Stochastic Up to Congestion Bidding Strategy in the Nodal Electricity Markets Considering Risk Management

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ABSTRACT Up to congestion (UTC) is a type of financial product available in the nodal electricity markets of the United States, based on which a financial participant can earn profits by utilizing the different congestion and loss components of the electricity prices in the day-ahead (DA) and real-time (RT) markets. This paper proposes the UTC bidding strategy by using stochastic optimization technique, where the uncertain electricity prices on the UTC transaction paths are represented via scenario sets. In the established stochastic model, the total expected profit and the Conditional Value at Risk (CVaR) of the UTC bidding strategy are maximized simultaneously considering risk management, where the risk preference of financial participant is characterized by using a risk aversion parameter. By solving the proposed stochastic model, non-increasing DA UTC bidding curves can be generated for all the time periods of the next operating day, where credit requirements for UTC transactions are taken into account in detail. Finally, to verify the effectiveness of the proposed strategy, case studies are carried out based on the historical data and trading policies of the Pennsylvania-New Jersey-Maryland (PJM) electricity market, and the UTC bidding strategies generated by different models are analyzed. The numeral results indicate that, compared to the deterministic UTC bidding strategy, the proposed stochastic strategy can bring much higher expected profit and lower potential risks for the financial participant. Moreover, by adjusting the risk aversion parameter in the proposed model, the risks can be managed efficiently according to the financial participant's preference.

INDEX TERMS Electricity market, financial participant, risk management, stochastic optimization, up to congestion.

NOTATIONS

INDEXES AND SETS

w	Index of scenarios, $w \in \{1, \ldots, N_w\}$.
d	Index of the paths for up to congestion (UTC) transactions, $d \in \{1, \ldots, N_d\}$.
t	Index of time periods, $t \in \{1, \ldots, N_t\}$.
s	Index of the pricing nodes in the electricity market, $s \in \{1, \ldots, N_s\}$.
$so(d)$	Source node of the path d for UTC transactions.
$si(d)$	Sink node of the path d for UTC transactions.

VARIABLES

$P_{d,t,w}^{U}$	UTC bidding capacity on path d in time period t for scenario w.
ζ	Auxiliary variable used to compute the CVaR.
η_w	Auxiliary variable used to compute the Conditional Value at Risk (CVaR) for scenario w.
$\pi_{d,t,w}^{U}$	Profit of the UTC bid used on path d in time period t for scenario w.
$E_{d,t,w}^{R}$	Risk exposure of the UTC bid used on path d in time period t for scenario w.
$E_{w}^{R,tot}$	Total Risk exposure of the UTC bids on the paths in the power network for scenario w.

PARAMETERS

$\lambda^D_{s,t,w}$ Day-ahead (DA) electricity price at node s in time period t for scenario w.

$\lambda^R_{s,t,w}$ Real-time (RT) electricity price at node s in time period t for scenario w.

C^{max} Maximum credit available for the financial participant with UTC transactions.

$P^{max}_{d,t}$ Maximum UTC bidding capacity on path d in time period t.

$z^{ref}_{d,t,w}$ Binary parameter which is equal to 1 if the risk exposure of the UTC bid on path d in time period t for scenario w is positive, and is equal to 0 otherwise.

$\lambda^{ref}_{d,t,w}$ Actual reference price for the UTC bid on path d in time period t for scenario w.

$\lambda^{ref}_{d,P}$ Reference price for the UTC bid on path d when it is in prevailing direction.

$\lambda^{ref}_{d,C}$ Reference price for the UTC bid on path d when it is in counter flow direction.

$\lambda^{AV,DA}_d$ Averaged historical hourly DA transmission price on path d provided by the market operator.

r Risk aversion parameter

α_s Confidence level of the CVaR.

I. INTRODUCTION

Most of the two-settlement electricity markets in the United States adopt a nodal pricing framework to determine the electricity price at each node in the power network, in which case the nodal electricity price consists of energy, congestion and loss components [1]. Since the day-ahead (DA) and real-time (RT) electricity markets are cleared on two days separately, the DA and RT electricity prices at a node would not be the same. From the perspective of the market operator, if the differences between DA and RT electricity prices are too large, the electricity market would be considered to be inefficient [2]. In this circumstance, virtual transactions are introduced by the market operators to converge the DA and RT electricity prices, based on which the financial participants can trade power in the DA and RT markets without generating or consuming it. Additionally, the financial participants using virtual transactions can increase market liquidity and reduce the market shares of the other participants with assets in the grid, such as the power producers and electricity retailers [1].

In the current US electricity markets, there are three types of virtual transactions available for the pure financial participants, including the increment (INC) offer, decrement (DEC) bid and up to congestion (UTC) transaction [3]. A profitable INC offer or DEC bid can help reduce the energy component differences between the DA and RT markets at each node in the power network, and a profitable UTC transaction can help reduce the congestion or loss component differences between DA and RT markets on each path. Currently, the INC

offers and DEC bids can be used in most of the major US electricity markets, and the UTC transactions are available in the markets operated by the Pennsylvania-New Jersey-Maryland (PJM) Interconnection and the Electric Reliability Council of Texas (ERCOT) [3].

Since virtual transaction was first introduced to the US electricity markets in the year 2000, it has been studied by many researchers from the industry and academia, and its main benefits and risks were addressed in [4]. In [5], the virtual bidders with perfect forecast results were studied in several electricity market clearing models, and it was concluded that virtual transactions could improve the market efficiency. In [6] and [7], the impacts of virtual transactions on the market outcomes was studied by analyzing the historical electricity price data in the two-settlement markets operated by the California Independent System Operator (CAISO) and the New York Independent System Operator (NYISO), and it was shown that the price differences between DA and RT markets were reduced after the introduction of virtual transactions. However, the authors of [8] found out that if a virtual bidder cannot forecast market outcomes accurately, its virtual transactions might decrease the total social welfare of the electricity market. In [9], it was addressed that virtual transactions can be used by FTR holders to manipulate the electricity prices and increase the value of their FTRs. The authors of [10] established an equilibrium model to investigate the characteristics of the FTR holders with virtual transactions. In [11] and [12], an analytical framework and a bi-level optimization model were developed for the cyber attacker with virtual transactions, respectively, and it was shown that the associated virtual bids might bring risks to the power system.

Virtual transaction has both advantages and disadvantages, while the author of [3] addressed that it is indispensable for the efficient electricity market design considering the risks face by the participants. Therefore, it is necessary to develop the optimal virtual bidding strategy used by the market participants considering the potential risks. In [13], risk-based stochastic virtual bidding strategy in California electricity market was generated based on hidden Markov models. In [14] and [15], stochastic virtual transaction models were developed for a financial participant and a solar power producer, respectively, where the electricity prices were characterized using autoregressive integrated moving average (ARIMA) models. In [16], the authors proposed a data-driven virtual bidding strategy by using an online learning algorithm, where the Sharpe ratio was used to measure its performance.

The literature on virtual bidding were summarized in Table 1, and it is shown most of the existing research work just focus on the INC offers and DECs used at the nodes, while the UTC transactions used on the paths have not been studied in detail. However, as shown in Table 2, the actual trading volume of the UTC transactions could be much larger than those of the INC offers and DEC bids in certain electricity market. In the year 2017, 2018 and 2019, the total cleared quantities of DA UTC transactions are 306.3%, 215.7% and

TABLE 1. A summary of the literature on virtual transactions.

Reference	Type of virtual transaction	Type of Model
[4], [6], [7], [9], [11] and [12]	INC offer and DEC bid	Deterministic
[5], [8], [10], and [13]-[16]	INC offer and DEC bid	Stochastic
[2] and [3]	INC offer, DEC bid and UTC transaction	Deterministic

TABLE 2. The average hourly cleared DA INC offers, DEC bids and UTC transactions from 2017 to 2019 in the PJM market [17]–[19].

Year	INC offers (MWh)	DEC bids (MWh)	UTC transactions (MWh)
2017	4562	4035	34927
2018	2676	2906	17624
2019	2889	3704	20862

216.4% higher than the those of the DA INC offers and DEC bids, respectively [17]–[19]. As shown in Table 1, the literature on UTC transactions in nodal electricity markets are quite limited. In [2], the typical UTC transactions occurred in the PJM electricity markets were illustrated, and its potential risks and benefits were discussed. The author of [3] analyzed the function of UTC transactions considering the uncertainties and risks faced by market participants. However, the models of UTC transactions in [2] and [3] are deterministic ones without considering the uncertainties and risks in the market, and the credit requirements were not formulated in detail.

In the electricity market, the participants needs to face various uncertainties, such as the electricity prices [21], renewable power productions [22], [23], and the electric demands of electricity consumers, such as [24]–[27]. To develop the bidding strategy considering these uncertainties in the market, stochastic optimization, robust optimization and information gap decision theory (IGDT) techniques were utilized by the participants [21]–[26]. In the IGDT and robust optimization-based models, the uncertain parameters are represented by using their upper and lower bounds [21]–[24]; in contrast, the uncertain parameters in a stochastic optimization model are represented using a large number of scenarios, which should be generated based on the full probability distributions [25], [26]. In this circumstance, the computational cost of solving a stochastic optimization model tends to be larger than that of solving a robust optimization-based or an IGDT-based model. However, robust optimization and IGDT techniques might lead to conservative solutions due to their simplified uncertainty characterization methods.

In this paper, we adopted the stochastic optimization technique to generate the UTC bidding strategy, which can utilize the full probability distributions of the electricity prices and help the financial participant seek higher expected profits. Additionally, since the financial participant does not have any physical assets, its stochastic optimization model does not include complicated physical constraints and is easy to be solved even with a large number of scenarios. Therefore,

this paper proposes the stochastic UTC bidding strategy in the nodal electricity market, which can maximize the expected profits and manage the risks for the financial participant. The contributions of this paper are as follows:

1) A stochastic DA UTC bidding strategy is proposed for a financial participant in nodal electricity markets. Compared to the existing deterministic UTC transaction models, the proposed stochastic model includes the details on credit requirements, and the uncertainties of the electricity prices on the UTC paths. By adjusting the risk aversion parameter, the financial participant can generate non-increasing DA UTC bidding curves considering its own risk preference.

2) Comparative studies are carried out for the deterministic and stochastic UTC bidding strategies with different risk aversion parameters in detail. The profitability and potential risks of the different UTC bidding strategies are analyzed based on the price data and trading policies in the PJM electricity market.

The remaining parts of this paper are organized as follows: Section III addresses the mechanism and market frame of the UTC transaction used by a financial participant, and the proposed stochastic UTC bidding strategy is presented in Section IV. In Section V, case studies are conducted to verify the proposed strategy. Finally, conclusions are obtained in Section VI.

II. MARKET FRAME OF UTC TRANSACTION
A. MECHANISM OF UTC TRANSACTION
The basic mechanism of virtual transaction is submitting generating offers or demand bids to the DA market without actually producing and consuming power in the gird, and in the RT market all the deviations caused by the DA commitments of virtual transactions are settled at the RT prices. Therefore, the profit of the virtual transaction depends on the price differences between DA and RT electricity markets. In the current nodal electricity markets in the United States, there are three types of virtual transactions, including the INC offer, DEC bid and UTC transaction. Specially, the INC offer is offering virtual power in the DA market at a pricing node and buying it back in the RT market; in contrast, the DEC bid is buying virtual power at a pricing node in the DA market and selling it back in the RT market. Different from the INC offer or DEC bid used at one node, the UTC transaction is selling and buying power at two pricing nodes of a path simultaneously. As shown in Fig. 1, a path in the power network consists of a source node and a sink node, where a DA virtual power injection and a virtual power withdrawal are used, respectively. Therefore, a cleared DA UTC transaction can be regarded as a virtual power flow on a path, and to settle the deviations caused by this DA power flow, a RT power flow in the opposite direction needs to be cleared at RT prices on the operating day.

When a financial participant wants to submit a DA UTC bid on a path, a virtual power generation offer and a virtual demand bid are submitted to the source and sink nodes of
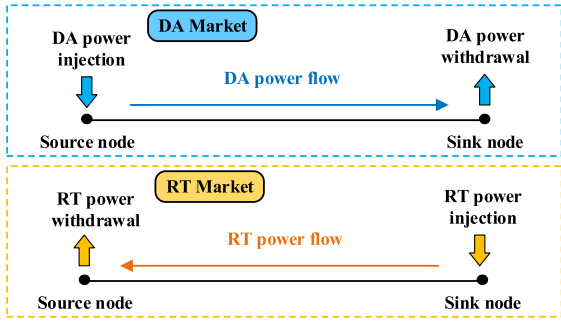
FIGURE 1. The illustration of the UTC transaction in DA and RT electricity markets.

FIGURE 2. Market frame of UTC transactions.

a path, respectively. If UTC bidding price is lower than the actual DA price differences between the sink and source nodes, the generation offer and demand would be cleared at DA prices of these two nodes simultaneously; then, in the RT market the deviations of the two nodes would be settled at RT prices. If the cleared UTC bid for path d in time period t is $P_{d,t}^U$, the profit of this UTC bid $\pi_{d,t}^U$ is calculated as follows:

$$\pi_{d,t}^U = \left[\left(\lambda_{si(d),t}^R - \lambda_{so(d),t}^R \right) - \left(\lambda_{si(d),t}^D - \lambda_{so(d),t}^D \right) \right] P_{d,t}^U \quad (1)$$

As shown in (1), the profitability of the UTC bid $P_{d,t}^U$ depends on the difference between $(\lambda_{si(d),t}^R - \lambda_{so(d),t}^R)$ and $(\lambda_{si(d),t}^D - \lambda_{so(d),t}^D)$, where the term $(\lambda_{si(d),t}^D - \lambda_{so(d),t}^D)$ can be regarded as the transmission price of delivering power from the source node to the sink node on path d in the DA market. When $\left[\left(\lambda_{si(d),t}^R - \lambda_{so(d),t}^R \right) - \left(\lambda_{si(d),t}^D - \lambda_{so(d),t}^D \right) \right]$ is positive and negative, the values of $P_{d,t}^U$ tend to be positive and negative, respectively. It should be noted that the power deviations between DA and RT markets caused by the UTC transactions are not charged with penalties in the current US electricity markets, and details on this policy were addressed in [28].

B. MARKET REQUIREMENTS FOR UTC TRANSACTION

As shown in Fig. 2, even though UTC transactions in the electricity market are not related to any generation or demand sources in the grid, the maximum UTC bidding capacity should still be limited by the credit available in trading account of the financial participant; otherwise, if the UTC bid is not profitable on the next day, the financial participant may fail to cover the losses due to its insufficient deposit, which may lead to default risks for electricity market. Therefore, the financial participant using UTC transactions should keep its credit higher than its total risk exposure, which should be formulated as a credit constraint in the optimization problem for generating the UTC bidding strategy.

According to the credit requirements for UTC transactions, the risk exposure of a UTC bid represents the potential loss that may occur in the electricity market, which is calculated based on the bidding capacity of the financial participant and the reference price of the path [20]. If the reference price of path d is λ_d^{Ref}, and the DA UTC bidding capacity and price
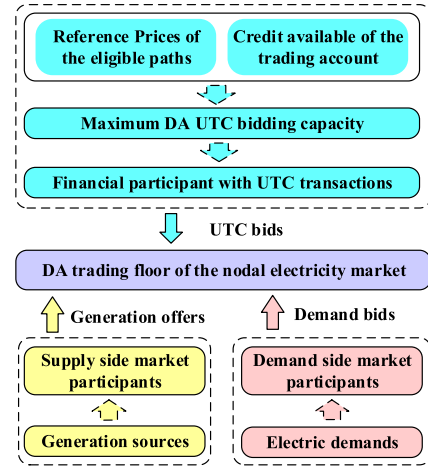
of the financial participant in time period t are $P_{d,t}^U$ and $\lambda_{d,t}^D$, respectively, the risk exposure of the UTC transaction should be calculated as follows:

$$E_{d,t}^R = P_{d,t}^U \left(\lambda_{d,t}^D - \lambda_{d,t}^{Ref} \right) \quad (2)$$

where the reference price λ_d^{Ref} is related to the UTC direction on the path, which is determined the sign of DA transmission price of path d.

Additionally, in order to have enough margin for alleviating the potential risks of UTC transactions, the time periods with negative risk exposures are not taken into account in the credit constraints, which indicates the total risk exposure of the financial participant with UTC transactions is the sum of all the positive hourly risk exposures on the paths for the next day. The detailed procedures of calculating the total risk exposure in the proposed stochastic UTC bidding strategy would be addressed in Section IV-B.

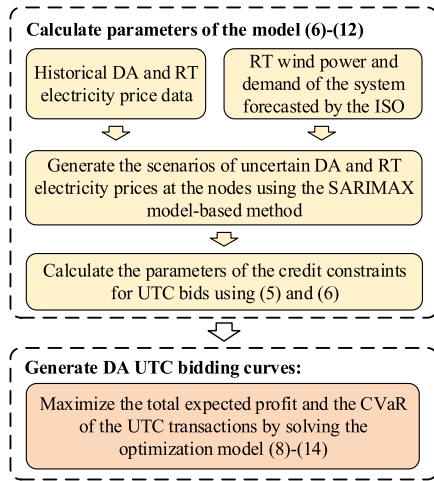### III. PROPOSED STOCHASTIC UTC BIDDING STRATEGY
A. OVERALL FRAMEWORK

The proposed stochastic UTC bidding strategy is described in this section and its overall framework is shown in Fig. 3. The model parameters related to the uncertain electricity prices and credit constraints are first calculated according to the market requirements specified by the market operator. Then, the DA UTC bidding curves are generated by solving a scenario-based stochastic optimization model. The detailed procedures of these two parts are addressed in Section IV-B and IV-C, respectively.

B. MODEL PARAMETER CALCULATION

In this paper, the financial participant is assumed to have limited credit and modelled as price-takers in both DA and RT markets, because the UTC bidding capacity of the financial participant is much smaller than the total DA and RT power trading volumes. Therefore, the uncertain DA and RT electricity price scenarios are represented using scenarios, which are generated without considering the financial participants'

FIGURE 3. Overall framework of the proposed stochastic UTC bidding strategy.

UTC bidding strategy [29]. Otherwise, if the financial participant is a price-maker, its bidding strategy may affect the electricity market outcomes, and the dependency between the electricity prices and the UTC bidding strategy needs to be further modelled by using additional methods, such as the bilevel programming approach used in [5].

The scenarios of uncertain parameters can be generated by using probabilistic models [30] or historical data [31]. In this paper, the scenarios of uncertain DA and RT electricity prices at the nodes are both generated by using the Seasonal Autoregressive Integrated Moving Average with Explanatory Variable (SARIMAX)-based method, where the forecasted RT wind power and demand are used as the explanatory variables. Specifically, a stochastic process Y characterized by using the SARIMAX model is expressed as follows:

$$\left(1-\sum_{l=1}^{L}\phi_l L^l\right)\left(1-\sum_{n=1}^{N}\Phi_n L^{nS}\right)(1-L)^d\left(1-L^S\right)^D y_t$$
$$=\left(1-\sum_{u=1}^{U}\theta_u L^u\right)\left(1-\sum_{v=1}^{V}\Theta_v L^{vS}\right)\varepsilon_t+\sum_{k=1}^{K}\rho_k x_t^k \quad (3)$$

where ϕ_p, Φ_n, θ_u, Θ_v, and ρ_k are the coefficients of autoregressive, moving average, seasonal autoregressive, seasonal moving average, and explanatory variable terms, respectively. ε_t is the forecast error in time period t that follows normal distribution, and L^d is the lag operator, and its function is expressed as follows:

$$L^d y_t = y_{t-d} \quad (4)$$

In the US electricity markets, the historical data of DA and RT electricity prices of all the nodes are public available on the official websites. Additionally, the electricity market operators usually provide the market participants with the forecasted RT wind power and demand of the system. In this circumstance, the parameters of the SARIMAX model can be estimated by using the historical data of electricity price and the forecasted RT wind power and demand [32]. The dependency between DA and RT electricity prices are characterized by using the variance-covariance matrix, which is addressed in [30]. The details on the estimation procedures for the SARIMAX model are provided in [33]. In the proposed UTC bidding strategy, the scenarios of DA price differences between the sink and source nodes of the paths are used as the prices of the UTC bidding curves, and the optimal UTC bidding capacities need to be calculated by the solving the optimization model provided in Section IV-C.

After the electricity price scenarios are generated, the parameters of the credit constraints need to be calculated based on the UTC bidding prices and reference prices. As mentioned in Section III, the UTC reference price of a path is related to the direction of the UTC bid. The UTC bid is in the prevalent direction if either the UTC bidding price or the averaged historical DA transmission price of the path is negative; otherwise, the UTC bid is considered to be in the counter flow direction. Therefore, the actual reference price on path d in time period t for scenario w can be expressed as follows:

$$\lambda_{d,t,w}^{ref} = \begin{cases} \lambda_{d,P}^{ref}, & \lambda_{so(d),t,w}^{D}-\lambda_{si(d),t,w}^{D}<0 \ or \ \lambda_d^{AV,DA}<0 \\ \lambda_{d,C}^{ref}, & \text{otherwise} \end{cases} \quad (5)$$

As is shown in (5), when the UTC bid is in the prevalent and counter flow directions, $\lambda_{d,t}^{ref}$ is equal to $\lambda_{d,P}^{ref}$ and $\lambda_{d,C}^{ref}$ respectively, and $\lambda_{d,t}^{AV,RT}$ is the averaged historical hourly DA transmission price of path d provided by the market operator.

When calculating the total risk exposure of the UTC bids on all the paths during one day, only the positive hourly risk exposures are taken into account according to the credit requirements. In this circumstance, an ancillary binary parameter $z_{d,t,w}^{ref}$ is used to mark the sign of the UTC bid's risk exposure on path d in time period t for scenario w, which is expressed as follows:

$$z_{d,t,w}^{ref} = \begin{cases} 0, & \lambda_{si(d),t,w}^{D}-\lambda_{so(d),t,w}^{D}-\lambda_{d,t}^{ref}\leq 0 \\ 1, & \lambda_{si(d),t,w}^{D}-\lambda_{so(d),t,w}^{D}-\lambda_{d,t}^{ref}>0 \end{cases} \quad (6)$$

After the above parameters regarding the credit constraints of the UTC transactions are calculated, the total risk exposure of the DA UTC bids for scenario w can be formulated as follows:

$$E_w^{R,tot} = \sum_{t=1}^{N_t}\sum_{d=1}^{N_d} z_{d,t,w}^{ref} P_{d,t,w}^{U}(\lambda_{si(d),t,w}^{D}-\lambda_{so(d),t,w}^{D}-\lambda_{d,t,w}^{ref}) \quad (7)$$

C. STOCHASTIC OPTIMIZATION MODEL FOR GENERATING UTC BIDDING CURVES

The stochastic optimization model for generating the DA UTC bidding curves is established to optimize the total expected profits and the risks of the UTC bidding strategies in the nodal electricity market for the financial participant.

The formulations of the proposed model include (8)-(14), which are given as follows:

$$\max_{\Xi} (1 - r) \sum_{w=1}^{N_w} \sum_{t=1}^{N_t} \sum_{d=1}^{N_d} P_{d,t,w}^U [\left(\lambda_{si(d),t,w}^R - \lambda_{so(d),t,w}^R \right)$$

$$- \left(\lambda_{si(d),t,w}^D - \lambda_{so(d),t,w}^D \right)]$$

$$+ r \left(\zeta - \frac{1}{1-\alpha} \sum_{w=1}^{N_w} pr_w \eta_w \right) \tag{8}$$

Subject to : $$\sum_{t=1}^{N_t} \sum_{d=1}^{N_d} z_{d,t,w}^{ref} P_{d,t,w}^U (\lambda_{si(d),t,w}^D - \lambda_{so(d),t,w}^D$$

$$- \lambda_{d,t,w}^{ref}) \leq C^{max} \quad \forall \omega \tag{9}$$

$$0 \leq P_{d,t,w}^U \leq P_{d,t}^{max} \quad \forall d, t, \omega \tag{10}$$

$$P_{d,t,w}^U = P_{d,t,w'}^U \quad \forall d, t, \omega, \omega' :$$

$$\lambda_{si(d),t,w}^D - \lambda_{so(d),t,w}^D = \lambda_{si(d),t,w'}^D - \lambda_{so(d),t,w'}^D \tag{11}$$

$$\left(\lambda_{si(d),t,w}^D - \lambda_{so(d),t,w}^D \right) \left(P_{d,t,w}^U - P_{d,t,w'}^U \right)$$

$$- \left(\lambda_{si(d),t,w'}^D - \lambda_{so(d),t,w'}^D \right) \left(P_{d,t,w}^U - P_{d,t,w'}^U \right)$$

$$\leq 0, \quad \forall d, t, \omega \tag{12}$$

$$\eta_w \geq 0, \quad \forall \omega \tag{13}$$

$$\zeta - (\sum_{t=1}^{N_t} \sum_{d=1}^{N_d} P_{d,t,w}^U [\left(\lambda_{si(d),t,w}^R - \lambda_{so(d),t,w}^R \right)$$

$$- \left(\lambda_{si(d),t,w}^D - \lambda_{so(d),t,w}^D \right)]) \leq \eta_w, \quad \forall \omega \tag{14}$$

where $\Xi = \{P_{d,t,w}^U, \zeta, \eta_w,$ and it is the set of the decision variables in the proposed optimization model.

The objective function (8) is the weighted sum of the total expected profits and the CVaR, which is the risk measure used in the stochastic model. In the CVaR, a confidence level α_s is required to be specified by the financial participant using UTC transactions, which is positive and smaller than 1. The CVaR with confidence level α_s is denoted as $CVaR_{\alpha_s}$, and its value is the expected profit of the UTC bidding strategy in the $(1 - \alpha_s) \times 100\%$ least profitable scenarios [34]. In practice, the confidence level α_s is usually set to be 0.9 or 0.95, because using a large α_s cannot help the UTC bidder manage the tail risks in the worst scenarios effectively. The weight assigned to the CVaR is the risk aversion parameter, which should be set based on the financial participant's risk preference, and a large risk averse parameter indicates the participant is risk averse and cares about the potential low profits or losses in the worst scenarios. The $\lambda_{si(d),t,w}^R$, $\lambda_{so(d),t,w}^R$, $\lambda_{si(d),t,w}^D$ and $\lambda_{so(d),t,w}^D$ in the objective function are the scenarios of the electricity prices on the paths, and their values are determined by the SARIMAX-based scenario generation process in Section IV-B.

Constraint (9) provides the credit constraints for the UTC bidding capacities, which guarantees that the total positive risk exposure of all the time periods and paths does not exceed the total credit available of the financial participant for any scenario w. The $z_{d,t,w}^{ref}$ and $\lambda_{d,t,w}^{ref}$ in constraint (9) are the parameters related to the credit constraints that are calculated by using (5) and (6), respectively.

Constraint (10) provides the lower and upper bounds of the UTC bidding capacity on each path, which are specified to avoid the potential unbounded solutions when solving the optimization problem. The properties of the non-increasing UTC bidding curve are taken into account in constraints (11) and (12). Constraint (11) means that the values of $P_{d,t,w}^U$ and $P_{d,t,w'}^U$ should be equal if the UTC bidding prices in scenario w and w' are the same. Constraint (12) ensures that UTC bidding curve is non-increasing, which indicates the UTC bidding capacity decreases with the DA transmission price of the path, and in this circumstance, if the expected DA transmission price on the path is too high, the corresponding UTC bidding capacity might be zero.

Constraints (13) and (14) are used for calculating the CVaR when the term $\zeta - \frac{1}{1-\alpha} \sum_{w=1}^{N_w} pr_w \eta_w$ is included in the objective function, and the details on the formulations of incorporating the CVaR in a stochastic optimization problem are addressed in [34].

IV. CASE STUDIES

A. SIMULATION SETUP

To verify the effectiveness of the proposed stochastic UTC bidding strategy of the financial participant, case studies are carried out based on the historical data in the PJM wholesale electricity market. The pricing nodes that can be used as the source or sink nodes of the UTC transaction paths are specified by the market operator, and the historical electricity price data and the UTC reference price data are both public available on the PJM's official website [35]. As mentioned in Section IV-B, the reference prices for the UTC bid in the prevailing and counter flow directions are not the same, and they are the 30th and 20th percentiles of the historical RT transmission price data, respectively [20]. The proposed model (8)-(14) is a linear programming problem, which is solved efficiently by using Yalmip toolbox [36] and Gurobi 7.0 in MATLAB [37] in this paper.

B. RESULTS OF RISK-NEUTRAL STOCHASTIC UTC BIDDING STRATEGY

In this section, the financial participant is assumed to submit its UTC bids on 12 paths associated with four pricing nodes in the PJM electricity market, and the names of Node 1-4 are WESTERN HUB, NEW JERSEY HUB, NYIS and IMO, respectively. In the proposed stochastic optimization model (8)-(14), the maximum credit in the financial participant's trading account is assumed to be \$600 and the maximum DA UTC bidding capacity on each path is set to be 40 MW. The risk aversion parameter and the confidence level are set to be 0 and 0.9, respectively. Afterwards, 100 scenarios are generated by using the SARIMAX-based method and

the historical electricity price data in the latest 3 months. Specifically, the historical DA and RT electricity price data from June 1,2019 to August 31, 2019 are used to fit the SARIMAX model and generate the DA UTC bidding strategy on September 1, 2019.
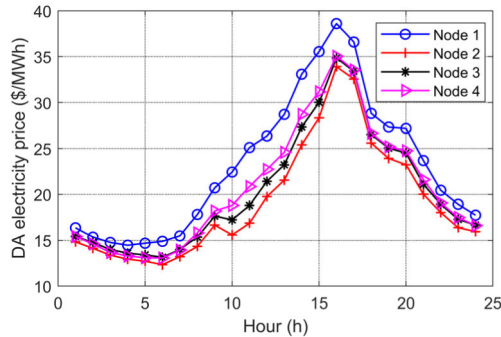

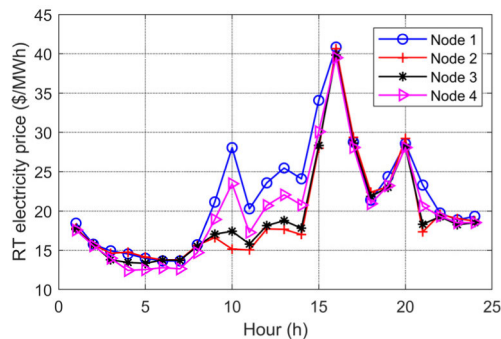**FIGURE 4.** Expected DA electricity prices at four pricing nodes of one day.

FIGURE 5. Expected RT electricity prices at four pricing nodes of one day.
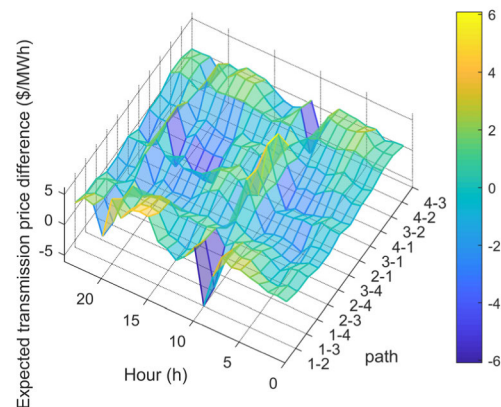

FIGURE 6. Expected transmission price differences between RT and DA markets for all the paths in the power network for one day.

Afterwards, the risk neutral stochastic UTC bidding strategies of the financial participant are generated by solving the stochastic model. Fig. 4 and 5 show the expected DA and RT electricity prices of one day, respectively. The electricity prices at Node 1-4 are not the same during most of time periods, which indicates the transmission prices of the paths are nonzero due to the power congestions and transmission losses in the power network. Moreover, as shown in Fig. 6,

the transmission price differences between RT and DA markets are also different in during most of time periods, which indicates the congestion or power loss components of the electricity prices are also different in DA and RT markets due to the separate clearing processes.
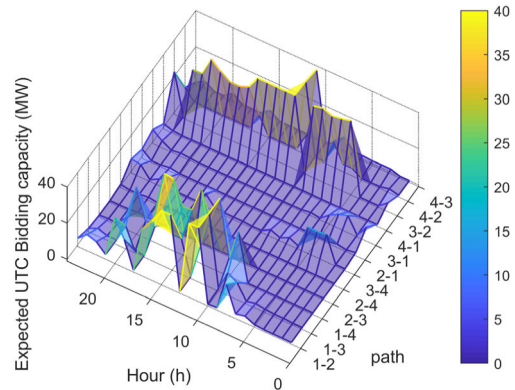

FIGURE 7. Expected DA UTC bidding capacities on all the paths in the power network for one day.
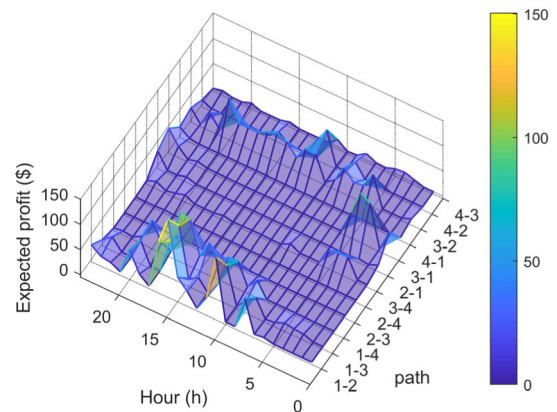

FIGURE 8. Expected profits of the UTC bids on all the paths in the power network for one day.

The expected UTC bidding capacities and profits of one day are provided in Fig. 7 and 8, respectively. It is shown that the expected UTC bidding capacity and profit are both related to the transmission price differences between RT and DA markets. For instance, the transmission price differences on path 2-4 are very small during most hours of the day and there is little incentive to earn profits for the financial participant, which makes the expected UTC bidding capacities and profits very small on this path in the electricity market; in contrast, the expected transmission price difference between RT and DA markets on path 1-2 are pretty large during some hours, thus making the financial participant trade power actively on this path and earn high expected profits from the associated UTC transactions.

C. IMPACTS OF MODEL PARAMETERS

In the proposed model, there are several parameters on that can affect the results of the proposed stochastic UTC bidding strategy significantly, which are analyzed in this section.
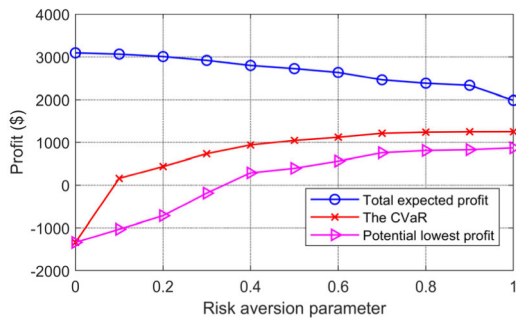
FIGURE 9. The impacts of different risk aversion parameters on the expected profits of the stochastic UTC bidding strategy.

FIGURE 11. The impacts of different confidence levels on the expected profits of the stochastic UTC bidding strategy.

First, the risk aversion parameter r is changed from 0 to 1 with an increment of 0.1, and the other model parameters are set to be the same as those in Section V-B. The total expected profits, the CVaR and the potential lowest profit are generated and provided in Fig. 9. It is shown that the total expected profit is decreased with the risk aversion parameter, while the CVaR and the potential lowest profit are both increased with the risk aversion parameter. Additionally, the DA UTC bidding curves based on different risk averse degrees in the 3rd hour for path 3-4 are provided in Fig. 10. When r is 0, 0.4 and 0.9, 40 MW UTC bid would be cleared in the DA market when the transmission prices are below -0.5/MWh, -0.81/MWh and -0.98/MWh, respectively, which indicates a risk-averse financial participant tends to trade less power in DA markets.

FIGURE 12. Impacts of different maximum credits and UTC bidding capacities on each path on the total expected profit.

In additional to the model parameters related to the risk management, the maximum credit of the financial participant and the maximum bidding on each path can also affect the results of the UTC bidding strategy. As shown in Fig. 12, when the other model parameters are set to be the same as Section V-B, increasing the maximum credit and the bidding capacity on each path can both improve the total expected profit, because larger total credit and bidding capacity on each path lead to larger trading flexibility for the financial participant using UTC transactions.

D. COMPARISON OF DIFFERENT UTC BIDDING STRATEGIES

In this section, in order to demonstrate the advantages of stochastic UTC bidding strategy over the deterministic one, and study the impacts of the risk aversion parameter on the simulation results, four cases are designed based on different UTC bidding strategies. In case 1, a deterministic UTC bidding strategy is generated by solving a deterministic model, and each uncertain parameter is represented by just one deterministic value, which is obtained by averaging the 100 scenarios used in the stochastic model of Section V-B. In Case 2-4, three different stochastic UTC bidding strategies are generated by solving three stochastic models, where the risk-aversion parameters are set to be 0, 0.1 and 1, respectively. In this circumstance, the uncertain parameter forecast accuracies in Case 1-4 are the same from the perspective of the average value; however, since the deterministic strategy in Case 1 only use one deterministic forecast value instead of a set of scenarios, it does not consider the complete probability
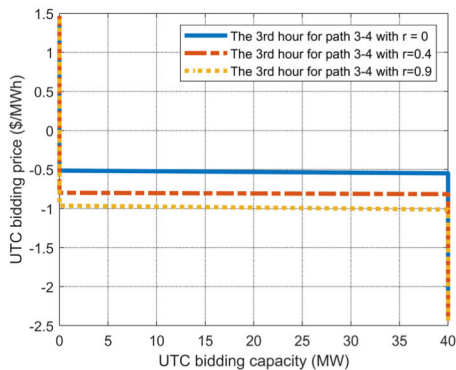

FIGURE 10. The DA UTC bidding curves based on different risk aversion.

Next, when the risk aversion parameter is set to be 0.1 and the confidence level α_s is increased from 0.1 to 0.9 with an increment of 0.1, the expected profits are calculated and provided in Fig. 11. Since the CVaR is expected profit of the worst $(1-\alpha_s)\%$ scenarios, the correlation between the CVaR and potential lowest profit is increased with α_s. As shown in Fig. 11, the potential lowest profit is increased with α_s, which indicates optimizing the CVaR with a larger α_s can minimize the risks the in the worst scenarios more effectively. Therefore, the confidence level is usually set to be 0.9 or 0.95 in the CVaR-constrained stochastic optimization models for managing the tail risks effectively.
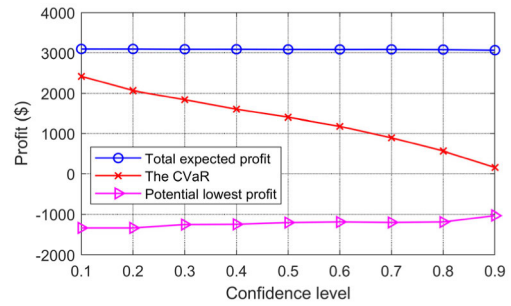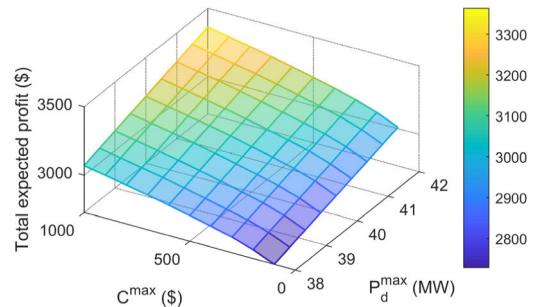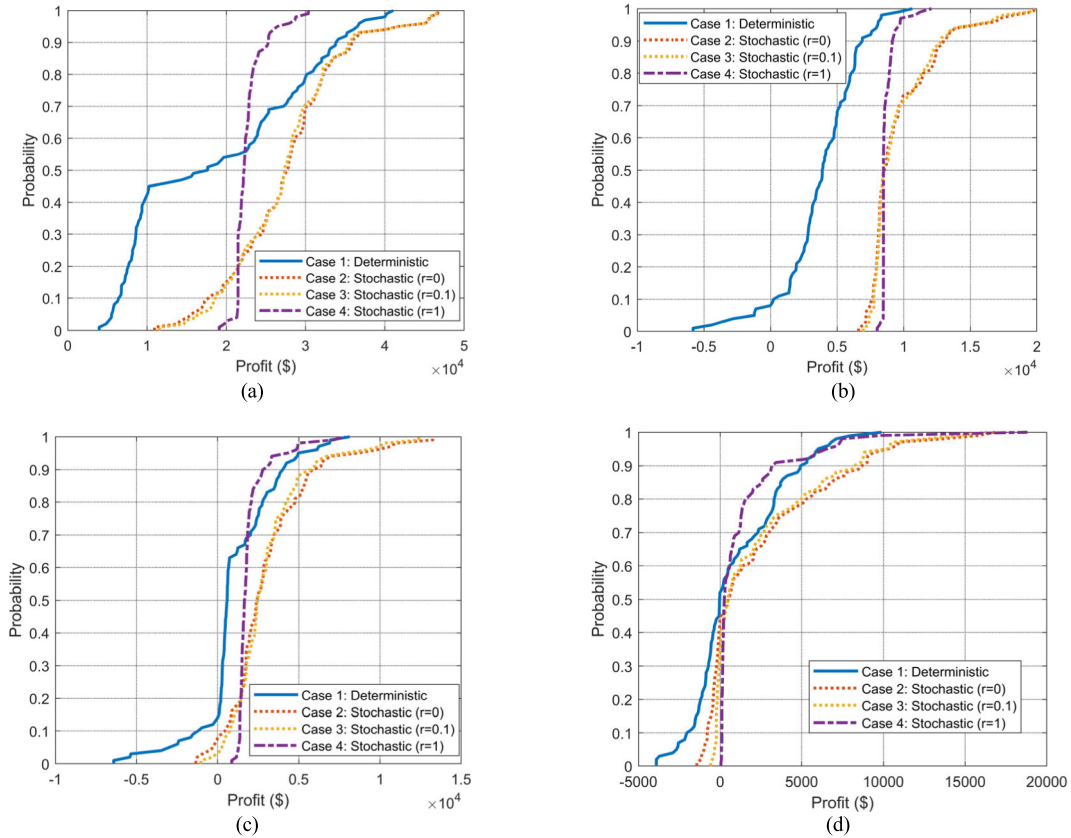
FIGURE 13. Cumulative distribution functions of the expected profits for four different UTC bidding strategies on (a) March 1, 2019, (b) June 1, 2019, (c) September 1, 2019 and (d) December 1, 2019.

distribution of the uncertain electricity prices like stochastic strategies in Case 2-4. Additionally, since the risk-averse parameters in Case 3 and 4 are both positive, the generated stochastic UTC bidding strategy in these two cases would be risk-averse, which would be more conservative than the risk neutral one generated in Case 2.

To show the effectiveness of the proposed UTC bidding strategy in different time periods of a year, the case studies in this section are carried out for 4 typical days during spring, summer, autumn and winter in 2019, which are March 1, June 1, September 1 and December 1, respectively. Fig. 13 provides the cumulative probability distributions of the expected profits obtained by four different UTC bidding strategies, and Table 3 shows some typical results in four cases. The probability distributions in Case 1 is much more heavy-tailed than those in Case 2-4 on the left side, which indicates the deterministic UTC bidding strategy has obvious tail risks from a probabilistic perspective. As shown in Table 3, the total expected profits and the CVaR of the stochastic UTC bidding strategies in Case 2-4 are higher than those of the deterministic one in Case 1. Therefore, compared to the deterministic UTC bidding strategy, the stochastic UTC bidding strategy can help the financial participant increase the total expected profits and decrease the potential risks that might occur in the worst scenarios.

For the stochastic UTC bidding strategies in Case 2-4, the expected UTC bidding capacity and profit are both decreased with the risk aversion parameter, while the CVaR is increased with risk-aversion parameter. For instance, when the risk aversion parameter is increased from 0 to 0.1, the CVaR and potential lowest expected profit on September 1, 2019 are increased by $1498.86 and $308.6, respectively, while the total expected profit is just decreased by $30.27. However, when the risk aversion parameter is increased from 0.1 to 1, even though the CVaR and expected lowest profit on September 1, 2019 are increased by $1093.49 and $1901.7, respectively, the total expected profit is decreased by $1080.64, which indicates the risk-averse bidding strategy in Case 4 became conservative due to the large risk-aversion parameter. Actually, when r is set to be 1 in the objective function in Case 4, the weight assigned to the total expected profit is zero and only the CVaR is maximized in the stochastic optimization model.

Therefore, the stochastic UTC bidding strategy in Case 3 might be good for a risk-averse financial participant with UTC transactions, because it can lower the potential risks in the worst scenarios significantly without decreasing the total expected profit too much. However, for a risk-neutral financial participant who does not care about the risks in the market, it might still adopt the stochastic strategy in Case 2 due to its high total expected profit.

TABLE 3. Comparison of the simulation results obtained by using the UTC bidding strategies in four cases.

Case No.		Total expected bid capacity (MW)	Total expected profit ($)	Potential highest profit ($)	$CVaR_{0.9}$ ($)	Potential lowest profit ($)
March 1, 2019	Case 1	3488.71	18735.55	41064.72	5503.23	3963.43
	Case 2	2949.72	27668.21	46710.03	10934.61	10934.63
	Case 3	2871.35	27615.63	46500.12	16457.23	11550.31
	Case 4	1986.63	22754.01	30373.42	20902.97	19100.01
June 1, 2019	Case 1	4533.34	3832.67	10650.03	-1982.83	-5814.18
	Case 2	3299.16	9714.97	19964.03	6609.94	6609.92
	Case 3	3281.52	9700.62	19795.75	7513.35	6961.16
	Case 4	2999.18	8723.65	12088.56	8380.81	8005.16
September 1,2019	Case 1	2630.21	1138.92	8139.02	-3290.32	-6409.13
	Case 2	1727.45	3096.08	13272.01	-1340.64	-1340.64
	Case 3	1684.67	3065.81	12393.02	158.22	-1032.04
	Case 4	1419.91	1985.17	7855.26	1251.71	869.66
December 1.2019	Case 1	2670.92	953.32	9884.81	-2855.41	-3905.72
	Case 2	1803.62	2413.64	16861.31	-1425.52	-1425.53
	Case 3	1671.75	2380.63	16319.46	-344.56	-578.06
	Case 4	1325.81	1353.43	18814.39	89.61	47.39

TABLE 4. Computational cost of solving the proposed stochastic model.

Number of the UTC transaction paths	56	90	110	156
Computational cost of solving proposed model (s)	66.14	116.21	189.72	276.53

E. COMPUTATIONAL ISSUE

The computer used in this paper has a 2.40-Ghz, 2-core CPU and a 16-GB RAM. To verify the applicability of the proposed stochastic UTC bidding strategy in larger systems, simulations are carried out considering more UTC transaction paths, where the model parameters are set to be same as those used in Section V-B. The computational cost of solving the proposed stochastic optimization model considering more UTC transaction paths are provided in Table 4, which are acceptable for the financial participants in practice.

V. CONCLUSION

This paper proposed the stochastic UTC bidding strategy for a financial participant in the nodal electricity markets. By solving the stochastic optimization models, optimal DA UTC bidding curves have been generated for the next operating day considering the credit constraints and risk preference of the financial participant, where the CVaR was used to manage the potential risks in the worst scenarios.

To prove the effectiveness of the proposed stochastic UTC bidding strategies, case studies have been carried out based on the historical data and policies in the PJM electricity market. Different types of UTC bidding strategies based on deterministic and stochastic models were studied. The numeral results indicate that, compared to the deterministic UTC bidding strategy, the proposed stochastic strategy can bring much higher expected profit and lower potential risks for

the financial participant. Additionally, the risk-averse UTC bidding strategy might lower the risks in the worst scenario significantly without decreasing the total expected profits too much. However, when the risk averse parameter in the model was too large, the risk averse UTC bidding strategy would be too conservative and its total expected profit could be much lower than that of the risk-neutral one. Therefore, to maximize the economic benefits of the financial participant's UTC transactions considering its risk preference, it would be necessary to carry out detailed simulations for selecting the proper risk averse parameter of stochastic model.

In the future research, the financial participant using UTC transactions can also be modelled as a price-maker in the electricity market if its UTC bidding capacity is large enough to affect the market outcomes. In this case, the correlation between the electricity prices and the financial participant's UTC bids can be modelled by using the bilevel programming technique adopted in [31]. Moreover, to ensure the profitability of financial participant's UTC transactions, other uncertainties, such as the other participants' bidding strategies and the transmission line outages, need to be characterized accurately using suitable scenario generation methodologies and explanatory variables. Moreover, the UTC transactions used by FTR holders or cyber data attackers can also be studied in the future research, and the proposed UTC transaction model can be utilized in the associated case studies without significant modifications.

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