Evaluation of Economic Values of Distributed Energy Resources Aggregation: Stochastic Programming Approach

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Abstract

In the transition to decentralized energy systems, the integration of distributed energy resources (DERs) and optimization of DER systems is essential. However, as renewable generation is inherently intermittent and real-time prices are hardly predictable, individual DER owners often face challenges when trying to optimize one's surplus energy usage. Aggregation arises as a tool to pool individual resources from multiple DER owners, mitigating these uncertainties at an aggregated level. This study aims to analyze the economic value of aggregation in managing DERs by comparing two cases: individual DER participation and aggregated DER participation. Using a two-stage stochastic programming model, uncertainties in renewable generation and real-time electricity prices are addressed. Aggregated DER participation was shown to significantly improve the economic and operational performance of DER participation, with 12.55% higher total profits and notably increased day-ahead commitments compared to individual DER participation. This research highlights the importance of pooling mechanisms in stabilizing individual profits and mitigating risks associated with generation variability, providing insights for optimizing DER systems.

Keywords: Distributed Energy Resources; Aggregation; Day-Ahead Commitment; Two-Stage Stochastic Programming.

1 Introduction

Energy industries are going through rapid transformation to address climate change and reduce greenhouse gas emissions. A cornerstone of this transition is the integration of renewable energy sources and the shift from centralized to decentralized energy models. Distributed energy resources (DERs) have emerged as a key factor in this process, providing localized and sustainable solutions to meet increasing energy demand, while simultaneously moving toward decarbonization goals. Distributed energy resources refer to small-scale energy generation and storage units that are located close to the point of consumption. DERs could include solar photovoltaic and wind turbine generation units, energy storage

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systems (ESS), electric vehicle (EV) chargers, microgrids, and more [1]. DERs play a significant role in decentralizing energy systems by stabilizing local energy supply from grid disruptions and reducing the dependency on centralized grids. Also, many DERs produce energy sustainably, as renewable energy sources are ideal for small-scale production due to their accessibility, scalability, and compatibility with localized energy systems. Individuals who own distributed energy resources can be broadly categorized into distributed generators and prosumers. Distributed generators focus solely on producing energy with one's own DER and feeding power into the grid, without self-consumption. Whereas, prosumers are individuals who utilize self-generated energy for personal consumption, and choose either to sell the residual to the grid or to store it in their energy storage systems [2]. The number of individuals who pursue energy automony as prosumers are increasing, due to advancements in renewable energy technologies and correspondingly decreased costs of renewable energy generators such as solar panels and battery storage.

Typically, conventional generators participate in the day-ahead market and Real-Time market through bidding processes. In the day-ahead market, market clearing prices for each hour are established for the following day based on forecasted supply and demand. Based on the established prices, generators and consumers submit their bids, agreeing to provide or consume a specific amount of energy. Meanwhile, real-time trading in the real-time market mitigates the discrepancy between expected supply and realized demand [3]. Similarly, individual DER owners can also participate in these markets; however, they are positioned as price-takers. DER owners cannot influence market prices due to limited production capacity, unlike large-scale generators that can affect clearing prices through economies of scale and strategic bidding. More critically, inherent uncertainties of renewable energy generation pose difficulties to individual DER owners in making stable commitments [4]. While conventional generators benefit from dispatchable outputs by enabling strategic and risk-minimized biddings, DER owners who rely on renewable energy generation face significant risks due to non-dispatchable outputs.

To address these challenges, the role of 'aggregators', as intermediaries, have emerged. Following the definition of [5], *"an aggregator is a company who acts as an intermediary between electricity end-users and DER owners and the power system participants who wish to serve these end-users or exploit the services provided by these DERs."* Nonetheless, based on specific contexts and regulations, the role of aggregator can be reduced and expanded. Aggregators fundamentally play a crucial role in lowering the entry barriers for individual DER owners to participate in grid transactions by providing necessary infrastructure for DER owners to profit from their excess energy [6]. Yet, beyond making the energy market more accessible, trading electricity through aggregators has its potential in bringing significant benefits to both DER owners and the localized energy system. This is mainly because aggregation ensures a relatively stable energy system that would be challenging for individual DER owners to achieve independently. The generation of renewable energy sources are inherently instable due to unpredictable factors such as weather conditions. This implies that deviations from day-ahead commitment are bound to occur, especially in cases of individual DER owners that rely on small-scale renewable energy generators. However, aggregators can mitigate the risk occurred due to the randomness of individual energy outputs by making commitments based on pooled generations of multiple individual DERs. Similarly, in the context of risk-taking, generation variability burdens individual DER owners of penalty costs incurred by generating less than their day-ahead commitment, while aggregations mitigate these risks of penalty costs by managing the variability of pooled resources [7]. Thus, by mitigating the randomness of generation and risks associated with deviation penalties can potentially lead to relatively aggressive commitment decisions. Ultimately, aggregation can contribute to the utility of the energy system, as more pooled resources increase the predictability in the day-ahead market and flexibility in the real-time market.

Through this study, we aim to evaluate the economical significance of aggregations, by analyzing its influence on both system-wide profitability and individual DER owners' outcomes. To achieve this, we develop a two-stage stochastic programming model that considers uncertainties in renewable generation and real-time price. The model optimizes the day-ahead commitments for two distinct cases: (1) individual DER participation and (2) aggregated DER participation. By comparing day-ahead commitment differences and the consequent real-time profits or penalties of these two cases, we aim to quantify the tangible benefits of aggregation, both at the system level, in terms of net profit and commitment stability, and at the individual level, in terms of gains of DER owners from remuneration.

The remainder of this paper is organized as follows. Section 2 provides a review of relevant literature, discussing the existing approaches for optimization of various aspects of the distributed energy resources systems. In Section 3, we provide the problem setting with the presumed assumptions and mathematical formulations for both individual and aggregated DER participation. Section 4 outlines the sampling-based stochastic optimization based solution approach, and Section 5 presents results for numerical experiments, comparing commitment levels and profits for both individual and aggregated DER participation. Section 6 concludes this study by discussing the economic implications of DER aggregation and suggesting future work to enhance the model's applicability.

2 Literature Review

Growing interest in distributed energy resource systems has led onto the development of optimization tools to manage various aspects of DER systems [8, 9, 10]. Among these tools, stochastic programming has often been utilized to address the inherent uncertainties in energy systems. For example, Beraldi et al. [6] designed a two-stage stochastic programming model that addresses uncertainties in energy demand, market prices, and renewable generation to optimize distributed energy resources in the viewpoint of an aggregator. Also, by integrating Conditional Value at Risk (CVaR) to the model, a relatively conservative framework for managing aggregated DERs were proposed. Similarly, Sarfarazi et al. [11] developed a stochastic bi-level optimization model for real-time pricing strategies that considers the price consequential interaction between the aggregators and prosumers. Rashidizadeh-Kermani et al.[12] also contributed by proposing a bi-level stochastic scheduling model that is tailored for the optimal bidding strategy for electric vehicle aggregators. This model aimed to maximize aggregator profits and minimize EV owners' energy procurement costs, simultaneously by optimizing the future decisions in day-ahead and real-time markets. Methodologies using game theory is also widely used as a tool to optimize profit and pricing mechanisms in DER systems. For instance, Dabbagh et al. [13] used cooperative game theory and accounted methods such as the Nucleolus and Shapley value to equitably distribute profits, considering the risk preferences of DER owners. Meanwhile, Liu et al. [14] adopted a Stackelberg game model and optimized the billing mechanisms between microgrid operators and photovoltaic prosumers, under the objective of creating a balanced and mutually beneficial system.

As shown in Table 1, in the majority of the existing literatures that aim to optimize distributed energy resource systems, either the role of an aggregator or the tool of aggregation is presumed as given. The contribution of this research lies in critically examining the validity of this premise by identifying the actual economic value of aggregation in DER system optimization. This study seeks to conduct an indepth analysis both at the system level, by investigating differences in day-ahead commitment quantities and net profit, and at the individual level, by examining whether individual DER owners participating in aggregation also realize tangible benefits.

Table 1: Summary of Related Literatures

Reference	Objective	Method	Data	Optimization Goal	Renewable Type	DER Owners
Beraldi et al. [6]	Resource Management	Stochastic Programming	Real-world	Min Risk	combined	generators
Sarfarazi et al. [11]	Real-time Pricing	Bi-level Optimization	Simulated	Max Collective Profit	combined	prosumagers
Rashidizadeh et al. [12]	Bidding Strategies	Bi-level Optimization	Real-world	Max Profit	EV	-
Dabbagh et al. [13]	Profit Allocation	Cooperative Game Theory	Real-world	Min Risk	-	prosumers
Liu et al. [14]	Billing Mechanism	Stackelberg Game	Simulated	Max Profit	PV	prosumers

3 Problem Description

3.1 Assumption

Individual DER owners can opt into grid transactions which are operated upon two core mechanisms, the day-ahead market and the Real-Time market. In the day-ahead market, market clearing prices are established for each hour of the following day, based on forecasted supply and demand. Participants, acknowledging market prices in advance, commit to energy production or consumption a day before the actual transaction. Consequently, to encourage rational commitment and ensure the stability of the energy system, penalties are imposed on those who failed to meet one's supply commitment [15].

Apart from using penalties for shortages in commitment, the discrepancies between the day-ahead commitments and actual real-time generations are balanced out in the Real-Time market. Given the inherent unpredictability in demand and the instability in renewable energy generation, the real-time market adjusts supply and demand by setting prices near real-time. Although it allows flexibility in managing unexpected deviations, participants are more exposed to high price fluctuations compared to the more stable day-ahead market price [16].

Throughout this study, individual DER owners are assumed to be energy prosumers in which self-generated energy are first subject to fulfill one's own energy demand. After satisfying one's own demand, DER owners can utilize their residual energy by participating in market transactions either directly or through an aggregator. Costs related to access to market platforms or infrastructure development are not explicitly accounted for in this analysis to limit external cost factors. Moreover, to focus on the intrinsic economic value of aggregation, we assume that the market offers the same price for energy transactions regardless of the quantity being traded. Ensuring equal price competitiveness allows us to isolate the value of pooling from quantity-based pricing effects.

3.2 Mathematical Model

3.2.1 Nomenclature

We first introduce the notation for sets, indices, parameters, and decision variables for the proposed optimization models as follows.

- Sets and Indices:

- I: Set of individual DER owners $i \in I = \{1, 2, \ldots, N^I\}$
- T: Set of elementary time periods (hours) $t \in T = \{1, 2, \ldots, N^T\}$
- S: Set of scenarios used to represent the evolution of uncertain parameters $s \in S = \{1, 2, \ldots, N^S\}$

- Deterministic Parameters:
  - P_t^{DA}: day-ahead market price for hour t
  - P_t^{PN}: Commitment shortage penalty price for hour t

- Stochastic Parameters:
  - $R_{it}(\xi)$: Amount of surplus energy by individual i for hour t
  - $P_t^{RT}(\xi)$: Real-time market price for hour t
  - ξ_s: Realization of uncertain parameters under scenario s
  - π_s: Probability of occurrence of scenario s

- Decision Variables:
  - x_{it}^{DA}: Amount of day-ahead commitment of individual i to aggregator for hour t
  - $y_{it}^{+}(\xi)$: Surplus of renewable energy generation of individual i for hour t, relative to the amount of day-ahead commitment to aggregator
  - $y_{it}^{-}(\xi)$: Shortage of renewable energy generation of individual i for hour t, relative to the amount of day-ahead commitment to aggregator
  - $z_{it}(\xi)$: Binary variable that ensures either $y_{it}^{+}(\xi)$ or $y_{it}^{-}(\xi)$ can take a nonzero value, but not both, for each individual i and hour t
  - α_t^{DA}: Amount of day-ahead commitment of aggregator for hour t
  - $\beta_t^{+}(\xi)$: Surplus of available renewable energy of aggregator for hour t, relative to the amount of day-ahead commitment to day-ahead market
  - $\beta_t^{-}(\xi)$: Shortage of available renewable energy of aggregator for hour t, relative to the amount of day-ahead commitment to day-ahead market
  - $z_t(\xi_s)$: Binary variable that ensures either $\beta_t^{+}(\xi)$ or $\beta_t^{-}(\xi)$ can take a nonzero value, but not both, for each individual i and hour t

3.2.2 Individual DER Participation

In this model, DER owners participate in the energy market by directly making commitments to the market individually. Individual DERs owners are subject to supply the committed amount on the next day which would be bought by the market, based on the established price. If energy is generated more than committed, DER owners would have enough incentive to sell the surplus to the real-time market regardless of the price, because we assume that DER owners do not have flexibility in energy storage. If commitment can not be met due to shortage in generation, penalty costs of unfulfillment are charged directly to the DER owner. Thus, the profit of DER owners in this model are highly dependent on randomness of generation and the fluctuations of real-time market price. The presented model below is designed to optimize the amount of day-ahead commitment for each hour that can maximize the profit of each individual DER owners $i \in I$ as follows:

$$\max \quad \sum_{t \in T} \left(P_t^{DA} x_{it}^{DA} + \mathbb{E}\left[P_t^{RT}(\xi) y_{it}^{+}(\xi) - P_t^{PN} y_{it}^{-}(\xi) \right] \right) \tag{1a}$$

$$\text{s.t.} \quad R_{it}(\xi) - x_{it}^{DA} = y_{it}^{+}(\xi) - y_{it}^{-}(\xi) \quad \forall t \in T \tag{1b}$$

$$R_{it}(\xi) \geq y_{it}^{+}(\xi) \quad \forall t \in T \tag{1c}$$

$$y_{it}^{+}(\xi) \leq M z_{it}(\xi) \quad \forall t \in T \tag{1d}$$

$$y_{it}^{-}(\xi) \leq M(1 - z_{it}(\xi)) \quad \forall t \in T \tag{1e}$$

$$x_{it}^{DA} \geq 0, y_{it}^{+}(\xi) \geq 0, y_{it}^{-}(\xi) \geq 0, z_{it}(\xi) \in \{0, 1\} \quad \forall t \in T. \tag{1f}$$

$$\tag{1g}$$

The objective function (1a) is set to maximize the daily profit of each individual DER owner I, over all time periods T. Profits consists of the revenue obtained from the day-ahead market ($P_t^{DA} x_{it}^{DA}$), the expected revenue from selling surplus renewable energy in the real-time market ($\mathbb{E}[P_t^{RT}(\xi) y_{it}^{+}(\xi)]$), and the expected penalty cost due to commitment shortages ($\mathbb{E}[P_t^{PN} y_{it}^{-}(\xi)]$). Constraint (1b) determines the mismatch between the actual renewable energy generated by a DER owner ($R_{it}(\xi)$) and their day-ahead market commitment (x_{it}^{DA}). The deviations from day-ahead commitment are caused by either a surplus ($y_{it}^{+}(\xi)$) or a shortage ($y_{it}^{-}(\xi)$) in renewable energy generation. The amount of surplus generation in which one can sell to the real-time market is bounded by the amount of actual generation, according to constraint (1c). Constraint (1f) ensures the non-negativity of the decision variables.

3.2.3 Aggregated DER Participation

This model explains how DER owners can indirectly participate in the energy market through an aggregator. The aggregator participates in the energy market and makes commitments on an aggregated level on the behalf of the all the individual DER owners involved. Unlike the direct participation model, this pooling mechanism mitigates the risk occurred by the randomness of generation and high market fluctuations. Here, the aggregator acts purely as a neutral intermediary for consolidating the individual generations and focuses solely on optimizing the level of aggregated commitment rather than pursuing its own business profit. Subsequently, shortage penalties and surplus rewards are evaluated on an aggregated level and are subject to remuneration on an individual level.

$$\max \quad \sum_{t \in T} \left(P_t^{DA} \alpha_t^{DA} + \mathbb{E}\left[P_t^{RT}(\xi) \beta_t^{+}(\xi) - P_t^{PN} \beta_t^{-}(\xi) \right] \right) \tag{2a}$$

$$\text{s.t.} \quad \sum_{i \in I} R_{it}(\xi) - \alpha_t^{DA} = \beta_t^{+}(\xi) - \beta_t^{-}(\xi) \quad \forall t \in T \tag{2b}$$

$$\sum_{i \in I} R_{it}(\xi) \geq \beta_t^{+}(\xi) \quad \forall t \in T \tag{2c}$$

$$\beta_t^{+}(\xi) \leq M z_t(\xi) \quad \forall t \in T \tag{2d}$$

$$\beta_t^{-}(\xi) \leq M(1 - z_t(\xi)) \quad \forall t \in T \tag{2e}$$

$$\alpha_t^{DA} \geq 0, \beta_t^{+}(\xi) \geq 0, \beta_t^{-}(\xi) \geq 0, z_t(\xi) \in \{0, 1\} \quad \forall t \in T. \tag{2f}$$

Objective function (2a) aims to maximize the total profit of when aggregation is used, by considering revenue from the day-ahead market ($P_t^{DA}\alpha_t^{DA}$), expected revenue from selling surplus energy in the real-time market ($\mathbb{E}[P_t^{RT}(\xi)\beta_t^+(\xi)]$), and expected penalties for shortages at the aggregated level ($\mathbb{E}[P_t^{PN}\beta_t^-(\xi)]$) for every hour t. Constraint (2b) expresses the mismatch between the total renewable energy generated by all DER owners ($\sum_{i=1}^{I} R_{it}(\xi)$) and the aggregated day-ahead commitment (α_t^{DA}) in terms of surplus ($\beta_t^+(\xi)$) and shortage ($\beta_t^-(\xi)$), both at an aggregated level. In constraint (2c), the amount of aggregated generation becomes the upper-bound for the amount of energy that can be sold in the real-time market. Constraint (2f) enforces non-negativity for all decision variables involved.

4 Solution Approach

A sampling-based approach is used to solve the problems (1a)-(1f) (for individual DER participation) and (2a)-(2f) (for aggregated DER participation). Without a sampling-based approach, both presented problems become intractable, as each random variable can account for an infinite number of possible realizations across all time periods and consumers. Thus, a sampling-based approach discretizes these infinite number of possible realizations into managable number of scenarios, which converts the problem into a tractable form that can consider uncertainty and maintain computational feasibility. In this way, the distribution of random variables corresponding to surplus energy and real-time electricity price for each consumer and time period will be represented as a finite, discrete set of scenarios with the same probability of occurrence. The set of scenarios can be generated from historical data, and then, the stochastic parameters and variables become scenario-dependent parameters and variables indexed as $\xi_s \ \forall s \in S$ [17]. By redefining second-stage decision variables and stochastic parameters into scenario-dependent parameters, constraints are duplicated for each scenario to ensure that all decision variables respect its scenario-specific realizations. Consequently, the expected cost accounted in the objective function (3a) and (4a) is also rewritten as the probabilistic summation of costs over all scenarios.

Based on the sampling-based approach, the problems (1a)-(1f) can be converted into (3a)-(3f) and formulated as a mixed-integer linear program for each individual DER owners $i \in I$ as the following.

$$\max \quad \sum_{t\in T}\left(P_t^{DA}x_{it}^{DA}\right) + \sum_{s\in S}\pi_s \sum_{t\in T}\left(P_t^{RT}(\xi_s)y_{it}^+(\xi_s) - P_t^{PN}y_{it}^-(\xi_s)\right) \tag{3a}$$

$$\text{s.t.} \quad R_{it}(\xi_s) - x_{it}^{DA} = y_{it}^+(\xi_s) - y_{it}^-(\xi_s) \quad \forall t \in T, \forall s \in S \tag{3b}$$

$$R_{it}(\xi_s) \geq y_{it}^+(\xi_s) \quad \forall t \in T, \forall s \in S \tag{3c}$$

$$y_{it}^+(\xi_s) \leq M z_{it}(\xi_s) \quad \forall t \in T, \forall s \in S \tag{3d}$$

$$y_{it}^-(\xi_s) \leq M(1 - z_{it}(\xi_s)) \quad \forall t \in T, \forall s \in S \tag{3e}$$

$$x_{it}^{DA} \geq 0, y_{it}^+(\xi_s) \geq 0, y_{it}^-(\xi_s) \geq 0, z_{it}(\xi_s) \in \{0,1\} \quad \forall t \in T, \forall s \in S. \tag{3f}$$

The model regarding aggregated DER participation (2a)-(2f) can be also be converted and formulated as a mixed-integer linear program, shown in the below equations (4a)-(4f).

$$\max \quad \sum_{t\in T}\left(P_t^{DA}\alpha_t^{DA}\right) + \sum_{s\in S}\pi_s \sum_{t\in T}\left(P_t^{RT}(\xi_s)\beta_t^+(\xi_s) - P_t^{PN}\beta_t^-(\xi_s)\right) \tag{4a}$$

$$\text{s.t.} \quad \sum_{i\in I} R_{it}(\xi_s) - \alpha_t^{DA} = \beta_t^+(\xi_s) - \beta_t^-(\xi_s) \quad \forall t \in T, \forall s \in S \tag{4b}$$

$$\sum_{i\in I} R_{it}(\xi_s) \geq \beta_t^+(\xi_s) \quad \forall t \in T, \forall s \in S \tag{4c}$$

$$\beta_t^+(\xi_s) \leq M z_t(\xi_s) \quad \forall t \in T, \forall s \in S \tag{4d}$$

$$\beta_t^-(\xi_s) \leq M(1 - z_t(\xi_s)) \quad \forall t \in T, \forall s \in S \tag{4e}$$

$$\alpha_t^{DA} \geq 0, \beta_t^+(\xi_s) \geq 0, \beta_t^-(\xi_s) \geq 0, z_t(\xi_s) \in \{0, 1\} \quad \forall t \in T, \forall s \in S. \tag{4f}$$

5 Numerical Experiment

In this section, we present and discuss the results obtained from various numercial experiments to fully analyze the economic value of aggregation. To do so, we compare the results of the presented cases, individual DER participation and aggregated DER participation, by optimizing commitment decisions under equivalent circumstances. Experiments are conducted upon data which is obtained from the Pecan Street Inc. Dataport [18] which includes electricity demand, amount of solar generation, day-ahead prices, and real-time prices for Texas households from 2018. From this dataset, 19 houses were selected as individual DER owners and each day's data were treated as one realized scenario for uncertainty. Electricity demand, solar generation, and price data were provided in 15-minute intervals, and for price data, four consecutive intervals were averaged to represent hourly prices.

To account for uncertainty in the data, random noise was introduced into the electricity demand, solar generation, and price data. Noise was applied by multiplying the original values with a randomly generated factor. For each individual DER owner, time interval, and scenario, the noise factor was drawn uniformly from the range $[0.5, 1.5]$. This process introduces variability into the dataset, simulating real-world fluctuations in electricity demand, solar energy output, and price data. By incorporating these uncertainties, we enable an analysis of the optimization model's robustness under different levels of variability.

Penalty costs were set at twice the day-ahead prices of each hour to prevent individuals or aggregators from overconfident commitment decisions. For solar generation, the sum of four 15-minute intervals was used to approximate hourly generation. As we treat individual DER owners as prosumers, we subtract the given electricity demand from the amount of solar generation to calculate the surplus energy available for prosumers to utilize in energy market transactions. Numerical experiments for the optimization tasks were conducted using GUROBI 11.0.2 [19], on an Intel Core i9-13900K processor with 32.00 GB of RAM.

5.1 Economic Values of Aggregation

The economic values of aggregation can be evaluated based on total profits, as the objective function of the optimization model for both individual and aggregated DER participation is to maximize profit. This allows for a direct comparison of the financial performance between individual DER participation and aggregated DER participation.

Table 2: Profit Comparison

	Individual DER Participation	Aggregated DER Participation
Profit ($)	10992.73	12372.77

The total profits of individual DER participation and aggregated DER participation are summarized in Table 2. Aggregated DER participation yields a higher total profit compared to individual DER participation. This demonstrates the economic significance of aggregation, as pooled management of DERs enables more efficient market participation and better utilization of surplus energy.

Table 3: Specified Profit Comparison

	Individual DER Participation	Aggregated DER Participation
Day-Ahead Profit ($)	2945.38	10698.74
Real-Time Profit ($)	8618.07	2055.51
Penalty Cost ($)	570.72	381.47

For further analysis, Table 3 provides a detailed breakdown of profits from day-ahead and real-time markets, as well as penalty costs. The following observations can be made:

- Day-ahead profit: Aggregated DER participation achieves significantly higher day-ahead profits than individual DER participation. As shown in Table 4, this is attributed to the aggregation's ability to commit larger amounts of energy in the day-ahead market, reducing exposure to real-time market uncertainties.

- Real-time profit: In contrast, individual DER participation exhibits higher real-time profits compared to aggregation, likely due to its reliance on real-time adjustments rather than day-ahead commitments. As Figure 1 shows, the average of real-time prices are generally lower than day-ahead prices. Thus, relying on real-time energy transaction leads to missed opportunities for greater profitability. However, as individuals burdened of risks regarding penalty costs, they are invoked to make conservative day-ahead commitments and depend more on real-time transactions.

- Penalty cost: Aggregated DER participation incurs lower penalty costs compared to individual DER participation, highlighting its ability to minimize deviation from committed energy levels. Whereas, individual DER owners, lacking tools to mitigate their generation variability, have to bear penalty costs individually.

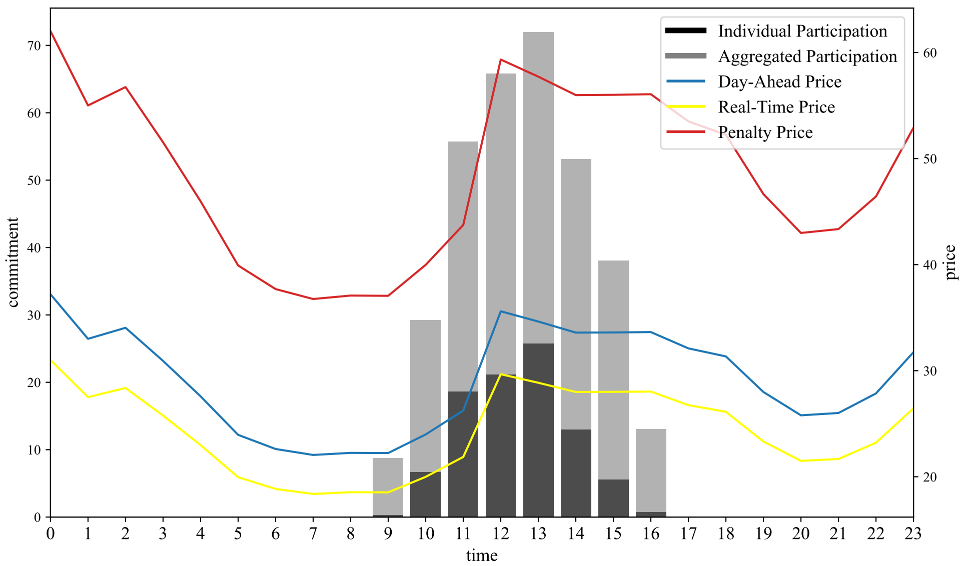

Figure 1: Hourly Commitment Differences Associated with Hourly Price Fluctuations

The daily commitment levels for individual and aggregated DER participation are presented in Table 4. Aggregated DER participation achieves a significantly higher average daily commitment compared to individual DER participation. Individual DER owners commit to the market in a conservative manner due to the high penalty costs associated with unmet commitments. However, even if surplus and shortage in generation occur randomly among participants as illustrated in Figure 2, the variability is balanced within the pool. Thus, the risks of deviations are significantly reduced at the aggregated level. Participants who contribute more surplus energy can be compensated through a profit remuneration process, and participants who face shortages benefit are reduced of one's risk. Thus, leading individuals to make more confident commitment decisions. This stability not only optimizes the management of pooled resources but also generates profits that could not have been achieved through individual participation alone. Aggregation thereby promotes both resource management efficiency and greater net profit for both system-wise and individually.

Table 4: Daily Commitment Comparison

	Individual DER Participation	Aggregated DER Participation
Total Surplus Energy (kW)	405.84	405.84
Day-Ahead Commitment (kW)	91.66	335.78
Real-Time Transaction (kW)	314.18	70.06

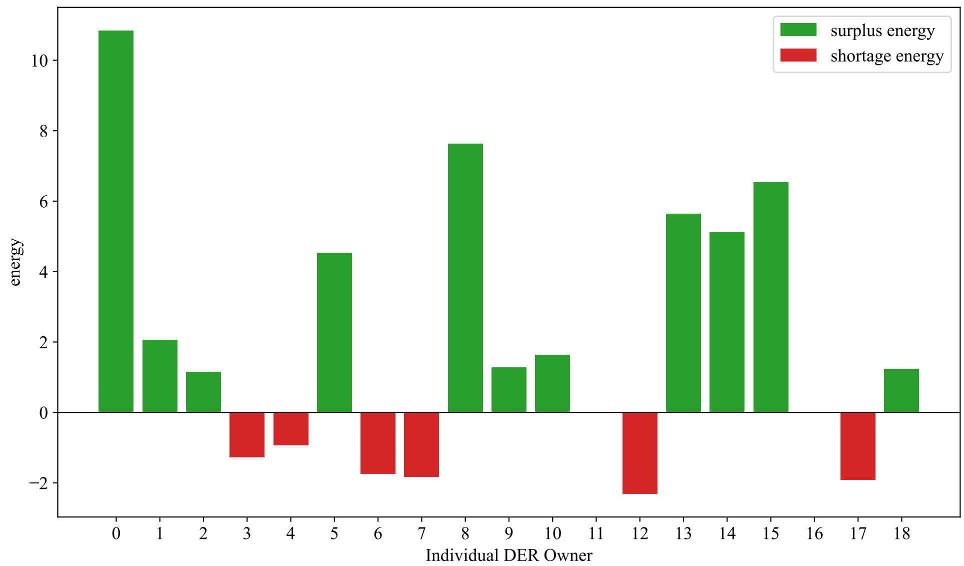

Figure 2: Individual Deviation from Commitment Decision in Hour 13 Scenario 3

5.2 Impact of Variability

We evaluated the value of the stochastic solution (VSS) [17] to highlight the necessity of a two-stage stochastic approach in addressing variability and uncertainty in decision-making. The VSS measures the cost of ignoring uncertainty by comparing the performance of a solution derived under stochastic optimization to the performance of a wait-and-see solution, which is obtained using the expected values of uncertain parameters. In stochastic programming, wait-and-see solutions refer to decisions made based on a single expected scenario, where all random variables are replaced by their expected values. By comparing the VSS of wait-and-see solutions and the solutions from the proposed model, we analyzed how increasing randomness impacts the results, validating the model's effectiveness for both individual and aggregated DER participation.

To derive wait-and-see solutions, an expected value problem (EV) is formulated by replacing all random variables with their expected values, as follows:

$$EV = \min_{x} z(x, \bar{\xi}), \tag{5}$$

where EV represents the deterministic objective function value obtained under the expected scenario. Here, the random variables $R_{it}(\xi_s)$ and $P_t^{RT}(\xi_s)$ are replaced with $R_{it}(\bar{\xi})$ and $P_t^{RT}(\bar{\xi})$, respectively. The performance of EV across all possible scenarios is evaluated using the optimal solution of EV, defined as $\bar{x}(\bar{\xi})$. To assess the performance of $\bar{x}(\bar{\xi})$ across all possible scenarios, we compute the expected result of using $\bar{x}(\bar{\xi})$ (EEV), defined as:

$$EEV = \mathbb{E}_{\xi} z(\bar{x}(\bar{\xi}), \xi), \tag{6}$$

where EEV measures how $\bar{x}(\bar{\xi})$ performs, allowing second-stage decisions to be chosen optimally as functions of $\bar{x}(\bar{\xi})$ and ξ. This involves applying $\bar{x}(\bar{\xi})$ to all scenarios ξ to compute the corresponding objective function values. In contrast, RP represents the objective function value obtained by solving the stochastic problem directly, where all scenarios are considered during the decision-making process. The VSS is then calculated as:

$$VSS = EEV - RP, \tag{7}$$

where VSS quantifies the potential benefit of considering variability and uncertainty in decision-making, representing the improvement in performance achieved by solving the stochastic problem instead of relying on the expected value solution. In maximization problems, a negative VSS indicates that the two-stage stochastic model achieves a higher objective value (RP) than the expected performance of the expected value solution (EEV).

Using these procedures, we derived the RP, EEV, and VSS for both models. Additionally, we adjusted the randomness of the sampled data to evaluate how higher randomness, corresponding to greater variability within scenarios, impacts the results. The randomness was categorized into three levels: low, medium, and high. The medium randomness, which serves as the baseline, applies a noise factor uniformly drawn from the range $[0.5, 1.5]$. In comparison, low randomness uses a narrower range of $[0.8, 1.2]$, while high randomness expands the range to $[0.2, 1.8]$, reflecting lower and higher levels of variability, respectively. The overall results of RP, EEV, and VSS for the individual and aggregated DER participation models under varying levels of randomness are summarized in Table 5.

Table 5: Comparison of RP, EEV, and VSS under Different Randomness Levels

Randomness	Individual DER Participation			Aggregated DER Participation		
	RP	EEV	VSS	RP	EEV	VSS
Low	10328.92	9747.65	-581.27	11015.43	10896.34	-119.09
Medium	10992.89	9250.52	-1742.38	12372.78	12069.92	-302.86
High	13181.51	10096.13	-3085.38	14950.21	14482.04	-468.17

As shown in Table 5, the proposed models effectively produced variability-aware solutions by adopting a two-stage stochastic approach for the DER model. Since the proposed model aims to maximize profit, a larger RP relative to EEV, resulting in a negative VSS, is preferred. For all models and levels of randomness, the VSS are negative, indicating that accounting for the variability in real-time prices and surplus energy is effective for generating robust solutions. Moreover, the VSS decrease for both DER models as randomness increases. This demonstrates that as the variability in real-time prices and generated surplus energy increases, two-stage stochastic programming models become essential for maximizing profits and ensuring robust solutions.

5.3 Remuneration of Profit

In this subsection, we address the post-aggregation process. As shown in Table 2, commitment made in aggregated levels result in higher system-wide profits compared to when commitments are made individually. To ensure the sustainability of aggregation, fair distribution of profits among the participants is essential. As shown in Table 6, the withdrawal of participants from aggregation reduces the significance of the pooling mechanism and ultimately threatens the stability of the aggregation system.

Table 6: Aggregation Effect Regarding the Number of Participants

Number of Participants	5	10	15
Individual DER Participation ($)	3821.97	7343.6	9582.41
Aggregated DER Participation ($)	4129.52	8115.26	10738.05
Profit Differences (%)	8.05	10.51	12.06

Freeman et al. [20] discuss two approaches regarding profit remuneration, either ex-ante or ex-post. Yet, ex-ante distribution poses challenges due to uncertainties in unrealized future scenarios. Especially, due to renewable energy generation variability and market price fluctuations, the accurate contributions of each participant is hard to estimate beforehand. Since misalignment between estimated and realized contributions can lead to perceptions of unfairness, we propose a ex-post method for profit remuneration. Our method takes considers both the hourly contribution of surplus by each individual DER owners and the corresponding day-ahead price at the time of contribution. In this way, participants who provided more surplus energy during periods of higher day-ahead prices are secured of higher profit remuneration.

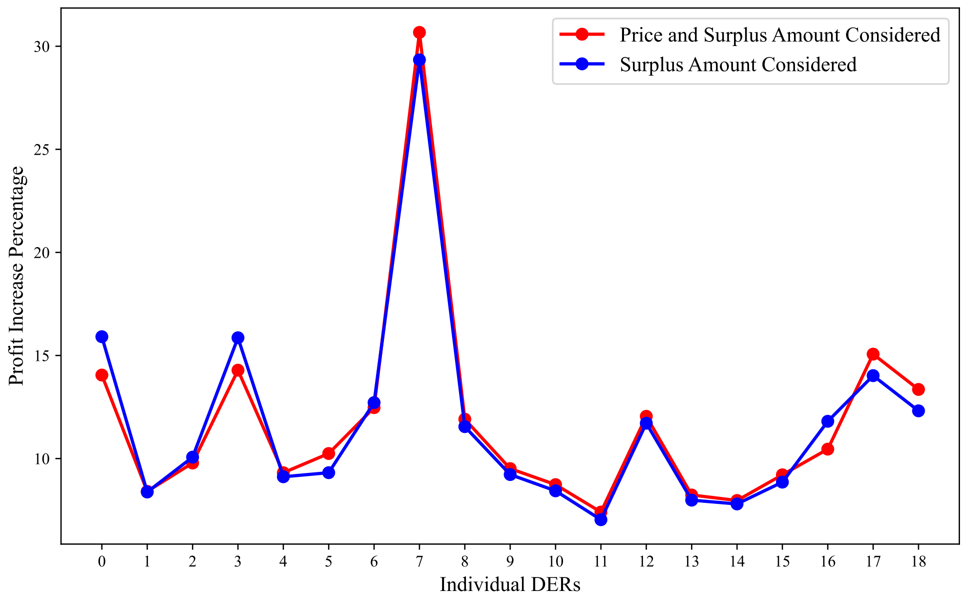

Figure 3: Profit Differences Regarding remuneration Methods

To validate the fairness of our method, we compared it to a simpler approach where remunerations standards only considered contributions of hourly surplus energy, without considering price differences. As shown in Figure 3, 26.31% of the participants (individuals 0, 2, 3, 6, 16), can perceive that they are undercompensated of their contributions, as their contributions made during hours of higher day-ahead prices were not reflected.

Therefore, when both the day-ahead price and the surplus energy contributed by each household are considered for each hour, the additional profit received by each DER owner is as shown in Table 7. This ensures that individual DER owners who provides more surplus energy during hours of higher day-ahead prices are rewarded proportionally to one's contribution to the aggregated profit; conseqently, aggregation remains sustainable.

Table 7: Individual Profit Increase by Participating in Aggregation

DER owner	Individual Participation Profit ($)	Aggregated Participation Profit ($)	Increase (%)
0	912.56	1040.78	14.05
1	595.73	645.82	8.40
2	941.71	1033.85	9.78
3	824.58	942.37	14.28
4	547.21	598.17	9.31
5	511.60	564.01	10.24
6	1159.64	1304.27	12.47
7	820.22	1071.79	30.67
8	423.17	473.56	11.90
9	606.97	664.70	9.51
10	371.07	403.49	8.73
11	87.75	94.24	7.40
12	664.97	745.09	12.04
13	533.53	577.46	8.23
14	581.47	627.78	7.96
15	467.51	510.57	9.21
16	91.94	101.55	10.45
17	498.09	573.13	15.06
18	352.92	400.04	13.35

6 Conclusion

In this study, we have addressed the economic value of aggregation in distributed energy resource systems and investigated its impact both at the system-wide level and on individual DER owners. To evaluate this, we developed a two-stage stochastic programming model that considers uncertainties in renewable generation and real-time price fluctuations. The Individual DER Participation model explains the scenario in which individual DER owners independently participate in the energy market. Meanwhile, the Aggregated DER Participation model illustrates the scenario where individuals trade energy in the market through an aggregator. By comparing between the two cases, our findings establish the significance of pooling mechanisms in stabilizing the inherent randomness of renewable energy generation. Aggregation not only can reduce deviation penalties and leverage collective resources to enhance system-level efficiency, but can also provide individual DER owners with elevated profit and reduced market risks.

The computational results showed that aggregation significantly enhances the economic and operational performance of DER participation, achieving 12.55% higher total profits compared to individual DER participation. Aggregation enables better resource pooling and risk mitigation, demonstrating its value in enhancing market efficiency and stabilizing decentralized energy systems. Moreover, by calculating the value of the stochastic solution across various levels of randomness, we demonstrated that a two-stage stochastic programming model effectively accounts for variability and uncertainty, further validating the benefits of aggregation. A comparative analysis between two cases, individual DER participation and aggregated DER participation, demonstrated the tangible benefits of aggregation in increasing the amount of day-ahead commitment, reducing penalty costs, and increasing net profits. Lastly, an ex-post profit remuneration method was proposed to ensure sustainability and fairness among aggregation participants.

While this study provides insight into system-wide benefits at the macroscopic level and impact at the microscopic level on individual DER owners, there still remain several aspects to consider in the future to increase the practicality and applicability of the proposed model. First, we can expand the model to incorporate cases where both DER owners and aggregators have storage availabilities. In the proposed model, the unavailability of storage incentivized individual DER owners to sell all residual energy, even when real-time price is low. By introducing storage flexibility, this model allows DER owners and aggregators to store or sell energy strategically as the price fluctuates. This structural expansion is expected to affect the degree of real-time market participation and influence the net profit of DER owners and aggregators, allowing more realistic and dynamic representation of market behavior. Second, addressing the issue of profit remuneration is critical to ensuring the sustainability of aggregation. For individual DER owners to not deviate from the aggregation coalition, it is essential to consider equity in the distribution of profits among participants. Future models should determine ways to incorporate equity, directly into the commitment decision process, to ensure fair outcomes for all participants beforehand of commitment.

In conclusion, this study highlights the significance of aggregation as a tool for increasing profits and mitigating risks of individual DER owners. By providing a quantitative foundation for its significance, this research contributes to the optimization of DER system by revealing the potential for aggregators to play a key role in stabilizing decentralized energy markets.

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