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Optimal Purchasing and Selling Strategies for Electricity-retailers Based on Scale Spatial Scenario Generation and Flexible Resource Integration

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***Abstract*—With the rapid development of China's electricity market, the purchasing and selling strategies of electricity-retailers (ER) have attracted great concern. Taking demand side response into account, this paper proposes a comprehensive profit optimization model, which takes bilateral risks in both purchasing and selling businesses of electricity market into consideration. In the proposed model, the scale spatial clustering method is used to generate multi-variant scenario with an adaptive gradient tracking, including the spot price, the output of renewable energy, demand-response (DR) behaviors and the random fluctuation of demand from users. Moreover, the external environment of demand response in power market is taken in consideration, which reflected in the interruptible load and transferable load profit model. Based on the probabilistic scenario, the day-ahead strategies of the ER are randomly optimized, considering the bilateral business of purchasing and selling profiles. Utilizing the simulation of case studies, the results show that the proposed model is suitable and effective to be used for determining the purchasing and selling strategy of the electricity-sales companies.**

Keywords—Electricity retailers, demand response, bilateral risks, scale spatial scenario generation, purchasing and selling businesses

I. INTRODUCTION

As the rapid increase of China's renewable energy generation, the demand for energy consumption in the market is becoming more and more urgent, and the retail companies will also be exposed to many uncertain risks [1]-[2]. In a competitive market for the electricity-sales company (ER), the bilateral businesses are subject to the fluctuations in spot prices, the output of renewable energy and demand. Therefore, it is necessary to conduct in-depth optimization strategy research from both the supply side and the demand side [3].

A considerable number of literatures focusing on the renewable energy access to the market. In [4], a hybrid MILP and Benders decomposition approach is presented to find the Nucleolus quota allocation for a renewable energy portfolio. The technical challenges for the power industry brought by renewable energies sources (RES) is discussed in [5]. This work reported introduces commercial challenges for RES integration. Financial mechanisms, such as feed-in tariffs and renewable auctions have been utilized to stimulate RES penetration in many researches [6].

Electricity market presents great opportunities for ERs to make profit. The ERs purchase electricity from the wholesale market and then sell it to the retail market in the emerging electricity market [7]. Therefore, optimizing the bilateral strategies under the stochastic scene is inevitable for ER. The optimal investment decision problem for a ER in emerging electricity market is investigated in [8]. However, only few studies have focused on scene generation in stochastic optimization, which is very significant for ER's day-ahead strategies [5].

In this paper, the major contributions of this work are summarized as follows.

1) In this proposed model, the scale spatial clustering method is used in stochastic optimization to generate the corresponding scenes. In addition, the reward of day-ahead information is modeled as a decoding function, in order to determine the probability of these scenes. Based on the idea of density clustering, the scale space drift technique is applied to high-dimensional data, and then the high-dimensional scene clustering results are obtained, which provide more comprehensive sample feature information and more reasonable scene probability expression for the ER's day-ahead purchasing and selling strategies.
2) Compared with the traditional decisions of ER, the user-side demand response business and VPP's resource integration behavior are included in this model. This paper provides technical support and theoretical guidance for more decentralized market design and ER's purchasing and selling decisions.

The paper is organized as follows. In section II, the scene-generation method based on scale spatial clustering is introduced. Section III discusses the modeling of purchasing and selling business for ER. Section IV shows the numerical case study of the proposed method, followed by the concluding remarks in Section V.

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II. SCENE-GENERATION BASED ON SCALE SPATIAL CLUSTERING

Apart from the volatility of spot price and user's demand, the main risk factors of ER's decision are also derived from the uncertainty of wind power and photovoltaic output in the bilateral business model. Since these risk factors are continuous random variables, the issues of ER's bilateral business decision and risk assessment can be transformed into stochastic planning decision problems. Given that stochastic programming problems with continuous random variables are often difficult to solve, most of the researchers use the method of scenario simulation to simplify the study [7].

However, for the day-ahead decision of ER's business, the traditional scenario simulation method lacks the feedback of the up to date market information. Therefore, for the sake of the accurate and efficient evaluation, this paper improves the traditional simulation method by using the scale spatial clustering method, which originated from a high-dimensional image processing method [9]. The scale spatial clustering algorithm is a density-based algorithm, which calculating the offset average of the current point, while moving the offset average of the point to its offset, and then moving as a new starting point until these points satisfy the distance less than the minimum distance. The scale spatial clustering algorithm derives from the kernel density estimation (KDE), as a non-parametric process, which can be used without assuming that the shape of the base density [10]. For a set of scenes, the number of points falling into the hypercube whose distance to the center is expressed by

$$\sum_{j=1}^{N_{scene}}\left[\begin{array}{l}\displaystyle\sum_{i=1}^{N_{demand}} k\left(\frac{\overline{demand_j}-demand_i}{h_{demand}}\right)+\\ \displaystyle\sum_{i=1}^{N_{price}} k\left(\frac{\overline{price_j}-price_i}{h_{price}}\right)+\\ \displaystyle\sum_{i=1}^{N_{wind}} k\left(\frac{\overline{wind_j}-wind_i}{h_{wind}}\right)+\sum_{i=1}^{N_{PV}} k\left(\frac{\overline{PV_j}-PV_i}{h_{PV}}\right)\end{array}\right] \tag{1}$$

where $k()$ means the following kernel function, h as bandwidth.

$$k(\mathrm{u})=\begin{cases}1 & \left|u_j\right|\le\frac{1}{2};\ j=1,\ldots,d\\ 0 & \text{otherwise}\end{cases} \tag{2}$$

$$\hat{p}(\mathrm{x})=\sum_{j=1}^{N_{scene}}\left[\begin{array}{l}\displaystyle\frac{1}{N_{demand}\cdot h_{demand}}\sum_{i=1}^{N_{demand}} k\left(\frac{\overline{demand_j}-demand_i}{h_{demand}}\right)+\\ \displaystyle\frac{1}{N_{price}\cdot h_{price}}\sum_{i=1}^{N_{price}} k\left(\frac{\overline{price_j}-price_i}{h_{price}}\right)+\\ \displaystyle\frac{1}{N_w\cdot h_w}\sum_{i=1}^{N_w} k\left(\frac{\overline{wind_j}-wind_i}{h_{wind}}\right)+\frac{1}{N_{PV}\cdot h_{PV}}\sum_{i=1}^{N_{PV}} k\left(\frac{\overline{PV_j}-PV_i}{h_{PV}}\right)\end{array}\right] \tag{3}$$

Therefore, the estimation of the spatial average density is given by (3), where x is the sets for all the uncertainties, including spot price, demand, and the renewable energy output. Then the window width h determines the volume of the hypercube and n is the total number of samples. Using the scale spatial procedure, this paper pays a particular attention to the meaningful areas (i.e., high-density areas) of $\hat{p}(\mathbf{x})$ rather than $\hat{p}(\mathbf{x})$ itself, without any parametric assumptions except a radially symmetric kernel. Then the following can be obtained

$$\hat{p}(\mathrm{x})=\frac{c}{nh^d}\sum_{i=1}^{n} k\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \tag{4}$$

$$\nabla\hat{p}(\mathrm{x})=\frac{2c}{nh^{d+2}}\sum_{i=1}^{n}(x-x_i)k'\left(\left\|\frac{x-x_i}{h}\right\|^2\right) \tag{5}$$

where c is a constant of scale-normalization, then $g(\mathrm{x})=-k'(\mathrm{x})$ introduced into (5) yields

$$\nabla\hat{p}(\mathrm{x})=\frac{2c}{nh^{d+2}}\left[\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)\right]\left[\frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}-x\right] \tag{6}$$

In (6), the last term is the scale spatial shift (namely, the difference between x, the center of window, and weighted average value) expressed as $\mathrm{m}(\mathrm{x})$, which can be infer further as

$$\mathrm{m}(\mathrm{x})=\frac{1}{2}h^2 c\frac{\nabla\hat{p}(\mathrm{x})}{\hat{p}(\mathrm{x})} \tag{7}$$

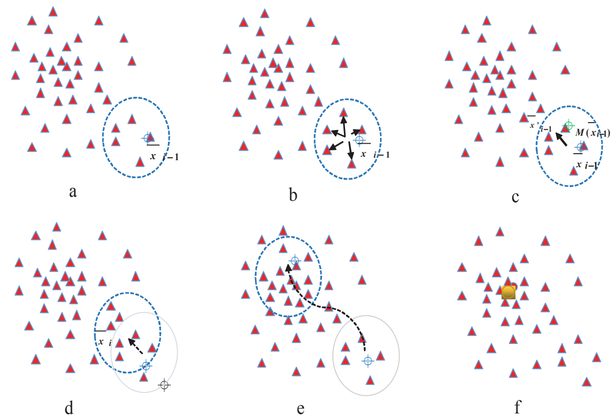


Fig. 1. Schematic diagram of scale spatial clustering process

It indicates that the scale spatial shift at x is proportional to the density gradient. Hence, m(x) always targets the increasing gradient direction of p(x). Therefore, m(x) can always find the path to the estimated density's saddle point. It should be noticed that an important characteristic of such a method, which making it different from other gradient algorithms, lies in that the explicit specification of the step size is not necessary, when moving along such a path (i.e., in the high-density region near the local maximum, the step size is small and vice versa, so the analysis is more meticulous).

Fig. 1 shows the density-approximation process of scale spatial clustering, which designed to reflect the construction of high-dimensional scenario for ER's investment decisions, including user's demand, spot price, and above all, VPP's bidding, which affected by the uncertainty of wind power and photovoltaic output further. In order to determine the probability of a certain scene, the soft-max function is used.

$$\sigma(\mathbf{z})_j = \frac{\exp(z_j)}{\sum_{j=1}^{J}\exp(z_j)} \tag{8}$$

where, $\mathbf{z}$ means the corresponding mapping metrics for high-dimensional clustering results, while the discretized value z_j is the distance value of the j-th cluster and the prediction, which determined by Standardized Euclidean distance (SED) [9], accumulated from each dimension.

$$\pi(w_j) = \frac{\exp(\sum_{i=1}^{N_i} \text{-}SED(\mathrm{pre}_i, \mathrm{w}_{ij}))}{\sum_{j=1}^{J}\exp(\sum_{i=1}^{N_i} \text{-}SED(\mathrm{pre}_i, w_{ij}))} \tag{9}$$

In (9), the w_{ij} is the j-th center of clustering at the i-th dimension, while the pre_i expressed as the prediction at the i-th dimension (i.e., the forecasting result of these factors).

III. Modeling of Purchasing and Selling Businesses

A. Analysis of the bilateral business model

According to the contract signed in the bilateral business, the main business of ER is divided into two categories: power purchasing business and power selling business. The existing business model is shown in the following Fig 2.

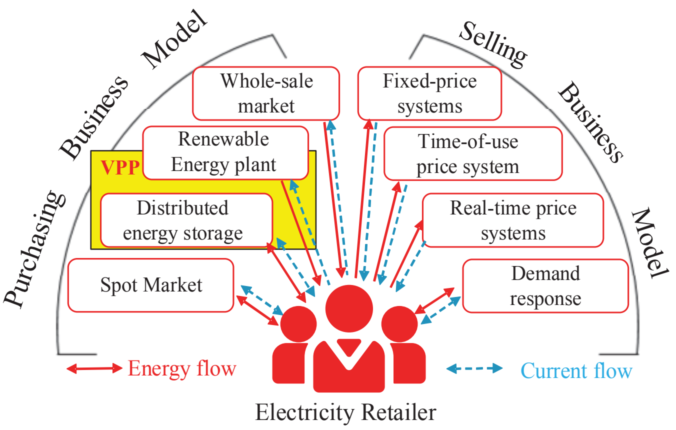


Fig. 2. Business flowchart of ER

In terms of the power purchasing business, in order to meet the power needs of end users, the ER can sign kinds of power purchasing contracts at different time scales in the centralized market in advance. Meanwhile, it's also beneficial for ER to sign bilateral agreements with other distributed power plants or virtual power plant (VPP) to improve the demand-response (DR) ability of the market signal mechanism, with the liquidation of the unbalanced power through the spot market.

For the power selling business, this paper divides the end-users into three categories, i.e., resident, industry and commerce. According to the typical power behavior of each user group, the ER can design different types of sales contracts for users to choose. Typical power selling contracts include: fixed electricity price contracts, time-of-use (TOU) electricity price contracts, and guaranteed capping real-time (RT) electricity price contracts. In addition, considering the subjective initiative of the end-users to participate in the demand response, this paper incorporates the user's participation in the interruptible load (IL) and the transferable load (TL) contract into the sales-side business modeling.

Since there are so many uncertain factors in the bilateral market, in order to avoid the NP-hard curse of stochastic optimization, it should be noted that among the electricity purchasing business, the trading of the distributed power plant and the renewable energy power plant (or together as VPP) to ER belongs to the option trading. The ER may choose to execute the option as the option owner or may only partially execute such a right. Nevertheless, determination of these options is out of the research scope of this paper.

This section pays particular attention to the VPP's option contract which conducive to the modeling of flexible resource integration, and the proposed demand response business. In addition, the procedure of risk management is based on the novel scene generation method introduced in Section II, which can not only provide the multi-dimensional associated scene, but also the relative probability using the day-ahead reward.

B. VPP model for flexible resource integration

In the VPP business mechanism proposed in this paper, VPP can flexibly sign the power curve in the day-ahead option (i.e., the maximum of real-time power that the actual option can exercise), based on the forecasting results of its new energy generation and the prices in the spot market.

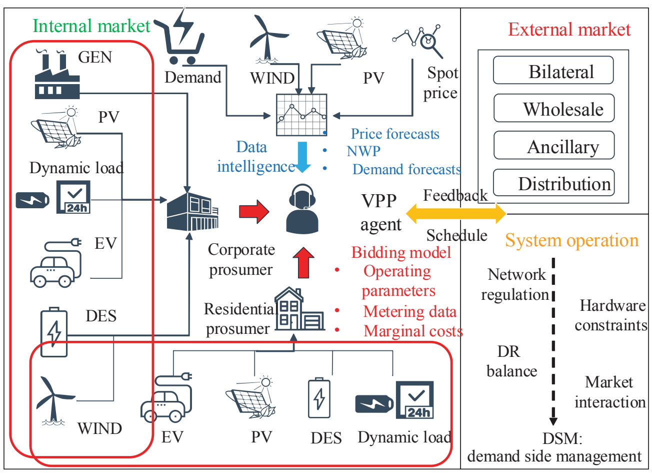


Fig. 3. Integrated VPP architecture used in purchasing business

Fig. 3 shows the integrated VPP architecture and the three types of subject in VPP's business model, including the interaction among internal market, external market and, above all, the system operation. After the establishment of VPP, a financial virtual energy framework is termed here with a high interoperability via demand side management (DSM). With financial models and data mining techniques for smart meters, VPP will fully evaluate the uncertainty of its systems and sign an option contract with ER for the day-ahead power curve, details in [11].

Especially for VPP's formulation of day-ahead power curve, this procedure will include the detailed modeling of DSM, considering the actual constraints of power system elements and regulation for renewable energy consumption under the stochastic scenarios, which will be presented in further research. In this paper, however, we only pay attention to the option contract from VPPs, which provides a channel to purchase electricity.

C. Demand side response model

In this model, the traditional contacts, such as fixed electricity price contracts, TOU electricity price contracts, and guaranteed capping RT electricity price contracts are included, where detailed formulation can be found in [8]. Furthermore, this paper incorporates IL and TL contracts into the selling business model, considering the subjective initiative of the end user to participate in the demand response.

For the sake of simplicity and rationality, the proportion h of users participating in IL and TL can be linearized as a piecewise linear function of the compensation price, instead of the logarithmic function, described in [5].

$$h_{IL}\left(\lambda_{tw}^{IL}\right)=\begin{cases}K_1^{IL}\cdot\lambda_{tw}^{IL}, & \lambda_{tw}^{IL}<\lambda_1^{IL}\\ K_2^{IL}\cdot(\lambda_{tw}^{IL}-\lambda_1^{IL})+K_1^{IL}\lambda_1^{IL}, & \lambda_1^{IL}\le\lambda_{tw}^{IL}<\lambda_2^{IL}\\ \overline{h}_{IL}, & \lambda_2^{IL}\le\lambda_{tw}^{IL}\end{cases}\tag{10}$$

where, λ_{tw}^{IL} is the compensation price paid to the user for the participation of IL and TL contacts respectively.

Further, let P_{tw}^{total} be the total demand load of the scene w corresponding to the time t, determined by the demands of all users e. Considering the reliability of power supply, this paper assumes that the longest outage period in one day is 4 h, and the interruptible capacity P_{tw}^{IL} can be represented as

$$P_{tw}^{IL}=P_{tw}^{total}\cdot h_{IL}\left(\lambda_{tw}^{IL}\right)\tag{12}$$

$$P_{tw}^{total}=\sum_{e=1}^{N_e}(P_{etw}^{RT}+P_{etw}^{fix}+P_{etw}^{TOU})\tag{13}$$

Similarly, the TL business contact can be obtained. Utility function based on risk management.

D. Utility function based on risk management

Under a random scenario, the retailer's expected profit function includes the expected revenue of ER selling business with different types of users, the expected cost of whole-sale and forward contracts, as well as the expected settlement cost/revenue of option contract and DR project.

The conditional risk value (CVaR) overcomes the defect that both MV and VaR fail not meet the consistency of risk measurement and has been applied to the risk assessment of the power retail business [7]. CVaR is defined as the conditional expectation of loss where the loss exceeds the threshold (i.e., VaR). In this paper, it is formulated as the value of expectation for the portfolio-loss function in the $(1-\beta)\times100\%$ worst case, at the confidence level β.

When ER develops a bilateral purchasing and selling strategy, it should maximize its expected profits while minimizing the loss of risk. Therefore, this paper establishes the following utility function with an auxiliary variable η_w [7].

$$\max\ R^{total}-\rho\left(VaR+\frac{1}{1-\mu}\sum_{w}\pi(w)\cdot\eta_w\right)\tag{17}$$

$$\eta_w=\left[loss_w-VaR\right]^+=\max\left\{0,loss_w-VaR\right\}\tag{18}$$

where ρ is the factor of risk aversion, which related to the degree of risk preference of the ER. Obviously, for risk-averse ER, the factor is larger, and vice versa.

IV. NUMERICAL CASE STUDY

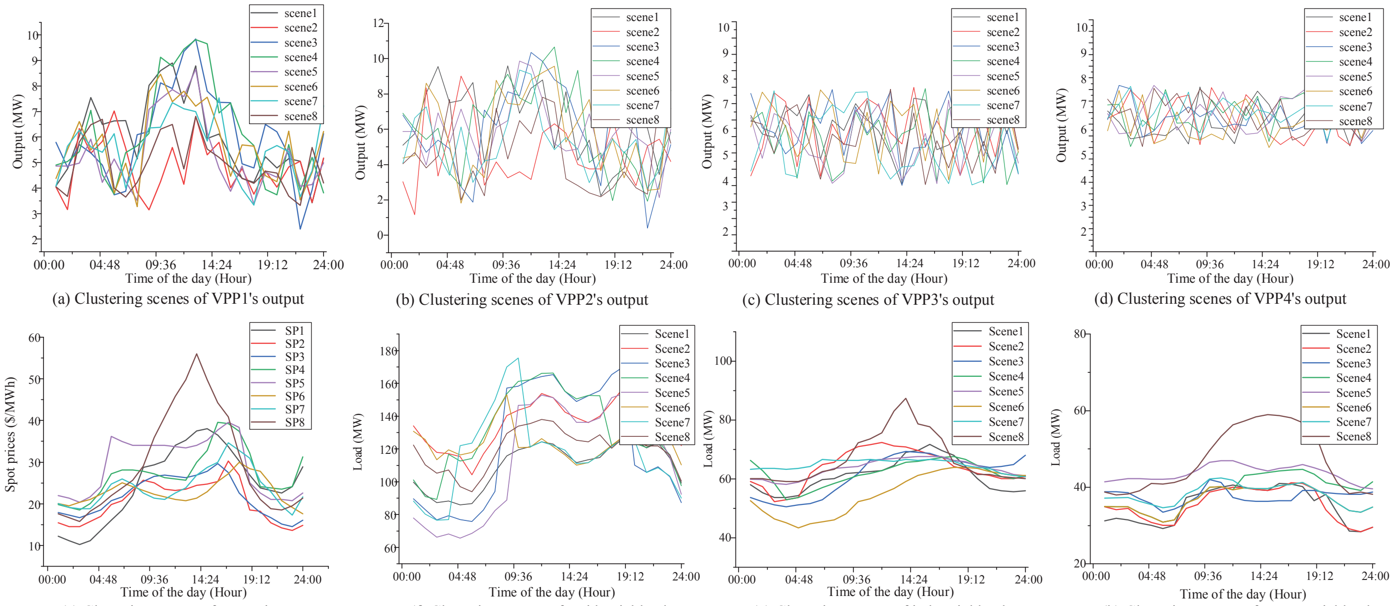
The performance of such a stochastic optimization method based on scene generation is illustrated through a case study of ER's optimal investment decision. A ER in New England is introduced in [12], while the contractual period considered to last 3 months in this paper.

A. Results of the scene modeling

First, a series of 24-hour data are used as the benchmark sample point for spatial scale clustering. It should be noted that the number of classification objects of this method is set to 8, which contains scene features of 6 dimensions, including the wind power, PV power, fluctuation of SP, as well as these three kinds of load.

In this paper, a set of forward contracts in wholesale market, and a certain amount of option contracts of VPPs are all set as input data. As stated in the previous paragraph, the option curve of VPP is related to numerous scene factors, which is far away from the focus of this paper. Therefore, for the sake of reducing model complexity, this paper simply sets the option curve of VPP to the accumulated value of photovoltaic and wind power output under the eight scenarios obtained by clustering.

Using the high-dimensional scene generation algorithm of spatial scale clustering, the clustering results of eight typical scenes are shown in Fig. 4, which represent the six dimensions of clustering respectively. From the generated scene, the clustering effect of the multi-dimensional scene is satisfactory, since it owns the most significant intra-class sample density and the largest distance between the different center points of the classes.



(a) Clustering scenes of VPP1's output (b) Clustering scenes of VPP2's output (c) Clustering scenes of VPP3's output (d) Clustering scenes of VPP4's output

(e) Clustering scenes of spot price (f) Clustering scenes of residential load (g) Clustering scenes of industrial load (h) Clustering scenes of commercial load

Fig. 4. Scene modeling based on scale spatial clustering

B. Purchasing and selling strategies under stochastic optimization

In this section, the efficacy of the proposed stochastic optimization in this paper is illustrated with a certain confidence level. In the simulation the number of VPP's option contract parameter details are shown below as Table I.

TABLE I. THE PARAMETERS OF OPTION CONTRACT FOR VPP

Contract	VPP1	VPP2	VPP3	VPP4
Price ($/MWh)	18	22	24	26
Sources	W, P, S	M, P, S	M, W, S	M, W, P, S
Total capacity	10	12	8	8

(W - wind, P - photovoltaic, M - micro gas turbine, S - storage)

It should be emphasized that the research object is the optimization of ER's day-ahead decision-making, which including the execution plan of each contract and the real-time purchase in the wholesale market. However, it should be recognized that the trading results in the spot market are virtual real-time simulations, where actual transaction may be deviated from the simulation one, due to fluctuations and prediction errors caused by random factors.

In Fig. 5, as it can be observed, the trading volumes of the detailed component corresponding to the optimal purchasing and selling strategy under each time period are shown in cumulative diagram of electricity transaction.

The total purchasing electricity is composed of forward contract, VPP's option and the electricity of spot market. Moreover, ER sold superfluous electricity back to the spot pool, which verifies the flexibility of the supply and demand balance in the spot market. It should be acknowledged that the arbitrage behavior, which beneficial to ER, is allowed in this paper. The sale of electricity in the spot market occurs mostly at the peak of renewable energy output. Accordingly, ER will implement a larger proportion of VPP option contracts, which reflecting the priority of renewable energy consumption under the VPP mechanism.

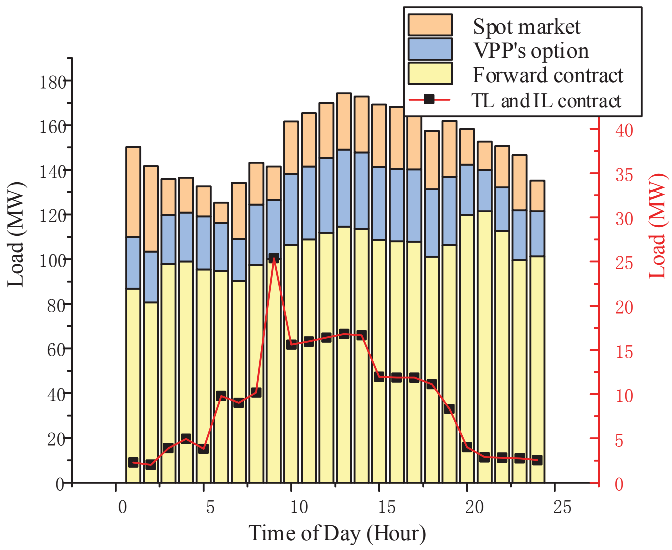


Fig. 5. Composition of the electricity purchasing business

In Fig. 6, the components of selling electricity are shown in a radar map, which are determined by the probabilistic predict of base scenes, introduced in section II. Among the selling business, the residential part dominates the total electricity, followed by the commercial part and the industrial part. It should be noticed that a more accurate forecasting method can be used as a modeling of selling uncertainty. However, it has been proved that due to the DR contracts on the power selling side, a prediction method that occupies more computational resources cannot significantly improve the accuracy, compared with the scene generation method.

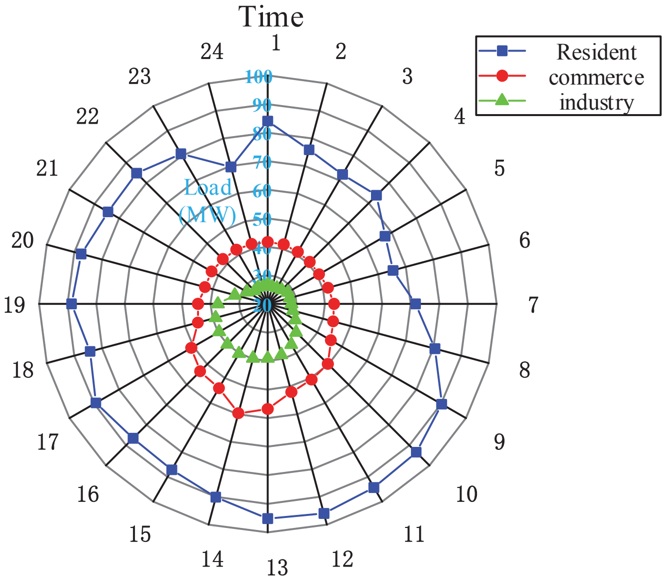


Fig. 6. Composition of the electricity selling business

Generally speaking, the execution of forward contract can guarantee a reliable and continuous electricity supply, while with a less opportunity benefit. However, the selling business of the transaction in spot market, the option contracts with VPPs and DR contracts characterize in high fluctuation, which lack the financial robustness, since the large variance of the spot price or the available VPP's and DR's capacity. In Table II, as the factor of risk aversion increases, the value of CVaR will also decline, which represents that investors of ER lost their appetite for risk.

TABLE II. THE COMPARISON OF OPTIMAL DECISION UNDER DIFFERENT FACTOR OF RISK AVERSION

risk aversion	Optimal decision		
	Total in spot market , VPP and IL (MWh)	*Total in Forward Contract (MWh)*	*CVaR ($)*
0.1	2.56 E+03	1.32 E+03	7.58E+06
0.5	2.11 E+03	1.77 E+03	3.76E+06
1	1.77 E+03	2.11 E+03	3.92E+05
5	9.41E+02	2.94 E+03	2.77E+04
10	8.12 E+02	3.47E+03	1.63E+03

In fact, it presents a more obvious trend that ER is more inclined to invest in forward contracts and reduce investment in spot market and VPP's options, as the degree of risk aversion increases.

V. CONCLUSION

In this paper, the uncertainties of multi-scene are modeled as a scenario generation problem with spatial clustering method. After the modeling of purchasing and selling decision, a well-designed case study is presented. Different from the traditional investment decision-making method, the method of this paper makes full use of the feedback of market information to form the investment decision-making scenarios. Meanwhile, the user-side demand response business and VPP's resource integration behavior are included in the model.

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References

[1] M. Behrangrad, "A review of demand side management business models in the electricity market," Renewable and Sustainable Energy, vol. 47, pp. 270-283, 2015.
[2] F. Blaabjerg, and D. M. Ionel, "Renewable energy devices and systems–state-of-the-art technology, research and development, challenges and future trends," Electric Power Components and Systems, vol. 43, no. 12, pp. 1319-1328, 2015.
[3] M. Charwand, M. Gitizadeh, and P. Siano, "A new active portfolio risk management for an electricity retailer based on a drawdown risk preference," Energy, vol. 118, pp. 387-398, 2017.
[4] J. Cheng, F. Chu, and M. Zhou, "An improved model for parallel machine scheduling under time-of-use electricity price," IEEE Transactions on Automation Science and Engineering, vol. 15, no. 2, pp. 896-899, 2017.
[5] J. C. do Prado, and W. Qiao, "A stochastic decision-making model for an electricity retailer with intermittent renewable energy and short-term demand response," IEEE Transactions on Smart Grid, 2018.
[6] N. Ghaffour, J. Bundschuh, H. Mahmoudi, and M. F. Goosen, "Renewable energy-driven desalination technologies: A comprehensive review on challenges and potential applications of integrated systems," Desalination, vol. 356, pp. 94-114, 2015.
[7] Y. Guo, P. Shao, J. Wang, X. Dou, and W. Zhao, "Purchase Strategies for Power Retailers Considering Load Deviation and CVaR," Energy Procedia, vol. 158, pp. 6658-6663, 2019.
[8] M. Yu, and S. H. Hong, "Supply–demand balancing for power management in smart grid: A Stackelberg game approach," Applied energy, vol. 164, pp. 702-710, 2016.
[9] T. Wiegand, S. Gunatilleke, N. Gunatilleke, and T. Okuda, "Analyzing the spatial structure of a Sri Lankan tree species with multiple scales of clustering," Ecology, vol. 88, no. 12, pp. 3088-3102, 2007..
[10] Y. Leung, J.-S. Zhang, and Z.-B. Xu, "Clustering by scale-space filtering," IEEE Transactions on pattern analysis and machine intelligence, vol. 22, no. 12, pp. 1396-1410, 2000.
[11] E. Mashhour, and S. M. Moghaddas-Tafreshi, "Bidding strategy of virtual power plant for participating in energy and spinning reserve markets—Part I: Problem formulation," IEEE Transactions on Power Systems, vol. 26, no. 2, pp. 949-956, 2010.
[12] ISO New England Inc. [Online]. Available: http://www.iso-ne.com