 8. The influence under various transmission line capacity.

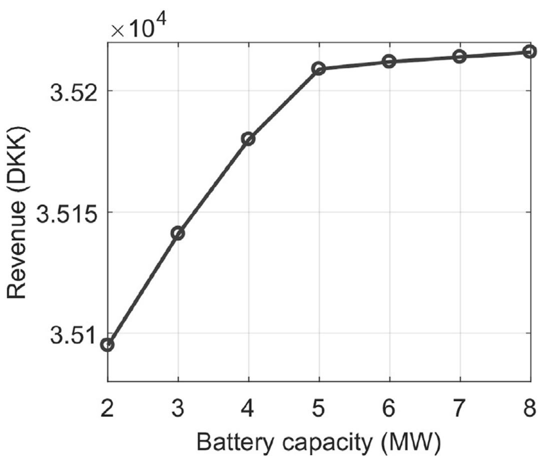

Fig. 9. The revenue under different battery capacity.

the impact of the battery capacity, Fig. 9 gives the revenue under different battery capacity with the fixed transmission line capacity (160 MW). As expected, the battery capacity increases from 2 MW to 8 MW. Consequently, the revenue of the wind-battery hybrid system improves but the incremental revenue per MW is smaller. As can be seen from Fig. 9, when the battery capacity changes from 2 MW to 5 MW, the revenue growth is very fast, and then the growth slows down. The 5 MW battery capacity can be regarded as a turning point. Therefore, the battery capacity is selected as 5 MW and regarded as a suitable choice.

4.3. Discussion

1) Comparison with SND: For the SND method, it is assumed that the uncertain wind power generation obeys a normal distribution with certain mean and variance. In this way, the original CC problem (14) can be reformulated to a deterministic constraint which is given below:

$$\left\{\mathbb{P}_t\left\{z^0(x_t)+z(x_t)\cdot\zeta_t\le 0\right\}\ge 1-\varepsilon\right\}$$
$$=\left\{z(x_t)\mu_t+z^0(x_t)+|z(x_t)|\sigma_t\Phi^{-1}(1-\varepsilon)\le 0\right\} \tag{27}$$

where $\Phi^{-1}(1-\varepsilon)$ is the $1-\varepsilon$quantile of the standard normal distribution. Notably, the mean and variance use the values mentioned before.

Table 2
Comparison with different methods.

Method	Degradation cost (DKK)	Penalty (DKK)	Revenue (DKK)	PSMTLC (%)
DRO	400.5	252.1	35209	100
SND	111.9	0	36414	84.64

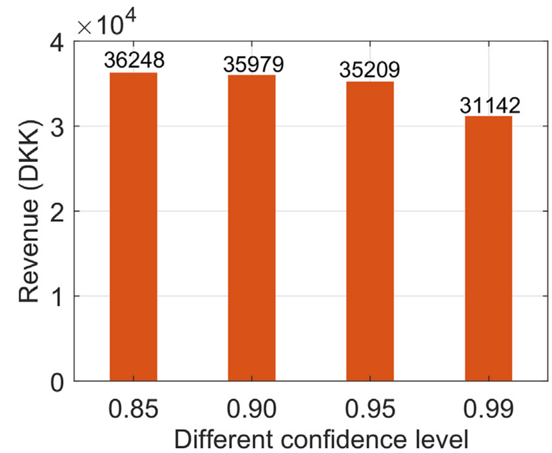

Fig. 10. Revenue under different confidence levels.

Table 2 gives the comparison results on one day. For the DRO method, it considers the worst scenario, thus, the revenue is lower comparing with the SND method. Under the worst scenario, the large deviations may occur which will lead to more wind power to be generated. And the battery will operate more frequently to store the wind power. Based on a worst-case CVaR approximation, the DRO method processes the CC scheduling problem of the wind-battery hybrid system in the electricity market. In order to verify the effectiveness of the obtained results, Monte Carlo simulations are applied. According to the estimated mean and variance of the wind power generation, 10000 scenarios under an assumed normal distribution are randomly produced. The results can be checked using these generated samples. All the scenarios can meet the transmission line constraint using DRO, which means the percentage of the scenarios that meet the transmission line constraint (PSMTLC) is 100%. This percentage is higher than the setting confidence level 95%. Hence, the results are validated to be reliable and robust. In addition, under the same confidence level, the results obtained by the SND is also checked, but the percentage of the scenarios that meet the transmission line constraint is 84.64%. Therefore, the DRO method is 15.36% more reliable than the SND. It can be concluded that the DRO is more robust and reliable than SND.

2) Influence of the different confidence level $1-\varepsilon$: Under different confidence levels, various results can be obtained for the scheduling problem of the wind-battery hybrid system in the electricity market. The uncertainty of the wind-battery hybrid system can be controlled by changing the confidence level $1-\varepsilon$. The above analysis is conducted under the confidence level $1-\varepsilon=0.95$. In addition, the impact of some other confidence level settings is studied in this paper. The revenue with various the confidence level $1-\varepsilon$, including 0.85, 0.90, 0.95 and 0.99, are summarized in Fig. 10.

5. Conclusion

With the liberation of the electricity market, the scheduling problem of the wind-battery hybrid system is of great importance in the future power grid. This paper designs a CC scheduling model for a wind-battery hybrid system. For such a scheduling problem, the objective function considers the revenue by selling power to the electricity market, the degradation cost of the battery and the curtailment penalty of wind power. A case study is given to show the effectiveness and reliability of the developed DRO model. Furthermore, comparison with SND indicates the advantage and robustness of the DRO method. Under the same setting confidence level $1-\varepsilon=95\%$, the percentage of the scenarios (10000 samples) that meet the transmission line constraint of the DRO and SND methods are 100% and 84.64% respectively. It can be concluded that the DRO is more robust and reliable than SND.

Declaration of competing interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

CRediT authorship contribution statement

Xiao Xu: Conceptualization, Methodology, Validation, Writing - original draft, Writing - review & editing. **Weihao Hu:** Supervision, Funding acquisition, Validation, Software. **Di Cao:** Validation, Visualization. **Qi Huang:** Data curation, Supervision. **Zhou Liu:** Formal analysis, Supervision. **Wen Liu:** Investigation, Supervision, Validation. **Zhe Chen:** Methodology, Supervision. **Frede Blaabjerg:** Resources, Supervision, Validation.

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