DECISION OF AGGREGATE QUOTIENT OPTIMIZATION BASED ON RESPONSE RANDOMNESS AND CORRELATION

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The demand response has certain uncertainty. In order to truly reflect the response of each uncertain user, this paper considers the correlation between spatial and temporal responsiveness of uncertain user resources represented by air conditioning. Firstly, the improved Latin hypercube sampling method is used to scale and correlate the responsivity, and the samples reflecting the response correlation are obtained. Secondly, the deterministic resources (DRs) are introduced to establish the optimal decision model of the load aggregator, and through random simulation and intelligence. The algorithm solves the decision-making scheme when the profit is the highest. Finally, an example is given to analyze the influence of the distribution parameters of DRs, correlation and responsiveness on decision-making schemes and profits. Verification of ordering DRs, signing negative related uncertain users, increasing the average of responsiveness, reducing the variance of responsiveness has a significant increase in profit.

Keywords: demand response; correlation; uncertainty; Latin hypercube sampling; load aggregator

1. Introduction

In recent years, in order to fully utilize the resources of the user side, the demand response has been well developed. However, the demand response has certain uncertainty [1-4]. Due to uncertainties such as communication delay, component failure, weather conditions of next day, and unexpected events, the actual response of the controllable users is random [5-6]. It is pointed out in literature [7] that for a given price and incentive, the response of adjustable load is an interval rather than a fixed value. However, these documents do not take into account the temporal and spatial correlation between the responsiveness of different users. Taking the user-side air conditioning load with good demand response characteristics as an example [9], the air conditioning load is generally low in the high temperature period in summer, and the air conditioning in the same area will also face the same weather and emergencies.

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The literature [9] uses Monte Carlo method to randomly sample and simulate the response, with the user responsiveness with uncertainty taken as the random variable. However, considering the correlation between multiple variables, the Monte Carlo method is no longer applicable. The Latin hypercube sampling method can control the correlation of samples while sampling and obtain a sample matrix reflecting the true correlation [8, 10-12]. The literature [13-14] point out that compared with the Monte Carlo method, the Latin hypercube sampling method has high sampling efficiency, wide sample coverage and good robustness.

As a major transaction subject in the demand response, the load aggregator can integrate the scattered resources on the user side [15-16]. For example, air-conditioning aggregators can integrate scattered air-conditioning resources, sign load reduction contracts with air-conditioning users and provide corresponding economic compensation [17]. However, due to the uncertainty of user response, the load aggregator will face the risk of default compensation while signing a contract with the system operator. Literature [18-19] propose that the introduction of energy storage devices by load aggregators can reduce the risk of default. However, after considering the response correlation, it remains studying about how to determine the order quantity of deterministic user resources represented by energy storage.

To this end, this paper uses air conditioning as the uncertainty resource on the user side. Firstly, this paper analyzes the correlation of responsiveness in space and time, using Latin hypercube sampling method to obtain samples reflecting the correlation of response. Then, the deterministic resources (DRs) are introduced, and the optimal decision model of the load aggregator is established. The decision plan of the maximum profit is calculated by stochastic simulation and intelligent algorithm. Finally, an example is given to analyze the impact of DRs, correlation and responsiveness distribution parameters on decision-making schemes and profits, which proves that adding DRs can increase the profit of the load aggregator, improve the fluctuation of the overall response level, and reduce the decision risk of the load aggregator.

2. Configurable capacity of cluster air conditioners

A. Air conditioning load modeling

Given proper simplification, the thermodynamic model of air conditioning can be expressed as [20-21]

$$\begin{cases} T_{\text{in}}^{t+1} = T_{\text{out}}^{t+1} - (T_{\text{out}}^{t+1} - T_{\text{in}}^{t})\varepsilon, \ s = 1 \\ T_{\text{in}}^{t+1} = T_{\text{out}}^{t+1} - \eta PR - (T_{\text{out}}^{t+1} - \eta PR - T_{\text{in}}^{t})\varepsilon, \ s = 0 \end{cases} \tag{1}$$

where T_{in}^{t+1}, T_{in}^{t} are the room temperature at time t+1 and t, respectively. T_{out}^{t+1} is the outdoor temperature at time t+1. ε is the heat dissipation coefficient, and $\varepsilon = \exp(-\Delta h / RC)$. Δh is the time interval. C, R are the equivalent heat capacity and thermal resistance, respectively. η, P are the Energy efficiency ratio and rated power of air conditioner, respectively. The product of η and P represents the rated cooling capacity of the air conditioner. s is the switch state, while s=1 means the switch is off, and s=0 means the switch is on.

B. Configurable capacity of cluster air conditioner

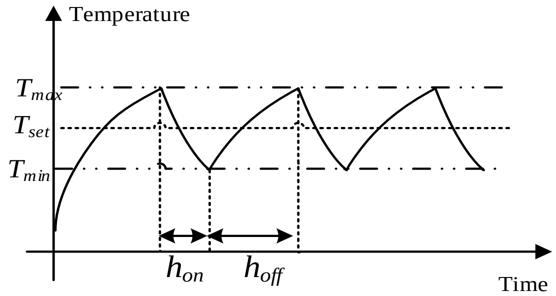

Fig. 1. Simulation model of air conditioning load

The air conditioner is the cyclic working load. When the air conditioner temperature reaches the upper limit $T_{\max}$, the air conditioner is turned on. When the lower limit $T_{\min}$ is reached, the air conditioner is turned off. The working process is shown in Fig. 1.

$$\begin{cases} h_{\text{off}} = n_{\text{off}} h = \ln\left(\dfrac{T_{\min} - T_{\text{out}}}{T_{\max} - T_{\text{out}}}\right) RC \\ h_{\text{on}} = n_{\text{on}} h = \ln\left(\dfrac{T_{\max} + \eta PR - T_{\text{out}}}{T_{\min} + \eta PR - T_{\text{out}}}\right) RC \end{cases} \tag{2}$$

where h_{off} and h_{on} are the closing and opening time in one control period h. n_{off} and n_{on} are the proportion of closing time and opening time in the control period, respectively. T_{out} is the outdoor temperature.

The load aggregator performs direct load control on the air conditioner. When the power grid is at a peak, the air conditioner is regulated according to the signed contract to achieve the purpose of peak clipping. Assuming a total number of n air conditioners, the total schedulable capacity C_{all} is

$$C_{\text{all}} = \sum_{i=1}^{n} \frac{h_{\text{off},i}}{h_i} \cdot P_i \tag{3}$$

where $h_{\text{off},i}$, h_i are the off time and control period of the i-th air conditioner. P_i is the rated power of the i-th air conditioner.

3. Uncertainty analysis of demand response considering correlation

A. Demand response uncertainty and correlation analysis

Due to uncertainties such as communication delay, component failure, weather conditions of the next day, and unexpected events, users have certain uncertainties in specific response while considering the actual response benefits and reputation [6]. It is defined that the responsiveness reflects the actual response of the user, and the responsiveness represents the ratio of the actual response of the user to the agreed response. Assuming that the user's responsiveness obeys the standard normal distribution, the uncertainty of the responsiveness is simulated by a large number of samples by Monte Carlo simulation. However, in the scheduling, the response of multiple users is a random variable with certain correlation. The correlation of responses can be analyzed from two perspectives, time and space.

(1) Correlation in time. There are generally multiple types of controllable loads managed by load aggregators. For example, air conditioners and water heaters are commonly used controllable loads. The peak usage periods of air conditioners and water heaters are different. In terms of time, the responsivity of the two is irrelevant or even negatively correlated, but the response of similar controlled loads in time is generally positive related. Taking air conditioning as an example, the temperature is high at noon and afternoon in summer, and users are reluctant to turn off the air conditioner. Correspondingly, the responsiveness of air conditioners is generally low.

(2) Correlation in space. The same geographical area generally has the same geographical environment, and even faces the same emergencies. For example, in the face of the same extreme hot weather, the responsiveness of air-conditioning users will be reduced, while the other side will have higher responsiveness if faced with cool rain. When a region is facing a communication failure at the same time, all air conditioning responses in that area will also be affected. The commonly used Monte Carlo method cannot reflect the correlation between the responsiveness of each variable. In order to reflect the correlation between responsiveness, this paper uses the Latin hypercube sampling method to perform random simulation.

B. Correlation analysis based on latin hypercube sampling method

The responsiveness of the air-conditioned user follows the standard normal distribution and the corresponding cumulative distribution function can be obtained. The principle of the Latin hypercube sampling method is to evenly divide the ordinate [0, 1] of the cumulative distribution function into *L* intervals, and sequentially extract a value from the inverse function transformation to obtain the sampled values of the corresponding interval, as shown in formula (4)[14]

$$r_{k,l} = F_{Z_k}^{-1}(\frac{l-a}{L}),\ l = 1, 2, \ldots, L \tag{4}$$

where $r_{k,l}$ is the sampled value of the lth interval of the kth variable. Z_k is the distribution function of the kth variable. $F_{Z_k}^{-1}$ is the inverse function of the cumulative distribution function. a is a random number on [0, 1].

The Spearman rank correlation coefficient is used to reflect the correlation, and the method is applicable to any distributed random variable. Suppose there are K variables, and each variable extracts N values. The correlation coefficient matrix between variables is $\boldsymbol{P}_{\text{real}}$, and the specific steps of correlation control are detailed as follows.

(1) The sample is extracted according to equation (4) to obtain a K-row N-column sample matrix $\boldsymbol{R}_0$, and a random order matrix $\boldsymbol{O}$ of the same size is generated. Find the correlation coefficient matrix of $\boldsymbol{O}$, and use Cholesky decomposition to find the lower triangular matrix $\boldsymbol{L}_0$.

(2) According to the transformation equation $\boldsymbol{O}_1 = \boldsymbol{L}_0^{-1}\boldsymbol{O}$, each row of samples in $\boldsymbol{R}_0$ is sorted according to the size of each corresponding row element in $\boldsymbol{O}_1$ to obtain $\boldsymbol{R}_1$. The correlation of $\boldsymbol{R}_1$ is greatly reduced, and there is no correlation between samples.

(3) In order to achieve the actual correlation coefficient matrix $\boldsymbol{P}_{\text{real}}$ between variables, the Cholesky decomposition is used for $\boldsymbol{P}_{\text{real}}$, and the lower triangular matrix $\boldsymbol{L}_{\text{real}}$ is obtained. Calculate $\boldsymbol{O}_{\text{real}} = \boldsymbol{L}_{\text{real}}^{-1}\boldsymbol{O}_1$.

(4) Sort each row of $\boldsymbol{O}$ according to $\boldsymbol{O}_{\text{real}}$ to get $\boldsymbol{O}_{\text{final}}$, and then sort $\boldsymbol{R}_0$ by $\boldsymbol{O}_{\text{final}}$ to get $\boldsymbol{R}_{\text{final}}$. $\boldsymbol{R}_{\text{final}}$ is the sample matrix whose correlation coefficient moment is $\boldsymbol{P}_{\text{real}}$.

4. Decision model analysis of load aggregators

A. Demand response resource type analysis

In the electricity market environment, the load aggregator will sign the reduced capacity and time with the user and provide corresponding economic compensation. Load aggregators face high risks if they rely solely on resources such as air conditioners with large response randomness. Therefore, DRs are introduced, and demand response resources are divided into two types: uncertain resources and DRs [18]. The uncertainty resources such as air conditioners are large in quantity, large in potential, and low in control costs, but relatively scattered and random. The DRs such as the energy storage device has high responsivity and strong anti-interference, but the capacity is small, and the regulation cost is high. The two resources can complement each other very well.

(1) User-regulated costs which represent uncertain resources. These regulation cost is the compensation cost, assuming that the load aggregator contracts with K users, and $F_{\text{unsure},i}$ represents the cost of compensation for the i-th user.

$$\begin{cases} F_{\text{unsure},i} = \gamma_i P_{\text{unsure},i} C_{\text{unsure},i} \\ F_{\text{unsure}} = \sum_{i=1}^{K} F_{\text{unsure},i} \end{cases} \tag{5}$$

where γ_i is the actual responsiveness of user i. $P_{\text{unsure},i}$ is the unit price of compensation provided by the load aggregator when signing with user i. $C_{\text{unsure},i}$ is the regulatable capacity provided when the user i is contracted by uncertainty. F_{unsure} is the total regulatory cost of a deterministic user. The load aggregator only compensates for the portion of the response.

(2) User regulation costs that represent DRs. The DRs purchased generally have a small capacity, so the default is set as 1 user. The corresponding regulation cost F_{sure} is composed of the order cost$F_{\text{sure},1}$ and the compensation cost $F_{\text{sure},2}$. The regulation of DRs is costly, so it is necessary to purchase the right to use in advance before responding. Even if the DRs are not regulated in the end, the subscription cost $F_{\text{sure},1}$ is required. The definition of $F_{\text{sure},2}$ is the same as the uncertainty resource, which compensates for the actual response.

$$\begin{cases} F_{\text{sure}} = F_{\text{sure},1} + F_{\text{sure},2} \\ F_{\text{sure},1} = P_{\text{sure},1} C_{\text{sure}} \\ F_{\text{sure},2} = P_{\text{sure},2} C_{\text{sure},2} \end{cases} \tag{6}$$

where $P_{\text{sure},1}$ is the order price. $P_{\text{sure},2}$ is the compensation unit price. C_{sure} is the capacity of the DRs ordered in total. $C_{\text{sure},2}$ is the capacity actually regulated. DRs default to a full response to the maximum.

(3) Other cost. Other cost F_{c} mainly includes loss cost $F_{\text{c},1}$ and compensation cost $F_{\text{c},2}$. $F_{\text{c},1}$ indicates that when the actual user response is greater than the capacity signed by the load aggregator to the system operator, this part of the capacity is lost because there is no contracted revenue. $F_{\text{c},2}$ means that when the actual user total response is less than the capacity signed by the aggregator to the system operator, it is necessary to bear the compensation caused by the breach of contract.

$$\begin{cases} F_{\text{c}} = F_{\text{c},1} = P_{\text{set}}(C_{\text{real}} - C_{\text{set}}),\ C_{\text{set}} \le C_{\text{real}} \\ F_{\text{c}} = F_{\text{c},2} = P_{\text{c},2}(C_{\text{set}} - C_{\text{real}}),\ C_{\text{set}} > C_{\text{real}} \end{cases} \tag{7}$$

where P_{set} is the settlement unit price provided when the system operator signs the contract with the load aggregator. C_{real} is the actual capacity provided by the final load aggregator. C_{set} is the capacity agreed upon when the system operator signs the contract with the load aggregator. $P_{\text{c},2}$ is the unit price of compensation when the demand is not met.

The revenue of the load aggregator comes from the system operator and the load aggregator who sign before the response: providing the corresponding capacity reduction at the specified time and providing economic compensation at a certain settlement price.

$$F_{\text{set}} = P_{\text{set}} C_{\text{set}} \tag{8}$$

where $\boldsymbol{F}_{\text{set}}$ is the revenue of the load aggregator.

B. Decision-making optimization analysis of load aggregator

The optimal decision of the load aggregator is to determine the values of the capacity C_{set} and C_{sure} through the optimization algorithm, so that the load aggregator has the largest profit. The profit function is represented by *f*.

$$f(C_{\text{set}}, C_{\text{sure}}) = \begin{cases} F_{\text{set}} - F_{\text{unsure}} - F_{\text{sure},1} - F_{\text{c},1}, & C_{\text{set}} < C_{\text{unsure}} \\ F_{\text{set}} - F_{\text{unsure}} - F_{\text{sure},1} - F_{\text{sure},2}, & C_{\text{unsure}} \le C_{\text{set}} \le C_{\text{real}} \\ F_{\text{set}} - F_{\text{unsure}} - F_{\text{sure},1} - F_{\text{sure},2} - F_{\text{c},2}, & C_{\text{set}} > C_{\text{real}} \end{cases} \tag{9}$$

where C_{unsure} is the total uncertainty users' response.

In order to further introduce responsiveness, the profit function is described in detail in sections.

(1) when $C_{\text{set}} < \sum_{i=1}^{K} \gamma_i C_{\text{unsure},i}$, the actual profit is:

$$\begin{aligned} f(C_{\text{set}}, C_{\text{sure}}, \gamma_i) = {} & P_{\text{set}} C_{\text{set}} - P_{\text{sure},1} C_{\text{sure}} - \\ & \sum_{i=1}^{K} \gamma_i P_{\text{unsure},i} C_{\text{unsure},i} - P_{\text{set}} \Big(\sum_{i=1}^{K} \gamma_i C_{\text{unsure},i} - C_{\text{set}}\Big) \end{aligned} \tag{10}$$

(2) when $\sum_{i=1}^{K} \gamma_i C_{\text{unsure},i} \le C_{\text{set}} \le \sum_{i=1}^{K} \gamma_i C_{\text{unsure},i} + C_{\text{sure}}$, the actual profit is:

$$\begin{aligned} f(C_{\text{set}}, C_{\text{sure}}, \gamma_i) = {} & P_{\text{set}} C_{\text{set}} - P_{\text{sure},1} C_{\text{sure}} - \\ & \sum_{i=1}^{K} \gamma_i P_{\text{unsure},i} C_{\text{unsure},i} - P_{\text{sure},2} \Big(C_{\text{set}} - \sum_{i=1}^{K} \gamma_i C_{\text{unsure},i}\Big) \end{aligned} \tag{11}$$

(3) when $C_{\text{set}} > \sum_{i=1}^{K} \gamma_i C_{\text{unsure},i} + C_{\text{sure}}$, the actual profit is:

$$\begin{aligned} f(C_{\text{set}}, C_{\text{sure}}, \gamma_i) &= P_{\text{set}} C_{\text{set}} - P_{\text{sure},1} C_{\text{sure}} - P_{\text{sure},2} C_{\text{sure}} \\ &- \sum_{i=1}^{K} \gamma_i P_{\text{unsure},i} C_{\text{unsure},i} - P_{\text{c},2} (C_{\text{set}} - \sum_{i=1}^{K} \gamma_i C_{\text{unsure},i} - C_{\text{sure}}) \end{aligned} \tag{12}$$

Due to the uncertainty of the responsiveness, the average value of the profit obtained by the stochastic simulation is used as the optimization target, and the profit is the optimization target. Therefore

$$\begin{cases} E_f = \max\{E[f(C_{\text{set}}, C_{\text{sure}}, \gamma_i)]\} \\ 0 < C_{\text{set}} \le C_{\text{unsure,max}} + C_{\text{sure}} \\ 0 < C_{\text{sure}} \le C_{\text{sure,max}} \end{cases} \tag{13}$$

where E_f is the maximum value of the profit average. $E[]$ is the average function. $C_{\text{unsure,max}}$, $C_{\text{sure,max}}$ are the maximum capacity that can be adjusted by the uncertainty resource and the maximum capacity that the DRs can order.

In this paper, the Latin hypercube sampling method is used to perform random simulation to obtain responsive samples. Since the load aggregator's optimization decision model needs to calculate the optimal value from the selectable declared capacity and the order quantity to get the maximum profit of the aggregator. Therefore, it is necessary to optimize the search by genetic algorithm to get the optimal decision-making scheme and the highest profit. The stochastic simulation is combined with the genetic algorithm, and the specific steps are detailed below.

(1) Considering the correlation between the K variable responses, the final sample matrix $\boldsymbol{R}_{\text{final}}$ is generated using the Latin hypercube sampling method, which represents the sampled values of the N responsiveness of the K uncertain users. The N samples of each variable follows a normal distribution.

(2) Use genetic algorithm to generate a population, and the population is a group represented by multiple groups (C_{set}, C_{sure}). Each group of chromosomes is substituted into the profit function. Respectively calculating the profit value under N responsivity samples, and the average value is the average profit for the group (C_{set}, C_{sure}).

(3) Calculate the profit averages of multiple groups (C_{set}, C_{sure}) in the population separately, and replace the low profit average of the original population with the high profit average through multiple cross-variation. Finally, the maximum profit and the corresponding (C_{set}, C_{sure}) are selected from the improved population. (C_{set}, C_{sure}) can be set as the final decision-making solution for the load aggregator.

5. Case analysis

A. Simulation parameters

Assume that there are 5 uncertain users, each of which is composed of multiple air conditioners. See Table 1 for the parameters of each user. The schedulable capacity of the five users can be calculated according to equation (3) as 12.6, 8.1, 4.8, 12.6, 12.6 MW, and $C_{\mathrm{sure,max}}$ is 6 MW. The relevant data about the load aggregator is shown in Table 2.

Table 1

The influence of different correlations on decision making and profit

User	P_i/kW	Number of AC	η	Distribution of R	Distribution of C	Distribution of γ_i
1	2.5	7000	2.8	N(0.18, 0.2^2)	N(5.56, 1.0^2)	N(0.7, 0.06^2)
2	2.0	6000	3.0	N(0.17, 0.2^2)	N(5.60, 1.0^2)	N(0.7, 0.06^2)
3	2.0	3500	2.9	N(0.17, 0.2^2)	N(5.90, 1.0^2)	N(0.8, 0.08^2)
4	2.5	6500	3.2	N(0.14, 0.2^2)	N(5.60, 1.0^2)	N(0.7, 0.08^2)
5	2.8	6000	2.9	N(0.16, 0.2^2)	N(5.40, 1.0^2)	N(0.8, 0.06^2)

Table 2

Price data and capacity data involved in the decision-making process

P_{set}/ (\$·MW^{-1})	P_{unsure}/ (\$·MW^{-1})	$P_{\mathrm{sure,1}}$/ (\$·MW^{-1})	$P_{\mathrm{sure,2}}$/ (\$·MW^{-1})	$P_{\mathrm{c,2}}$/ (\$·MW^{-1})
56	5	10	67	100

As shown in Table 1, the responsiveness γ_i of the five uncertain air conditioner users follows a normal distribution. The correlation between the responsiveness of the five users is

$$\mathbf{P}_{\mathrm{real}} = \begin{bmatrix} 1.0 & 0.4 & 0.3 & 0.5 & 0.8 \\ 0.4 & 1.0 & 0.5 & 0.3 & 0.6 \\ 0.3 & 0.5 & 1.0 & 0.4 & 0.4 \\ 0.5 & 0.3 & 0.4 & 1.0 & 0.6 \\ 0.8 & 0.6 & 0.4 & 0.6 & 1.0 \end{bmatrix} \tag{14}$$

B. The impact of DRs on decision outcomes and profits

In order to analyze the impact of DRs on the decision and profit of the load aggregator, the corresponding C_{set}, C_{sure} and profit averages are obtained using the settings in Section 4.1, as shown in Table 3.

Table 3

The comparative analysis of adding and not adding DRs

Adding DRs	C_{set}/MW	C_{sure}/MW	E_f/$
Yes	39.57	3.80	1 798.60
No	38.68	0.00	1 767.40

As can be seen from Table 3, after adding certain resources, the profit average is increased.

In order to analyze the impact of DRs on stability, the profit deviations of the two in the actual response process are simulated. Substituting the corresponding C_{set} and C_{sure}, the responsiveness of the five air-conditioner users randomly selects the samples satisfying the probability distribution. In order to reflect the response more comprehensively, the average value of the 1,000 profit is taken as the profit value of the actual response process, and the repetition is 100. Thus 100 actual profit values are got. The actual profit deviation is calculated with $(E_f - E'_f)/E_f \times 100\%$, where E'_f is the actual profit value obtained by simulating the actual response. The comparison of the profit deviation of adding and not adding DRs is shown in Fig. 2. The actual profit deviation obtained by adding the DRs simulation is less than the non-addition of DRs, and it is maintained at 1%, and the error is small. In general, the addition of DRs can increase the profit while reducing the fluctuation of profits in the actual response process.

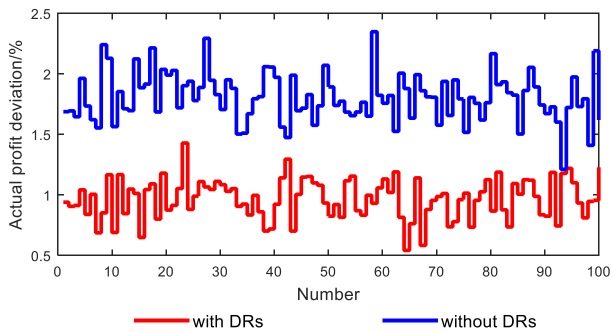

Fig. 2. The comparative analysis of adding and not adding the profit deviation of DRs

C. The impact of relevance on decision outcomes and profits

The correlation between different uncertain users is different. In order to study the impact of relevance on decision results and profit, it is assumed that the correlation coefficients between the 5 users are the same, and the correlation coefficient is set to -0.5~0.9. Correlation between users has experienced a negative correlation to an irrelevant to positive correlation to a strong positive correlation. Fig. 3 shows the impact of different correlations on decision making and profit after adding DRs. It can be found from Fig. 3 that the profit at the time of negative correlation is greater than the profit at the time of positive correlation, and as the positive correlation increases, the profit continues to decrease. The DRs purchased at the same time have the opposite trend, from negative correlation to positive correlation, and the capacity of DRs continues to rise. The reason is that when there is a positive correlation between uncertain users, especially strong positive correlation, it is easy to generate a large compensation cost with low user's responsiveness. If the user's responsiveness is high, it will be generally high, and it is easy to generate a large loss of cost.

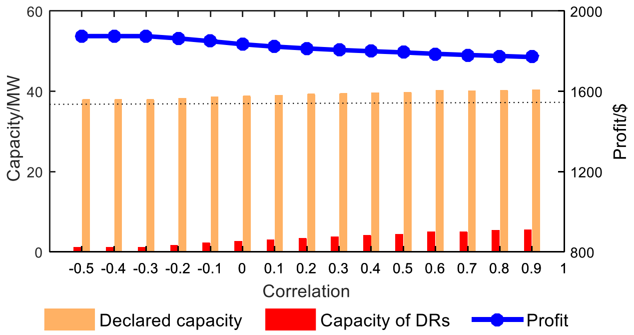

Fig. 3. The influence of different correlations on decision making and profit after adding DRs

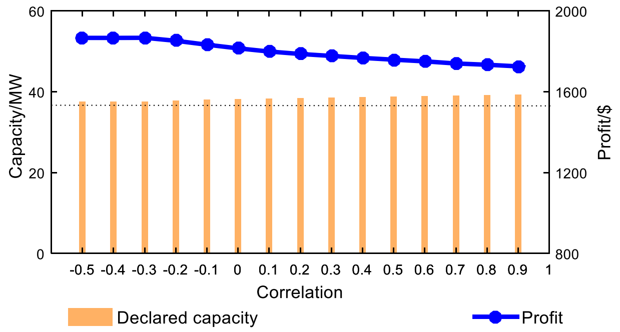

Fig. 4. The influence of different correlations on decision making and profit after not adding DRs

Fig. 4 shows the impact of correlation on decision making and profitability without adding DRs. As can be seen from Fig. 4, different correlations have the same impact on the decision-making scheme that does not include DRs and profit. In the same situation, the average profit of adding certain resources is always greater than the non-addition of DRs. And while the correlation changing from negative correlation to positive correlation, the profit without adding certain resources will drop more. This is also consistent with the conclusions in Section 4.2.

D. Impact of responsiveness distribution parameters on decision results and profits

Each responsiveness distribution follows a normal distribution, but changes in the mean and standard deviation of the distribution also affect the outcome and profit of the decision. Table 4 shows the average values of the responsiveness distribution for all users set by Section 4.1, in units of 0.05, from reducing 0.10 to increasing 0.15, respectively. As can be seen from Table 4, as the mean increases, the average profit increases significantly, with a 42% increase. As the mean value of the responsiveness distribution increases, the response level increases and the order quantity of DRs also decreases.

Table 4

The influence of the mean response distribution on decision making and profit

Parameter increment	with DRs			without DRs	
	C_{sure}/MW	C_{set}/MW	E_f/$	C_{set}/MW	E_f/$
-0.10	4.170	34.50	1540.3	33.56	1509.8
-0.05	4.040	37.14	1669.0	36.11	1638.5
+0	3.798	39.57	1798.6	38.68	1767.4
+0.05	4.070	42.23	1927.9	41.18	1897.4
+0.10	3.800	44.64	2057.5	43.68	2026.8
+0.15	3.980	47.20	2186.3	46.23	2156.1

Table 5

The influence of standard deviation of responsiveness distribution on decision making and profit

Parameter increment	with DRs			without DRs	
	C_{sure}/MW	C_{set}/MW	E_f/$	C_{set}/MW	E_f/$
-0.03	38.49	2.140	1843.9	37.98	1827.1
-0.02	38.72	2.650	1829.1	38.19	1807.5
-0.01	39.18	3.360	1814.0	38.41	1787.8
+0	39.57	3.798	1798.6	38.68	1767.4
+0.01	40.07	4.680	1784.1	38.85	1749.6
+0.02	40.21	4.900	1768.6	39.04	1728.1
+0.03	40.50	5.720	1753.9	39.28	1708.3

Table 5 shows the variance of the variability distribution for all users set by Section 4.1, in units of 0.01, from reducing 0.03 to increasing 0.03. It can be seen from Table 5 that as the variance becomes larger, the volatility of the response increases, and the profit also decreases. To compensate for the volatility of the response, the DRs for ordering are also increasing.

6. Conclusion

(1) Adding DRs can increase the profit of the load aggregator, improve the fluctuation of the overall response level, and reduce the decision risk of the load aggregator.

(2) The correlation between uncertain users has a great influence on the decision and profit of the load aggregator. As the correlation changes from negatively correlated to uncorrelated to strong positive correlation, the DRs of the order are increasing and the profits are declining. Therefore, in order to improve profits, the load aggregator should sign different types of controllable users in different regions to achieve complementary responsiveness.

(3) As the average value of the responsiveness distribution increases, the profit increases substantially, and the order quantity of DRs also decreases. At the same time, as the standard deviation increases, the volatility of the response increases, and the profit continues to decline.

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