Protection and Control of Modern Power Systems

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Integrated risk measurement and control for stochastic energy trading of a wind storage system in electricity markets

Dongliang Xiao[1], Haoyong Chen[1*], Weijun Cai[1], Chun Wei[2] and Zhendong Zhao[1]

Abstract

To facilitate wind energy use and avoid low returns, or even losses in extreme cases, this paper proposes an integrated risk measurement and control approach to jointly manage multiple statistical properties of the expected profit distribution for a wind storage system. First, a risk-averse stochastic decision-making framework and multi-type risk measurements, including the conditional value at Risk (CVaR), value at risk (VaR) and shortfall probability (SP), are described in detail. To satisfy the various needs of multi-type risk-averse decision makers, integrated risk measurement and control approaches are then proposed by jointly considering the expected, boundary and probability values of the extreme results. These are managed using CVaR, VaR and SP, respectively. Finally, the effectiveness of the proposed risk control strategy is verified by conducting case studies with realistic market data, and the results of different risk control strategies are analyzed in depth. The impacts of the risk parameters of the decision maker, the energy capacity of the battery storage and the price difference between the day-ahead and real-time markets on the expected profits and risks are investigated in detail.

Keywords Electricity market, Risk measurement, Stochastic optimization, Wind storage system, Shortfall probability

1 Introduction

An efficient electricity market can help to ensure stable operation of the power system, sustainable development of the power industry, and the optimal allocation of large-scale energy resources [1]. However, in the context of large-scale integration of intermittent renewable energy, such as wind power and photovoltaics, the price volatility of the electricity market is also increasing, which brings huge risks to various types of power trading entities [2].

In the process of integrating wind energy into the power grid, system operators and wind power producers face a series of challenges and risks associated with high penetration levels of intermittent energy resources, where advanced risk measurement and control methods are becoming more and more crucial [3]. Various energy storage types, such as those using battery, compressed air, and pumped storage, have the capability of stabilizing wind power fluctuation, peak load shifting, and improving power system reliability. Thus the joint participation of wind energy resources and energy storage in the electricity market has become an efficient strategy, and has received more and more attention in recent years [4, 5].

In current research, wind energy resources and various energy storages are coordinated to optimize the expected operation or planning results considering different types of market mechanisms, such as energy markets, reserve markets, bilateral transactions, gas markets, etc. In [6], renewable resources and energy storage systems are coordinated to improve the overall market revenue and reduce the deviation penalty caused by renewable power

*Correspondence:
Haoyong Chen
eehychen@scut.edu.cn
[1] School of Electric Power, South China University of Technology, Guangzhou, China
[2] College of Information Engineering, Zhejiang University of Technology, Hangzhou, China

outputs in real-time balancing energy markets. In [7], a bi-objective optimization model is established to generate offering strategies for a wind-thermal-storage system in energy and reserve markets, where both the expected profits and carbon emissions are minimized. Reference [8] proposes an optimal decision-making model for wind power and pumped storage to participate in the electricity spot market and bilateral transactions. In [9], considering both the electricity and the natural gas markets, a trading model of wind power providers and power-to-gas equipment, gas units and gas storage devices is proposed. The Shapley value method is used to distribute the profits under a cooperative joint venture mode. In [10], the wind storage system can optimize the operating schedule of the BESS and maximize the expected profit by developing optimal price thresholds for the electricity trading decision at each instant of time. Reference [11] shows that the wind storage system can optimize dispatch strategy, increase the operating profit and determine the optimal capacity of energy storage through a 'receding horizon' approach. Reference [12] studies the risk-oriented multi-regional economic dispatch problem in depth, while also considering the application of compressed air energy storage with a large-scale access of wind power. In [13], the energy storage and transmission lines are jointly optimized in an electricity market environment, so as to manage the intermittent output of wind power and maximize expected profits.

To further improve the profits of wind storage systems, cooperative operation strategies of multiple energy storages have also been developed to improve the overall benefits. Reference [14] considers that multiple wind farms can improve market revenue and reduce the real-time market deviation penalty by coordinated operation with shared energy storage. [15] suggests that multiple wind storage systems can optimize their electricity trading strategies and increase overall expected profits by solving the two-stage stochastic problem at the upper level and the electricity market clearing problem at the lower level. Additionally, deep reinforcement learning approaches have also been employed by wind storage systems in recent years. In [16], the wind storage system implements self-dispatch to ensure robustness and improve operating profitability through deep reinforcement learning. Reference [17] adopts this type of learning to optimize the expected system operation results of the wind power producers, where the dual uncertainties of wind generation and electricity price are reduced.

To handle the uncertainties in the electricity market effectively, stochastic optimization and conditional value at risk (CVaR) have been widely adopted by wind storage systems, where only one risk measurement is usually considered to control the risks. Based on the CVaR and stochastic optimization method, reference [18] uses three-stage stochastic optimization to help wind power and a commercial air compression energy storage system participate in day-ahead, intra-day and real-time electricity markets, where CVaR is adopted for risk management. In [19], the time series and cross-correlation of random parameters are fully considered to establish a multi-objective stochastic model of a micro-energy network, with the minimum life cycle cost and carbon emissions as the optimization objectives. In [20], new energy and energy storage power plants are modeled as a price taker to participate in electricity markets, and CVaR and stochastic optimization methods are used to generate the optimal bidding strategy. In [21], a two-stage stochastic programming is used to optimize the bidding strategy of a joint wind-photovoltaic-storage system in the day-ahead market, while in [22] it shows that a risk-averse wind storage system can reduce the rick-in-cost and improve the expected operational cost by considering a scenario-based stochastic approach, downside risk constraints and a price-responsive demand response program. In [23], stochastic optimization and linear decision rules are employed by the wind storage systems in electricity markets to generate day-ahead and real-time strategies, and CVaR is incorporated into the model to manage the risks.

As shown in the above research, the existing risk control strategies tend to only consider CVaR or boundaries in the optimization model, while other risk measurements that decision makers may expect to optimize, such as value at risk (VaR) and shortfall probability (SP), have not been fully investigated. In [24], the definition and computing methods of VaR are illustrated in detail. It shows that the concept of VaR can be easily understood and the computation of a boundary value is not affected by extreme high tail losses. This makes it stable and more widely used than CVaR by the financial institutions such as banks and fund companies. In [25], a mathematical model is proposed for a transmission investment game, and shortfall probability is adopted to control the transmission investment risk. Different from CVaR and VaR, SP is used to describe the probability of risk or loss. When the decision maker has an expected minimum profit or maximum loss as a benchmark value, minimizing SP can become a better choice.

Therefore, the benefits of various risk measurements are different for decision makers faced with uncertainties. However, in the existing research on wind storage systems, the integrated control of multiple risk measurements in decision making model has not been reported.

To fill the above research gaps, this paper investigates the integrated risk measurement and control of a wind storage system in depth. The main contributions of this paper are:

An integrated risk measurement is proposed for a decision maker to jointly consider multi-type tail risks of the expected results. Using the proposed risk measurement, multiple statistical properties of the expected profit distribution, including the expected, boundary and probability values of the extreme results in the worst scenarios, are characterized by using CVaR, VaR and SP, respectively.

A scenario-based risk-ware stochastic optimization model is established to realize the integrated risk control of a wind storage system with uncertainties in electricity markets. The expected profits and three types of tail risks related to the extreme results in worst scenarios can be managed flexibly by changing the integrated risk aversion parameters and sub-risk aversion parameters of the wind storage system.

The remainder of this paper is organized as follows: Section II presents the risk-ware stochastic decision framework and employed risk measurements, while Section III develops the integrated risk measurement and control approaches of the wind storage system. Section IV conducts the case studies, and Section V concludes the paper and proposes future work.

2 Stochastic programming and risk control

2.1 Decision framework under risk-aware stochastic optimization

In recent years, stochastic optimization methodology has been widely adopted for the uncertain-aware decision-making problems considering risk management. In the framework of stochastic programming, the objective function of the risk-neutral decision maker is the expected value of its objective function, where each random parameter is characterized by a set of limited scenarios, with each scenario assigned a probability weight. This scenario set can be regarded as a discrete probability distribution of random parameters. For risk-averse decision makers, the objective function needs to incorporate a risk measurement term into the objective function to measure and manage low returns or losses in extreme scenarios. Specifically, the objective function of a risk-averse decision maker in a stochastic optimization problem can be expressed as:

$$\max_{\boldsymbol{x}} \; (1-\beta_{\mathrm{r}})E_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\} + \beta_{\mathrm{r}}R_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\} \tag{1}$$

where $\mathbf{x}$ and $\boldsymbol{\zeta}$ are the vectors of decision variables and random parameters, respectively. $f(\mathbf{x},\boldsymbol{\zeta})$ is the distribution function of expected profit, and $E_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ is the total expected profit of decision makers. $R_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ is the risk measure of $f(\mathbf{x},\boldsymbol{\zeta})$, such as SP, VaR and CVaR. The weight coefficient β_{r} of $R_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ is the risk aversion parameter. For the wind storage system, both $E_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ and $R_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ are positive. When β_{r} increases, the weight coefficients of expected profit and risk measurement in (1) will decrease and increase, respectively, while the risk aversion degree of decision makers will increase. This makes the optimal solution of the stochastic optimization problem more conservative.

2.2 Risk control methodologies based on different risk measurements

2.2.1 Risk control based on SP

The value of the loss probability can be represented as $F^{\mathrm{SP}}(\mathbf{x},\eta^{\mathrm{SP}})$ and it is the probability that the expected profit is less than the reference profit value η^{SP}. The formulation of calculating $F^{\mathrm{SP}}(\mathbf{x},\eta^{\mathrm{SP}})$ is expressed as:

$$F^{\mathrm{SP}}(\mathbf{x},\eta^{\mathrm{SP}}) = P\left(\frac{f(\mathbf{x},\zeta_w) < \eta^{\mathrm{SP}}}{\zeta_w \in \boldsymbol{\zeta}}\right)w \tag{2}$$

where $\boldsymbol{\zeta} = \{\zeta_w\}_{w=1}^{\Omega}$ and ζ_w is the w scenario in the scenario set $\boldsymbol{\zeta}$, and the total number of scenarios is Ω.

To reduce the potential risk and improve the profit value of extreme scenarios, a smaller SP is usually expected for the decision makers. Therefore, $R_{\boldsymbol{\zeta}}\{f(\mathbf{x},\boldsymbol{\zeta})\}$ of the objective function (1) of the stochastic programming model will be set to $-F^{\mathrm{SP}}(\mathbf{x},\eta^{\mathrm{SP}})$, and the maximization of the negative value of SP is equivalent to the minimization of the SP. The defect of using the risk measurement SP is that it cannot give the statistical information of the profit exceeding the reference value η^{SP}, and thus, the SP cannot measure the risk associated with a fat tail. In addition, because SP is a probability value rather than a profit value, it has no units and is not a consistent risk measure.

2.2.2 Risk control based on VaR

VaR is the maximum possible loss or minimum low income of decision makers in a certain period in the future at a certain confidence level. It was first proposed by the G30 group in 1993 in the report of *Practice and Rules of Derivatives*. Given the confidence level parameter $\alpha^{\mathrm{VaR}} \in (0,1)$, VaR can be represented as $F^{\mathrm{VaR}}(\alpha^{\mathrm{VaR}},\mathbf{x})$ and calculated by:

$$F^{\mathrm{VaR}}(\alpha^{\mathrm{VaR}},\mathbf{x}) = \max\left\{\eta^{\mathrm{VaR}} : P\left(\frac{f(\mathbf{x},\zeta_w) < \eta^{\mathrm{VaR}}}{\zeta_w \in \boldsymbol{\zeta}}\right) \le 1-\alpha^{\mathrm{VaR}}\right\} \tag{3}$$

where the value of expected profit being less than η^{VaR} is not greater than $1-\alpha^{\mathrm{VaR}}$, and the value of VaR is the maximum value of η^{VaR}. VaR can be regarded as an upper bound of potential loss or low return in the $(1-\alpha^{\mathrm{VaR}}) \times 100\%$ worst case scenario, which is a quantile of the expected profit distribution function.

Similar to SP, VaR also cannot give the profit distribution information beyond the reference value η^{VaR}, and it cannot measure the risk related to a fat tail, so it is not a consistent risk measure. However, VaR satisfies all other properties of consistent risk measures except homogeneous additivity. In addition, VaR is more intuitive and relatively simple to calculate, so it has become the most commonly used risk measure in the financial industry.

2.2.3 Risk control based on CVaR

CVaR is a risk measurement model developed on the basis of VaR. It was proposed by RockafeUar and Uryasev in 1997 to calculate the expected return of the trading strategy when the profit is lower than a given VaR value. Given the confidence level parameter $\alpha^{CVaR} \in (0,1)$, CVaR can be represented as $F^{\mathrm{CVaR}}(\alpha^{\mathrm{CVaR}}, \mathbf{x})$ and calculated by:

$$CVaR(\alpha^{\mathrm{CVaR}}, \mathbf{x}) = \max\left\{\eta^{\mathrm{VaR}} - \frac{1}{1-\alpha^{\mathrm{CVaR}}} E_{\zeta}\left[\max\left(\eta^{\mathrm{VaR}} - f(\mathbf{x}, \boldsymbol{\zeta}), 0\right)\right]\right\} \quad \forall \alpha^{\mathrm{CVaR}} \in (0,1) \tag{4}$$

where η^{CVaR} is an auxiliary variable for calculating CVaR, and is similar to its role in (3) and is the $(1-\alpha^{\mathrm{CVaR}})$ quantile of the expected profit distribution. If the probability weights of all scenarios are equal, the value of $F^{\mathrm{CVaR}}(\alpha^{\mathrm{CVaR}}, \mathbf{x})$ is the expected profit of the worst scenario of $(1-\alpha^{\mathrm{CVaR}})$%. The advantage of CVaR is that it is a consistent risk measure and can effectively manage tail risk beyond VaR. In addition, when CVaR is introduced into stochastic optimization problems, no additional integer variable needs to be introduced. In recent years, CVaR has been widely used in various risk-aware decision-making problems in the field of electric energy systems.

2.3 Risk control using integrated risk measurement

By simultaneously considering the above risk measurements provided in Sections II-B for the expected profit distribution, an integrated risk measurement $F^{\mathrm{IRM}}(\mathbf{x}, \eta^{\mathrm{SP}}, \alpha^{\mathrm{VaR}}, \alpha^{\mathrm{CVaR}})$ can be obtained, expressed as:

$$\begin{aligned} &F^{\mathrm{IRM}}\left(\mathbf{x}, \eta^{\mathrm{SP}}, \alpha^{\mathrm{VaR}}, \alpha^{\mathrm{CVaR}}\right) \\ &= \beta^{\mathrm{SP}} F^{\mathrm{SP}}\left(\mathbf{x}, \eta^{\mathrm{SP}}\right) \\ &\quad + \beta^{\mathrm{VaR}} F^{\mathrm{VaR}}\left(\alpha^{\mathrm{VaR}}, \mathbf{x}\right) \\ &\quad + \beta^{\mathrm{CVaR}} F^{\mathrm{CVaR}}\left(\alpha^{\mathrm{CVaR}}, \mathbf{x}\right) \end{aligned} \tag{5}$$

where the three risk parameters η^{SP}, α^{VaR} and α^{CVaR} are determined by the decision maker to control the tail risks of the expected profit distribution according to its specific risk preference. As shown in Fig. 1, CVaR, VaR and SP can be used to manage the expected, boundary and probability values of the extreme profits in the worst scenarios, and the objective function can be adjusted by revising the risk parameters of different risk measurements.

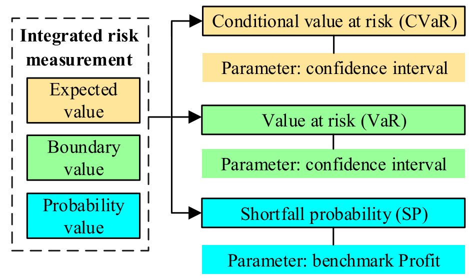


Fig. 1 Structure of proposed integrated risk measurement

3 Proposed integrated risk measurement and control methodologies for a wind storage system

3.1 Market framework and random parameter characterization

The basic framework of a typical two-settlement electricity market is depicted in Fig. 2, and is mainly composed of the day-ahead market and the real-time market. On the day before the power system operating day, the wind storage

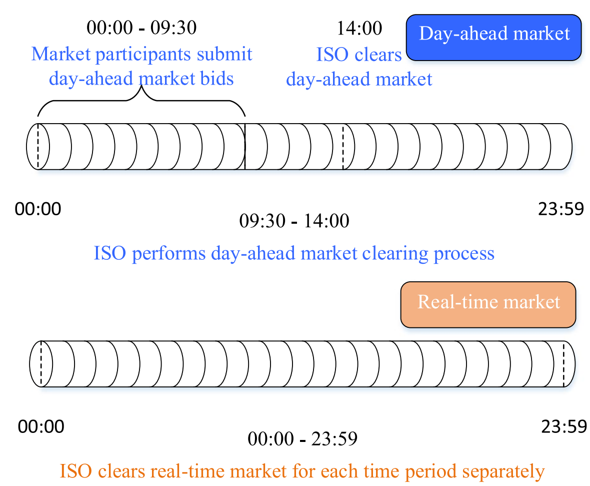


Fig. 2 The basic framework of typical two-settlement electricity market

system generates a day-ahead trading strategy before the submission closure time of the day-ahead market, and the cleared energy is settled at the day-ahead electricity price. On the power system operating day, the power system must guarantee the real-time power balance through the real-time market, and the deviations caused by the day-ahead submissions of the wind storage system will be settled by the real-time electricity price considering deviation penalty costs.

Based on the above market framework, the random parameters faced by the wind storage system in electricity markets include wind power production, day-ahead and real-time electricity prices. In this paper, the scenarios of random parameters are generated using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. Taking the random parameter day-ahead electricity price $\lambda_{t,w}^{\mathrm{DA}}$ as an example, its mathematical formula based on the SARIMA model is expressed as:

$$\left(1-\sum_{g=1}^{G}\phi_g B^g\right)\left(1-\sum_{i=1}^{P}\Phi_i B^{iS}\right)(1-B)^d(1-B^S)^D\lambda_{t,w}^{\mathrm{DA}} =\left(1-\sum_{h=1}^{H}\theta_h B^h\right)\left(1-\sum_{j=1}^{Q}\Theta_j B^{jS}\varepsilon_{t,w}^{\mathrm{DA}}\right) \tag{6}$$

where S is the seasonal order, $\phi_1, \phi_2, \cdots, \phi_G$ denote G autoregressive parameters, $\theta_1, \theta_2, \cdots, \theta_H$ denote H moving average parameters, $\Phi_1, \Phi_2, \cdots, \Phi_P$ denote P seasonal autoregressive parameters, and $\Theta_1, \Theta_2, \cdots, \Theta_Q$ denote Q seasonal moving average parameters. $\varepsilon_{t,w}^{\mathrm{DA}}$ denotes the error term of scenario w, which follows the independent normal probability distribution for the SARIMA model. B is the backward shift operator, and its function can be defined by:

$$B^d\lambda_{t,w}^{\mathrm{DA}}=\lambda_{t-d,w}^{\mathrm{DA}} \tag{7}$$

where d is the difference order of the SARIMA model.

3.2 Trading strategy based on integrated risk measurement and control

3.2.1 Objective function

The objective function of the wind storage system is the weighted sum of the total expected profit and all the risk measurements. The weight coefficients β^{SP}, β^{VaR}, and β^{CVaR} are defined as the sub-risk aversion degree of SP, VaR and CVaR, respectively. The value range of these risk averse degree parameters is [0,1] and they need to satisfy the following equation, as:

$$\beta^{SP}+\beta^{VaR}+\beta^{CVaR}=\beta_r \tag{8}$$

Based on (8) and the framework of stochastic optimization, the objective function of the proposed risk control problem can be established as:

$$\max_{\Xi}\left\{\left(1-\beta^{\mathrm{SP}}-\beta^{\mathrm{VaR}}-\beta^{\mathrm{CVaR}}\right)\sum\nolimits_{w=1}^{W}pr_w\pi_w^{\mathrm{WS}}+\beta^{\mathrm{SP}}\left(-\pi^{\mathrm{SC}}\theta^{\mathrm{SP}}\right)+\beta^{\mathrm{VaR}}\pi^{\mathrm{VaR}}+\beta^{\mathrm{CVaR}}\pi^{\mathrm{CVaR}}\right\} \tag{9}$$

where Ξ is the set of all the decision variables of the proposed risk-aware stochastic optimization problem. pr_w and π_w^{WS} are the probability and expected profit of the scenario w, respectively, and π^{SC} is the scale parameter of SP. θ^{SP}, π^{VaR} and π^{CVaR} are the SP, VaR and CVaR of the wind storage system, respectively, while the sub-risk aversion degree parameters of the wind storage system are β^{SP}, β^{VaR} and β^{CVaR}.

The expected profit π_w^{WS} for the stochastic energy trading of the wind storage system in the electricity market is calculated as:

$$\pi_w^{\mathrm{WS}}=\sum_{t=1}^{T}\left\{\begin{array}{l}\lambda_{t,w}^{\mathrm{DA}}P_t^{\mathrm{DA}}+\lambda_{t,w}^{\mathrm{RT}}P_t^{\mathrm{RT}}\\ -(F^{\mathrm{DEV+}}P_{t,w}^{\mathrm{RT+}}+F^{\mathrm{DEV-}}P_{t,w}^{\mathrm{RT-}})\\ -(F^{\mathrm{BS,dis}}P_{t,w}^{\mathrm{BS,dis}}+F^{\mathrm{BS,ch}}P_{t,w}^{\mathrm{BS,ch}})\end{array}\right\} \tag{10}$$

where $\lambda_{t,w}^{\mathrm{DA}}$ and $\lambda_{t,w}^{\mathrm{RT}}$ are the day-ahead and real-time electricity prices in the electricity market in the period t of scenario w, respectively. P_t^{DA} and P_t^{RT} are the energy sold by the wind storage system in the day-ahead and real-time markets, respectively, where negative values mean the wind storage system is buying energy from the markets. $P_{t,w}^{\mathrm{BS,ch}}$ and $P_{t,w}^{\mathrm{BS,dis}}$ are the respective charging and discharging energy of the battery storage in the period t of scenario w, while $P_{t,w}^{\mathrm{RT+}}$ and $P_{t,w}^{\mathrm{RT-}}$ are the positive and negative power deviations in RT markets, respectively. $F^{\mathrm{DEV+}}$ and $F^{\mathrm{DEV-}}$ are the respective positive and negative deviation penalty costs for real-time power of the wind storage system, while $F^{\mathrm{BS,ch}}$ and $F^{\mathrm{BS,dis}}$ are the charging and discharging operation costs of the battery storage, respectively.

3.2.2 Constraints of the risk measurements

In the stochastic optimization problem, the constraints used to calculate SP include:

$$\theta^{\mathrm{SP}}=\sum_{w=1}^{W}pr_w z_w^{\mathrm{SP}} \tag{11}$$

$$\eta^{SP} - \pi_w^{WS} \le Mz_w^{SP} \tag{12}$$

$$z_w^{SP} \in \{0, 1\} \tag{13}$$

where η^{SP} represents the reference profit of the shortfall probability, z_w^{SP} is the binary auxiliary variable, which is 1 when $\pi_w^{WS} \le \eta^{SP}$ and is 0 otherwise, while M is a sufficiently large constant.

The constraints used for calculating the VaR include:

$$\sum_{w=1}^{W} pr_w z_w^{VaR} \le 1 - \alpha^{VaR} \tag{14}$$

$$\pi^{VaR} - \pi_w^{WS} \le Mz_w^{VaR} \tag{15}$$

$$z_w^{VaR} \in \{0, 1\} \tag{16}$$

where α^{VaR} is the confidence level parameter of the VaR, z_w^{VaR} is the binary auxiliary variable used to calculate it, and equals 1 when $\pi_w^{WS} \le \pi^{VaR}$ and 0 otherwise.

The constraints used for calculating the CVaR include:

$$\pi^{CVaR} = \zeta - \frac{1}{1 - \alpha^{CVaR}} \sum\nolimits_w pr_w g_w \tag{17}$$

$$g_w \ge 0 \quad \forall w \tag{18}$$

$$\zeta - g_w \le \pi_w^{WS} \quad \forall w \tag{19}$$

where α^{CVaR} is the confidence level parameter, while g_w and ζ are the auxiliary variables used to calculate the CVaR. The detailed derivation and proof process of this calculation method are shown in detail in [26].

3.2.3 Constraints of energy balance and energy trading

The energy balance constraint of the wind storage system participating in the electricity market is expressed as:

$$P_t^{DA} + P_{t,w}^{RT} = P_{t,w}^{BS,dis} + P_{t,w}^{RES} - P_{t,w}^{BS,ch} \quad \forall t, w \tag{20}$$

where $P_{t,w}^{RES}$ is the wind power production in the period t of scenario w. The total energy sold by the wind storage system in the day-ahead and real-time markets is equal to the sum of wind power production, and battery discharging energy minus charging energy.

The trading volume of the wind storage system in the day-ahead market is constrained by the installed capacity of the energy storage and wind farm. This capacity can be expressed as (21). Specifically, the maximum day-ahead purchasing energy of the wind- storage system should not be higher than the maximum power capacity of the energy storage device, and the maximum day-ahead selling power shall not be higher than the sum of the installed capacity of the wind power plant and the power capacity of the energy storage device, i.e.:

$$-P^{BS,max} \le P_t^{DA} \le P^{RES,max} + P^{BS,max} \quad \forall t \tag{21}$$

The positive and negative deviations of the wind storage system in the real-time electricity market are calculated by:

$$P_{t,w}^{RT} = P_{t,w}^{RT+} - P_{t,w}^{RT-} \tag{22}$$

$$0 \le P_{t,w}^{RT+}, P_{t,w}^{RT-} \tag{23}$$

3.2.4 Constraints of battery storage

The operating cost of battery storage is related to the charging and discharging power, expressed as:

$$C_w^{BS} = \sum_{t=1}^{T} \left(g^{BS,dis} P_{t,w}^{BS,dis} + g^{BS,ch} P_{t,w}^{BS,ch} \right) \quad \forall w \tag{24}$$

The energy levels of battery storage in different periods are calculated by:

$$E_{t,w}^{BS} = E^{BS,0} - \frac{P_{t,w}^{BS,dis}}{\eta^{BS,dis}} + \eta^{BS,ch} P_{t,w}^{BS,ch} \quad t = 1, \forall w \tag{25}$$

$$E_{t,w}^{BS} = E_{t-1,w}^{BS} - \frac{P_{t,w}^{BS,dis}}{\eta^{BS,dis}} + \eta^{BS,ch} P_{t,w}^{BS,ch} \quad \forall t \ge 2, w \tag{26}$$

where $E_{t,w}^{BS}$ is the real-time energy level of the battery in the period t of scenario w, and $E^{BS,0}$ is the initial energy level of battery storage. $\eta^{BS,ch}$ and $\eta^{BS,dis}$ are the charging and discharging efficiencies of the battery storage, respectively.

The energy level and charge–discharge power constraints of the battery are given as:

$$E^{BS,min} \le E_{t,w}^{BS} \le E^{BS,max} \quad \forall t, w \tag{27}$$

$$0 \le P_{t,w}^{BS,dis} \le P^{BS,max} z_{t,w}^{BS,dis} \quad \forall t, w \tag{28}$$

$$0 \le P_{t,w}^{BS,ch} \le P^{BS,max} z_{t,w}^{BS,ch} \quad \forall t, w \tag{29}$$

$$z_{t,w}^{BS,dis} + z_{t,w}^{BS,ch} \le 1 \quad \forall t, w \tag{30}$$

$$z_{t,w}^{\mathrm{BS,dis}}, z_{t,w}^{\mathrm{BS,ch}} \in \{0,1\} \quad \forall t, w \tag{31}$$

where $z_{t,w}^{\mathrm{BS,ch}}$ is a binary variable representing the charging state, which is 1 when the battery is charged and 0 otherwise, while $z_{t,w}^{\mathrm{BS,dis}}$ is a binary variable representing the discharging state, which is 1 when the battery is discharged and 0 otherwise. $E^{\mathrm{BS,max}}$ and $E^{\mathrm{BS,min}}$ are the highest and lowest energy levels of the battery, respectively. $P^{\mathrm{BS,max}}$ determines the maximum charging and discharging power of the battery.

3.3 Energy trading strategies based on different risk control methodologies

By simplifying the proposed stochastic optimization model based on integrated risk control methodology, the stochastic optimization models of a risk-neutral energy trading strategy and three other risk-averse trading strategies can be obtained.

When $\beta^{\mathrm{SP}} = \beta^{\mathrm{VaR}} = \beta^{\mathrm{CVaR}} = 0$, only the total expected profit is considered in the objective function of the stochastic optimization model. This strategy can be called risk neutral strategy, and its optimization model includes (9)–(10), and (20)-(31).

When $\beta^{\mathrm{SP}} > 0$, $\beta^{\mathrm{VaR}} = 0$, and $\beta^{\mathrm{CVaR}} = 0$, the total expected profit and risk measurement SP will be considered in the objective function of the stochastic optimization model. This strategy can be called SP risk control strategy, and its optimization model includes (8)–(13), and (20)–(31).

When $\beta^{\mathrm{SP}} = 0$, $\beta^{\mathrm{VaR}} > 0$, and $\beta^{\mathrm{CVaR}} = 0$, the objective function of the stochastic optimization model will consider the total expected profit and the risk measurement VaR. This strategy can be called VaR risk control strategy, and its corresponding optimization models include (9)–(10), (14)–(16), and (20)–(31).

When $\beta^{\mathrm{SP}} = 0$, $\beta^{\mathrm{VaR}} = 0$, and $\beta^{\mathrm{CVaR}} > 0$, the total expected profit and risk measurement CVaR will be considered in the objective function of the stochastic optimization model. This strategy can be called the CVaR risk control strategy, and its corresponding optimization model includes (8)-(10), and (17)-(31).

When $\beta^{\mathrm{SP}} > 0$, $\beta^{\mathrm{VaR}} > 0$, and $\beta^{\mathrm{CVaR}} > 0$, the total expected profit and three different risk measures of SP, VaR, and CVaR will be considered in the objective function of the stochastic optimization model, and this strategy is the integrated risk control strategy proposed in this paper, and its corresponding optimization model includes (9)–(31). These have been explained in Section III-B in detail.

4 Case studies

4.1 Simulation set-up

To verify the effectiveness of the proposed integrated risk measurement and control methodologies, a wind power plant with an installed capacity of 16 MW, and a battery storage device with 6 MWh energy capacity and 3 MW power capacity are analyzed. The historical wind power data are obtained from the website of the National Renewable Energy Laboratory [27], and the charging and discharging operational costs of the battery storage is 0.015 \$/MWh. The historical day-ahead and real-time electricity price data are obtained from IMO, which is the trading hub node of the Pennsylvania-Jersey-Maryland electricity market in the United States [28]. The penalty cost of real-time power deviation is 1 \$/MWh. The number of scenarios for each random parameter is 50, and the probability weight of each scenario is 0.02. All the optimization models in this paper are solved by YALMIP toolbox and commercial solver Gurobi 6.52 in the environment of MATLAB 2019b [29].

4.2 Compare risk-neutral and risk-averse strategies

This part first compares the risk neutral strategy with the integrated risk control strategy, with the risk parameters $\beta^{\mathrm{SP}} = \beta^{\mathrm{VaR}} = \beta^{\mathrm{CVaR}} = 0.2$. The expected values of wind power generation, day-ahead and real-time electricity prices on one day are shown in Fig. 3. It can be seen that the fluctuations of real-time electricity price are more obvious than those of wind power production and day-ahead electricity price.

The trading results of the risk neutral strategy and the integrated risk control strategy in the day-ahead market and the real-time market are shown in Fig. 4, and

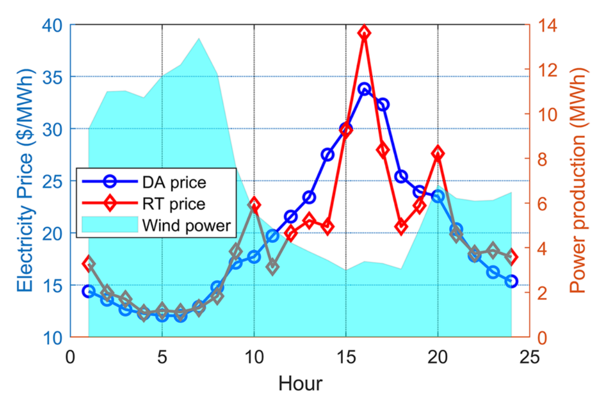
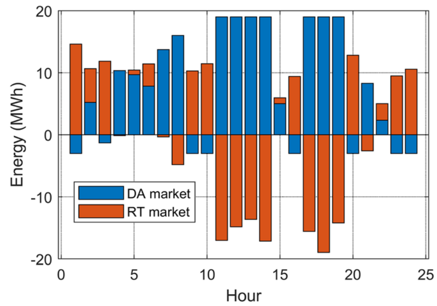
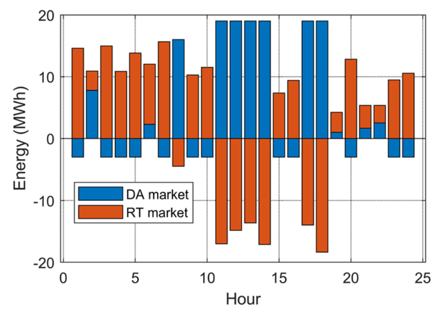


Fig. 3 The expected values of day-ahead and real-time electricity prices and wind power productions



(a) Energy trading results under risk-neutral strategy



(b) Energy trading results under integrated risk control strategy

Fig. 4 The expected power trading results of wind storage system with risk-neutral and integrated risk control strategies

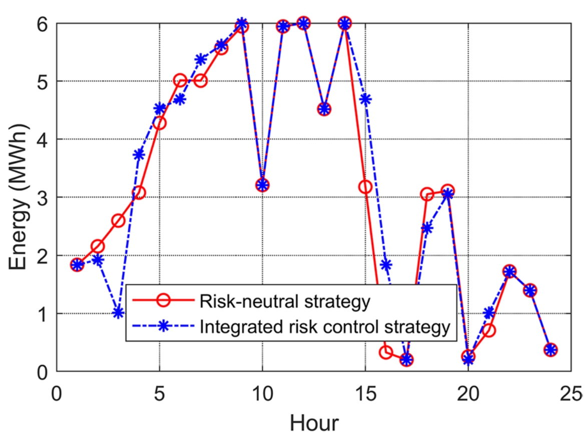


Fig. 5 The expected energy levels of storage device under risk-neutral and integrated risk control strategies

the energy level of the battery storage device is shown in Fig. 5. The results show that the wind storage system is more inclined to sell energy to the trading floors during the periods with high electricity prices. The expected day-ahead prices during 11:00–14:00 are significantly higher than the real-time prices, and thus the wind storage system chooses to sell energy in the day-ahead market and buy them back in the real-time market for both strategies. The energy storage device tends to discharge when the electricity price is high. For instance, since the electricity price is high at 15:00–17:00, the energy storage device chooses to discharge quickly to earn income, resulting in a rapid decline in its energy level.

As shown in Figs. 3, 4, 5, it is also found that the impact of risk management on the trading strategy of the wind storage system is closely related to the difference between day-ahead and real-time electricity prices. For instance, that difference during 11:00–14:00 is large, and the trading strategy of the wind storage system is relatively stable, and almost unaffected by the risk control methodologies. By contrast, when the difference between the day-ahead and the real-time electricity prices during 4:00–6:00 is close to 0 the uncertainties faced by the wind storage system are severe, resulting in significantly different trading results between its risk-neutral strategy and integrated risk control strategy.

To further investigate the effectiveness and compare the characteristics of different risk control strategies, Table 1 compares and analyzes the results of five different risk control strategies described in Section III-C. β^{SP} of SP risk control strategy, β^{VaR} of VaR risk control strategy, and β^{CVaR} of CVaR risk control strategy are all set to 0.6. From the statistical results of the expected profits, it can be seen that these four risk control strategies can effectively help the wind storage system to avoid the tail risks of extreme scenarios. The minimum profits obtained by using the CVaR, VaR, SP and integrated risk strategies are respectively 74.96%, 74.78%, 71.20% and 75.67% higher than that obtained by solving the risk-neutral strategy. In contrast, the total expected

Table 1 Expected profit distribution results based on different risk control models

Strategy	CVaR/$	VaR/$	SP (%)	Minimum profit/$	Expected profit/$
Risk-neutral strategy	727	1056	18	559	3734
CVaR risk control strategy	1170	1289	18	978	3673
VaR risk control strategy	1147	1455	16	977	3677
SP risk control strategy	1116	1400	12	957	3683
Integrated risk control strategy	1146	1427	12	982	3675

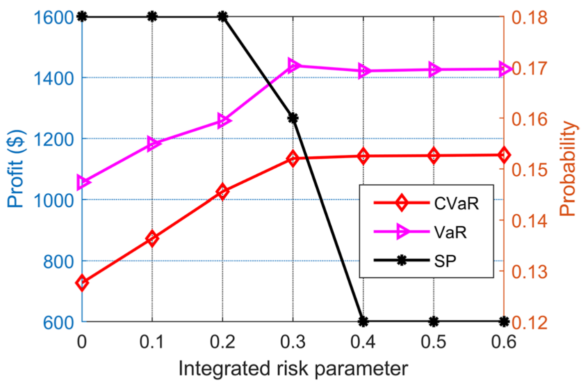


Fig. 6 The risk measurement results of wind storage system with different integrated risk parameters

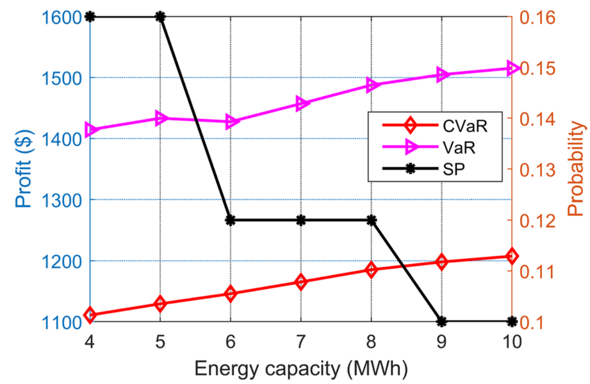


Fig. 8 The risk measurement results of a wind storage system with different storage energy capacities

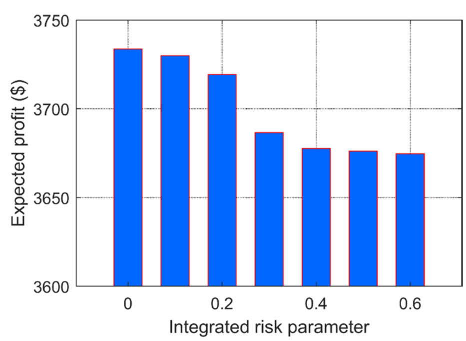


Fig. 7 The expected profits of wind storage system with different integrated risk parameters

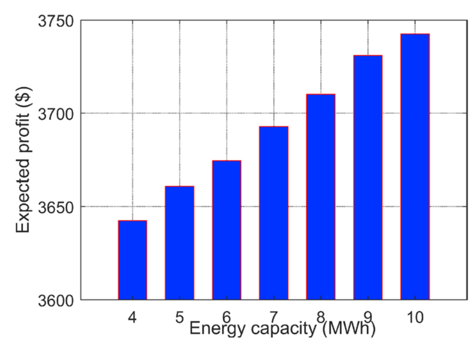


Fig. 9 The expected profits of a wind storage system with different storage energy capacities

profits obtained by using the CVaR, VaR, SP and integrated risk strategies are respectively only 1.6%, 1.53%, 1.37% and 1.58% lower than that obtained by solving the risk-neutral strategy.

The integrated risk control strategy proposed here can simultaneously reduce the SP by 33.33%, and increase VaR and CVaR by 57.63% and 35.13%, respectively. Thus the proposed integrated risk control method can effectively manage multi-type statistical properties of the expected profit distribution simultaneously. This increases the flexibility of the risk-aware energy trading process. Additionally, the SP, VaR and CVaR obtained from the respective SP, VaR and CVaR risk control strategies are optimal. Thus, the different types of risk control strategies can well meet the risk management needs of multiple decision makers who may prefer different risk measurement indicators.

4.3 Sensitivity analysis of risk parameter

The value of integrated risk parameter β_r is gradually increased from 0 to 0.6, and the values of each sub-risk coefficient are equal to $\beta_r/3$. The risk measurement results and the expected profits of the relevant risk measures are shown in Figs. 6 and 7, respectively. These results show that as the risk coefficient increases, CVaR and VaR are also increased, while SP is decreased, and the total expected profit is gradually decreased.

When the integrated risk coefficient increases from 0 to 0.4, the expected profit and risk measures change more obviously, e.g., VaR and CVaR increase by 33.43% and 55.9%, respectively, while SP and the total expected profit decrease by 33.3% and 1.5%, respectively. When the integrated risk coefficient increases from 0.4 to 0.6, its impacts on the expected profit and risk measurements are not significant, e.g., VaR and CVaR are only increased by 0.42% and 0.35%, respectively, and the total expected profit is decreased by 0.08%, while the SP does not change. As a result, if the decision maker is concerned about CVaR and VaR, choosing an integrated risk parameter lower than 0.3 is a good choice, since it can decrease CVaR and VaR significantly without noticeably decreasing the expected profit. However, if the decision maker needs to decrease SP, setting the integrated risk parameter to be 0.3 or 0.4 is better.

4.4 Sensitivity analysis of battery capacity

The energy capacity of the battery storage is gradually increased from 4 to 10 MWh, and the expected profit results and the risk measurements are shown in Figs. 8 and 9, respectively. The results indicate that as the energy capacity of the energy storage device increases, CVaR and VaR and total expected profit are all significantly increased, while SP is decreased. Additionally, the growth trend of CVaR and the total expected profit are relatively stable, while the variations of SP and VaR have a certain randomness. For example, when the energy capacity of battery storage is increased from 5 to 6 MWh, SP and VaR are decreased and increased by 25% and 0.42%, respectively. In comparison, when the energy capacity of battery storage is increased from 6 to 7 MWh, SP is not changed while VaR is increased by 2.1%.

5 Conclusion

This paper has proposed integrated risk measurement and control methodologies for the stochastic energy trading strategy of a wind storage system, where three types of risk measurements, i.e., SP, VaR and CVaR, are incorporated into the stochastic optimization model. The proposed strategy fully considers the uncertainties of day-ahead electricity price, real-time electricity price and wind power production, and can satisfy various risk preferences of decision makers. By conducting the simulation analysis based on realistic data, the following conclusions can be obtained:

The proposed integrated risk control strategy can simultaneously optimize the three risk measurements, including SP, VaR and CVaR, which can flexibly and effectively control the statistical properties of the expected profit distribution and reduce multi-type tail risks faced by decision makers.

The impacts of risk control on a wind storage system are closely related to the difference between the expected day-ahead and real-time electricity prices. If the expected price difference is small, the uncertainties and risks of the expected profit of the wind storage system will be severe. Consequently, stochastic electricity trading strategy is more likely to be affected by the risk preference of the decision maker.

The values of risk aversion parameters are closely related to the risk preference of the decision maker. Larger risk aversion parameters can improve the capability of managing the tail risks of expected profit distribution for the wind storage system, while at the same time reducing the total expected profit.

Increasing the energy capacity of battery storage increases the arbitrage capability of a wind storage system during different periods in two-settlement electricity markets. This can improve the total expected profit and risk management performance simultaneously.

In future research, the value of other flexible resources, such as electric vehicles [30], gas fired units [31], etc., will be further investigated for the wind energy system with an integrated risk control strategy. Additionally, other market mechanisms, such as long-term power trading and ancillary service markets [32], may also affect multi-type risk measurements and profits, and can be considered by the wind storage system in electricity markets.

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Author contributions
DX and HC carried out theoretical analysis and conduct case studies to verify the proposed method, WC proposed methods for solving the optimization model, CW and ZZ offered help in theory and practice, and provide suggestions. All authors read and approved the final manuscript.

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Availability of data and materials
Data will be made available on reasonable request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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