Risk-Based Traded Demand Response Between Consumers’ Aggregator and Retailer Using Downside Risk Constraints Technique

LIPING GUO1, THANAPORN SRIYAKUL2, SAYYAD NOJAVAN3, AND KITTISAK JERMSITTIPARSERT4

1School of Economics and Management, Zhongyuan University of Technology, Zhengzhou 450007, China
2Faculty of Business Administration, Mahanakorn University of Technology, Bangkok 10530, Thailand
3Department of Electrical Engineering, University of Bonab, Bonab 5551761167, Iran
4Social Research Institute, Chulalongkorn University, Bangkok 10330, Thailand

Corresponding author: Kittisak Jermsittiparsert (kittisak.j@chula.ac.th)

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ABSTRACT Electric retailer is the most critical player in the restructured electricity market. Retailer’s electricity procurement problem is a big challenge for them. Electricity retailer can purchase their energy from various options such as pool market, forward contracts, and etc. A relatively new way with a lesser investigation is the demand response exchange market. In this paper, the risk-constrained stochastic power procurement problem of electricity retailers is formulated by modeling the uncertainty of pool-market price and consumers’ electricity demand. The Downside risk constraints (DRC) risk-evaluation method is used to obtain risk-based power procurement scheduling of electricity retailers. By using the proposed method, conservative electricity retailer can experience a scenario-independent strategy over the stochastic optimization. In other words, the proposed risk strategy is such that impose more cost for electricity retailer while having an equal cost in all scenarios. Based on the obtained results, the operation cost of electricity retailers in all scenarios is closed to about $4827570, which is a relatively zero-risk strategy due to equality overall scenarios. Besides, results are compared in two cases to demonstrate the advantages of the proposed risk-evaluation method. Also, the Pareto front between risk-in-cost and expected cost can introduce an optimal risk-strategy for electricity retailers in the presence of uncertainties. Finally, the risk-averse strategy of electricity retailer is proposed to obtain the retailer’s optimal conservative schedule during power procurement in the presence of uncertainties.

INDEX TERMS Electricity retailer, demand response exchange (DRX) market, downside risk-constraint (DRC), risk evaluation.

NOMENCLATURE

A. INDEXES

| Symbol | Description |
|--------|-------------|
| \( t \) | Index of time |
| \( \omega \) | Index of scenario |
| \( j \) | Index of reward-based DR intervals |
| \( f \) | Index of forward-DR |
| \( b \) | Index of block number in the forward-DR option |
| \( po \) | Index of pool-order option |

B. NUMBERS

| Symbol | Description |
|--------|-------------|
| \( N_{BDR} \) | Number of blocks in forward DR |
| \( N_F \) | Number of forward contracts |
| \( N_{FB} \) | Number of blocks in forward contracts |
| \( N_{FDR} \) | Number of contract in forward DR |
| \( N_J \) | Number of steps in reward-base DR |
| \( N_{po} \) | Number of pool-order options |

C. PARAMETERS

| Symbol | Description |
|--------|-------------|
| \( d(t) \) | Period |
| \( P_{DR,\text{MAX}}^{f,b}(t) \) | Max demand in \( b^{th} \) block of forward DR contract \( f \) [MW] |
Electricity retailer is the most crucial participant in the deregulated electricity market. Retailers can procure their energy in various ways, such as from the pool market and bilateral contracts. Besides, electricity retailers may be the owner of self-generation units, which can use from these units to supply their customers. Also, retailers after procure required energy can sell at specific pre-determined prices to electricity customers [1]. In addition to the mentioned ways, electricity retailers can use the demand response (DR) programs to reduce the financial risks imposed from the uncertainties [2]. A simple way to make benefits of DR programs is participating in the demand response exchange (DRX) market. In the DRX market, DR is trading as a general good between sellers and buyers of DR [3]. To introduce the potential users in the DR programs, in addition to residential, commercial, and industrial users [4], the agricultural users are also interested in participating in DR programs in [5]. Various uncertainties exist in the electricity market, such as electricity demand and pool market price are threats to the players, mainly electricity retailers’ profit. Therefore, the risk evaluation of electricity retailers in the decision-making process is critical for them [6].

A. LITERATURE REVIEW

In the technical works of literature for an electricity retailer, various models proposed for the electricity retailer to participate in the wholesale electricity market, forward contracting, etc. On the other hand, in order to deal with various uncertainties, several methods proposed in the literature. In [7], in order to model the optimal behavior of household appliances in the retail market, a new approach proposed, in which the uncertainty of electricity market price and output power from wind and solar units are modeled using stochastic programming. As a competitive game and by considering demand response programs (DRP) and dynamic line rating constraints, in [8] competition among microgrid and electricity retailers modeled. Also, the retail market equilibrium of the designed bi-level model is calculated using the KKT condition. In [9], [10] the electricity selling price of electricity retailers is determined in which to deal with the uncertainty of retailers, bilateral contracts, distributed units and various energy storages such as containing electrolyzer (EL), hydrogen storage system (HSS), and fuel cell (FC) [11], hydrogen storage tanks (HST) are used and modeled using stochastic programming. Reference [12] determines the retail selling price of electricity in the competitive retail market as a Stackelberg competition game in which the upper-level electricity retailer competes with various electricity customers at the lower-level. In [13], bi-level model is used to model the midterm decision-making model of electricity retailer, which in addition to modeling the uncertainties using stochastic programming, competition between retailers and client response to the offered retail price are modeled in the proposed bi-level model.

In [14], in order to handle the uncertainty of day-ahead electricity prices, and coping with financial losses, a risk management strategy proposed for an electricity retailer. In addition, incentive-based DRP and optimal schedule of retailer generation units and energy storage are explained using two-stage stochastic programming. Reference [15] is used the mean-variance framework to design an optimal approach to select appropriate forward contracts for off-peak and peak periods. In [16], a bi-level and two-stage model has been used to model the pricing problem in the retail market, which in the first stage the characterizing of demand response and in the second stage, risk-averse energy dispatch problem of a retailer is modeled.

D. VARIABLES

| Symbol | Description |
|--------|-------------|
| $P_{DR}(t)$ | Electricity Demand in $j$th step of reward-based DR [MW] |
| $P_{MAX}(t)$ | Highest demand in block $b$ of forwarding contract in period $t$ [MW] |
| $P_{po}(t)$ | Max demand of pool-order option DR [MW] |
| $R_{i}(t)$ | Max value of $i$th step in reward-base DR [$/MWh$] |
| $\lambda_{po}(t)$ | Pool-order DR price [$/MW$] |
| $\lambda_{f,b}(t)$ | Price of $b$th block in forward-DR contract [$/MW$] |
| $\lambda_{f,b}(t)$ | Price of $f$th block in bilateral contract $f$ in [$/MW$] time period $t$ |
| $\tilde{P}(t)$ | Forecasted pool market price [$/MW$] |
| $\lambda(t, \omega)$ | Actual pool market price [$/MW$] |
| $\pi(\omega)$ | Probability of scenario w |

I. INTRODUCTION

Electricity retailer is the most crucial participant in the deregulated electricity market. Retailers can procure their energy in various ways, such as from the pool market and bilateral contracts. Besides, electricity retailers may be the owner of self-generation units, which can use from these units to supply their customers. Also, retailers after procure required energy can sell at specific pre-determined prices to electricity customers [1]. In addition to the mentioned ways, electricity retailers can use the demand response (DR) programs to reduce the financial risks imposed from the uncertainties [2]. A simple way to make benefits of DR programs is participating in the demand response exchange (DRX) market. In the DRX market, DR is trading as a general good between sellers and buyers of DR [3]. To introduce the potential users in the DR programs, in addition to residential, commercial, and industrial users [4], the agricultural users are also interested in participating in DR programs in [5]. Various uncertainties exist in the electricity market, such as electricity demand and pool market price are threats to the players, mainly electricity retailers’ profit. Therefore, the risk evaluation of electricity retailers in the decision-making process is critical for them [6].
The robust optimization approach is a common technique to consider the risk associated with uncertainty. In order to consider the caused risks by the pool market price uncertainty, in [17] robust optimization approach has been considered to evaluate the effects of DRP on the retailer cost. Also, in [18], the robust schedule of aggregated DRP is provided to improve the power system robustness. Besides, the information gap decision theory (IGDT) is another way to consider risks that creates uncertain parameters. In reference [19], IGDT is used to model an optimal bid curve for an electricity retailer, which can be proposed to the pool market. IGDT in reference [20], is used to obtain the robust strategy of an electricity retailer by considering the uncertainty of pool market price. Beside in [21] using a linear two-step robust approach, a risk-aversive strategy for an electricity retailer is proposed to obtain a non-dominated bid curve that aims to maximize the retailer’s daily profit. Also, in most works related to retailer decision-making problems such as [22], [23] conditional value-at-risk (CVaR) is a risk evaluator to handle the risk faced by the electricity retailer. In [24], a risk measures method called risk-adjusted recovery on capital (RAROC) is proposed to measure the different forward contracts risk for a retailer, which determines the ratio among the return of expected investment and economic capital. Besides, to hedge against financial risk, the electricity retailers use the various future contracts to optimal operate in the uncertain enviroment [25].

Explaining the optimal decision-making problem of an electricity retailer may be modeled as a multi-stage stochastic problem, which is non-convex, nonlinear, and maybe the normal distribution is not appropriate for stochastic parameters. These reasons would lead to that risk measure methods such as variance are not suitable to model the retailer’s risk in the decision-making problem. Because VaR is not a “coherent” risk measuring method, therefore, it may not be a proper model [26]. The average value-at-risk is defined as conditional value at risk and known as CVaR, in which linear programming can be used to model CVaR formulation [27]. Because CVaR is coherent, it is preferred in most researches [28]. However, in [29] provide that because of estimation errors of CVaR, results obtained from solving CVaR models are fragile and invalid. Despite reviewed papers, an efficient and straightforward risk measurement method, like the method introduced in [30], is required to manage the financial risk of electricity retailers. The used method is called downside risk constraints method that is used in the retailer’s pricing problem in the presence of self-generation units. Finally, a comparison among the scenario-based risk-measurement methods, including CVAR and chance constraints methods, is carried out in [31] for the power procurement problem of electricity retailers.

B. NOVELTY AND CONTRIBUTIONS

Electricity retailers are faced with various risks at supplying their consumers in power procurement problem. These financial risks are rooted in uncertainty imposed from the stochastic parameters such as markets price and electricity demand, etc. Hence, financial risk management is essential for electricity retailers that a large number of researches are discussed about it. In order to deal with the mentioned uncertainties, two different methodologies are proposed. One is demand response programs that almost is a safe approach for electricity market players. Therefore in this paper, demand response exchange market are used in power procurement problem of electricity retailer. In the demand response exchange market, three options, such as pool-order DR, forward-DR contracts, and reward-based DR programs, are used. Another is implementing a powerful risk-management approach to manage financial risks. Hence, the main contribution of the present work is the applicable and straightforward risk management method called downside risk constraints method. As we know, various scenario-based stochastic programming methods have been used widely in uncertainty modeling problems. In these problems, the value-at-risk (VaR) and CVaR are widely used to evaluate the financial risk. As a simple risk measurement approach, in this paper, the downside risk constraints method is used to measure the financial risk imposed from the stochastic parameters. The advantage of the downside risk constraints method is that the electricity retailer by using the proposed method can obtain an optimal trade-off between risk-in-cost and expected cost while minimizing total risk. As a considerable advantage, in the risk-averse strategy, the proposed strategy by the DRC is a scenario independent strategy. Hence, by using the proposed approach, electricity retailers can obtain a relatively risk-guaranteed strategy in the stochastic-based optimization problem. Despite the increasing cost, the proposed strategy by the DRC is proper for conservative retailers. Finally, mixed-integer linear programming (MIP) is used to model the power procurement problem of electricity retailer, which the finding of optimal global results are guaranteed and solved by CPLEX solver of GAMS software.

Therefore, the novelty and contribution of this paper can be categorized as follows:

- Use of downside risk constraints for the retailer’s decision-making problem in the DRX market to measure the financial risks in stochastic programming.
- Introducing a scenario independent independent strategy with a lower risk for the operation of retailer’s in DRX market that is relatively a risk-guaranteed strategy.
- Risk-based operation of retailers in the presence of market and DRX options derived from DRC by proposing a risk-averse strategy and risk-neutral strategy respectively for conservative and risky retailers.

C. PAPER STRUCTURE

The remainder of this paper is structured as follows: Section 2 represents the stochastic-based formulation of the retailer’s power procurement problem. Section 3 presented a general explanation of the downside risk-constrained method. In section 4, required data, case studies, and analytical
results with and without DRC have been presented. Finally, Section 5 concludes this paper.

II. PROBLEM FORMULATION

Electricity retailer can purchase their required power from various options such as producers, consumers, and likely self-generation units. Pool market and the forward contract is one of the most known ways that retailer procures energy from producers. Another way is self-generation units. Since the self-generation units are not popular with retailers in most countries, these units are not considered in this paper. A roughly new way for energy procurement is the DRX market that paid in this paper. In this market, DR is traded as a general good between DR seller (DR aggregator/consumers) and Buyers (retailer). The summary of available energy options for electricity retailer which proposed in this paper is shown in Fig. 1.

A. DEMAND RESPONSE EXCHANGE MARKET

In the demand response exchange market, electricity retailers can sign various contracts with consumers, which by paying cash to them, can reduce their demand if is required. It should be noted that in this paper, consumers can only sell their demand to electricity retailers. However, they can sell their demand in various energy markets such as real-time market and ancillary services [32].

The DR sellers are responsive to the implementation of the DRP contracts and should pay the penalty if not execute. Besides, electricity retailers do not have information about the technical aspects of DR contracts. In this paper, three kinds of DR contracts are introduced to use by the electricity retailer. These contracts are the pool-order option, forward-DR contract, and reward-based DR. details of mentioned DR contracts are provided in the following of this section. Fig. 2 is illustrated the scheme of proposed new demand response exchange market.

1) POOL-ORDER DR

Electricity retailer as a DR buyer can sign a pool-order option contract with DR sellers, which designed in specific volume and prices. This contract is set such that if market price increase, the use of this contract is to avoid more increment in the retailers’ total power procurement cost. Avoiding from the cost increment are done such that electricity retailer can procure their required energy from aggregated contracts in demand response exchange market if the pool market price is increased. This contract will keep electricity retailers safe from any rising in the pool market prices. On the other hand, electricity retailers do not have to enforce to implementation of the contract and will execute the contract if the implementation cost of the contract is economically feasible. If the implementation cost of contracts is not feasible, the retailer, by paying the predetermined penalty to the DR seller, withdraws from the contract. The mathematical formulation of pool-order option can be modeled as follow:

\[
C(PO) = \sum_{t \in T} \sum_{po=1}^{N_{po}} P_{po}(t, \omega) \cdot \lambda_{po}(po) \cdot v_{po}(t) \cdot d(t) \tag{1}
\]

\[
0 \leq P_{po}(t, \omega) \leq P_{Max_{po}}(t) \quad \forall po = 1, 2, \ldots, N_{po} \tag{2}
\]

\[
P_{total_{po}}(t, \omega) = \sum_{po=1}^{N_{po}} P_{po}(t, \omega) \cdot v_{po}(t, \omega) \tag{3}
\]

In order to set a pool-order contract by the retailer, Eq. (1) calculates the total cost that an electricity retailer should be pay to the DR seller at a specified time interval. Also, Eq. (2) defines the maximum and minimum power that in
each pool-order option contract can be agreed by the retailer. Finally, the total procured demand by electricity retailer from the pool-order contract during the defined time horizon is represented in Eq. (3).

2) FORWARD-DR CONTRACTS

A forward contract is a bilateral contract that can be used to buy power at a specific price and volume for future periods. By adopting these contracts with DR agreements, electricity retailers can buy specific DR from DR sellers (DR aggregators/consumers) at a specific price and DR quantity [33]. This type of DR contract called forward DR contracts, which consist of various blocks. Each block of the forward-DR contracts has a different price and quantity. In this type of contract, pricing processes are done in two methods. In the first method, the price of each block is determined agreement contract, pricing processes are done in two methods. In the second method, each block of the forward-DR contracts are bounded in Eq. (5). Finally, Eq. (6) calculates the total power that electricity retailer is contracted by the pool-order contract during the defined time horizon is represented in Eq. (3).

The advantage of the second method is that a specialist center clears prices. Because in this paper, contracts are directly agreed between the DR seller (DR Aggregator/consumers) at a specific price and DR quantity [33].

Because in this paper, contracts are directly agreed between the DR seller (DR Aggregator/consumers) and the DR buyer (Retailer). Therefore, the first method of pricing is used to proposed forward-DR contracts. Calculation of retailer total cost in forward-DR contracts can be carried out using the following formulation:

\[
C(FDR) = \sum_{t \in T} \sum_{f=1}^{N_{FDR}} \sum_{b=1}^{N_{DR}} p_{f,b}(t, \omega), \lambda_{f,b}(t), d(t) \tag{4}
\]

Eq. (7) represents the total reduced demand by the DR seller (DR aggregator/consumer). Also, total paid rewards by electricity retailer to DR sellers are calculated in Eqs. (7), (8), respectively. The minimum/maximum limits of reward in each step of introduced function in Fig. 4, is bounded in Eq. (9). Also, using Eq. (10), the total selected reward-based DR by electricity retailer is limited to the unit. Finally, the total cost that the electricity retailer pays to the DR seller in the reward-based DR agreement can be calculated by Eq. (11).

\[
EC(RDR) = \sum_{t \in T} \left[ \sum_{j=1}^{N_t} P_{f,b}(t, \omega), \lambda_{f,b}(t), d(t) \right] \tag{11}
\]

3) REWARD-BASE DR

Problem formulation of the reward-based DR scheme is introduced in Eqs. (7)–(10).

\[
P^{DR}(t, \omega) = \sum_{j=1}^{N_t} P_{f,b}(t, \omega) \tag{7}
\]

\[
R^{DR}(t, \omega) = \sum_{j=1}^{N_t} R_{f,b}(t, \omega) \tag{8}
\]

\[
\tilde{P}_{f,b}^{DR}(t, \omega), \lambda_{f,b}(t), d(t) \tag{9}
\]

\[
\sum_{j=1}^{N_t} \lambda_{f,b}(t, \omega) = 1 \tag{10}
\]

B. MARKET OPTIONS

The pool market is an always available option for an electricity retailer in which retailers can be bought power from this market from various ways such as real-time market, day-ahead market, and forward contracts market.

1) POOL MARKET

One of the market options is the real-time market in which retailers can sell and buy power in this market. In this paper, the pool market price is one of the uncertain parameters, which modeled using the stochastic framework.
Various scenarios are generated for this parameter, which represents the possible pool market price at any period.

The expected cost of traded power with the pool market can be formulated as follow:

\[ EC(P) = \sum_{\pi \in \Omega} \pi(\omega) \sum_{t \in T} P^F(t, \omega) \cdot \lambda^F(t, \omega) \cdot d(t) \] (12)

2) FORWARD CONTRACT MARKET

Forward contracts are another popular option for an electricity retailer, which is an agreement for the future. Using these contracts, electricity retailers can procure their fixed power (agreed with the consumer) in a specific volume and at a lower price than the pool-market. This contract also consists of blocks with different specific volume and price, which price and power of each block are incremental in a step-wise trend. The mathematical model of the forward contracts can be formulated as below:

\[ C(F) = \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P^F_{f,b}(t, \omega) \cdot \lambda^F_{f,b}(t) \cdot d(t) \] (13)

\[ 0 \leq P^F_{f,b}(t, \omega) \leq P^\text{MAX}_{f,b}(t) \] (14)

Eq. (13) represent the total cost of the signed forward contract by the electricity retailer. The bounds of power which can be purchased by each forward-contract blocks are considered by Eq. (14). Finally, total contracted power at period \( t \) can be calculated by Eq. (15).

\[ P^F(t, \omega) = \sum_{f=1}^{N_F} \sum_{b=1}^{N_{FB}} P^F_{f,b}(t, \omega) \] (15)

C. POWER BALANCE AND OBJECTIVE FUNCTION

The power balance equation, which represents the balance between the total procured energy from the mentioned available options and the total demand of consumers, is represented by Eq. (16). It should be noted that the retailer’s total demand is considered as an uncertain variable, in which various scenarios are generated for consumers’ demand for electricity retailers.

Finally, the expected power procurement cost of electricity retailer as an objective function of this paper can be presented in Eq. (17), which expected cost of electricity retailer is equal to the summation of the power procurement cost from the pool market, forward contracts, pool-order DR, forward DR, and reward-based DR.

\[ P^\text{eq}(t, \omega) = P^P(t, \omega) + P^F(t, \omega) + P^\text{total}(t, \omega) + P^\text{FDR}(t, \omega) + P^\text{DR}(t, \omega) \] (16)

\[ \text{Min} \ C(p, \lambda) = EC(P) + C(F) + C(PO) + C(\text{FDR}) + C(\text{RDR}) \] (17)

III. DOWNSIDE RISK CONSTRAINTS (DRC)

As mention, due to the intermediate-based role of electricity retailer, risk management is essential for retailers in the optimal operation. A robust and straightforward risk management method is required for electricity retailers in power procurement problems. Thus, in this section, the constraints that are modeled the relationship between risk and retailer’s power procurement costs are provided. Electricity retailers seek to reduce their power procurement cost to a lesser than a specified cost that is the retailer’s desired cost (TargetCost). The favorable scenarios for electricity retailers are the scenarios that retailer power procurement cost is less than the desired cost (TargetCost). The scenarios with higher operation cost can be defined as downside risk. Hence, in order to find the risk of non-desired (downside risk) scenarios, when the objective is the cost function, the DRC can be modeled as follows [34]:

\[
\begin{align*}
\text{Cost}_w &> \text{Target}_\text{Cost} \quad \text{then Risk}_w = \text{Cost}_w - \text{Target}_\text{Cost} \\
\text{Cost}_w &\leq \text{Target}_\text{Cost} \quad \text{then Risk}_w = 0
\end{align*}
\] (18)

In Eq. (18), \( \text{Cost}_w \) and \( \text{Risk}_w \) are power procurement cost and risk-in-cost of electricity retailer in \( w^{th} \) scenario, respectively. Note that risk-in-cost is the subtraction between the cost of each scenario with the target cost. Eq. (18) can be rewritten mathematically linear as follow:

\[
0 \leq \text{Risk}_w - \left( \text{Cost}_w - T \arg \text{cost}_w \right) \leq M_1(1 - U_w)
\] (19)

\[
0 \leq \text{Risk}_w \leq M_2 \cdot U_w
\] (20)

In Eqs. (19) and (20), \( M_1 \) and \( M_2 \) are big and positive constant amounts and \( U_w \) is a binary variable which is equal 1 if \( \text{Cost}_w > \text{Target}_\text{Cost} \) and is 0 otherwise.

According to the mentioned context, expected downside risk (EDR) for the power procurement cost function of an electricity retailer can be mathematically formulated as follows.

\[
\sum_{w=1}^{N_s} \rho_{w} \cdot \text{Risk}_w \leq \alpha \cdot \text{EDR}
\] (21)

\[
\text{EDR} = \sum_{w=1}^{N_s} \rho_{w} \cdot (\text{Cost}_{w}^{\text{NoRisk}} - \text{TargetCost})
\] (22)

In Eq. (21), \( \text{Cost}_{w}^{\text{NoRisk}} \) is the total cost of electricity retailer in each scenario without considering the DRC and \( \alpha \) is the fixed coefficient lies within 0 to 1, which named the risk control coefficient. Finally, EDR is expected downside risk. In the proposed method, by adding the proposed constraints to the primary formulation (1)–(17), the new problem is solved iteratively for different amounts of \( \alpha \) that obtained results report a different risk strategy with different risk and cost.

IV. NUMERICAL RESULTS

In this section, first, the required data will be presented, and then analytical results are demonstrated in the remainder of this section.

A. DATA

In this study, the considered time horizon is the peak times of winter and summer seasons. The total time horizon consists of 32 periods, which each period consists of average
TABLE 1. Risk-neutral strategy of retailer from stochastic optimization without DRC (case 1).

| \( \alpha \) | Total cost (\$) | Risk-in-cost (\$) |
|---|---|---|
| 1 | 4695796 | 37293.18 |
| 2 | 46607206 | 0 |
| 3 | 4698087 | 39584.74 |
| 4 | 4497457 | 38354.72 |
| 5 | 4696857 | 38678.81 |
| 6 | 4747181 | 0 |
| 7 | 4619369 | 0 |
| 8 | 4566832 | 0 |
| 9 | 4874650 | 216147.2 |
| 10 | 4610811 | 0 |

FIGURE 5. Selected market price scenarios.

weekly peak times. Therefore, 32 weeks considered in this study to evaluate the effect of the proposed DR scheme. Twelve weeks from these 32 weeks belong to January–March months, 17 weeks belong to June–September, and three weeks belong to December. It must be mentioned that each period is considered as average peak times of Monday to Friday of each week, which are weekdays. Work times (peak times) in summer is 11 to 21 and in winter is 6-10 to 16-22. Therefore, by averaging from amounts of demand and price in mentioned peak times of weekdays, we can calculate the demand and prices for each period.

The proposed scheme is modeled to real data from Queensland jurisdiction within the NEM 2012. Input data for the modeled problem are derived from [35]. In this study, the pool market price and total demand of consumers are two uncertain parameters that modeled using stochastic programming. For each uncertain parameter, using normal distribution, 30 scenarios are generated, which by the combination of generated scenarios, 900 scenarios can be formed. The scenario reduction approach is an appropriate option in such cases. Therefore, a fast forward selection algorithm based on Kantorovich distance [36] is used to reduce the number of total scenarios to 10 with a different probability. Selected scenarios by fast forward selection reduction algorithms for demand and pool market price are shown in Figs 4 and 5, respectively.

### B. ANALYSIS OF RESULTS

In order to evaluate the impacts of uncertain variables on the risk of electricity retailer, a risk-constrained stochastic optimization approach is used in this study. This risk evaluation approach is the downside risk constraints which are applied to the power procurement problem of electricity retailer. In order to evaluate the effect of this approach on the proposed problem, two cases can be defined as below.

**Case 1:** Stochastic optimization problem of electricity retailer without Downside Risk Constraints (risk-neutral strategy)

**Case 2:** Stochastic optimization problem of electricity retailer with Downside Risk Constraints (risk-averse strategy).

Case 1 is a conventional stochastic programming problem which objective function is the expected cost of an electricity retailer in the introduced power procurement problem. This case represents the risk-neutral strategy of electricity retailer in the power procurement process, which results, in this case, is indicated in Table 1. In Table 1, the retailer’s total power procurement cost and risk-in-cost in each scenario are represented, respectively. According to Table 1 can be shown that in scenarios 2-4-7-8-10, the total cost of electricity retailer is less than the expected cost; therefore, risk-in-cost in these scenarios is equal to zero. Average amounts of cost and risk-in-cost in the risk-neutral strategy for ten scenarios can obtain from Table 1, which are equals to $4,661,427 and $42,005.87, respectively. In case 2, DRC is applied to the electricity retailer stochastic power procurement problem, and positive results of this method are shown in Tables 2 and 3 (risk-averse strategies). Tables 2 and 3 respectively represent the cost and risk-in-cost of electricity retailer in each scenario versus the various amounts of the risk control parameter (\( \alpha \)). According to table 2 can be concluded that in the scenarios with total cost more than the expected cost, decreasing the risk control parameter has a small effect on the retailer’s total cost. On the other hand, the important result is indicated in the last row of Table 2 in \( \alpha = 0.1 \). According to the last row of Table 2, it can be shown that the cost of all-scenarios is reached to $4827570, thus \( \alpha = 0.1 \) is a scenario independent strategy. Also, from Table 3 can be concluded that in some scenarios such as scenario 9, which is the worst scenario, risk cost will never be zero. Finally, in table 4, analytical results include average and total risk cost, and the total cost of electricity retailer for different amounts of the risk control parameter is demonstrated. According to table 4, due to the implementation of DRC for various amounts of the risk control parameter, retailer risk will be decreased while the power procurement cost of electricity retailers is increased. As shown in Table 4, in the \( \alpha = 1 \) and close amounts to it, decreasing in risk and increasing in cost is less than about \( \alpha = 0.1 \) and close amount to it. For example, from \( \alpha = 1 \) to \( \alpha = 0.9 \), the risk-in-cost decrease by about 9% while from \( \alpha = 0.2 \) to \( \alpha = 0.1 \), risk-in-cost is increased by 11%. These percent...
TABLE 2. The cost of electricity retailer in each scenario versus risk control parameter.

| α  | 1       | 2       | 3       | 4       | 5       | 6       | 7       | 8       | 9       | 10      |
|----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 1  | 4695796 | 4607206 | 4698087 | 4447457 | 4669857 | 4747181 | 4619396 | 4566832 | 4874650 | 4610811 |
| 0.9| 4695796 | 4624777 | 4698087 | 4528328 | 4696857 | 4747181 | 4626126 | 4576960 | 4874650 | 4619558 |
| 0.8| 4695796 | 4648012 | 4698087 | 4570890 | 4696857 | 4747181 | 4626608 | 4577895 | 4874650 | 4620389 |
| 0.7| 4695796 | 4669432 | 4698087 | 4614924 | 4696857 | 4747181 | 4626608 | 4579463 | 4874650 | 4621503 |
| 0.6| 4695796 | 4689901 | 4698087 | 4649480 | 4696857 | 4747181 | 4638794 | 4583003 | 4874650 | 4621620 |
| 0.5| 4696719 | 4696719 | 4698087 | 4695973 | 4696857 | 4747181 | 4654995 | 4583067 | 4874650 | 4621977 |
| 0.4| 4718189 | 4718189 | 4718189 | 4718189 | 4718189 | 4747181 | 4618530 | 4874650 | 4625234 |
| 0.3| 4740620 | 4740620 | 4740620 | 4740620 | 4740620 | 4747181 | 4698155 | 4874650 | 4633125 |
| 0.2| 4780490 | 4780490 | 4780490 | 4780490 | 4780490 | 4780490 | 4780490 | 4780490 | 4874650 | 4676693 |
| 0.1| 4827570 | 4827570 | 4827570 | 4827570 | 4827570 | 4827570 | 4827570 | 4827570 | 4874650 | 4779974 |

TABLE 3. Risk-in-cost of electricity retailer in each scenario.

| α  | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
|----|----|----|----|----|----|----|----|----|----|----|
| 1  | 37293.18 | 0  | 39584.74 | 0  | 38554.72 | 0  | 88678.81 | 0  | 0  | 216147.2 |
| 0.9| 29693.65 | 0  | 31985.21 | 0  | 30755.19 | 0  | 81079.28 | 0  | 0  | 208547.7 |
| 0.8| 22094.12 | 0  | 24385.68 | 0  | 23155.66 | 0  | 73479.75 | 0  | 0  | 200948.1 |
| 0.7| 14494.58 | 0  | 16786.14 | 0  | 15556.12 | 0  | 65880.21 | 0  | 0  | 193348.6 |
| 0.6| 8994.05  | 0  | 9186.61  | 0  | 7956.59  | 0  | 58280.68 | 0  | 0  | 185749.1 |
| 0.5| 0       | 0   | 1368.306 | 0  | 138.2861 | 0  | 50462.38 | 0  | 0  | 177930.8 |
| 0.4| 0       | 0   | 0       | 0   | 28992.73 | 0  | 51421.1  | 0  | 0  | 156461.1 |
| 0.3| 0       | 0   | 0       | 0   | 6561.443 | 0  | 134029.8 | 0  | 0  | 94159.93 |
| 0.2| 0       | 0   | 0       | 0   | 0       | 0   | 47079.97 | 0  | 0  | 47079.97 |

TABLE 4. Analytical results versus risk control parameter.

| α  | Total risk | Average risk | % decrease of average risk | Average cost | % increase of average cost |
|----|------------|--------------|--------------------------|-------------|---------------------------|
| 1  | 420058.7   | 42005.87     | 0                        | 4661427     | 0                         |
| 0.9| 382061     | 38206.10     | 9.05                     | 4668832     | 0.1589                    |
| 0.8| 344063.3   | 34406.33     | 18.09                    | 4675637     | 0.3048                    |
| 0.7| 306065.7   | 30606.57     | 27.14                    | 4682450     | 0.4510                    |
| 0.6| 268068     | 26806.80     | 36.18                    | 4689473     | 0.6017                    |
| 0.5| 229899.7   | 22989.97     | 45.27                    | 4696623     | 0.7550                    |
| 0.4| 185453.9   | 18545.39     | 55.85                    | 4717473     | 1.2023                    |
| 0.3| 140591.3   | 14059.13     | 66.53                    | 4739683     | 1.6788                    |
| 0.2| 94159.93   | 9415.99      | 77.58                    | 4779526     | 2.5335                    |
| 0.1| 47079.97   | 4708.00      | 88.79                    | 4827518     | 3.5631                    |

for total cost according to table 4 is equal to 0.15% and 1% for α = 1 to α = 0.9 and α = 0.2 to α = 0.1 respectively. This result means that small amounts of α not economically proper. An optimal amount of α is about α = 0.5 because from α = 0.5 to α = 0.4, the cost is suddenly increased by 0.5% while risk-in-cost is increased with the former trend.
Moreover, in order to show the advantages of the proposed DRC method, Fig. 6 and 7 are derived from Table 2, and 3, respectively. According to Fig. 6, it can be shown that by reduction of $\alpha$ from 1 to 0.1, the cost of all scenarios is closed to a specific cost that is equal in all scenarios. In other words, the cost of all scenarios are closed to a scenario independent cost, thus the scenario variation not affected the operation cost of retailers. Besides, Fig. 7, represents the risk-in-cost in all the scenarios versus the different amounts of risk control coefficient. According to Fig. 7, it can be seen that risk-in-cost in the downside risk scenarios are reduced to zero by closing the risk control parameter to 0.1. Therefore, it can be concluded from the Figs. 6 and 7 that by reduction of risk control parameter ($\alpha$) from the 1 to 0.1, the total cost is closed to a scenario independent cost ($4827570) while reducing the risk-in-cost to zero. According to stated results, Pareto optimally fronts among the expected cost of electricity retailer and expected risk-in-cost of electricity retailer for different amounts of $\alpha$ is demonstrated in Fig 8. According to Fig. 8, it can be shown that expected cost reduction more significant in lower amounts of risk-in-cost, while in the higher risk-in-cost, the expected cost reduction is reduced in each iteration of the DRC method.

The changes in electricity demand and traded power with the pool market, which are two uncertain parameters in this work, are indicated in Figs 9 and 10 for both risk-averse strategy and risk-neutral strategies. According to Fig 9, it can be shown that in risk-averse strategy in which DRC is applied, electricity demand in some period is reduced than the risk-neutral strategy which DRC not considered.

By applying the DRC procured power from the real-time market by electricity retailer will be changed, which is demonstrated in Fig 10. According to Fig 10, by applying the DRC, the retailer in the risk-averse strategy less rely on the purchasing power from the real-time market. It seems that in the summer that electricity usage is more the winter, retailers purchase their most power from the real-time market, which
by applying DRC reduces their purchasing power from the real-time market.

Forward contracts are another market option for an electricity retailer, which by applying DRC in risk-averse strategy electricity retailer reduce their buying from this option to reduce their power procurement cost. The pattern of reduction is shown in Fig. 11. As shown in Fig 11, electricity retailer in the winter days has been relyed on forward contracts, which by applying the DRC, reduced their procured power from forward contracts.

In this paper, as a relatively new scheme, the demand response exchange market is considered to energy procurement by the electricity retailer. In Figs 12-14, the changes of power trading by three options of demand response exchange market (the pool-order option, forward DR contracts, and reward-based DR) are illustrated. As shown in Fig 12, in the risk-averse strategy in which the DRC is applied, electricity retailer will increase their purchasing power from forward-DR in summer while decreases in the winter. According to Fig. 12, it can be shown that forward-DR contracts are long time contracts that are signed in large volumes for supplying the baseload.

Another option of demand response exchange market for electricity retailers is pool-order option. This option is a real-time option designed for times that real-time market
price has fluctuation over the period. According to Fig 13, traded power in the pool-order option will not be significantly changed by applying DRC in risk-averse strategy.

Finally, the last option from demand response exchange market options is reward-based DR. Reward-based DR is a real-time option designed for consumers who are willing to reduce their load in real-time. In this option, consumers/DR-aggregators reduce their demand by receiving more rewards from retailers. According to Fig 14, it can be shown that by applying the DRC electricity retailer more rely on the reward-based DR in risk-averse strategy. The reason for this is that in this paper, we assume that the DR aggregators/consumers will accept any reduction suggested by the retailer.

V. CONCLUSION

In this paper, the risk-constrained stochastic power procurement problem of electricity retailer in the presence of the various uncertainties such as pool market price and electricity demand uncertainty was modeled. Considering an appropriate choice between risk and expected cost can be an acceptable result, therefore downside risk-constraints method is used to risk evaluation of the proposed model. Results are presented for different amounts of the risk-control parameter, which indicates the various amount of expected cost and risk-in-cost. Also, by using the proposed DRC method, a strategy can be obtained that is independent of the scenario. In other words, the results are presented versus different amounts of the risk-control parameter, in which a strategy can be obtained in the last iteration that has the same cost independent of each scenario realization. According to obtained results by reduction of $\alpha$ from 1 to 0.1, risk-in-cost is decreased by 88.79 % while the expected cost is increased by 3.56 %. Therefore, electricity retailer accepts by a 3.56 % increase in the its expected cost, obtain a strategy that has equal cost over all scenarios.

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**Liping Guo** born in Xuanhua, Hebei. He received the Doctor’s degree from East China Normal University and the Ph.D. degree in applied economics from the Shanghai University of Finance and Economics. He is currently an Associate Professor and the Master Tutor. His main research direction is international economy and innovation management. He has published more than 40 articles. It has a deep and prospective research on transnational investment and risk management.

**Thanaporn Sriyakul** received the Ph.D. degree in social sciences from Kasetsart University, Thailand. He is currently an Associate Professor with the Political Science of the Department of Management, Faculty of Business Administration, Mahanakorn University of Technology. His areas of expertise are political science, public and private administration, economics, and energy.

**Sayyad Nojavan** received the B.Sc., M.Sc., and Ph.D. degrees in electrical power engineering from the University of Tabriz, Tabriz, Iran, in 2010, 2012, and 2017, respectively. He was a Postdoctoral Researcher with the Faculty of Electrical and Computer Engineering, University of Tabriz, from September 2017 to September 2018. He is currently an Assistant Professor with the Department of Electrical Engineering, University of Bonab, Bonab, Iran. His research areas include distribution networks operation, power system operation and economics, electricity market, demand response applications, hybrid energy systems, uncertainty modeling, and risk management. He has also edited several books in the electrical and energy fields in Springer and Elsevier publications.

**Kittisak Jermsittiparsert** received the Ph.D. degree in social sciences from Kasetsart University, Thailand. He is currently a Researcher with the Social Research Institute, Chulalongkorn University, a part-time Researcher with Ton Duc Thang University, and the Secretary General of the Political Science Association, Kasetsart University. His areas of expertise are politics, public policy, business, development, and energy management.

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