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Two-Stage Minimax Regret-Based Offering and Generation Scheduling Strategy for Virtual Power Plants

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***Abstract*—The market and renewable generation uncertainties bring challenges to the profit-oriented offering and generation scheduling problem of commercial virtual power plants (VPP). To address the challenges, this paper proposes a two-stage minimax regret (MMR) model to obtain an optimal VPP offering and generation scheduling strategy. To solve the strongly NP-hard two-stage MMR problem, we firstly reformulate it into a two-stage robust optimization (TSRO) problem with fixed recourse, then solve it using the column-and-constraint generation algorithm, which has been proved efficient for solving TSRO problems. In the numerical experiments, we evaluate the performance of the MMR approach by comparing it with the maximin profit approach and the perfect information approach under different assumptions.**

***Index Terms*—Virtual Power Plant (VPP), uncertainty, minimax regret (MMR), two-stage robust optimization (TSRO), column-and-constraint generation (C&CG)**

NOMENCLATURE

Parameters

η	Penalty factor of the balancing market
γ	Uncertainty parameter used to adjust the range of the uncertainties
$\overline{\lambda}_{DA,t}$	Upper bound of day-ahead market price at time t
$\overline{P}_{th,i}$	Maximum power output of thermal unit i
$\overline{P}_{w,t}$	Upper bound of wind power output at time t
$\underline{\lambda}_{DA,t}$	Lower bound of day-ahead market price at time t
$\underline{P}_{th,i}$	Minimum stable power output of thermal unit i
$\underline{P}_{w,t}$	Lower bound of wind power output at time t
$RD_{th,i}$	Ramp down limits of thermal unit i
$RU_{th,i}$	Ramp up limits of thermal unit i

Sets and Indices

$i(I)$	Indices and set of thermal units
$t(\tau)$	Index and set of time in the offering and scheduling horizon
U'	Enlarged uncertainty set in the reformulated problem
$u(U)$	Index and set of uncertainty scenario of market price and wind generation

Variables

$\lambda_{BM,b,t}$	Balancing market buying price at time t
$\lambda_{BM,s,t}$	Balancing market selling price at time t
$\lambda_{DA,t}$	day-ahead market price at time t
θ	Auxiliary variable used to represent the objective value of the slave problem in the C&CG algorithm
$P_{BM,t}$	Power exchange with the balancing market at time t
$P_{O,t}$	Offering power in the day-ahead market at time t
$P_{th,i,t}$	thermal unit i power output at time t
X	Second-stage decisions in the MMR model
X_u	Optimal second-stage decisions given u and Y_u in the MMR model
Y	First-stage decisions in the MMR model
Y_u	Optimal first-stage decisions under scenario u in the MMR model

I. INTRODUCTION

Electricity is vital for human society development, however, traditional centralized power generation and long-distance power transmission strategy faces problems like environmental issues, high transmission loss, high penetration of renewable generations and low reliability. Transforming from centralized generation and long-distance supply strategy to distributed generations (DGs) and local supply strategy is a promising way to address the aforementioned challenges.

VPP as a cloud-based aggregation of DGs has recently attracted intensive attention. Its main objective is to maximize the profit via optimally bidding in the electricity market and scheduling its DGs. However, VPP's potential of participating in the market and maximizing the utility of the DGs has been hindered by various uncertainties such as the market price and renewable generation. Currently, the most common practices in dealing with uncertainties in VPPs include the stochastic optimization and robust optimization [1]. Stochastic optimization as a probabilistic approach has been extensively studied in the literature. In [2] [3] [4], uncertainties of load, market prices and renewable outputs are described using scenarios generated from certain probability distributions.

Robust optimization as a alternative approach for dealing with uncertainties, only requires a deterministic uncertainty set instead of accurate probability distribution [5]. In [6], a two-stage robust Stackelberg game is proposed to solve the

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problem of day-ahead (DA) energy management of a VPP, the uncertainties of intermittent renewable energy output and market price are modeled using uncertainty sets. In [7], the authors established the DA scheduling model of VPP. In this work, the robust optimization method is adopted to deal with the uncertainty of wind power output and the scenario method is used to deal with the uncertainty of market price. In [8], cardinal uncertainty set is used to describe the renewable uncertainties in the robust optimization model, tuning parameters are used to control the degree of influence of the uncertainty offset in the scheduling problem of a VPP.

Though stochastic and robust programming approaches have provided efficient tools for dealing with uncertainties in the VPP offering and generation scheduling problem, they still have drawbacks. The need for accurate probabilistic distributions of the uncertain parameters, along with requiring a large number of scenario samples to achieve higher accuracy, have hindered the application of the stochastic method [5]. In this sense, conventional robust optimization is advantageous since it is distribution-free, but it is generally considered to be too conservative. To overcome these drawbacks, we propose a MMR-based optimization model for the VPP offering and generation scheduling problem under market and renewable uncertainties. The MMR approach as a distribution-free and less conservative approach has been applied to several fields in the power system researches. In [1], the authors compared the performances of the MMR approach and the minimax cost (MMC) approach in a transmission expansion problem, it is concluded that MMR and MMC approaches may outperform each other when making transmission expansion plans. In the unit commitment problem described in [9], the MMR approach has been applied to address the uncertain wind generation. In [10], the authors developed a thermal power generator bidding strategy under price uncertainty based on the MMR criterion.

In this paper, we propose a MMR-based model for the VPP DA offering and generation scheduling problem under renewable and price uncertainties. We characterize the uncertainties using intervals and the formulated two-stage MMR problem is strongly NP-hard. To solve the two-stage MMR problem, we first reformulate it into a TSRO problem with fixed recourse, then solve it under the C&CG framework [11]. The rest of this paper is organized as follows. In Section II, we describe the VPP offering and generation scheduling problem and present our two-stage MMR model. In Section III, we propose a solution method including a TSRO reformulation of the original problem and a detailed C&CG framework to solve the problem. Section IV provides and analyzes the results of the numerical tests. Finally, we conclude our work in Section V.

II. MODEL FORMULATION

We assume the VPP to be a price-taker in the DA market and a deviator in the balancing market (BM). In the DA market, the VPP only needs to submit hourly quantity offers for the next day. In the BM, the power deviations of the VPP will be balanced at penalty prices. The penalty prices in the BM are related to the DA prices through a penalty factor η. In this section, we first present the uncertainty models and the BM pricing scheme, then give the MMR formulation of the VPP DA offering and generation scheduling problem under price and renewable uncertainties.

A. Uncertainty Models for DA Market Price and Wind Generation

We assume that the uncertain wind power generation and DA price at time t lie in deterministic intervals denoted by $[\underline{P}_{w,t}, \overline{P}_{w,t}]$ and $[\underline{\lambda}_{DA,t}, \overline{\lambda}_{DA,t}]$, respectively. Also, we assume the uncertainty intervals are symmetrical about the forecast value and an uncertainty parameter γ ranging between [0,1] is used to control the range of the intervals. Denote $P_{wf,t}$ as the wind power generation forecast at time t, the uncertainty interval of wind generation can be expressed as $[P_{wf,t} \times (1-\gamma), P_{wf,t} \times (1+\gamma)]$. Similarly, the uncertainty interval for DA market price at time t can be expressed as $[\lambda_{f,t} \times (1-\gamma), \lambda_{f,t} \times (1-\gamma)]$, where $\lambda_{f,t}$ is the DA price forecast at time t.

B. BM Price Model

A dual pricing scheme is applied to the BM, where the purchasing and selling prices are related to the DA market price $\lambda_{DA,t}$ by:

$$\lambda_{BM,b,t} = \frac{1}{1-\eta} \times \lambda_{DA,t} \tag{1a}$$

$$\lambda_{BM,s,t} = (1-\eta) \times \lambda_{DA,t} \tag{1b}$$

By adjusting the penalty factor η, we can simulate different market penalty levels towards deviations. Specifically, by increasing the penalty factor η, the market punishes the VPP more for its deviations.

C. MMR-Based Problem Formulation

In our work, the regret is defined as the absolute profit difference between the optimal solution with perfect information and our compromise solution. The optimal solution can only be determined after all the uncertainties are revealed. The optimal solution profit $Q(u)$ for a given scenario u can be obtained by solving the following deterministic problem:

$$\begin{aligned} Q(u) = \max_{P_{th,i,t}, P_{O,t}, P_{BM,t}} \Big\{ &\sum_{t\in\tau} P_{O,t} \times \lambda_{DA,u,t} \\ &- \sum_{i\in I} h(P_{th,i,t}) - g(P_{BM,t}) \Big\} \end{aligned} \tag{2a}$$

s.t

$$\sum_{i\in I} P_{th,i,t} + P_{BM,t} + P_{w,u,t} = P_{O,t} \tag{2b}$$

$$P_{th,i,min} \le P_{th,i,t} \le P_{th,i,max}, \forall \tag{2c}$$

$$RD_{th,i} \le P_{th,i,t+1} - P_{th,i,t} \le RU_{th,i} \tag{2d}$$

Where the first term in the objective function is the revenue from the DA market, the second and third terms represent the generator fuel costs and deviation costs in the BM,

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respectively. Constraint (2b) is the power balance constraint, constraints (2c) and (2d) restrict the power output and ramping limits of the thermal generators, respectively. It should be noted that, for different uncertainty realizations, the optimal solutions can be different.

In a two-stage MMR model where Y is the first-stage decision and X is the second-stage decision, the regret $Reg(Y)$ for a fixed first-stage decision Y is defined as:

$$Reg(Y) = \max_{u \in U} \left\{ Q(u) - \max_{X \in D(Y,u)} \{f(Y,u) - h(Y) - g(X)\} \right\} \tag{3}$$

Where $Q(u)$ is the maximum perfect information profit achieved under scenario u, $D(Y,u)$ is the feasible domain of X for a given first-stage decision Y and an uncertainty realization u. In the VPP DA offering and scheduling problem, $f(Y,u)$ is the revenue in the DA market, $h(Y)$ and $g(X)$ are the generators fuel costs and the deviation costs in the BM, respectively.

The MMR problem tries to identify the best first-stage Y such that its regret is the smallest among all feasible first-stage decisions.

$$\min_{Y} Reg(Y) \tag{4a}$$

s.t.

$$AY \leq b \tag{4b}$$

$$EY + GX + Mu \leq d \tag{4c}$$

$$u \in U \tag{4d}$$

Where constraints in (4b) are the feasibility constraints for the first-stage decisions. Specifically, in the VPP offering and generation scheduling problem, it represents the power output limits and the ramping limits of the generators, as well as the limits of power offered in the DA market. Constraints in (4c) restrict the feasible region of X and Y; constraints in (4d) state the intervals of the uncertainties.

III. SOLUTION METHODOLOGY

In this section, we first provide a TSRO reformulation of the original MMR problem, then decompose the TSRO problem into a master and a slave problem. Finally, we present a detailed C&CG framework to solve the problem.

A. Problem Reformulation and Decomposition

The detailed expression of $Reg(Y)$ is:

$$Reg(Y) = \max_{u \in U} \left\{ \max_{Y_u, X_u} \{f(Y_u,u) - h(Y_u) - g(X_u)\} - \max_{X \in D(Y,u)} \{f(Y,u) - h(Y) - g(X)\} \right\} \tag{5}$$

To integrate the inner optimization problem, we enlarge our uncertainty set $U = R^u$ to $U' = R^{u \times Y_u \times X_u}$ by adding the optimal decisions into the uncertainty set [12]. The $Reg(Y)$ becomes:

$$Reg(Y) = \max_{(u,Y_u,X_u) \in U'} \left\{ f(Y_u,u) - h(Y_u) - g(X_u) - \max_{X \in D(Y,u)} \{f(Y,u) - h(Y) - g(X)\} \right\} \tag{6a}$$

$$= \max_{(u,Y_u,X_u) \in U'} \left\{ \min_{X \in D(Y,u)} \{h(Y) + g(X) - f(Y,u) + f(Y_u,u) - h(Y_u) - g(X_u)\} \right\} \tag{6b}$$

$$= h(Y) + \max_{(u,Y_u,X_u) \in U'} \left\{ \min_{X \in D(Y,u)} \{g(X) - f(Y,u) + f(Y_u,u) - h(Y_u) - g(X_u)\} \right\} \tag{6c}$$

In (6b), we rewrote the inner maximization problem as a minimization problem by changing its signs. In (6c), we take the term $h(Y)$ out of the optimization problem since the generators fuel costs will not be affected in the second-stage problem. Now the MMR problem (4) can be rewritten as:

$$\min_{Y} \left\{ h(Y) + \max_{u,Y_u,X_u} \left\{ \min_{X} \{g(X) - f(Y,u) + f(Y_u,u) - h(Y_u) - g(X_u)\} \right\} \right\} \tag{7a}$$

s.t.

$$AY \leq b \tag{7b}$$

$$EY + GX + Mu \leq d \tag{7c}$$

$$EY_u + GX_u + Mu \leq d \tag{7d}$$

$$u \in U \tag{7e}$$

Problem (7) is a typical TSRO problem with fixed recourse and we can apply the C&CG algorithm to solve it. To apply the C&CG algorithm, we need to decompose the TSRO problem into a master and a slave problem.

Given problem (7), we define the slave problem as the embedded maximin problem:

$$\Theta(Y) = \max_{u,Y_u,X_u} \min_{X} \{g(X) - f(Y,u) + f(Y_u,u) - h(Y_u) - g(X_u)\} \tag{8a}$$

s.t.

$$EY + GX + Mu \leq d \tag{8b}$$

$$EY_u + GX_u + Mu \leq d \tag{8c}$$

$$u \in U \tag{8d}$$

We use an auxiliary variable θ to represent the optimal objective value of the slave problem (8), the master problem is then defined as:

$$\min_{Y,\theta} h(Y) + \theta \tag{9a}$$

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s.t.

$$AY \leq b \tag{9b}$$

$$EY + GX_l + Mu_l^\star \leq d \tag{9c}$$

$$EY + GX_l + Mu \leq d \tag{9d}$$

$$\theta \geq g(X_l) - f(Y, u_l^\star) + f(Y_{u,l}^\star, u_l^\star) - h(Y_{u,l}^\star) - g(X_{u,l}^\star) \tag{9e}$$

$$\theta \in R \tag{9f}$$

Where X_l are new variables added to the master problem in the lth iteration, $u_l^\star, Y_{u,l}^\star$ and $X_{u,l}^\star$ are the calculated values from the slave problem in the lth iteration.

B. Solving Algorithm

Under the C&CG framework, we first relax the constraints of the original problem, then gradually add them back by solving the slave problem using different first-stage decisions. If we add enough constraints to the relaxed problem, its optimal objective value will approach the true optimal objective value of the original problem. There are two kinds of constraints under the C&CG framework, namely, the feasibility constraints when the slave problem is not feasible, and the optimality constraints when the slave problem is feasible. We assume that the BM can settle the power deviations of the VPP for any wind generation and offering as well as generation scheduling decisions, under this assumption, the second-stage problem is always feasible. Therefore, we only need to consider the optimality constraints in this problem. We will update the lower and upper bounds of the original problem by solving the master and slave problems. Specifically, by solving the master problem, we will obtain a lower bound of the original problem, this is because the master problem is a relaxation of the original minimization problem and its result is over-optimal. Similarly, we can acquire an upper bound by solving the slave problem since the feasible region in the slave problem is reduced (by restricting Y to a fixed value) compared to the original problem and the obtained result is sub-optimal.

C&CG Framework

1) Set lower bound $LB = -\infty$, upper bound $UB = \infty$, iteration number $l = 0$; set tolerance ϵ to a satisfactory level.
2) Solve the master problem (9), derive an optimal solution of $(Y_{l+1}^\star, \theta_{l+1}^\star)$. Update the lower bound of the problem to $\max\{LB, h(Y_{l+1}^\star) + \theta_{l+1}^\star\}$.
3) Solve the slave problem by substituting the optimal first-stage decision $Y_{l+1}^\star$ into it. Derive an optimal solution ($u_{l+1}^\star, Y_{u,l+1}^\star$ and $X_{u,l+1}^\star$) and its optimal objective value $\Theta(Y_{l+1}^\star)$, Update the upper bound to $min\{UB, h(Y_{l+1}^\star) + \Theta(Y_{l+1}^\star)\}$.
4) If $UB - LB \leq \epsilon$, return $Y_{l+1}^\star$ and terminate the algorithm. Otherwise, create new variables X_{l+1} and add the following constraints to the master problem, return to step 2.

$$EY + GX_{l+1} + Mu_{l+1}^\star \leq d \tag{10a}$$

$$EY + GX_{l+1} + Mu \leq d \tag{10b}$$

$$\theta \geq g(X_{l+1}) - f(Y, u_{l+1}^\star) + f(Y_{u,l+1}^\star, u_{l+1}^\star) - h(Y_{u,l+1}^\star) - g(X_{u,l+1}^\star) \tag{10c}$$

IV. Computational Results

In this section, we first describe the details of the experiment setup, then present and analyze the numerical results. We apply two distribution-free approaches, the proposed MMR approach and the maximin profit (MMP) approach, to the VPP offering and generation scheduling problem and compare their performances. We also apply the perfect information approach (PIA) to the same problem, where decisions are made after all the uncertainties are known. We use the performance of the PIA as the benchmark for evaluation.

A. Numerical Settings

a) VPP and Market Configuration The considered VPP consists of one wind generator and two thermal units, the generators characteristics are present in Table I. The VPP participates in both the DA market and the BM. In the DA market, the VPP only needs to submit hourly quantity offers and will accept the market-clearing prices. In the BM, the VPP power deviations will be balanced at penalty prices calculated from equations (1a) and (1b).

TABLE I
CHARACTERISTICS OF GENERATORS

	P_{min} (MW)	P_{max} (MW)	a (£)	b (£/MW)	c (£/MW^2)	RU (MW/h)	RD (MW/h)
Diesel	5	38	49	16	0.15	10	10
Gas	5	40	23	18	0.24	15	15
Wind	0	60	0	0	0		

b) Uncertainty Modelling The uncertainties considered in this work include the DA market price and the wind power generation. The wind power forecast data is obtained from [13]. The price forecast data are obtained using the seasonal ARIMA model $arima(1,0,1)(1,1,1)_{24}$, where real-world price data is from [14]. The uncertainty interval calculations are presented in section II, by changing the uncertainty parameter γ, we can adjust the range of the uncertainties. Specifically, when γ increases, the range of uncertainties increases.

B. Results and Discussion

Define the profit percentages of the MMP and MMR approaches as $(Profit_{MMP}/Profit_{PIA}) \times 100\%$ and $(Profit_{MMR}/Profit_{PIA}) \times 100\%$, respectively. We compare the performances of the two distribution-free approaches by *1)* The average profit percentage, *2)* The sensitivity of the profit percentages to different uncertainty parameters and *3)* The sensitivity of the profit percentages to different penalty factors. For each parameter setup, we generate 1000 evaluating scenarios based on the forecast values and the uncertainty parameter γ to obtain a statistically significant result.

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TABLE II
PROFITS AND PROFIT PERCENTAGES UNDER DIFFERENT UNCERTAINTY PARAMETERS

γ	0.3	0.4	0.5	0.6	0.7	0.8	Average
MMR %	59563 92.40%	56431 89.52%	56714 86.50%	54457 82.80%	52016 79.47%	50646 75.73%	54971 84.32%
MMP %	54685 84.83%	47946 76.06%	42352 64.60%	33493 50.92%	26231 40.08%	21194 31.69%	37650 57.75%
PIA	64465	63039	65562	65773	65453	66873	65194

Table II presents the profits and profit percentages of each method under different values of the uncertainty parameter γ, the penalty factor η is set to be 0.6 in this case. In Table II, profit percentages of the MMP approach vary between [31.69%,84.83%], the average profit is 57.75% of the PIA average profit. Profit percentages of the MMR approach vary between [75.73%,92.40%] and the average profit of the MMR approach reaches 84.32% of the PIA average profit. It is indicated that the proposed approach can provide a solution that is close to the optimal solution in terms of the average profit percentage. Also, we observe that as the uncertainty parameter γ increases, namely, the uncertainty intervals increase, the profit percentages of both the MMR approach and the MMP approach will decrease. As we increase the uncertainty parameter η from 0.3 to 0.8, the profit percentage of the MMP approach dropped from 84.83% to 31.69%, whereas the profit percentage of the MMR approach only dropped from 92.40% to 75.73%, this small reduction in profit percentage shows that the proposed MMR approach is robust in a highly volatile environment.

TABLE III
PROFITS AND PROFIT PERCENTAGES UNDER DIFFERENT UNCERTAINTY PARAMETERS

η	0.2	0.3	0.4	0.5	0.6	0.7	Average
MMR %	62097 94.56%	58748 92.91%	59796 91.21%	57740 88.79%	55395 86.37%	53579 83.13%	57892 89.50%
MMP %	49123 74.80%	45662 72.21%	45745 69.77%	43544 66.96%	41196 64.23%	40127 62.26%	44233 68.39%
PIA	65673	63234	65562	65032	64135	64452	64681

Table III displays the profits and profit percentages of each method for different values of penalty factor η, the uncertainty factor γ is set to be 0.5 in this case. In Table III, profit percentages of the MMP approach vary from 62.26% to 74.80% with an average of 68.39%. However, the profit percentages of the MMR approach vary between 83.13% and 94.56%, which means that even the smallest profit percentage of the MMR approach is larger than the largest profit percentage of the MMP approach. The average profit percentage of the MMR approach is 89.50%, which indicates that the proposed approach can find a solution that is very close to the optimal one. From Table III, we observe that as the penalty factor η increases, namely, the market punishes more for deviations, the profit percentages of both the MMR and MMP approaches will decrease. As we increase η from 0.2 to 0.7, the profit percentage of the MMP approach dropped by 53.14%, while the profit percentage of the MMR approach only slightly dropped by 11.43%. Therefore, we can conclude that our approach is robust against highly penalizing pricing schemes.

V. CONCLUSION

In this work, we proposed a two-stage MMR model for the VPP offering and generation scheduling problem with renewable and market uncertainties. To solve the resulting problem, we developed a solution method including a TSRO reformulation of the two-stage MMR problem and a C&CG framework. Numerical experiments are conducted to evaluate the performance of the proposed model, we also provided the results obtained from the MMP approach and the PIA. By comparing the performances of the three methods, we conclude that our approach can find a solution that is very close to the optimal one, and its performance is robust in a highly volatile environment and a significantly penalizing balancing market.

REFERENCES

[1] Chen, Bokan and Wang, Jianhui and Wang, Lizhi and He, Yanyi and Wang, Zhaoyu, “Robust optimization for transmission expansion planning: Minimax cost vs. minimax regret” IEEE transactions on power systems, vol. 29, pp. 3069–3077, 2014.

[2] Tajeddini, Mohammad Amin and Rahimi-Kian, Ashkan and Soroudi, Alireza, ”Risk averse optimal operation of a virtual power plant using two stage stochastic programming,” Energy ,vol. 73 pp, 958–967 . 2014

[3] Zhao, Yuzhou and Liu, Rongpeng and Lei, Shunbo and Hou, Yunhe, ” Look-Ahead Strategic Offering for a Virtual Power Plant: A Multi-Stage Stochastic Programming Approach,” 2019 IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia) pp, 2991–2996 .2019

[4] Hadayeghparast, Shahrzad and Farsangi, Alireza SoltaniNejad and Shayanfar, Heidarali, ” Day-ahead stochastic multi-objective economic/emission operational scheduling of a large scale virtual power plant,” Energy ,vol.172 pp.630–646 , 2019

[5] Bertsimas, Dimitris and Litvinov, Eugene and Sun, Xu Andy and Zhao, Jinye and Zheng, Tongxin, ”Adaptive robust optimization for the security constrained unit commitment problem ,” IEEE transactions on power systems vol.28 pp. 52–63, 2012.

[6] Yin, Shuangrui and Ai, Qian and Li, Zhaoyu and Zhang, Yufan and Lu, Tianguang, ”Energy management for aggregate prosumers in a virtual power plant: A robust Stackelberg game approach,” International Journal of Electrical Power & Energy Systems , vol. 117 pp. 105605 , 2020

[7] Baringo, Ana and Baringo, Luis and Arroyo, Jose M, ”Day-ahead self-scheduling of a virtual power plant in energy and reserve electricity markets under uncertainty,” IEEE Transactions on Power Systems , vol. 34 pp.1881–1894 , 2018

[8] Kong, Xiangyu and Xiao, Jie and Liu, Dehong and Wu, Jianzhong and Wang, Chengshan and Shen, Yu, ”Robust stochastic optimal dispatching method of multi-energy virtual power plant considering multiple uncertainties,” Applied Energy , vol.279 pp.115707 ,2020

[9] Jiang, Ruiwei and Wang, Jianhui and Zhang, Muhong and Guan, Yongpei, ”Two-stage minimax regret robust unit commitment,” IEEE Transactions on Power Systems , vol.28 pp. 2271–2282 , 2013

[10] Fan, Lei and Wang, Jianhui and Jiang, Ruiwei and Guan, Yongpei, ”Min-max regret bidding strategy for thermal generator considering price uncertainty,” IEEE Transactions on Power Systems , vol.29 pp. 2169–2179 , 2014

[11] Zeng, Bo and Zhao, Long, ”Solving two-stage robust optimization problems using a column-and-constraint generation method,” Operations Research Letters , vol. 41 pp. 457–461 , 2013

[12] Poursoltani, Mehran and Delage, Erick,”Adjustable robust optimization reformulations of two-stage worst-case regret minimization problems, ”Available at Optimization Online, 2019

[13] UK generation forecast [Online],”https://www.rensmart.com/UKGeneration Forecast”

[14] NORDPOOL UK - DA MARKET DATA [Online], ”https://www.nordpoolgroup.com/Market-data1/GB/Auction-prices/UK/Hourly/?view=table”