Statistical Measure for Risk-seeking Stochastic Wind Power Offering Strategies in Electricity Markets

Dongliang Xiao, Haoyong Chen, Chun Wei, and Xiaoqing Bai

***Abstract*—This study proposes a statistical measure and a stochastic optimization model for generating risk-seeking wind power offering strategies in electricity markets. Inspired by the value at risk (VaR) to quantify risks in the worst-case scenarios of a profit distribution, a statistical measure is proposed to quantify potential high profits in the best-case scenarios of a profit distribution, which is referred to as value at best (VaB) in the best-case scenarios. Then, a stochastic optimization model based on VaB is developed for a risk-seeking wind power producer, which is formulated as a mixed-integer linear programming problem. By adjusting the parameters in the proposed model, the wind power producer can flexibly manage the potential high profits in the best-case scenarios from the probabilistic perspective. Finally, the proposed statistical measure and risk-seeking stochastic optimization model are verified through case studies.**

***Index Terms*—Electricity market, risk-seeking, statistical measure, stochastic optimization, wind power.**

I. Introduction

In deregulated electricity markets, wind power producers need to develop optimal offering strategies while considering their risk preferences (e. g., risk-neutral, risk-averse, or risk-seeking) [1]. A risk-neutral participant seeks to maximize its expected profit, whereas risk-averse and risk-seeking participants might minimize the risks in the worst-case scenarios and maximize profits in the best-case scenarios, respectively, as depicted in Fig. 1. A typical real-world risk-seeking example is that people are interested in lotteries because of the potential for winning large prizes, even though the expected returns from lotteries are usually negative [2]. In [3] and [4], the prospect theory and regulatory focus theory are utilized to explain risk-seeking behaviors, respectively. Risk-seeking behaviors have been extensively studied in the markets of multi-type products such as stock [5], crude oil [6], and cryptocurrency [7]. However, most existing decision-making models in electricity markets have been developed for risk-neutral and risk-averse participants. By contrast, the research on risk-seeking electricity market participants has been quite limited.

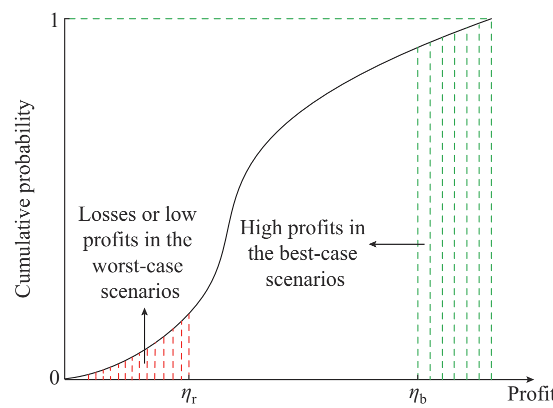

Fig. 1. Cumulative probability distribution of expected profit.

Stochastic optimization [8], robust optimization [9], and information gap decision theory (IGDT) [10] have been widely used by electricity market participants facing risks. In stochastic optimization models, uncertain parameters are represented by the scenarios generated based on their probability distributions, and risk-averse participants can manage the risks in the worst-case scenarios by using risk measures such as value at risk (VaR) and conditional value at risk (CVaR). By contrast, the stochastic optimization models used by risk-seeking participants have not been reported. The robust optimization model is suitable only for risk-averse participants because it only considers the worst-case scenarios. The non-probabilistic IGDT models with robust and opportunistic functions can be used by risk-averse and risk-seeking participants, respectively. However, IGDT models do not utilize the full probability distributions of uncertain parameters. Thus, high profits cannot be quantified or managed from the probabilistic perspective.

Specifically, IGDT and stochastic optimization are risk-aware optimization techniques suitable for different cases.

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IGDT is a non-probabilistic method without strict statistical assumptions and can be used when the probability distributions of uncertain parameters are difficult to estimate. Thus, it cannot manage expected profit from the probabilistic perspective. By contrast, the stochastic optimization is a probabilistic approach that requires the probabilistic forecasting results of uncertain parameters and can therefore fully utilize the statistical properties of uncertain parameters to manage the expected profit more accurately and flexibly. Risk-seeking IGDT methods have been proposed in many studies, whereas the risk-seeking stochastic optimization method has yet to be developed. This is the research gap that this study intends to fill.

Thus, this study proposes a statistical measure and stochastic optimization model for risk-seeking participants in electricity markets. This study shows that, when probabilistic forecasting results of uncertain parameters are available, the proposed risk-seeking stochastic optimization method is more accurate and flexible than the existing risk-seeking IGDT method. The main contributions of this study are twofold: ① a statistical measure is proposed to quantify potential high profits in the best-case scenarios with expected profit distribution of a decision maker; ② a risk-seeking stochastic optimization model is developed to generate wind power offering strategies in electricity markets.

II. Proposed Statistical Measure

In a stochastic optimization model, a risk-neutral participant seeks to maximize the total expected profit when considering all possible scenarios, whereas a risk-averse participant can manage the risks in the worst-case scenarios by incorporating a risk measure into its objective function, which can be expressed as:

$$\max_{\boldsymbol{x}}\ (1-\beta_r)E_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta}))+\beta_r R_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta})) \tag{1}$$

where $\boldsymbol{x}$ and $\boldsymbol{\zeta}$ are the vectors of the decision variables and uncertain parameters, respectively; $f(\boldsymbol{x},\boldsymbol{\zeta})$ is the profit distribution function; $E_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta}))$ is the expected value; $R_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta}))$ is a risk measure of $f(\boldsymbol{x},\boldsymbol{\zeta})$ such as VaR and CVaR; and β_r is the risk-averse degree, and a larger β_r indicates that the participant is more risk-averse. Given a confidence level parameter $\alpha_r \in (0,1)$, the VaR of $f(\boldsymbol{x},\boldsymbol{\zeta})$ is denoted as $VaR(\alpha_r,\boldsymbol{x})$ and is equal to the largest η_r, which ensures that the probability of making a profit less than η_r is not more than $1-\alpha_r$. If $\boldsymbol{\zeta}$ is approximated by a scenario set $\{\zeta_w\}_{w=1}^{N_\Omega}$ consisting of N_Ω scenarios, $VaR(\alpha_r,\boldsymbol{x})$ can be expressed as:

$$VaR(\alpha_r,\boldsymbol{x})=\max\{\eta_r: P(\zeta_w|f(\boldsymbol{x},\zeta_w)<\eta_r)\le 1-\alpha_r\}\quad \forall \alpha_r\in(0,1) \tag{2}$$

where $VaR(\alpha_r,\boldsymbol{x})$ is the upper bound of the potential losses or low profits in the $(1-\alpha_r)\times 100\%$ worst-case scenarios.

A risk-seeking participant is sensitive to high profits in the best-case scenarios and can adopt an objective function consisting of the total expected profit and a statistical measure of high profits. This can be expressed as:

$$\max_{\boldsymbol{x}}\ (1-\beta_s)E_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta}))+\beta_s B_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta})) \tag{3}$$

where $B_{\zeta}(f(\boldsymbol{x},\boldsymbol{\zeta}))$ is a statistical measure of the high profits in the best-case scenarios of the profit distribution $f(\boldsymbol{x},\boldsymbol{\zeta})$; and β_s is the risk-seeking degree, and a larger β_s indicates that the participant is more risk-seeking.

Inspired by the risk measure VaR used by risk-averse participants, a statistical measure is proposed to quantify the high profits of a risk-seeking participant, which is referred to as the value at best (VaB) in the best-case scenarios. Given a probability parameter $\alpha_s \in (0,1)$, the VaB of profit distribution $f(\boldsymbol{x},\boldsymbol{\zeta})$ can be denoted as $VaB(\alpha_s,\boldsymbol{x})$ and is equal to the largest η_b, which ensures that the probability of making a profit equal to or higher than η_b is not less than α_s. This can be expressed as:

$$VaB(\alpha_s,\boldsymbol{x})=\max\{\eta_b: P(\zeta_w|f(\boldsymbol{x},\zeta_w)\ge\eta_b)\ge\alpha_s\}\quad \forall \alpha_s\in(0,1) \tag{4}$$

where the proposed statistical measure $VaB(\alpha_s,\boldsymbol{x})$ can be regarded as the lower bound of the potential high profits in the $\alpha_s\times 100\%$ best-case scenarios for profit distribution. Because VaR and VaB are both quantiles of the expected profit probability distribution, VaB may have some properties similar to those of VaR such as the non-convexity of the associated stochastic optimization problem, which is discussed in Section III-B.

III. Proposed Stochastic Optimization Model

A. Market Framework and Uncertainty Characterization

A typical U.S. electricity market includes day-ahead (DA) and real-time (RT) markets. The wind power producer submits DA offers before the closure time of DA market. In the RT market, the deviations between the DA offers and actual wind power are settled at RT prices and charged with deviation penalties. Thus, the uncertain parameters faced by the wind power producer include wind power and electricity prices in the DA and RT markets. In this study, the scenarios with uncertain parameters are generated using the seasonal autoregressive integrated moving average (SARIMA) model, and their dependency is characterized through a variance-covariance-based method [11].

B. Proposed Risk-seeking Stochastic Optimization Model Based on VaB

In this section, mathematical formulas of the proposed risk-seeking stochastic optimization model based on VaB used by a wind power producer in electricity market are illustrated, which consists of (5)-(13). The objective function of the proposed risk-seeking stochastic optimization model can be expressed as:

$$\max_{\Xi}\ (1-\beta_s)\sum_{w=1}^{N_\Omega} Pr_w\cdot\pi_w+\beta_s\eta_b \tag{5}$$

where $\Xi=\{\pi_w,\eta_b,z_w,P_{tw}^{WD},\Delta_{tw}^{+},\Delta_{tw}^{-}\}$ is the decision variable set of the model, and z_w is a binary variable that is equal to 1 when $\pi_w\ge\eta_b$ and 0 otherwise, P_{tw}^{WD} is the wind power sold in the DA market, Δ_{tw}^{+} and Δ_{tw}^{-} are positive and negative RT wind power deviations, respectively; and Pr_w and π_w are the probability and profit of scenario w, respectively, and $\sum_{w=1}^{N_\Omega} Pr_w\cdot\pi_w$ is the total expected profit of N_Ω scenarios. In addition, η_b is used to quantify the high profits by the statistical measure VaB in the best-case scenarios, which can be calculated using constraints (6)-(9).

$$\pi_w - \eta_b \le M z_w \quad \forall w \tag{6}$$

$$\eta_b - \pi_w \le M(1 - z_w) \quad \forall w \tag{7}$$

$$z_w \in \{0, 1\} \quad \forall w \tag{8}$$

$$\sum_{w=1}^{N_\Omega} Pr_w \cdot z_w \ge \alpha_s \quad \forall w \tag{9}$$

where M is a sufficiently large constant. Constraints (6)-(8) indicate that for each scenario w, z_w is equal to 1 when $\pi_w \ge \eta_b$ and 0 otherwise. By maximizing η_b in the objective function (5), constraint (9) ensures that the probability of obtaining a profit equal to or higher than η_b is no less than α_s. The weight parameter β_s assigned to VaB in (5) is the risk-seeking degree, where a larger β_s indicates that the VaB is maximized more significantly and the wind power producer is more risk-seeking.

The profit of wind power producer in each scenario is calculated using constraints (10)-(13).

$$\pi_w = \lambda_{tw}^{DA} P_t^{WD} + \lambda_{tw}^{RT} (\Delta_{tw}^+ - \Delta_{tw}^-) - \lambda_t^P \Delta_{tw}^+ - \lambda_t^N \Delta_{tw}^- \quad \forall t, w \tag{10}$$

$$P_{tw}^{WR} - P_{tw}^{WD} = \Delta_{tw}^+ - \Delta_{tw}^- \quad \forall t, w \tag{11}$$

$$\Delta_{tw}^+ \ge 0,\ \Delta_{tw}^- \ge 0 \quad \forall t, w \tag{12}$$

$$0 \le P_t^{WD} \le P^{W\max} \quad \forall t \tag{13}$$

where P_{tw}^{WR}, λ_{tw}^{DA}, and λ_{tw}^{RT} are the uncertain RT wind power production, DA electricity price, and RT electricity price, respectively; and $P^{W\max}$, λ_t^P, and λ_t^N are the maximum wind power capacity, positive deviation penalty, and negative deviation penalty, respectively. Constraint (10) provides the profit in scenario w, which is equal to the revenue of selling wind power in DA markets plus the profits or minus the losses caused by RT power deviations. Specifically, a positive deviation Δ_{tw}^+ and a negative deviation Δ_{tw}^- would be sold and bought at RT electricity prices, respectively, and both Δ_{tw}^+ and Δ_{tw}^- would be charged with deviation penalties. Constraints (11) and (12) calculate the positive and negative RT power deviations, respectively. Constraint (13) limits the DA wind power offering quantities to be the installed capacity.

In addition to electricity prices and wind power production, other uncertain parameters can also be incorporated into the proposed risk-seeking stochastic optimization model by using their scenario sets. Because the binary variable is used in constraints (6)-(9), the proposed stochastic optimization model is not convex, which indicates that its computational cost might be high when a large number of scenarios are considered. In this circumstance, the scenario reduction method in [12] or the model decomposition method in [13] can be adopted to simplify the stochastic optimization model and decrease the computational cost.

It should be noted that the proposed constraints (5)-(9) used to calculate VaB can be incorporated into a general stochastic optimization model without adding additional nonlinear terms. Therefore, by changing constraints (10)-(13) used to calculate the expected profit, risk-seeking stochastic optimization models can be developed for other decision-makers with different physical properties and market rules and policies.

C. Risk-averse Stochastic Optimization Models based on VaR and CVaR

To make this study self-contained, the risk-averse stochastic optimization models based on VaR and CVaR are described in this subsection, which will then be used in Section IV to conduct a comparative study. Specifically, the objective function of a risk-averse stochastic optimization model is the weighted sum of the total expected profit and a risk measure, which is expressed as:

$$\max_{\Xi} (1 - \beta_r) \sum_{w=1}^{N_\Omega} Pr_w \cdot \pi_w + \beta_r \eta_r \tag{14}$$

where η_r is a risk measure such as VaR or CVaR.

The VaR in a risk-averse stochastic optimization model can be calculated using constraints (15)-(17).

$$\eta_r - \pi_w \le M y_w \quad \forall w \tag{15}$$

$$y_w \in \{0, 1\} \quad \forall w \tag{16}$$

$$\sum_{w=1}^{N_\Omega} Pr_w \cdot y_w \le 1 - \alpha_r \quad \forall w \tag{17}$$

where y_w is a binary variable that is equal to 0 when $\pi_w \ge \eta_r$ and 1 otherwise. Therefore, the risk-averse stochastic optimization model based on VaR is composed of (10)-(17).

The CVaR in a risk-averse stochastic optimization model can be calculated using constraints (18)-(20).

$$\eta_r = \zeta - \frac{1}{1 - \alpha_r} \sum_{w=1}^{N_\Omega} Pr_w \cdot g_w \quad \forall w \tag{18}$$

$$g_w \ge 0 \quad \forall w \tag{19}$$

$$\zeta - g_w \le \pi_w \quad \forall w \tag{20}$$

where g_w and ζ are the continuous ancillary variables. As a result, the risk-averse stochastic optimization model based on CVaR is composed of (10)-(14) and (18)-(20).

IV. Case Studies and Results

Case studies are conducted for a wind farm with an installed capacity of 16 MW. The historical electricity price and wind power data are obtained from the websites of the Pennsylvania New Jersey Maryland market [14] and National Renewable Energy Laboratory [15], respectively. The deviation penalties are set to be 0.5 MWh/$, and the probability parameter α_s of the VaB is specified in each section separately. The historical data of pricing node IMO from January 1, 2019 to May 30, 2019 are used to fit the SARIMA model and generate scenarios for June 1, 2019. All the stochastic optimization models are solved using the Yalmip toolbox [16] in MATLAB and Gurobi 6.52 [17].

A. Illustrative Example

An illustrative example considering 2-hour periods and 10 scenarios with equal probabilities is studied in this subsection, where scenario values are listed in Table I. Figure 2 shows the cumulative probability distributions of the wind power producer's profit, and Table II lists the generated DA wind power offering quantities. The parameter α_s is set to be 0.2, and it is shown that VaB is equal to the second largest profit among those in the 10 scenarios. Thus, the probability of gaining a profit of no less than VaB is equal to 0.2. Table I shows that the RT electricity prices are more volatile than the DA electricity prices. Thus, the RT market may lead to high profits in best-case scenarios and low profits in the worst-case scenarios. When β_s increases from 0 to 0.6, the DA wind power offering quantity decreases by 56.4%, and more power are traded in RT markets. As a result, the VaB increases from \$442.89 to \$470.23, whereas the total expected profit decreases from \$340.22 to \$327.98.

TABLE I
SCENARIO VALUES OF UNCERTAIN PARAMETERS

Scenario index w	$t=1$ hour			$t=2$ hour		
	$\lambda_{1,w}^{DA}$ (MWh/\$)	$\lambda_{1,w}^{RT}$ (MWh/\$)	$P_{1,w}^{WR}$ (MW)	$\lambda_{2,w}^{DA}$ (MWh/\$)	$\lambda_{2,w}^{RT}$ (MWh/\$)	$P_{2,w}^{WR}$ (MW)
1	17.62	22.18	12.18	16.87	17.92	12.22
2	3.96	7.24	16.00	3.20	0.97	16.00
3	19.89	11.22	10.04	19.14	15.83	10.07
4	17.22	18.03	12.01	16.46	15.68	12.05
5	17.22	8.03	16.00	16.46	11.41	16.00
6	16.60	22.10	13.51	15.84	16.72	13.54
7	11.94	22.09	9.69	11.19	11.39	9.72
8	19.43	19.42	8.49	18.67	18.80	8.52
9	14.89	20.83	8.39	14.14	14.23	8.42
10	13.64	0.55	10.66	12.89	1.68	10.69

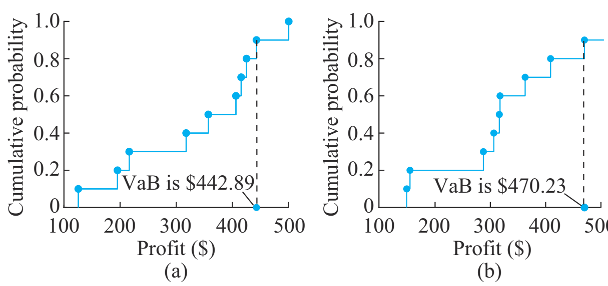

Fig. 2. Cumulative probability distributions of wind power producer's profit. (a) $\beta_s=0$. (b) $\beta_s=0.6$.

TABLE II
DA WIND POWER OFFERING QUANTITIES

Time (hour)	P_t^{WD} (MW)	
	$\beta_s=0$	$\beta_s=0.6$
$t=1$	12.01	16.00
$t=2$	0	12.22

B. Larger Case Studies

Larger case studies considering 24-hour periods and additional scenarios are conducted to further verify the proposed risk-seeking stochastic optimization model. First, 1000 scenarios are generated for uncertain parameters and then reduced to 100, where the other parameters are the same as those adopted in Section IV-A. Simulation results with different risk-seeking degrees are obtained, as shown in Fig. 3. When β_s increases from 0 to 0.1, the VaB increases by \$479, whereas the total expected profit decreases by only \$25.5, indicating that the potential high profits increase significantly without considerably decreasing the total expected profit. The computational time of solving these stochastic optimization models is between 0.9 s and 18.3 s, which are acceptable for electricity market participants in practice.

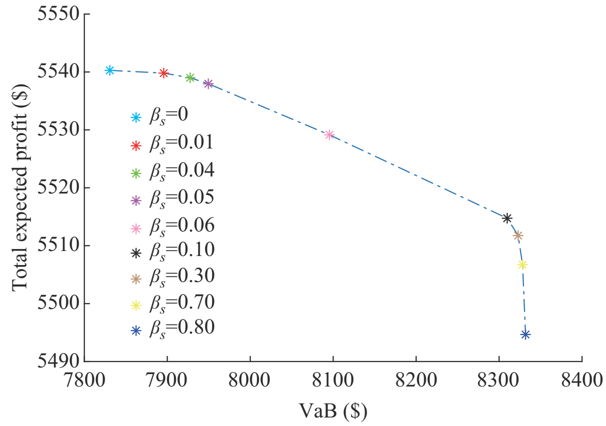

Fig. 3. Effects of risk-seeking degrees on simulation results.

C. Effects of Scenario Number on Simulation Results

To analyze the performance of the proposed risk-seeking stochastic optimization models based on VaB with different scenario numbers, case studies are conducted when the scenario number increases from 50 to 100 with an increment of 10. β_s is set to be 0.1, and the other parameters are the same as those adopted in Section IV-A. The simulation results of the risk-neural stochastic optimization model with $\beta_s=0$ and the proposed risk-seeking stochastic optimization model with $\beta_s=0.2$ are presented in Fig. 4.

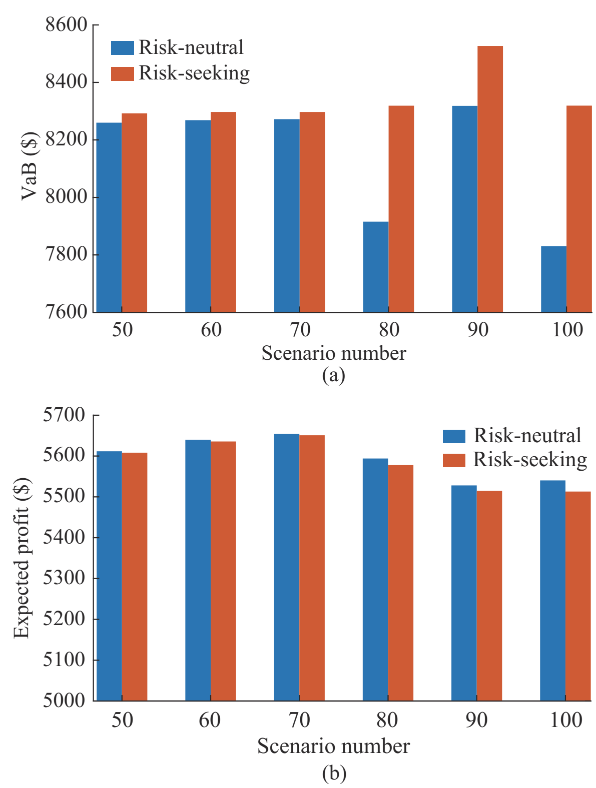

Fig. 4. Simulation results of risk-neutral and risk-seeking stochastic optimization models. (a) VaB. (b) Total expected profit.

In the six cases with different scenario numbers, when the risk-seeking parameter increases from 0 to 0.2, the VaBs increase by 0.39%, 0.34%, 0.3%, 5%, 2.5%, and 6.24%, respectively. By contrast, the total expected profits in the six cases decrease by 0.06%, 0.08%, 0.07%, 0.29%, 0.24%, and 0.49%, respectively. Therefore, the proposed risk-seeking stochastic optimization models base on VaB with different scenario numbers are found to significantly increase the potential high profits without considerably decreasing the total expected profit. In this circumstance, the proposed risk-seeking offering strategy could be attractive for wind-power producers in electricity markets.

D. Comparative Study of Different Stochastic Optimization Models

To further verify the effectiveness of the proposed statistical measure and risk-seeking stochastic optimization model based on VaB, a comparative study is conducted for risk-neutral, risk-seeking, and risk-averse stochastic wind power offering strategies. For the sake of comparison, 100 scenarios with equal probabilities are generated and used in models 1-4, the details of which are as follows:

1) Model 1: risk-neutral stochastic optimization model consisting of (5) and (10)-(13) with $\beta_s=0$;

2) Model 2: risk-seeking stochastic optimization model based on VaB consisting of (5) - (13) with $\beta_s=0.2$ and $\alpha_s=0.1$;

3) Model 3: risk-averse stochastic optimization model based on VaR consisting of (10)-(17) with $\beta_r=0.2$ and $\alpha_r=0.9$;

4) Model 4: risk-averse stochastic optimization model based on CVaR consisting of (11)-(14) and (18)-(20) with $\beta_r=0.2$ and $\alpha_r=0.9$.

As shown in Table III, the VaB and the highest profit of model 2 are both higher than those of the other stochastic optimization models, indicating that the proposed statistical measure based on VaB could be used to effectively maximize the high profits in the best-case scenarios. In addition, the total expected profits of models 2-4 are lower than that model 1. This is because the objective functions of risk-seeking and risk-averse participants include statistical measures such as VaB and VaR.

TABLE III
SIMULATION RESULTS OF RISK-NEUTRAL, RISK-SEEKING, AND RISK-AVERSE STOCHASTIC OPTIMIZATION MODELS

Model type	VaB ($)	The highest profit ($)	VaR ($)	The lowest profit ($)	Total expected profit ($)
Model 1	9318	13256	1805	−1017	5263
Model 2	9467	13446	1660	−1222	5240
Model 3	8871	13339	2515	−145	5226
Model 4	9108	13236	1951	−858	5262

V. CONCLUSION

This study proposes a statistical measure and scenario-based stochastic optimization model to generate risk-seeking wind power offering strategies in electricity markets. The results of case studies show that the high profits in the best-case scenarios could be managed effectively from the probabilistic perspective by using the proposed risk-seeking stochastic optimization method. In future, the proposed statistical measure could be used to model and investigate other risk-seeking participants with other power system assets or electricity market policies such as demand response [18], virtual bidding [19], and microgrid operation [20]. In addition, risk-seeking portfolio optimization theory should be further investigated, and other types of statistical measures with different properties should be developed and studied to address risk-seeking stochastic optimization problems.

REFERENCES

[1] A. J. Conejo, M. Carrión, and J. M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. New York: Springer, 2010.
[2] M. Friedman and L. J. Savage, "The utility analysis of choices involving risk," *Journal of Political Economy*, vol. 56, no. 4, p. 279, Aug. 1948.
[3] D. Kahneman and A. Tversky, "Prospect theory: an analysis of decision under risk," in *Handbook of the Fundamentals of Financial Decision Making: Part I*. Singapore: World Scientific, 2013, pp. 99-127.
[4] A. A. Scholer, X. Zou, K. Fujita *et al*., "When risk seeking becomes a motivational necessity," *Journal of Personality and Social Psychology*, vol. 99, no. 2, pp. 215-231, Aug. 2010.
[5] T. Post and H. Levy, "Does risk seeking drive stock prices? A stochastic dominance analysis of aggregate investor preferences and beliefs," *The Review of Financial Studies*, vol. 18, no. 3, pp. 925-953, May 2005.
[6] H. H. Lean, M. McAleer, and W. Wong, "Preferences of risk-averse and risk-seeking investors for oil spot and futures before, during and after the Global Financial Crisis," *International Review of Economics & Finance*, vol. 40, pp. 204-216, Nov. 2015.
[7] M. Pelster, B. Breitmayer, and T. Hasso, "Are cryptocurrency traders pioneers or just risk-seekers? Evidence from brokerage accounts," *Economics Letters*, vol. 182, pp. 98-100, Sept. 2019.
[8] D. Xiao, M. K. AlAshery, and W. Qiao, "Optimal price-maker trading strategy of wind power producer using virtual bidding," *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 3, pp.766-778, May 2022.
[9] B. Li, X. Wang, M. Shahidehpour *et al*., "Robust bidding strategy and profit allocation for cooperative DSR aggregators with correlated wind power generation," *IEEE Transactions on Sustainable Energy*, vol. 10, no. 4, pp. 1904-1915, Oct. 2019.
[10] F. S. Gazijahani and J. Salehi, "IGDT-based complementarity approach for dealing with strategic decision making of price-maker VPP considering demand flexibility," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 4, pp. 2212-2220, Apr. 2020.
[11] J. M. Morales, R. Mnguez, and A. J. Conejo, "A methodology to generate statistically dependent wind speed scenarios," *Applied Energy*, vol. 87, no. 3, pp. 843-855, Mar. 2010.
[12] J. M. Morales, S. Pineda, A. J. Conejo *et al*., "Scenario reduction for futures market trading in electricity markets," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 878-888, May 2009.
[13] E. Moiseeva and M. R. Hesamzadeh, "Strategic bidding of a hydropower producer under uncertainty: modified benders approach," *IEEE Transactions on Power Systems*, vol. 33, no. 1, pp. 861-873, Jan. 2018.
[14] PJM market. (2020, Aug.). [Online]. Available: https://www.pjm.com/
[15] National Renewable Energy Laboratory. (2020, Aug.). [Online]. Available: https://www.nrel.gov/grid/wind-integration-data.html
[16] J. Lofberg, "YALMIP: a toolbox for modeling and optimization in matlab," in *Proceedings of the 2004 IEEE International Conference on Robotics and Automation*, Taipei, China, Sept. 2004, pp. 284-289.
[17] Gurobi. (2020, Aug.). [Online]. Available: https://www.gurobi.com/
[18] Z. Chen, Y. Sun, A. Xin *et al*., "Integrated demand response characteristics of industrial park: a review," *Journal of Modern Power Systems and Clean Energy*, vol. 8, no. 1, pp. 15-26, Jan. 2020.
[19] D. Xiao and W. Qiao, "Hybrid scenario generation method for stochastic virtual bidding in electricity market," *CSEE Journal of Power and Energy Systems*, vol. 7, no. 6, pp. 1312-1321, Nov. 2021.
[20] B. Zhou, J. Zou, C. Y. Chung *et al*., "Multi-microgrid energy management systems: architecture, communication, and scheduling strate-

gies," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 3, pp. 463-476, May 2021.

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