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Research paper

A prospect-theoretic game approach to demand response market participation through energy sharing in energy storage systems under uncertainty

Jeseok Ryu, Jinho Kim *

Department of Energy Convergence, Gwangju Institute of Science and Technology (GIST), Gwangju 61005, Republic of Korea

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ABSTRACT

The Paris Agreement, which is carried out in a bottom-up manner, is giving great vitality to the transition to low-carbon energy system. Accordingly, as the spread of renewable energy increases, securing flexibility resources is emerging as a keyword in the power system and power market, and many studies on demand response (DR) and energy storage system (ESS) classified as demand-side flexible resources are being conducted. However, most of the studies on DR are on voluntary DR programs that participate through bidding among incentive-based DR or price-based DR programs, and ESS faced difficulties in its distribution due to low economic feasibility. Therefore, in this work, we propose a feasible process for participating in a reliability DR program that guarantees high profitability but involves high uncertainty, and non-cooperative game model is suggested to mitigate the uncertainty through surplus electricity-trading model of ESS. In addition, a subjective decision-making based on prospect theory is proposed to reflect the impact of the uncertainty about the incentive-based program's engagement. Case study results performed in an environment formed based on actual operation data of the Korean DR market prove that participants' uncertainty is mitigated when participating in the DR market through power trading of ESS through the proposed model. In addition, a small-scale ESS with an average benefit–cost ratio of 0.78 improves by up to 1.08 (1.04 with a standard scenario).

1. Introduction

Top-down methods of reducing carbon emissions, which began in 1997 in several countries, became an opportunity to promote the spread of eco-friendly energy resources; however, there exists the limitation that forcing adoption of such methods is not possible in most countries. The Paris Agreement was distributed in a bottom-up manner to overcome this limitation and to promote global interest in the environment. The Agreement has influenced various fields, including the electric power sector (UNFCCC, 2015). Consequently, a radical expansion of distributed energy resources (DERs) has been observed worldwide. For example, photovoltaic (PV) sources have proliferated over the past decade, approximating 623.2 GW by the end of 2019, and approximately 112 GW which charge 18% of total capacity is constructed in 2019 (Ryu and Kim, 2022). In contrast, the importance of securing flexible resources is becoming evident during the diffusion of renewable energy. Securing eco-friendly flexible resources is essential to reach a common consensus on the Paris Agreement.

Among the six categories of flexible resources as suggested by the National Renewable Energy Laboratory in the United States, demand response (DR) and energy storage systems (ESSs) are representative demand-side flexible resources (Cochran et al., 2014). They are expected to play a vital role in future power systems due to their contribution to load management (Wang et al., 2013; Tushar et al., 2016). However, the potential of ESSs in power systems is often described as the "Holy Grail" of the power industry, which implies that the anticipated investment will be significant in terms of time, money, and difficulties (Dunn et al., 2011). It takes considerable time to reduce the cost of energy storage technology (Schmidt et al., 2017). Despite these limitations, utility- or grid-scale battery ESSs can provide cost-effective solutions in power systems to mitigate avoidance of power generation facilities, congestion in transmission, or load-leveling (Stecca et al., 2020; Yan et al., 2019). Due to these advantages, more than 73% of ESS batteries are utilized by independent system operators and regional transmission organizations in the United States (EIA, 2020). In contrast, only 234 MW of small-scale ESSs are in operation, which accounts for only 21% of the total ESS power capacity, of which the commercial, industrial, and residential components account for 50%, 15%, and 31%, respectively (EIA, 2020). Thus,

* Corresponding author.
E-mail addresses: jsryu274@gist.ac.kr (J. Ryu), jeikim@gist.ac.kr (J. Kim).

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Nomenclature

Indices

c	Index of consumer
t	Index of time slots
o	Index of scenario
i	Index of prosumer type

Parameters and Variables

C^{CBL}	CBL constraint
G_t^{PV}	PV generation output at time t
L_t	Total load demand at time t
R^{PV}	Revenue from PV generation
R^{ESS}	Revenue from ESS operation by arbitrage
R^{ESS2}	Revenue from ESS operation by ESS tariff
R^{CER}	Revenue from carbon emission reduction
π_t^{TOU}	TOU tariff at time t
π^{Basic}	TOU basic tariff regardless of the use
π^{CER}	Weight factor for carbon emission reduction
C_t^{CO2}	Carbon emission coefficient
SOC_t	State of charge of EV battery at time t
SOC_{min}/SOC_{max}	Minimum, Maximum SOC of EV battery

Sets

C	Set of consumers
S_c	The set of strategies of consumer c
σ_o	Set of scenarios
ψ_c^{σ}	Probability sets of player c under scenario σ
P_t^d / P_t^c	Amount of ESS Discharge/ Charge
$P_{t,min}^d$, $P_{t,max}^d$	Min., Max. discharge amount of ESS
$P_{t,min}^c$, $P_{t,max}^c$	Min., Max. charge amount of ESS
η^d / η^c	Discharge, Charge efficiency
$\mho$	Strategy profile
P_c	The payoff of consumer c
A_c	Action profile of consumer c
δ_C	A discount factor of consumer c
μ_i^c	Probability distribution of consumer c
b_c^{σ}	Demand Response Basic Payment (DRBP)
BP	Capacity payment constant
C_c	Mandatory reduction capacity of DR resource
EP_c^{σ}	The expected payoff of consumer c

efforts to complement the low economic feasibility of small-scale ESSs can be implemented in many ways: minimizing expenses by finding the optimal size needed for ESS operations (Zhao et al., 2015; Harsha and Dahleh, 2011; Wen et al., 2016), as well as sharing installed storage devices to divide investment costs (Fernandez et al., 2018; Sun et al., 2020; Li et al., 2021). Moreover, studies have been conducted of the optimal strategy to maximize the profitability of ESS by participating in the energy market (Xinjing et al., 2021), or participating in a DR program (Lee et al., 2018).

Typical demand response programs include price-based DR (PBDR), in which load consumption change is triggered by electricity prices, and incentive-based DR (IBDR), which is classified as a classical, market-based program (Albadi and El-Saadany, 2008). Market-based programs are also divided into emergency DR (reliability DR) and demand bidding (economic DR). By analogy with the wholesale electricity market, economic DR approximates the energy market, whereas reliability DR is a concept that combines the energy and capacity markets. Moreover, reliability DR is a relatively real-time program, receiving higher settlements than those received by other programs due to the high trustworthiness of DR resources; thus, participation in reliability DR, as well as relevant studies, have been limited to date. Many studies have been conducted of participation in PBDR through load management with electricity tariffs (Jing et al., 2021; Dharmaraj and Natarajan, 2021; Tang and Wang, 2019; Hasnain, 1998; Klein et al., 2017) or IBDR programs with demand bidding (Lee et al., 2018).

There is consensus that game theory is the most powerful tool for solving compound interactions by rational decision-makers (Mohsenian-Rad et al., 2010); further, the load management algorithm can more efficiently reach conclusions via coordinated decision-making based on game theory (Fernandez et al., 2018). Given these advantages, many studies of participation in DR programs have been conducted using game-theoretic approaches (Tang and Wang, 2019; Tang et al., 2019a,b; Wei et al., 2017; Yu and Hong, 2016). However, game-theoretic approaches to the load management problem have primarily been studied for PBDR participation (Tang and Wang, 2019; Tang et al., 2019a,b; Wei et al., 2017; Yu and Hong, 2016; Lu and Zhang, 2022). There do exist studies that used game models of participation in more complicated DR programs. For example, Motalleb used a non-cooperative game model to derive a strategy for a DR aggregator to participate in the DR market through bidding; that is, to participate in an economic DR by trading electricity in the ESS (Motalleb and Ghorbani, 2017). Further, a study proposed a two-loop Stackelberg game model of participation in the hierarchical incentive-based DR market (Yu and Hong, 2017). However, all of the studies conducted to date assessed strategies for participating in an economic DR, namely an IBDR program that involves day-ahead markets through demand bidding. We found no study of participation in emergency DR, likely because of its uncertain payoff (Lee et al., 2018).

Meanwhile, the classical game-theoretic approach assumes complete rationality of an economic participant, so that decision-making is based on expected utility. However, this is too impractical to reflect the impact of uncertainty on consumers' decision-making. Thus, a more appropriate approach should be examined to model consumer decision-making with respect to uncertainty-infused DR engagement. As Kahneman and Tversky demonstrated in their ground-breaking study (Kahneman and Tversky, 1979), prospect theory, which assumes that consumers make decisions with limited rather than complete rationality (especially in risky situations), is more relevant to model subjective decisions that reflect consumers' real-life status given risk-constrained conditions. Accordingly, a prospect theory framework was used to incorporate demand-side management (Wang et al., 2016; Rahi et al., 2019), and games were played based on prospect theory to help consumers make realistic decisions (Xiao et al., 2015; Wang et al., 2018).

In short, many studies of DR and ESSs, which are demand-side flexible resources, have been conducted. However, most prior research focused on PBDR, and research on IBDR has considered only economic DR programs. Incentives to improve the economic feasibility of ESSs are limited, due to their low profitability compared to emergency DR. Although participation in reliability DR through an ESS has not been considered to any great extent due to

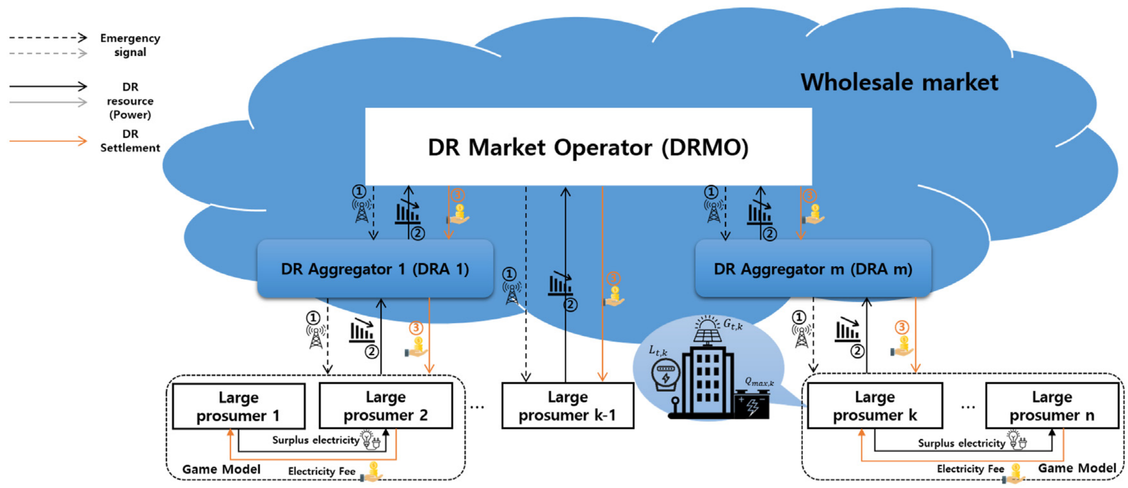

Fig. 1. A framework of the proposed model.

the high level of uncertainty, this could guarantee higher profits compared to other DR programs. To address the aforementioned limitations of risk-constrained reliability DR participation and small-scale ESSs, which are typical flexible resources on the demand side, this study proposed a framework for incentive-based program participation through ESSs in the Korean DR market environment. Therefore, this study primarily pertains to addressing IBDR participation uncertainty through a non-cooperative game model and a prospect theory-based decision-making model. This approach is expected to retain flexible resources by activating the DR market and improving the economic feasibility of small-scale ESS.

The highlights of this study are as follows:

- We proposed a feasible process of participating in the incentive-based DR market, specifically a risk-constrained reliability DR program, with an ESS.
- A non-cooperative game model was devised to mitigate the uncertainty of participating in a reliability DR program.
- We introduced a prospect theory-based prosumer model to better reflect subjective decision-making given risk-constrained market participation.
- A cost–benefit analysis (CBA) of small-scale ESSs based on the Korean market circumstances was performed to examine the economic feasibility of the suggested model.

2. System model

The framework for DR market participation is presented in Fig. 1. Prosumers participate in the DR market through demand response aggregators (DRAs), while few large prosumers participate in the DR market independent of DRAs (prosumer k-1 in Fig. 1), which is outside the scope of this study. DRAs participate in the incentive-based DR program, economic DR, and reliability DR, by aggregating DR resources. According to market operation rules in Korea, (1) DRMO sends a signal when the reserve margin is five million kW or less to DRAs, and finally, the signal is delivered to prosumers. In response, (2) DR participants who receive the signal provide their DR resource, which corresponds to their ESS in this study; (3) they finally receive a settlement fee corresponding to the amount they serve. Meanwhile, a target market and an incentive settlement are needed to ensure flow and perform the simulations of the reliability DR participation process; thus, we conducted simulations based on the Korean DR market. The details of market rules, operating results, and settlement rules necessary for the study are detailed in our previous work (Ryu and Kim, 2020). Moreover, for the game formulation, the opponents are matched by the DRAs. If the incentives of prosumers to participate in reliability DR increase by mitigating uncertainty through games, they will be willing to join the reliability DR through a suggested game model (game model in Fig. 1). Thus, it would become easier to secure more reliable DR resources from the perspective of DRAs, who are incentivized to match the game players through superiority of information.

In this model, a set C of n $(1, 2, \ldots, n)$ prosumers and m DRAs are present in a grid. There were 5034 prosumers, and 27 DRAs in Korea in January 2022. Each prosumer has DERs, a PV generation capacity that produces an amount of $G_{t,k}$ $(k \in C)$ per hour, and an ESS, which has a capacity of $Q_{max,k}$. The daily load profile $L_{t,k}$ is measured hourly by a smart meter. An overall schematic of participation in the incentive-based program (IBP) is presented in Fig. 2. First, each prosumer operates its ESS optimally according to their types. As an extension of the approach proposed in Naeem et al. (2015), three types of customer behavior models are considered in this study: non-green seeking behavior (NGB), green seeking behavior (GSB), and median-green seeking behavior (MGB). Each prosumer participates in the IBDR by forecasting the DR event or emergency signal. The model for predicting the DR signal was designed based on the actual operating performance data of the Korean market. A sampling model with a Gaussian mixture model that can predict the emergency signal was derived based on the operation result, and its equation and shape are as shown in Fig. 2. Then, the DR participation uncertainty could be determined from the GMM sampling model and Monte Carlo simulation techniques, which compared DR participation results with 100,000 scenarios. Meanwhile, as noted in our previous work (Ryu and Kim, 2020), the incentive for prosumer participation in the IBDR is coupled with the activation amount of ESS capacity. Thus, a high level of ESS participation in the IBDR program entails high return; hence, there is a high DR participation uncertainty, which implies a high probability that the prosumer will not receive DR settlement. Finally, the uncertainty of not receiving DR settlement becomes the condition to form the game. Prosumers are willing to take actions to reduce the uncertainty, and the interaction of their actions requires a game-theoretic approach. We thus propose an energy trading model with a non-cooperative game among prosumers who are participating in the IBDR through their ESS. The mathematical models for each prosumer, DR, and game are presented in Fig. 2 and described in detail in Section 3.

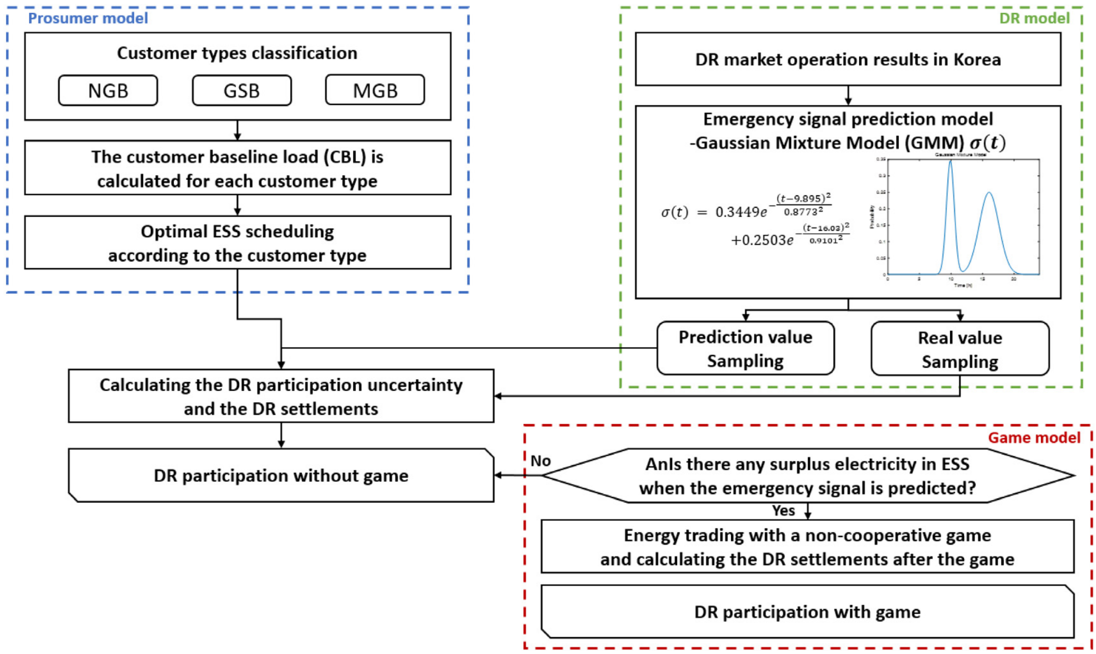

Fig. 2. Overall IBP participation process.

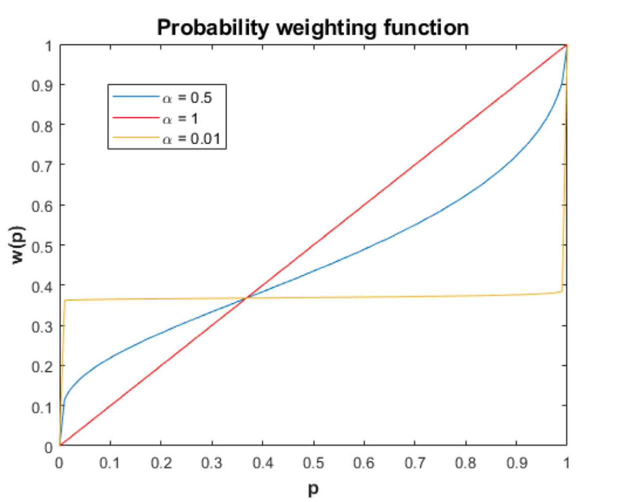

Fig. 3. Probability weighting function $\omega(p)$. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.1. Game formulation

Each DRA tries to match prosumers with similar capacity ESSs for fair competition among participants. Thus, a player can infer who the opponent is, what strategy the opponent may adopt, and the payoff according to the opponent's strategy. Therefore, the proposed game is complete but imperfect.

In general, the following elements are required to establish a game: players, a finite set of strategies, and the payoff for each player (Osborne and Rubinstein, 1994). Accordingly, players are matched with prosumers who participate in the IBDR. Each player has a set of strategies $S_c = \{\mho_c\}$, which is related to the marginal capacity. Marginal capacity is the concept that, if the registered capacity of DR of ESSs is slightly increased, the uncertainty of DR participation is dramatically increased (Ryu and Kim, 2020). For example, if ESSs participate in a DR program with 71% of ESS capacity, the uncertainty is about 0.15, while uncertainty is about 0.65 with 72% of capacity (See Fig. 3(b) in our previous work: Ryu and Kim (2020)); in this case, the marginal capacity is determined with 71% of ESS capacity. The available resources for trade will vary depending on the participation capacity of the ESS. The player can participate in the game with more or less than the marginal capacity, but marginal capacity can guarantee the highest expected payoff. Thus, the degree of ESS engagement for IBDR becomes a strategy for the game. Finally, the strategy profile is $\mho \in K$ with $K = S_1 \times S_2 \times \cdots S_c$. Thus, the game is illustrated as follows:

$$G = \{C, S_c, P_c\} \tag{1}$$

where C is the set of prosumers and P_c is the payoff for prosumer c from the chosen strategy. Further, the game is determined by the interrelation of each player (Osbornet et al., 1994). Thus, the payoff can be recorded as

$$P_c\left(\overline{A_c}\right) = p_c\left(A_c, \overline{A_{-c}}\right) \tag{2}$$

The payoff is not only determined by one's action A_c but also influenced by the action of all opponents participating in the game. Thus, $\overline{A_{-c}}$ denotes the action profiles of all players, excluding prosumer c. Finally, as long as participating in IBDR ensures a stable profit, the prosumer participates in the IBDR every year, not just once. Therefore, a repeated game is also considered to observe how prosumer behavior changes during repeated IBDR participation via an ESS.

2.2. Prospect theory-based decision making

The expected utility theory as adopted in the classical game-theoretic approach does not realistically reflect the impact of uncertainty on decision-making. Meanwhile, participation in the IBDR through the ESS involves the aforementioned uncertainty. Therefore, a more realistic decision-making model of prosumers participating in the IBDR is supported by following Kahneman's prospect theory (Kahneman and Tversky, 1979).

3. Mathematical formulation

This section describes the mathematical formulation of the proposed model. A prosumer model is presented in Section 3.1: an optimization process for ESS optimal operation and a behavioral model for the decision-making of prosumers in risk-constrained circumstances. Section 3.2 presents a non- cooperative game model in which prosumers participate to mitigate the uncertainty.

3.1. Prosumer model

Each prosumer optimally operates their ESS according to their goals, as determined by their behavior model. Type 1 of the prosumer behavior model, non-green seeking behavior (NGB), prioritizes profit maximization and Type 2, green seeking behavior (GSB), prioritizes carbon emission minimization by replacing the peak generator. Finally, Type 3 or median-green seeking behavior (MGB) behaves like NGB during peak time, but like GSB in off-peak time.

3.1.1. ESS optimization formulation

i. The objective function for Type 1:
The objective function of prosumer n, whose type is NGB, consists of the electric charge and the benefits from DERs (3a). The revenue from PV is equal to the sum of the amount of PV generation multiplied by the time of use tariff (3b). Meanwhile, the revenues of ESSs are divided into two groups: those earned through arbitrage trading (3c) and those based on the ESS discount plan (Jung et al., 2021) implemented in South Korea. Customers can get a basic tariff discount for peak hours and a discount on usage fees for off-peak hours through the ESS discount plan (3d).

$$Min \sum_t (L_{t,n} * \pi_t^{TOU}) - R_n^{PV} - R_n^{ESS} - R_n^{ESS2} \tag{3a}$$

$$R_n^{PV} = \sum_t G_{t,n} * \pi_t^{TOU} \tag{3b}$$

$$R_n^{ESS} = \sum_t \left(\frac{P_t^d}{\eta^d} * \pi_t^{TOU} - P_t^c \eta^c * \pi_t^{TOU} \right) \tag{3c}$$

$$R_n^{ESS2} = \sum_{t \in peak} \left(\frac{P_t^d}{\eta^d} - P_t^c \eta^c \right) * \pi^{Basic} + \sum_{t \in off-peak} \frac{1}{2} \left(P_t^c \eta^c * \pi_t^{TOU} \right) \tag{3d}$$

ii. The objective function for Type 2:
The objective function is the same as that of the NGB type, except for an environmental factor (4b). The result in (4b) shows how the ESS reduced carbon emissions by replacing the marginal generator at time t. C_t^{CO2} denotes the carbon emission coefficient of the marginal generators at time t, and π^{CEM} is a weight parameter that reflects the prosumer's preference. Consequently, R_n^{CER} is calculated by the product of carbon emission reductions of marginal generators and weights reflecting the customer's type.

$$Min \sum_t (L_{t,n} * \pi_t^{TOU}) - R_n^{PV} - R_n^{ESS} - R_n^{ESS2} - R_n^{CER} \tag{4a}$$

$$R_n^{CER} = \sum_t \left(\frac{P_t^d}{\eta^d} - P_t^c \eta^c + P_t^{PV} \right) * C_t^{CO2} * \pi^{CER} \tag{4b}$$

iii. The objective function for Type 3
Type 3, the ESS is operated to minimize cost during peak time, but the environment is prioritized during off-peak time. Thus, unlike the GSB type, the factors related to carbon emission are considered only in the off-peak time (5b).

$$Min \sum_t (L_{t,n} * \pi_t^{TOU}) - R_n^{PV} - R_n^{ESS} - R_n^{ESS2} - R_n^{CER} \tag{5a}$$

$$R_n^{CER} = \sum_{t \in off-peak} \left(\frac{P_t^d}{\eta^d} - P_t^c \eta^c + P_t^{PV} \right) * C_t^{CO2} * \pi^{CER} \tag{5b}$$

iv. ESS operation constraints
The constraints are related to the physical limitations of the ESS. Thus, the constraints required for ESS operation are the same, regardless of the type of prosumer.

$$SOC_t = SOC_{t-1} + \left(\frac{P_t^d}{\eta^d} - P_t^c \eta^c \right) \tag{6a}$$

$$SOC_{min} < SOC_t < SOC_{max} \tag{6b}$$

$$P_{t,min}^d < P_t^d < P_{t,max}^d \tag{6c}$$

$$P_{t,min}^c < P_t^c < P_{t,max}^c \tag{6d}$$

3.1.2. Decision-making model

Since prospect theory was proposed by Kahneman and Tversky (1979), there have been growing research efforts to model the subjective behavior of consumers. Meanwhile, Prelec presented a model that was very intuitive and inherited its focus well (Prelec, 1998). This model is formulated in (7), using which the subjective probabilities of consumers in uncertain circumstances are easily implemented mathematically.

$$\omega(p) = exp\left(-(-logp)^{\alpha}\right), 0 \le \alpha \le 1 \tag{7}$$

where p is the objective probability used in expected utility theory and $\omega(p)$ is the subjective probability that reflects prosumer behavior. α denotes a signal of how rational an individual consumer is. For example, if α is close to 1 (red line in Fig. 3), subjective probability behaves like an objective probability in the expected utility theory; that is, the consumer behaves with complete rationality based on the expected utility theory assumed for the classical game, else α is close to 0 (yellow line in Fig. 3), the consumer behaves irrationally. They will choose the same subjective probabilities for situations where uncertainty is 0.1 or 0.9, that is, their decision-making is very irrational. Thus, to avoid these extremes, we want to reflect the prosumer's decision-making through a subjective probability model with an α value of 0.5.

3.2. Non-cooperative game formulation

This subsection describes a model for a non-cooperative game for energy sharing by prosumers participating in the IBDR. For the scheme of this work, the expected payoffs for the prosumer earned by participating in the game should be calculated first. Sequentially, players' strategies to maximize the calculated expected payoff and corresponding Nash equilibrium point would be derived. The game model is formulated based on the development of Motalleb and Ghorbani (2017). Furthermore, the game is modeled with two players because energy sharing through IBDR participation is conducted one-on-one in our proposed model.

3.2.1. Probability distribution

MCS must be performed for simulating participation in the IBDR. Thus, we consider the scenarios for MCS noted as σ_d, and as suggested in Ryu and Kim (2020), each scenario is divided into three cases. The probability of each scenario is given as follows:

$$\sum_o P(\sigma_o) = 1, for\ o = 1, 2, 3 \tag{8}$$

For players c and d ($c, d \in C$), each player has m, n strategies correspondingly without loss of generality of the game model described in Section 2.1. The strategy set is defined as follows:

$$\mho_c = \left[s_1^c, s_2^c, \ldots, s_m^c\right] \tag{9a}$$

$$\mho_d = \left[s_1^d, s_2^d, \ldots, s_n^d\right] \tag{9b}$$

The probability distribution for the type of consumer is as follows:

$$\mu_i^c = \left[\mu_1^c, \mu_2^c, \ldots, \mu_i^c\right] \tag{10a}$$

$$\mu_j^d = \left[\mu_1^d, \mu_2^d, \ldots, \mu_j^d\right] \tag{10b}$$

Meanwhile, the probability that each player chooses each strategy m and n under scenario σ is defined as $\psi_c^\sigma(m)$, $\psi_d^\sigma(n)$, and the probability sets of each player are given by

$$\psi_c^\sigma = \left[\psi_c^\sigma(1), \psi_c^\sigma(2), \ldots, \psi_c^\sigma(m)\right] \tag{11a}$$

$$\psi_d^\sigma = \left[\psi_d^\sigma(1), \psi_d^\sigma(2), \ldots, \psi_d^\sigma(n)\right] \tag{11b}$$

Thus, conditional probability ϑ_c^m means the probability that player c whose type is i will choose strategy m, while player d whose type is j will choose strategy n:

$$\vartheta_c^m(n) = \sum_d P(\sigma_d) P\left(\mu_i^c\right) \psi_c^\sigma(m) P\left(\mu_j^d\right) \psi_d^\sigma(n) \tag{12}$$

3.2.2. Expected payoff

The incentive of a prosumer participating in the IBP is calculated as demand response basic payment (DRBP) which is indicated as b_c^σ. DRBP consists of the following components by power market operation rules in Korea (KPX, 2022).

$$b_c^\sigma = C_c * BP * 1000 \tag{13}$$

where C_c is the mandatory reduction capacity of the DR resource, which corresponds to the DR participation capacity of ESS in this study, and BP is a constant obtained as a product of capacity payment and some weights accounting for the Korean power market. As mentioned previously, this is the point where the marginal capacity is derived. If the participation capacity of an ESS, i.e., C_c^{ESS}, is high, the DRBP is also high. However, as the C_c^{ESS} increased, the uncertainty to receive DRBP also raised. On the other hand, the benefits of player c under scenario σ determined by each player's strategy are as follows:

$$B_c^\sigma\left(s_m^c, s_n^d\right) = \begin{bmatrix} X_{11} & \cdots & X_{m1} \\ \vdots & \ddots & \vdots \\ X_{1m} & \cdots & X_{mn} \end{bmatrix} \tag{14a}$$

$$X_{mn} = b_{c,mn}^\sigma - \varphi_{mn,total}^\sigma + \phi_{mn,total}^\sigma \tag{14b}$$

$b_{c,mn}^\sigma$ is calculated through the mechanism in (13), and unless they participate in the game, the value of $b_{c,mn}^\sigma$ will be the same as b_c^σ. However, each prosumer will receive $b_{c,mn}^\sigma$, and not b_c^σ, by participating in the game, and $b_{c,mn}^\sigma$ is determined by the strategies of both players. Meanwhile, the transaction of electricity requires the following constraints:

$$\varphi_{mn,total}^\sigma + \phi_{mn,total}^\sigma = 0 \tag{15a}$$

$$\varphi_{mn,total}^\sigma = \sum_{day \epsilon \sigma} \sum_{t=1}^{24} \varphi_{mn,t}^\sigma \tag{15b}$$

$$\varphi_{mn,t}^\sigma = P_{mn,t}^\sigma\left(\delta_{t,utility} + \varepsilon\right), \varepsilon > 0 \tag{15c}$$

As $\varphi_{mn,total}^\sigma$ and $\phi_{mn,total}^\sigma$ are opposites, the summation of the two fees must be zero (15a), and the total transaction fee $\varphi_{mn,total}^\sigma$ consists of the sum of transaction fee over time $\varphi_{mn,t}^\sigma$ on the day of the DR event (15b). Finally, the transaction fee at each time t, $\varphi_{mn,t}^\sigma$ is divided into the traded amount and the price at time t (15c) with a higher price when selling to utility $\delta_{t,utility}$.

Thus, the expected payoff of player c is derived as follows:

$$EP_c^\sigma = \sum_{n \in N} \vartheta_c^m(n) \cdot B_c^\sigma\left(s_m^c, s_n^d\right) \tag{16a}$$

Likewise, we can find the expected payoff for player d with strategy n as follows:

$$EP_d^\sigma = \sum_{m \in M} \vartheta_d^n(m) \cdot B_d^\sigma\left(s_n^d, s_m^c\right) \tag{16b}$$

where

$$\vartheta_c^m(n) = \sum_d P(\sigma_d) P\left(\mu_i^c\right) \psi_c^\sigma(m) P\left(\mu_j^d\right) \psi_d^\sigma(n) \tag{17a}$$

$$B_d^\sigma\left(s_n^d, s_m^c\right) = \begin{bmatrix} Y_{11} & \cdots & Y_{m1} \\ \vdots & \ddots & \vdots \\ Y_{1m} & \cdots & Y_{mn} \end{bmatrix} \tag{17b}$$

$$Y_{mn} = b_{d,mn}^\sigma + \varphi_{mn,total}^\sigma - \phi_{mn,total}^\sigma \tag{17c}$$

3.2.3. Repeated game

Even if immediate betrayal provides a bigger reward in the short run, each player takes a cooperative attitude considering the opponent's "punishing" and discount factor δ_C in the long run. However, in a finitely repeated game, the results are the same with a single game by backward induction (Fudenberg and Maskin, 1986). However, since participation in IBDR through ESS is possible during the lifetime of ESS, we assume a repeated game is constructed infinitely through a 15-year long-run lifetime of ESS. Moreover, we consider two representative strategies: a grim strategy, and a tit-for-tat strategy.

i. Grim strategy

A grim strategy is the toughest strategy wherein a player always cooperates with C until the other defects D, but if the other player deviates and chooses the D strategy, he no longer chooses C. A grim strategy can be described as follows:

$$t = 1 : s_c^1 = C, \forall C \tag{18a}$$

$$t \geq 2 : s_c^t = \begin{cases} C\ if\ \left(s_c^k, s_d^k\right) = (C, C), k = 1, \ldots, t-1 \\ \qquad D\ otherwise \end{cases} \tag{18b}$$

ii. A tit-for-tat strategy

In contrast, a tit-for-tat strategy is slightly softer than grim. All players begin with a cooperative approach and follow the other player's strategy from the previous period. That is, even if the other player betrays (by choosing action D) at a specific point in time $t = k$, and he selects action C again at $t = k + 1$, the other player punishes once for a betrayal (by choosing action D at $t = k + 1$). Thus, the tit-for-tat strategy can be defined as follows:

$$t = 1 : s_c^1 = C, \forall C \tag{19a}$$

$$t \geq 2 : s_c^t = \begin{cases} C & if\ s_d^{t-1} = C \\ D & otherwise \end{cases} \tag{19b}$$

Table 1
The expected payoff of IBP participation.

Scenario	Strategy									
	Type 1				Type 2				Type 3	
	Strategy 1 (23%)	Strategy 2 (35%)	Strategy 3 (71%)	Strategy 4 (100%)	Strategy 5 (71%)	Strategy 6 (100%)	Strategy 7 (23%)	Strategy 8 (35%)	Strategy 9 (71%)	Strategy 10 (100%)
scenario 1	2,142,167	1,964,559	3,338,184	1,994,498	5,058,592	3,228,389	2,099,218	1,959,865	3,179,917	2,087,100
scenario 2	1,396,361	543,179	689,938	0	1,859,410	0	1,445,621	616,655	803,550	0
scenario 3	697,081	0	0	0	916,259	0	959,916	0	0	0

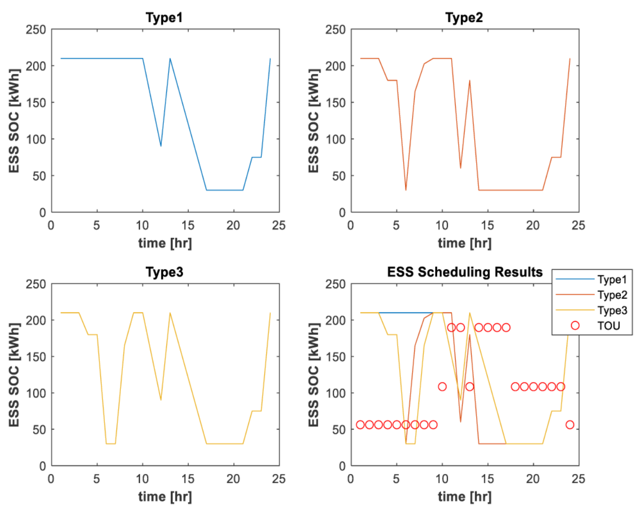

Fig. 4. Results of ESS scheduling.

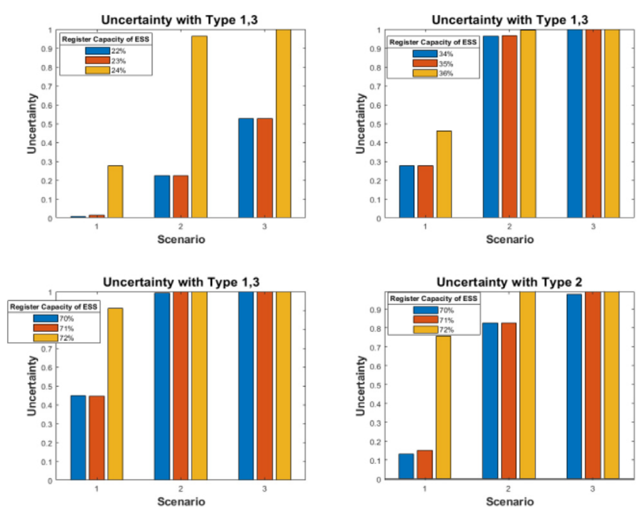

Fig. 5. DR participation uncertainty.

4. Simulation, case study, and discussion

4.1. ESS scheduling for each type

The assumptions to operate the ESSs are detailed in Table 4, and the results of solving mixed integer non-linear programming (MINLP) problems of (3) to (5) through the general algebraic modeling system (GAMS) are shown in Fig. 4.

Fig. 4 shows that the ESS charging scheduling is the same during the peak times (t = 09∼20) for NGB and MGB types, and the ESS scheduling differs for the off-peak time. These observations can be easily inferred from (3) and (5). Further, the GSB type has different scheduling during peak time; however, it has a similar pattern during the off-peak time to the MGB type, which can be inferred from (4) and (5).

4.2. DR participation uncertainty with MCS

To measure the uncertainty a scenario-based MCS was performed. Scenario 2 is a case in which an emergency signal is generated on 15 days per year according to the average in Korea, Scenario 1 and 3 are assumed that 5 and 25 signals are dispatched respectively (Ryu and Kim, 2020). In Fig. 5, there are sections defined as the marginal capacity, where the uncertainty sharply increases depending on the participating capacity. The NGB and MGB types have four marginal capacities (23%, 35%, 71%, 100%), while the GSB type has only two marginal capacities (71%, 100%). In addition, as DRBP is calculated by the registered capacity C_c (13), the marginal capacity ensures higher profit for each prosumer. That is, if C_c is 24% of ESS capacity, the DRBP is bigger than the 0.23 rate, but the expected payoff is lower because the uncertainty increases dramatically by choosing the 0.24 rate. Thus, rational prosumers will participate in the DR with the marginal capacity and the expected payoff for each marginal capacity considering the subjective probability suggested in (7) is summarized in Table 1.

For scenario 1, which has the smallest number of DR events (5 days during a year), the participation capacity will be set to 71%, the highest expected payoff, regardless of their types. However, as the number of DR event days increased (scenarios 2 and 3), due to the increased uncertainty from high registration capacity, each prosumer will tend toward risk aversion and choose the strategy with the lowest registration 23% capacity.

4.3. Results of the game

4.3.1. Results of the single game

As mentioned in Section 2, players are matched against a partner with a similar level of ESS capacity by DRA. Thus, the assumption that the ESS condition of each prosumer is the same leads to the following equations.

$$\psi_c^\sigma = \psi_d^\sigma = \psi^\sigma \tag{20a}$$

$$\mu_{c,i}^\sigma = \mu_{d,j}^\sigma = \mu_k^\sigma \tag{20b}$$

$$B_c^\sigma = B_d^\sigma = B^\sigma \tag{20c}$$

$$EP_c^\sigma = EP_d^\sigma = EP^\sigma \tag{20d}$$

Furthermore, we assume that prosumers prefer the MGB type the most, followed by the NGB type and the GSB type. Thus, the probability for the type and scenario are as follows:

$$\mu_1^\sigma = 0.3, \mu_2^\sigma = 0.2, \mu_3^\sigma = 0.5 \tag{21a}$$

$$P(\sigma_1) = 0.2, P(\sigma_2) = 0.6, P(\sigma_3) = 0.2 \tag{21b}$$

When we assume three scenarios, we regard scenario 2 as a standard case considering the reliability DR market operation results in Korea, so the probability of scenario 2 is highest (21b). From these beliefs, the expected payoffs of both players are calculated using (7), and (16). The results are in Table 2 and all

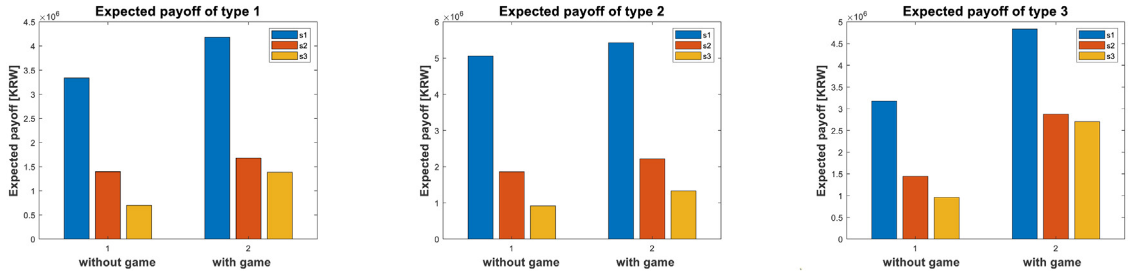

Fig. 6. Comparison of the game results . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
The game results of each prosumer in scenario 2 (with equilibrium points in red color).

$EP_c^2 EP_d^2$	s_1^d	s_2^d	s_3^d	s_4^d	s_5^d	s_6^d	s_7^d	s_8^d	s_9^d	s_{10}^d
s_1^c	(1.62, 1.62)	(1.70, 0.86)	(1.65,1.31)	(1.67, -0.05)	(1.65, 2.44)	(1.68, -0.04)	(1.66, 1.65)	(1.67, 0.88)	(1.64, 1.21)	(1.73, 7.06)
s_2^c	(0.86, 1.70)	(0.86, 0.86)	(0.88, 1.32)	(0.91, -0.03)	(0.87, 2.41)	(0.92, 0.71)	(0.86, 1.61)	(0.85, 0.87)	(0.89, 1.42)	(0.93, 2.66)
s_3^c	(1.31, 1.65)	(1.32, 0.88)	(1.27, 1.27)	(1.33, -0.02)	(1.29, 2.44)	(1.27, 0.71)	(1.23, 1.67)	(1.33, 0.85)	(1.33, 1.34)	(1.29, 1.72)
s_4^c	(-0.05, 1.67)	(-0.03, 0.91)	(-0.02, 1.33)	(-0.00, 0.00)	(-0.05, 2.50)	(-0.01, 2.50)	(-0.05, 1.65)	(-0.03, 0.92)	(-0.02, 1.36)	(0.00, 0.00)
s_5^c	(2.44, 1.65)	(2.41, 0.87)	(2.44, 1.29)	(2.50, -0.05)	(2.60, 2.60)	(2.75, -0.04)	(2.38, 1.63)	(2.43, 0.89)	(2.42, 1.20)	(2.42, 3.79)
s_6^c	(-0.04, 1.68)	(0.71, 0.92)	(0.72, 1.27)	(0.01, -0.01)	(0.04, 2.75)	(0.74, 0.74)	(-0.05, 1.67)	(0.71, 0.93)	(0.72, 1.37)	(0.74, -0.01)
s_7^c	(1.65, 1.66)	(1.61, 0.86)	(1.67, 1.23)	(1.65, -0.05)	(1.63, 2.38)	(1.67, -0.05)	(1.67, 1.67)	(1.67, 0.85)	(1.67, 1.30)	(1.69, 7.28)
s_8^c	(0.88, 1.67)	(0.87, 0.85)	(0.85, 1.33)	(0.92, -0.03)	(0.89, 2.43)	(0.93, 0.71)	(0.85, 1.67)	(0.88, 0.88)	(0.85, 1.27)	(1.02, 2.56)
s_9^c	(1.21, 1.64)	(1.42, 0.89)	(1.34, 1.33)	(1.36, -0.02)	(1.20, 2.42)	(1.37, 0.72)	(1.30, 1.67)	(1.27, 0.85)	(1.37, 1.37)	(1.29, 1.73)
s_{10}^c	(7.06, 1.73)	(2.66, 0.93)	(1.72, 1.29)	(0.00, 0.00)	(3.79, 2.42)	(0.01, 0.74)	(7.28, 1.69)	(2.56, 1.02)	(1.73, 1.29)	(0.00, 0.00)

Table 3
Simulation results of the MGB type.

	scenario 1 (million KRW)	scenario 2 (million KRW)	scenario 3 (million KRW)
Single-game	30.80	0	0
Grim strategy	43.24	17.03	13.05
Tit-for-tat strategy	50.37	43.74	31.79

results are represented as a value divided by a million South Korean won (KRW) for convenience. To help observe the game results, the game was divided into subgames according to their types. In each subgame, the Nash equilibrium is derived very easily (indicated in red in Table 2). The results intuitively indicate the optimal strategy for each type of prosumer through the game in scenario 2. The prosumer whose type is NGB will choose s_1, GSB type will choose s_5, and MGB type will choose s_{10}. Furthermore, the optimal strategy for scenarios 1 and 3 is also derived and the results are included in the Appendix.

The blue bar in Fig. 6 represents scenario 1, the orange bar represents scenario 2, and the yellow bar represents scenario 3. In scenario 1, with the fewest DR events, the expected payoff is the highest, which corresponds to the results summarized in Table 1. Moreover, the three bars on the left show the payoff for not participating in the game, while the three bars on the right show the payoff for participating in the game. The results demonstrate that all prosumers can expect better payoffs regardless of their type by participating in the game.

4.3.2. Results of the repeated game

In the subgame where both players are MGB type, the aspect of the result is similar to the prisoner's dilemma. For scenario 2 (22), if both players choose s_7, each player can get 1.67 million KRW. However, the game ends at the point where both players choose s_{10} as the prisoner's dilemma is terminated.

$$\begin{array}{cc} & \begin{array}{cc} s_7 & s_{10} \end{array} \\ \begin{array}{c} s_7 \\ s_{10} \end{array} & \begin{bmatrix} 1.67, 1.67 & 1.69, 7.28 \\ 7.28, 1.69 & 0, 0 \end{bmatrix} \end{array} \tag{22}$$

Table 4
Assumptions for ESS operation.

Parameters	Assumptions
ESS & PCS installation cost	500,000 KRW/kW
ESS & PCS capacity	300 kW
Annual O & M cost	1% of installation cost
ESS life span	15 years
Round-trip efficiency	86%
Depth of discharge (DoD)	60% (SoC10-SoC70)
Discount rate	5.26%

Table 5
Results of cost–benefit analysis of ESS.

Items	Costs (million KRW)
Installation cost	150
O & M cost	16.1
Total	166.1
Items	**Benefits (million KRW)**
Base charge reduction	46.7
Usage charge reduction	24.6
Benefits of ESS discount plan	57.5
Total	128.9

Table 6
B/C ratio of ESS considering DR market participation.

	scenario 1	scenario 2	scenario 3
Single-game	0.96	0.78	0.78
Grim strategy	1.04	0.88	0.85
Tit-for-tat strategy	1.08	1.04	0.97

In the prisoner's dilemma, it has been proved that each player takes a cooperative attitude through repeated games (Osborne and Rubinstein, 1994). Thus, we would compare the change in the actions of each prosumer through a repeated game. In general, the more patient the prosumer is, the closer the discount factor δ is to 1, so we assume the discount factor of both prosumers is 0.95.

$$\delta_c = \delta_d = \delta = 0.95 \tag{23}$$

i. A grim, grim strategy

When both players use the grim strategy, we need to see if a player has any incentives to betray. The rational player will deviate as soon as possible because of the discount factor δ. Thus, if player c is deviating at $t = 1$, that is player c is off the path, then the expected payoff for scenario 2 is:

$$P_c^{off} = 7.28 + 1.69\left(\delta_c + \delta_c^2 + \cdots + \delta_c^{14}\right) = 24.51 \tag{24a}$$

Meanwhile, the expected payoff when player c did not deviate, meaning player c for scenario 2 is on the path, is

$$P_c^{on} = 1.67\left(1 + \delta_c + \delta_c^2 + \cdots + \delta_c^{14}\right) = 17.03 \tag{24b}$$

There is an incentive for each player to deviate. However, in the complete game, a player can infer the strategy of another player would be the same as his strategy. Therefore, both players know that choosing s_{10} by betraying is a better option, but they choose s_9, predicting that it will result in the same with a single game due to the opponent's betrayal. As mentioned earlier, a repeated game will only occur if all players are of the MGB type.

ii. A tit-for-tat, tit-for-tat strategy

Likewise, we should consider the deviation condition for the tit-for-tat strategy. When both players use the tit-for-tat strategy, if player c is deviating at $t = 1$, that is, player c is off the path, then the expected payoff for scenario 2 is

$$P_c^{off} = 7.28\left(1 + \delta_c^2 + \cdots + \delta_c^{14}\right) + 1.29\left(\delta_c + \delta_c^3 + \cdots \delta_c^{13}\right) = 43.74 \tag{25}$$

The on-the-path payoff is the same as when both players use a grim strategy (24b). As the deviation can yield a higher expected payoff for the tit-for-tat strategy, the player is willing to deviate. This result also has the same consequence in scenarios 1 and 3. Thus, betrayal always occurs with a tit-for-tat strategy. To observe the effect of a repeated game, we obtained the expected payoffs of a single game and repeated games for 15 years, the lifespan of ESSs in Table 3.

The single-game results (Fig. 6) show that each player can get better profits through game participation. However, a result of the repeated game is superior to a single game for MGB-type prosumers. Moreover, Table 3 summarizes that the highest reward is obtained when both the MGB-type players use the tit-for-tat strategy. This result has a different pattern from the general repeated games where the grim strategy produces the best results, it is possible because a player who selects a risk-averse strategy helps the others whose strategy is very risky but will ensure a high return to hedge a lot of risks. In other words, in the case of the grim and grim strategies, both players get a stable profit by taking a risk-averse strategy s_7, in the case of the tit-for-tat strategy, taking advantage of the repeated game and one-time retaliation, each player can get a higher expected return by taking a risk-averse s_7 and risk-seeking strategy s_{10} alternatively.

4.4. Cost–benefit analysis (CBA) of ESS in Korea

As mentioned earlier, participation in reliability DR through ESS should provide economic incentives to small-scale ESS owners. Therefore, we intend to verify the effectiveness of the proposed model through a cost–benefit analysis (CBA) of the small-scale ESS. The parameters for performing a CBA of an ESS, according to previous studies (Jeon et al., 2019), are shown in Table 4.

If the ESS with the parameters listed in Table 4 is operated in an industrial building, the benefit–cost ratio (B/C ratio) is about 0.78, with costs of 166 million KRW and benefits of 129 million KRW. These details are presented in Table 5. Considering the economic loss caused by lowering the DoD to 60% considering Korea's situation wherein strict operation conditions are enforced due to previous fires in ESSs (MOTIE, 2019), the B/C ratio seems reasonable compared to the previous study (Jeon et al., 2019).

Meanwhile, participation in IBDR following the proposed game framework creates the additional benefit items shown in Table 3 by improving the B/C ratio. The resulting improved B/C ratio in Table 6 indicates that a small-scale ESS with a B/C ratio of 0.78 can be economically feasible in the proposed model.

It is a very encouraging achievement to secure the economic feasibility of small-scale ESS through the proposed model. In particular, the steady DR participation of MGB-type prosumers will guarantee a net profit of 6.6 million KRW through a small-scale ESS in scenario 2, which is the most probable case in Korea. However, in scenario 3, with frequent DR events, it is still difficult to obtain economic feasibility. These results indicate that currently, a concurrent expansion of DR resources and ESS is limited in Korea. That is, frequent DR events would be decreasing the incentive for consumers to install small-scale ESSs.

5. Conclusion

In this study, an energy sharing scheme was proposed for hedging the uncertainty that occurs when participating in a mandatory incentive-based DR program. A novel energy trading framework was suggested. First, each prosumer operates the ESS optimally based on their type, considering the environment or financial benefit, and they participate in a reliability DR program according to their type, which results in different ESS operation scheduling by predicting DR events. However, a completely accurate prediction of DR events is not possible in the current DR market; therefore, a non-cooperative game model for trading surplus electricity in ESSs was suggested to mitigate the DR participation uncertainty. Moreover, a subjective decision-making model based on prospect theory was introduced to construct a practical consumer behavior model. Finally, the results of a case study based on actual Korean DR market operation data and industrial building load data showed that prosumers can participate in a DR program, which is dispatched by an emergency signal that calls upon their ESS, through the suggested game model by mitigating DR participation uncertainty. Furthermore, an increased B/C ratio of small-scale ESSs will help the policymaker by promoting the deployment of small-scale ESSs. These results will be helpful for the Korean government to achieve the goals of the Paris Agreement of reducing carbon emissions, by utilizing small-scale ESSs, which represent a flexible resource. However, the participation of ESSs in reliability DR must be supervised annually to ensure the economic feasibility of small-scale ESSs. Accordingly, a policymaker or DR aggregator should determine how extant customer churn can be prevented.

Furthermore, from a macro perspective, involving DR aggregators or policymakers to encourage prosumers to engage in the DR market through their ESSs is necessary to improve the economic

Table 7
The game results of each prosumer in scenario 2 (with equilibrium points in red color).

$EP_c^2 EP_d^2$	s_1^d	s_2^d	s_3^d	s_4^d	s_5^d	s_6^d	s_7^d	s_8^d	s_9^d	s_{10}^d
s_1^c	(2.18, 2.18)	(2.15, 2.30)	(2.19, 4.20)	(2.23, 3.11)	(2.20, 5.44)	(2.14, 3.80)	(2.17, 2.20)	(2.21, 2.32)	(2.28, 4.16)	(2.25, 9.48)
s_2^c	(2.30, 2.15)	(2.30, 2.30)	(2.29, 4.21)	(2.30, 3.16)	(2.27, 5.42)	(2.32, 3.86)	(2.31, 2.17)	(2.34, 2.30)	(2.32, 3.97)	(2.34, 6.70)
s_3^c	(4.20, 2.19)	(4.21, 2.29)	(4.26, 4.26)	(4.24, 3.12)	(4.15, 5.37)	(4.26, 4.11)	(4.06, 2.11)	(4.09, 2.27)	(4.26, 4.09)	(4.15, 5.87)
s_4^c	(3.11, 2.23)	(3.16, 2.30)	(3.12, 4.24)	(3.06, 3.06)	(2.89, 5.32)	(2.99, 4.02)	(3.13, 2.20)	(3.00, 2.36)	(3.21, 4.21)	(3.04, 3.11)
s_5^c	(5.44, 2.20)	(5.42, 2.27)	(5.37, 4.15)	(5.32, 2.89)	(5.66, 5.66)	(5.75, 3.98)	(5.24, 2.19)	(5.45, 2.34)	(5.32, 4.21)	(5.37, 7.81)
s_6^c	(3.80, 2.14)	(3.86, 2.32)	(4.11, 4.26)	(4.02, 2.99)	(3.98, 5.75)	(3.93, 3.93)	(4.04, 2.26)	(3.97, 2.31)	(3.90, 4.16)	(3.92, 4.08)
s_7^c	(2.20, 2.17)	(2.17, 2.31)	(2.11, 4.06)	(2.20, 3.13)	(2.19, 5.24)	(2.26, 4.04)	(2.24, 2.24)	(2.22, 2.34)	(2.18, 4.21)	(2.21, 9.48)
s_8^c	(2.32, 2.21)	(2.30, 2.34)	(2.27, 4.09)	(2.36, 3.00)	(2.34, 5.45)	(2.31, 3.97)	(2.34, 2.22)	(2.25, 2.25)	(2.34, 4.15)	(2.39, 6.92)
s_9^c	(4.16, 2.28)	(3.97, 2.32)	(4.09, 4.26)	(4.21, 3.21)	(4.21, 5.32)	(4.16, 3.90)	(4.21, 2.18)	(4.15, 2.34)	(4.24, 4.24)	(4.13, 5.87)
s_{10}^c	(9.48, 2.25)	(6.70, 2.34)	(5.87, 4.15)	(3.11, 3.04)	(7.81, 5.37)	(4.07, 3.92)	(9.48, 2.21)	(6.92, 2.39)	(5.87, 4.13)	(3.02, 3.02)

Table 8
The game results of each prosumer in scenario 3 (with equilibrium points in red color).

$EP_c^2 EP_d^2$	s_1^d	s_2^d	s_3^d	s_4^d	s_5^d	s_6^d	s_7^d	s_8^d	s_9^d	s_{10}^d
s_1^c	(1.28, 1.28)	(1.27, 0.43)	(1.34, 0.47)	(1.33, -0.09)	(1.29, 1.19)	(1.34, -0.08)	(1.31, 1.23)	(1.29, 0.41)	(1.29, 0.55)	(1.35, 5.38)
s_2^c	(0.43, 1.27)	(0.45, 0.45)	(0.44, 0.51)	(0.51, -0.06)	(0.46, 1.28)	(0.40, -0.05)	(0.39, 1.28)	(0.41, 0.42)	(0.45, 0.67)	(0.47, 1.11)
s_3^c	(0.47, 1.34)	(0.51, 0.44)	(0.00, 0.00)	(0.64, -0.04)	(0.48, 1.29)	(0.76, -0.03)	(0.47, 1.30)	(-0.01, 0.49)	(0.52, 0.65)	(0.64, -0.04)
s_4^c	(-0.09, 1.33)	(-0.06, 0.51)	(-0.04, 0.64)	(-0.00, -0.00)	(-0.09, 1.45)	(-0.02, 0.01)	(-0.09, 1.29)	(-0.06, 0.46)	(-0.04, 0.64)	(0.00, 0.00)
s_5^c	(1.19, 1.29)	(1.28, 0.46)	(1.29, 0.48)	(1.45, -0.09)	(1.63, 1.63)	(1.62, -0.07)	(1.30, 1.26)	(1.31, 0.43)	(1.34, 0.48)	(1.34, 2.18)
s_6^c	(-0.08, 1.34)	(-0.05, 0.40)	(-0.03, 0.76)	(0.01, -0.02)	(-0.07, 1.62)	(-0.00, -0.00)	(-0.08, 1.36)	(-0.05, 0.47)	(-0.03, 0.03)	(0.01, -0.02)
s_7^c	(1.23, 1.31)	(1.28, 0.39)	(1.30, 0.47)	(1.29, -0.09)	(1.26, 1.30)	(1.36, -0.08)	(1.28, 1.28)	(1.29, 0.43)	(1.29, 0.47)	(1.15, 5.38)
s_8^c	(0.41, 1.29)	(0.42, 0.41)	(0.49, -0.01)	(0.46, -0.06)	(0.43, 1.31)	(0.47, -0.05)	(0.43, 1.29)	(0.43, 0.43)	(0.44, 0.58)	(0.45, 1.28)
s_9^c	(0.55, 1.29)	(0.67, 0.45)	(0.65, 0.52)	(0.64, -0.04)	(0.48, 1.34)	(0.03, -0.03)	(0.47, 1.29)	(0.58, 0.44)	(0.52, 0.52)	(0.64, 0.70)
s_{10}^c	(5.38, 1.35)	(1.11, 0.47)	(-0.04, 0.64)	(0.00, 0.00)	(2.18, 1.34)	(-0.02, 0.01)	(5.38, 1.15)	(1.28, 0.45)	(0.70, 0.64)	(0.00, 0.00)

feasibility of small-scale ESSs and ensure the reliability of aggregated DR resources. However, despite these efforts, CBA results from scenario 3 demonstrate that the greater the DR events, the more difficult is the participation in DR of ESSs. Thus, in a dynamic power system, a reasonable plan for the coexistence of DR resources and ESSs should be arranged. Finally, further research is needed on an estimation of ESS capacity, as DR resources will be beneficial to DR market operators and system operators.

CRediT authorship contribution statement

Jeseok Ryu: Data curation, Software, Investigation, Writing – original draft, Visualization. **Jinho Kim:** Conceptualization, Methodology, Investigation, Supervision, Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

See Tables 7 and 8.

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