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Risk-Based Allocation of Demand Response Resources Using Conditional Value-at Risk (CVaR) Assessment

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Abstract – In a demand response (DR) market run by independent system operators (ISOs), load aggregators are important market participants who aggregate small retail customers through various DR programs. A load aggregator can minimize the allocation cost by efficiently allocating its demand response resources (DRRs) considering retail customers' characteristics. However, the uncertain response behaviors of retail customers can influence the allocation strategy of its DRRs, increasing the economic risk of DRR allocation. This paper presents a risk-based DRR allocation method for the load aggregator that takes into account not only the physical characteristics of retail customers but also the risk due to the associated response uncertainties. In the paper, a conditional value-at-risk (CVaR) is applied to deal with the risk due to response uncertainties. Numerical results are presented to illustrate the effectiveness of the proposed method.

Keywords: Demand Response (DR), Demand Response Resource (DRR), Load Aggregator, Conditional Value-at-Risk (CVaR).

1. Introduction

As demand response (DR) [1] has been attracting increasing attention as a means to control the electricity demand efficiently, load aggregators have begun to play an important role in the DR market. Load aggregators join together retail customers and participate in the DR market on their behalf. Furthermore, load aggregators operate DR programs for retail customers to help them manage their loads effectively during a power system emergency or a lack of power supply. The objective of load aggregators is to maximize their profits. In order to achieve this goal, it is imperative for them to establish a demand response resource (DRR) allocation strategy. When load aggregators set up such a strategy, they should consider not only retail customers' physical characteristics but also the economic risk due to the uncertainty of retail customers' response behaviors.

During the past years, various studies related to DR [2-7] have been conducted. DR is studied with new equipment in a smart grid environment, i.e., renewable energy resources [2], electric vehicles [3], smart appliances [4], and so on. Nevertheless, these studies did not consider the physical characteristics of customers. Although reference [5] considers the physical characteristics of the DR participants, it does not take into account the economic risk due to the uncertainty of DR participants' response behaviors. The risk associated with the uncertainties in load reductions is considered by load serving entities (LSEs) in [6]. However, the research in [6] is not related to the allocation of DRRs for retail customers from the load aggregators' perspective. A concept of DRR allocation is described in [7], but it depends only on DR participants' opinion without taking into account retail customers' physical characteristics and the economic risk due to their response uncertainties.

This paper presents a risk-based DRR allocation method that incorporates both retail customers' physical characteristics and the economic risk associated with the uncertainties in load reductions. The risk makes it difficult to determine the allocation of DRRs because it increases the expected economic losses in a DRR allocation. In order to minimize the risk due to the uncertainty of load reductions in the DRR allocation, it is essential for the load aggregator to assess the risk. The conditional value-at-risk (CVaR) is employed in this study to deal with the economic risk due to the uncertain response behaviors of retail customers. In addition, the DR participation rate of the retail customer is proposed in this study to calculate the CVaRs of retail customers. The mixed-integer nonlinear programming (MINLP) is also applied in this paper to solve the DRR allocation problem of the load aggregator.

2. Problem Formulation

The DR market is usually opened by an independent system operator (ISO) the day before a power system emergency or a lack of power supply [8]. After the ISO informs DR market participants about the total duration of

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a DR event, participants enter load reduction bids in the DR market. Some participants such as large customers can take part in the DR market directly, but the participation of retail customers is restricted by the ISO. This is because only a customer with a larger load reduction capacity than pre-specified minimum load can participate in the DR market. In order to involve small retail customers in the DR market, new entities called load aggregators, who bring together retail customers and take part in the DR market on their behalf, appear in the DR market. Moreover, load aggregators operate DR programs for retail customers to help them manage their loads efficiently.

After the load reduction bidding ends, the ISO clears the DR market and notifies the DR event information on the scheduled DR amounts and DR market prices to participants. Based on the DR event information notified by the ISO, load aggregators allocate the scheduled DR amounts to retail customers; that is, load aggregators establish the DRR allocation strategy before the DR event takes place. Because the sum of the actual amounts of load reductions of retail customers expects to be equal to the overall load reduction achievement of load aggregators, the appropriate DRR allocation strategy is needed for load aggregators to meet the scheduled DR amounts in the DR event. However, the uncertain response behaviors of retail customers affect the DRR allocation of load aggregators because uncertainties in load reductions cause an economic risk for them. Thus, load aggregators need to assess the risk associated with the uncertainties in load reductions and consider both retail customers' physical characteristics and the risk due to response uncertainties when they allocate DRRs to retail customers.

In the DR event, load aggregators indirectly reduce loads by operating DR programs for retail customers while large customers fulfill load reductions directly. After the DR event, a load aggregator gets paid from ISO based on the actual amounts of load reductions of each DR participant. Further, load aggregators calculate the financial incentives for the actual amounts of load reduction achieved by each retail customer.

In this study, the total amount of load reductions of the load aggregator expects to be equal to the DR amount scheduled by the ISO. Then, the profit maximization can be achieved by allocation cost minimization under the assumption that the scheduled DR amount expects to be met by the load aggregator and its revenue from ISO remains constant. The DRR allocation problem of the load aggregator can be formulated as the following Eqs. (1-9). The objective function minimizes the allocation cost of the load aggregator as follows:

$$\underset{DR_{it},u_{it}}{Minimize}\ Cost_{LA} = \underset{DR_{it},u_{it}}{Minimize}\sum_{t=1}^{T}\sum_{i=1}^{N}(Inct_t^{type}\cdot DR_{it}\cdot u_{it}) \quad (1)$$

where T is the total duration of the DR event; N is the number of retail customers; $Inct_t^{type}$ is the incentive of the DR programs of the load aggregator at time t; DR_{it} is the DRR allocated to retail customer i at time t; u_{it} is the status of retail customer i at time t (i.e., its value is 1 if the DRR is allocated and 0 otherwise).

The various constraints on the characteristics of retail customers are as follows [5, 9, 10]:

a) The DRR balance equation:

$$\sum_{i=1}^{N}DR_{it}\cdot u_{it} = DR_{ISO,t}\ ,\ \ \forall t \quad (2)$$

where $DR_{ISO,t}$ is the DR amount scheduled by the ISO at time t. Eq. (2) states that the sum of the DRRs allocated to each retail customer needs to be equal to the DR amount scheduled by the ISO at time t.

b) The minimum and maximum DRR limits:

$$DR_i^{\min}\cdot u_{it} \le DR_{it}\ ,\ \ \forall i,t \quad (3)$$

$$DR_i^{\max}\cdot u_{it} \ge DR_{it}\ ,\ \ \forall i,t \quad (4)$$

where $DR_i^{\min}$ is the minimum DRR limit of retail customer i and $DR_i^{\max}$ is the maximum DRR limit of retail customer i. In (3), the minimum DRR limit defines the lowest limit of load reductions that the retail customer should fulfill in the DR event. Likewise, the retail customer should reduce loads under the maximum DRR limit in the DR event according to (4).

c) The up and down maximum ramping rate DRR limits:

$$DR_{it} - DR_{i,(t-1)} \le RU_i\cdot\Delta t\ ,\ \ \forall i,t \quad (5)$$

$$DR_{i,(t-1)} - DR_{it} \le RD_i\cdot\Delta t\ ,\ \ \forall i,t \quad (6)$$

where RU_i is the up maximum DRR ramping rate of retail customer i; RD_i is the down maximum DRR ramping rate of retail customer i; Δt is the dispatch time interval. The up and down maximum DRR ramping rates of retail customers represent the ramping capacity for reducing and consuming electricity, respectively. These measures identify the rate at which a retail customer would change its loads.

d) The minimum up and down time DRR limits:

$$\sum_{k=t}^{t+MU_i-1}u_{ik} \ge MU_i\cdot(u_{it}-u_{i,(t-1)})\ ,\ \ \forall i,t \quad (7)$$

$$\sum_{k=t}^{t+MD_i-1}(1-u_{ik}) \ge MD_i\cdot(u_{i,(t-1)}-u_{it})\ ,\ \ \forall i,t \quad (8)$$

where MU_i is the minimum up time DRR limit of retail customer i and MD_i is the minimum down time DRR limit of retail customer i. The minimum up time DRR limit defines the minimum consecutive hours for which the retail customer should continue to reduce its load in the DR event. Likewise, the minimum down time DRR limit is the minimum consecutive hours for which the retail customer should stop reducing its load in the DR event.

e) CVaR of the load aggregator:

$$CVaR^{\max,\beta}(Cost_{LA,t}) \le \delta_{LA,t}^{\beta}, \ \forall t \tag{9}$$

where $CVaR^{\max,\beta}(Cost_{LA,t})$ is the maximum CVaR of the allocation cost of the load aggregator within a given confidence level of β ($\beta \in [0,1]$) at time t; $\delta_{LA,t}^{\beta}$ is the load aggregator-defined coefficient within a given confidence level of β at time t. The load aggregator-defined coefficient indicates the affordable risk level established by the load aggregator [11]. If the load aggregator's risk preference is high, the load aggregator-defined coefficient is assigned a high value, whereas if the load aggregator is risk averse, the load aggregator-defined coefficient is assigned a low value.

3. Risk-Based DRR Allocation Method

3.1 CVaR constraint for DRR allocation

The economic risk in the DRR allocation strategy of the load aggregator is caused by the uncertainty of retail customers' response behaviors. In order to handle the uncertainty associated with the DRR allocation, risk assessment techniques can be used for the load aggregator to determine the DRR allocation strategy. The value-at-risk (VaR) is widely employed as a simple risk assessment. The VaR, the expected maximum loss within the given confidence level β over the holding period, can be formulated by the following Eq. (12, 13):

$$VaR^{\beta} = \inf[x \mid Prob(R \ge x) \le \beta] \tag{10}$$

where $Prob(R \ge x)$ is the probability distribution of the returns R in the highest bound.

The VaR tends to ignore potential losses exceeding the VaR value. As an alternative measure of VaR, the CVaR is a useful technique for accurate risk assessment. The CVaR is defined as the weighted average of the losses exceeding the VaR value [14]. Using the computed VaR, the expected CVaR is calculated by the following Eq. (13):

$$CVaR^{\beta} = E[R \mid R \ge VaR^{\beta}] \tag{11}$$

The CVaR has a relatively larger value than the VaR. The CVaR can also measure the tail of the distribution more accurately than the VaR can [15].

In the DRR allocation strategy, the CVaR of the allocation cost of the load aggregator within the confidence level β at time t can be calculated as follows:

$$CVaR^{\beta}(Cost_{LA,t}) = CVaR^{\beta}(\sum_{i=1}^{N} Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot p_i), \forall t \tag{12}$$

where p_i is the DR participation rate of retail customer i. With the sub-additivity property of the CVaR, the right-hand-side term of (12) can satisfy the following equation:

$$\begin{aligned} & CVaR^{\beta}(\sum_{i=1}^{N} Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot p_i) \\ & \le \sum_{i=1}^{N} CVaR^{\beta}(Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot p_i), \ \forall t \end{aligned} \tag{13}$$

Accordingly, the maximum CVaR of the allocation cost of the load aggregator within the given confidence level β at time t is equal to the right-hand-side term of (13). Using the (positive) homogeneity of the CVaR, the right-hand-side term of (13) can be expressed as follows:

$$\begin{aligned} & \sum_{i=1}^{N} CVaR^{\beta}(Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot p_i) \\ & = \sum_{i=1}^{N} \{Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot CVaR^{\beta}(p_i)\}, \ \forall t \end{aligned} \tag{14}$$

Based on (12)-(14), the CVaR constraint (9) can be rewritten as follows:

$$\sum_{i=1}^{N} \{Inct_t^{type} \cdot DR_{it} \cdot u_{it} \cdot CVaR^{\beta}(p_i)\} \le \delta_{LA,t}^{\beta}, \ \forall t \tag{15}$$

Therefore, the load aggregator needs to assess the CVaRs of retail customers for the solution of the DRR allocation problem, taking into account the economic risk due to response uncertainties.

3.2 DR participation rate of retail customer

In this section, retail customers' DR participation rates are introduced for solving the DRR allocation problem considering the economic risk. In this study, the DR participation rate of a retail customer is proposed to represent the uncertainty of response behaviors of retail customers. The DR participation rate of retail customer i is given by:

$$p_i = \frac{\sum_{t=1}^{T} DR_{it,actual}^{past}}{\sum_{t=1}^{T} DR_{it}^{past}}, \ \forall i \tag{16}$$

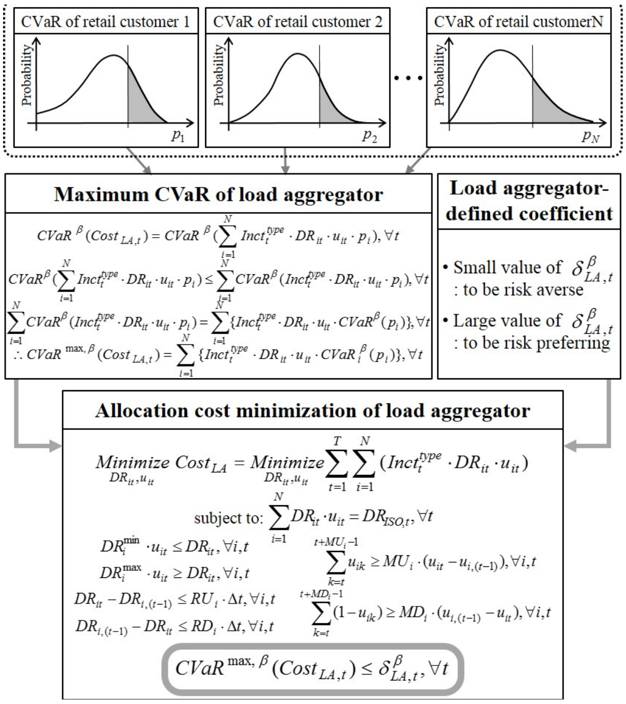

Fig. 1. Load aggregator's DRR allocation strategy based on the CVaR.

where DR_{it}^{past} is the DR amount allocated by the load aggregator to retail customer i at time t in the past DR event and $DR_{it,actual}^{past}$ is the actual amount of load reduction by retail customer i at time t in the past DR event. Based on the DR participation rate of the retail customer, the probability distributions of the DR participation rates of retail customers can be obtained to assess the CVaRs of retail customers. Fig. 1 illustrates the load aggregator's DRR allocation strategy based on the CVaR.

3.3 CVaR constrained DRR allocation method

In this subsection, the MINLP is applied to solve the DRR allocation problem. The procedure of the proposed method can be summarized as follows:

Step 1) Calculate the DR participation rates of retail customers using the historical DR amounts scheduled by the load aggregator and the historical amounts of actual load reductions of retail customers.

Step 2) Obtain the probability distribution of the DR participation rates of retail customers.

Step 3) Calculate the CVaRs of retail customers within the given confidence level.

Step 4) Determine the load aggregator-defined coefficient within the given confidence level at time t in the DR event.

Step 5) Solve the DRR allocation problem subject to the constraints of the physical characteristics and CVaRs of retail customers.

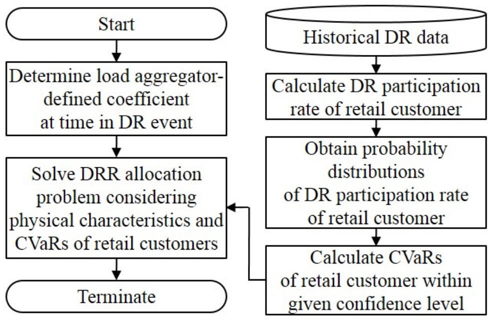

Fig. 2. Overall procedure of the proposed method.

The overall procedure of the proposed method is illustrated in Fig. 2.

4. Numerical Example

In this section, the results of a numerical example are presented to validate the effectiveness of the proposed method. Retail customers' maximum load reduction capacities, the historical DR amounts scheduled by the ISO, and the historical amounts of actual load reductions of retail customers were obtained from the Korea Power Exchange (KPX). It is assumed in this study that the load aggregator operates two DR programs, and retail customers participate in only one DR program. Retail customers who take part in the DR programs of the load aggregator voluntarily reduce their loads in case of the DR event. The load aggregator pays incentives to these retail customers without imposing the financial penalties of DR programs.

In order to establish the optimal DRR allocation strategy,

Table 1. Physical characteristics and DR participation rates of retail customers

i	DR program	$DR_i^{\max}$ (kW)	$DR_i^{\min}$ (kW)	RU_i (kW/min.)	RD_i (kW/min.)	MU_i (30 min.)	MD_i (30 min.)	p_i
1	A	50	5	12	10	1	2	0.478
2	A	200	20	50	40	2	1	0.341
3	A	110	11	28	22	3	1	0.437
4	A	260	26	65	52	1	2	10.324
5	A	290	29	72	58	2	1	12.617
6	B	180	18	45	36	3	1	0.224
7	B	200	20	50	40	1	2	0.938
8	B	290	29	73	60	2	1	0.943
9	B	249	25	62	49	3	1	0.970

Table 2. DR event information given by the ISO

t	DR amount scheduled by ISO (kW)	DR market price (won/kWh)
1	860	700
2	950	700
3	970	1,076
4	1,010	1,171
5	930	1,050
6	850	1,050

Table 3. Incentives of load aggregator's DR programs (won/kWh)

t	DR programs	
	A	B
1	350	280
2	350	280
3	538	430
4	586	468
5	525	420
6	525	420

the load aggregator needs to consider the DR participation rates of retail customers as well as the physical characteristics of retail customers, which are listed in Table 1.

In Table 1, nine retail customers are assumed to participate in the DR programs of the load aggregator. All these retail customers have maximum load reduction capacities that are lower than 300 kW. Because only entities that can provide a load reduction capacity larger than 300 kW are assumed to participate directly in the DR market, the retail customers in Table 1 should participate in the DR market indirectly through the DR programs of the load aggregator [8]. Physical characteristics of retail customers are arbitrarily selected in Table 1. It is also assumed in this study that the probability distributions of the DR participation rates of retail customers follow a normal distribution, and the standard deviations of probability distributions, i.e., the volatilities of the load reductions of retail customers, are 2% of the means of the DR participation rates of the retail customers.

Table 2 shows some of the information given to the participants when the ISO notifies a DR event in the DR market.

In Table 2, DR market prices are obtained from KPX data on May 22, 2012. The unit time of the DR event is 30 minutes, so the DR event in Table 2 proceeds for 3 hours [8]. Furthermore, DR market prices differ depending on the times of the DR event in Table 2.

Based on the DR market prices in Table 2, the load aggregator can determine the incentives of the DR programs. Table 3 shows the incentives of the DR programs of the load aggregator.

In Table 3, it is assumed that the load aggregator set the incentives of DR programs A and B as 50% and 40% of the DR market prices, respectively.

In order to evaluate the effectiveness of the proposed method, this paper introduces a baseline method and compares the outputs of the proposed method with those of the baseline method. In the baseline method, the load aggregator establishes the DRR allocation strategy considering the physical characteristics of retail customers, but the CVaR of the load aggregator is not taken into account. In addition, the proposed method is divided into two confidence levels: 97.5% and 99.0%. On the basis of [16, 17], this study estimates the CVaRs of the DR participation rates of retail customers when the confidence levels are 97.5% and 99.0%, individually.

In this study, the load aggregator-defined coefficient in (9) is set as follows:

$$\delta_{LA,t}^{\beta} = \omega_{LA} \cdot MP_t \cdot DR_{ISO,t}\ , \quad \forall t \tag{17}$$

where ω_{LA} is the risk tolerance level of the load aggregator and MP_t is the DR market price at time t. Eq. (17) implies that the average allocation cost of the load aggregator in β % of the worst cases must not exceed ω_{LA} times the income of the load aggregator at time t.

Table 4 shows the results of the DRR allocation of the load aggregator when the risk tolerance level is fixed as 0.3. In Table 4, regardless of the method type, retail customers 6-9 receive more allocated DRRs from the load aggregator than retail customers 1-5. This is because retail customers 6-9 participate in DR program B, whose incentives are lower than DR program A. Thus, the incentives of the DR programs of the load aggregator have a great influence on the allocation of DRRs to retail customers under various constraints. In Table 4, the total DRRs allocated to retail customers 2, 6, 7, and 8 with the proposed methods within all the confidence levels are greater than those with the baseline method. However, retail customers 3 and 9 receive less total DRRs with the proposed methods than with the baseline method, as shown in Table 4. This is why retail customers 6, 7, and 8 have lower CVaRs than retail customer 9 among the retail customers who participated in DR program B. Likewise, retail customer 2 has a lower CVaR than retail customer 3 among the retail customers

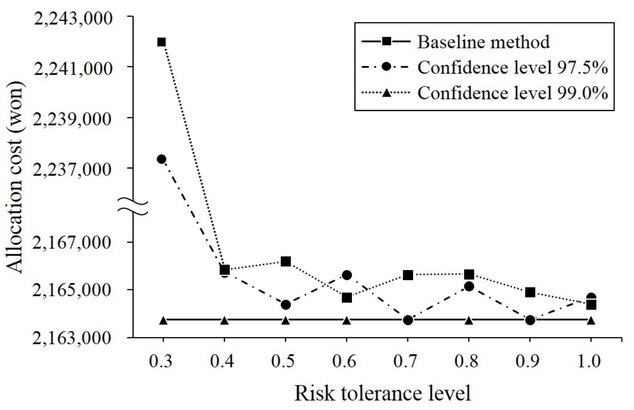

Fig. 3. Changes in the allocation costs as the risk tolerance level increases.

Table 4. Results of DRR allocation (kW)

T \ i	1			2			3			4			5			6			Total		
	Baseline method	Proposed method		Baseline method	Proposed method		Baseline method	Proposed method		Baseline method	Proposed method		Baseline method	Proposed method		Baseline method	Proposed method		Baseline method	Proposed method	
		97.5%	99.0%		97.5%	99.0%		97.5%	99.0%		97.5%	99.0%		97.5%	99.0%		97.5%	99.0%		97.5%	99.0%
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	127.75	134.32	20.00	169.68	176.94	31.19	177.94	185.36	67.71	196.75	195.92	0.00	160.36	158.89	0.00	123.10	121.01	118.9	955.58	972.44
3	0.00	0.00	0.00	11.00	0.00	0.00	19.81	0.00	0.00	23.29	0.00	11.00	11.00	0.00	11.00	0.00	0.00	11.00	65.10	0.00	33.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	166.10	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	180.00	163.84	180.00	180.00	1049.94	1080.00	1080.00
7	185.21	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	200.00	183.18	200.00	200.00	1168.39	1200.00	1200.00
8	274.85	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	290.00	271.69	290.00	290.00	1706.54	1740.00	1740.00
9	233.84	62.25	55.68	249.00	110.32	103.06	249.00	122.06	114.64	249.00	143.25	133.08	249.00	99.64	90.11	231.29	56.90	47.99	1461.13	594.42	544.56

Table 5. Allocation cost with proposed method and difference percentage of allocation cost between baseline method and proposed method

ω_{LA}	$\beta = 97.5\%$		$\beta = 99.0\%$	
	Allocation cost (won)	Difference %	Allocation cost (won)	Difference %
0.3	2,237,196	3.394%	2,242,103	3.621%
0.4	2,165,746	0.092%	2,165,851	0.097%
0.5	2,164,399	0.030%	2,166,201	0.113%
0.6	2,165,641	0.087%	2,164,696	0.044%
0.7	2,163,751	0.000%	2,165,641	0.087%
0.8	2,165,151	0.065%	2,165,668	0.089%
0.9	2,163,751	0.000%	2,164,906	0.053%
1.0	2,164,696	0.044%	2,164,399	0.030%

who take part in DR program A. Consequently, Table 4 implies that the load aggregator allocates DRRs to retail customers who have low CVaRs in the DRR allocation strategy.

Fig. 3 illustrates the changes in the allocation costs as the risk tolerance level increases in the CVaR constraint of the proposed methods within 97.5% and 99.0% confidence levels.

Moreover, in addition to the allocation costs of the load aggregator with the proposed methods, the difference percentages of the allocation costs between the baseline method and proposed methods when the risk tolerance level increases are listed in Table 5.

In Fig. 3 and Table 5, the allocation cost of the load aggregator in the baseline method is fixed at 2,163,751 won. Fig. 3 and Table 5 show that all the allocation costs with the proposed methods are equal to or higher than the allocation costs with the baseline method. This result implies that the CVaR constraint influences in allocation costs of the load aggregator in the DRR allocation strategy. In addition, higher risk tolerance levels tend to lower the allocation costs of the load aggregator with the proposed method within all the confidence levels, as shown in Fig. 3 and Table 5. This is why the higher the risk tolerance level the load aggregator sets up, the greater the economic risk the load aggregator can take. In Fig. 3 and Table 5, the allocation costs when the confidence level is 99.0% are generally higher than the allocation costs when the confidence level is 97.5%. Because the CVaRs of retail customers increase as the confidence level increases, the allocation costs within 99.0% confidence level are more influenced by the CVaR constraint than the allocation costs within 97.5% confidence level. Unexpectedly, the allocation costs within 97.5% confidence level are higher than the allocation costs within 99.0% confidence level for the risk tolerance levels 0.6 and 1.0. The reason for this difference is that other physical constraints in addition to the CVaR constraint also influence the DRR allocation strategy of the load aggregator. In Fig. 3 and Table 5, the risk tolerance level begins from 0.3 because the load aggregator cannot establish the DRR allocation strategy when the risk tolerance levels are 0.1 and 0.2. This result implies that risk tolerance levels that are too low to restrict the DRR allocation of the load aggregator in the DR event. The results of this numerical example show that the risk preference of the load aggregator has an influence on the allocation of DRRs. The proposed risk-based DRR allocation method can be useful as a decision-making tool to help the load aggregator allocate DRRs to retail customers based on its risk preference.

5. Conclusion

This paper presents a risk-based DRR allocation method that considers CVaRs as well as the physical characteristics of retail customers. In the paper, the DR participation rate of the retail customer is proposed to evaluate the uncertainties of load reductions. Further, CVaR is used for assessing the economic risk associated with the response uncertainties of retail customers. The numerical example shows that the proposed risk-based DRR allocation method can be used to help the load aggregator establish a DRR allocation strategy that considers the risk due to the response uncertainties of retail customers.

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