

RESEARCH ARTICLE

Selection Game for Consensus-Based Decentralized Aggregators of Distributed Energy Resources in a Blockchain Ecosystem

ZHENYA JI¹, (Member, IEEE), HAO LI¹, YUQING BAO¹, (Member, IEEE),

WEI WANG¹, (Member, IEEE), XUELIANG HUANG², (Member, IEEE),

ZHONG CHEN², (Member, IEEE), ZIQI ZHANG², AND YE RUI³

¹School of Electrical and Automatic Engineering, Nanjing Normal University, Nanjing 210046, China

²School of Electrical Engineering, Southeast University, Nanjing 210096, China

³Beijing East Zhongtong Technology Development Company Ltd., Beijing 102200, China

Corresponding author: Zhenya Ji (jizhenya@njnu.edu.cn)

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ABSTRACT Aggregators can be effective in organizing distributed energy resources (DERs) for smart grids and electricity markets. The recent development of blockchain and peer-to-peer (P2P) networks provides a new ecosystem for aggregating DERs. Initial studies have mainly used off-the-shelf consensus, which may struggle to balance node sizes and computational intensities. Moreover, the dynamics of DERs changing their selection among multiple aggregators over time are rarely considered in most related literature. This freedom of selection, which is encouraged by the electricity market, can be better activated by a blockchain. In this study, a game-dynamic-based selection framework for multiple aggregators of DERs is proposed in a decentralized blockchain ecosystem. First, a proof-of-dual-credibility (Po2C) protocol is established so that DERs in such an aggregator can reach consensus. At the same time, for one DER node, both an unavoidable objective credit and a malicious subjective credit constitute its credibility with different weights. Then, a function with triple payoffs motivates DERs in terms of both the physical characteristics of being power supply devices and P2P nodes, the latter including consensus winning and data propagation. Third, the selection game of DERs among aggregators is modeled as an evolutionary game under replicator dynamics to find equilibrium. Numerical simulations with two and four aggregators show general stability in the selection game of DERs. Performance achieved with different consensus and incentives are compared as well. The framework shows its great potential to organize DERs in a decentralized but aggregated mechanism in open electricity markets.

INDEX TERMS Aggregation, consensus protocol, distributed generator, equilibrium, game dynamics, peer-to-peer network.

I. INTRODUCTION

A. MOTIVATIONS

Developing a smart, low-carbon power grid involves the integration of distributed energy resources (DERs), such as micro renewable energy generators, flexible loads, electric

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vehicles, energy storage systems, *etc.* [1]. The rapid diffusion of these various and numerous DERs poses a great challenge to power systems. Compared with traditional grid-side generators, these consumer-side DERs are much smaller in capacity, more geographically dispersed, and more complex to schedule due to different uncertainties [2]. Thus, aggregators are widely adopted to act as an intermediary between power system operators and DERs [3]. For instance, the Federal

Energy Regulatory Commission (FERC) in the U.S. issued a notice that would require transmission organizations and system operators to create rules to enable aggregated DERs to participate in wholesale markets. An open market allows DER individuals to select among many aggregators in which it is willing to participate [4].

With the help of DER aggregators, the scheduling pressure of power system operators can be shifted downstream [5]. However, aggregators themselves have to find an effective way to organize profit-seeking DER individuals and their volatile outputs. At the same time, competitors emerge in the open electricity market environment. In the traditional form of centralized organization, there must be a central unit with which each DER has to establish interactive communication, putting significant pressure on reliability and expandability. In addition, the cybersecurity of centralized aggregators must be carefully addressed [6].

Recently, blockchain-enabled ecosystems in the energy sector, especially in smart grids, have been developed, and they can be utilized as a decentralized and self-organized intermediary with a guarantee of transparency and tamper resilience [7]. This thriving technology is envisaged as promising to overcome the challenges of centralized systems. At the same time, the peer-to-peer (P2P) network allows one individual node to share sources or data directly to others, without relying on a centralized controller [8]. That is, DERs can organize as nodes allowing P2P communication among any individuals. Aggregators from these DERs forms a typical P2P network. A blockchain-enabled P2P network can theoretically provide an equal, trusted, and open-access environment for power trading and settlement. Thus, in such a blockchain-enabled aggregator, a centralized organization is no longer needed, and DERs can autonomously organize themselves and the aggregator they select to join [9].

A growing number of studies are interested in designing blockchain-enabled energy communities. Related topics include trading energies [10], supporting P2P trades [11], motivating prosumers [12], etc. Pilot projects, e.g., the Brooklyn microgrid [13], have also been reported. Meanwhile, there are still some questions that need to be further answered, which constitutes the main motivations of this paper. (Q1) Which kind of consensus should be adapted for DER peers in a blockchain-enabled aggregator? (Q2) What properties should be incentivized for DERs in a blockchain-enabled aggregator? (Q3) Do DER individuals behave as they would in an open electricity market when selecting among multiple aggregators?

B. RELATED WORKS

Some recent works can be introduced to further depict the three questions that are essential to establish a decentralized aggregator of DERs above.

For an arbitrary blockchain ecosystem, one of the essential problems is to find an appropriate consensus protocol. This also corresponds to the first question, Q1, here. Individuals are expected to reach an agreement, i.e., consensus, based on

specific properties. A straightforward approach is to directly adopt an off-the-shelf protocol, e.g., the Byzantine fault tolerant (BFT) protocol in [10], [12] or the proof-of-work (PoW) protocol applied in [11] and [14].

Various BFT protocols are developed to tolerate Byzantine attacks and random failures. On the other hand, the PoW protocol achieves consensus by making nodes compete to win a puzzle-solving process [15]. The different principles result in advantages and drawbacks for each of these two types of protocols, and it is difficult to strike a balance between complexity and intensity [16]. For a large population of DERs, an appropriate consensus paradigm must be carefully chosen and improved [17].

The second question, Q2, further affects the design of consensus, which is closely related to Q1. While traditional centralized aggregators are generally concerned with the energy characteristics of DERs, most studies with the blockchain structure tend to focus on their nature as nodes. Considering that the original PoW wastes too many resources on solving an unnecessary hash puzzle, the puzzle-solving race can be changed into the rank of other characteristic. In specific, when this characteristic is a certain type of credit, a Proof-of-Credit (PoC) consensus can be developed under the PoW paradigm. For Internet-of-Things (IoT) devices, a credit-based PoW consensus is proposed in [18], where the credit is defined as their obedience to system rules. Another PoC blockchain protocol for electronic currency transactions is presented in [19], where the credit is defined as a special stake that quantifies how much the activities of nodes are beneficial to the whole system.

Although there are some consensus for DERs, it is still in the early stage of development and needs some specific improvement. On the one hand, unlike traditional incentive models in centralized aggregators, DERs in decentralized P2P networks need to take on more functions in terms of information propagation and consensus [20], which should also be reflected. On the other hand, uncertainties in DER outputs are inevitable, so it may not be appropriate to use only this single dimension to evaluate their credits [21].

The third question, Q3, evolves the dynamics in which the DERs select among multiple aggregators and corresponding equilibrium over time. Blockchain-enabled aggregators can better establish an open environment, which has a great positive effect on non-monopolistic electricity markets in the real world.

Existing studies generally do not focus on the freedom of selection for DERs. It is a general default that DERs always participate in the same aggregator given initially and have no freedom to change, e.g., in [22] and [23]. In another case, there is only one aggregator, either for the traditional centralized structure, e.g., in [24], or the P2P structure, e.g., in [25].

Once the aggregator-selection of DERs is considered, the equilibrium dynamics should be studied as well. Although there are few studies specifically on this topic, the balance of energy production and consumption within an aggregator

or among multiple aggregators can provide some examples. Game dynamics are considered in [26], while equilibrium is obtained inside one P2P trading network. By using a leading energy sharing node, the equilibrium of the demand response of DERs is achieved under a leader-follower game [27]. The evolutionary game in [28] shows the solvability of curtailed load amounts for DERs to obtain evolutionary stability.

C. CONTRIBUTIONS

This paper is motivated to fill the gaps when answering the three inevitable questions. The main contributions of this paper are organized as follows.

- 1) A novel framework is organized to aggregate DERs in a decentralized manner with the freedom of selection. Derived from the PoC consensus, a more comprehensive proof-of-dual-credibility (Po2C) is proposed along with its payoff mechanism. In specific, the dual credibility constitutes two inherent features of DERs as power devices and P2P nodes, and is measured by the uncertainties that DERs may behave.
- 2) To better reflect the freedom and dynamics that DERs should have among aggregators, their aggregating process is mathematically described as game dynamics. Furthermore, the proportional imitation rule is used to obtain evolutionary stability among a population of DERs.
- 3) Numerical simulations verify that, in the proposed framework, free selections of DERs among multiple aggregators can be activated. This process is independent of the distributions at previous time intervals. Moreover, the prescheduled powers of aggregators and the payoffs of being power supply devices and P2P nodes for DERs are the factors that determine the equilibrium states of each selection.

The remainder of this paper is organized as follows. To answer Q1 along with Q2, Section 2 presents the proposed framework of blockchain-enabled aggregators for DERs and formulations of the Po2C consensus protocol and the incentive model. As a response to Q3, a theoretical analysis of equilibrium for aggregator-selection dynamics by DERs is provided in Section 3. Section 4 demonstrates the case study and results. The conclusion is discussed in Section 5.

II. FRAMEWORK AND CONSENSUS OF BLOCKCHAIN-ENABLED AGGREGATORS FOR DERs

This section presents how DERs can perform and select aggregators as a blockchain ecosystem. Necessary models, i.e., consensus and incentives for DERs, are also provided.

A. FRAMEWORK

DERs include not only distributed generators (DGs) in the distribution networks, e.g., rooftop photovoltaic units, microturbines, and stationary energy storage devices, but also demand-side resources (DRs) that can adjust load profiles, e.g., electric vehicles, temperature-controlled loads, dryers, *etc.* DERs are often equipped with advanced

controlling, metering, and communicating functionalities. Therefore, DERs can be organized autonomously through P2P and blockchain technologies for a decentralized aggregator.

The P2P links can be built over nodes in a blockchain-enabled network. The term node refers to a logical entity, which means a physical device is allowed to be associated with different functionalities and with multiple networks [16]. A node can not only provide the primary functionality of data propagation by maintaining routes but can also win the leadership competition in a decentralized consensus protocol. With the development of smart-grid-related technologies, e.g., IoT devices and the edge computing infrastructure, DERs can behave as autonomous, distributed, and multifunctional nodes in a blockchain ecosystem [18].

Blockchain networks were initially intended to be completely decentralized in blockchain practices. Due to the explosion of computational capability, it is common for individual nodes to join a so-called mining pool to increase their chance of sharing the winning of mining competitions. Thus, many theoretical studies and practices suggest that individuals are free to choose and join different mining pools. This is similar to the organization of power scheduling, e.g., aggregators in electricity markets. The decentralized self-regulating ability enabled by the blockchain ecosystem can be adapted for aggregating autonomous DERs.

Specifically, enabled by a blockchain, an aggregator of autonomous DERs can operate as a network without any single authority. Moreover, an arbitrary DER in one of these aggregators can be selected to join another aggregator as desired. The proposed framework for the DER components in a blockchain-enabled decentralized aggregator is shown in Figure 1. The following settings are introduced without disrupting the equity of decentralized DERs or being incompatible with the rules of mainstream electricity markets.

DERs can constitute nodes in the ecosystem by adapting their consensus. They are not only devices capable of supplying power but also providing necessary functionalities. They become a peer in the network that activates propagation, consensus participation, etc. Codes can be implemented in DERs to make the process fully automated and unmanned.

A P2P network is created among multiple DER nodes as peers. To boost participation without undermining scalability, peers communicate in a gossip manner, similar to the Bitcoin network. Instead of communicating with a centralized node or with each other, each DER selects a small number of random peers to gossip with and does not require a full connection as topology. In addition, one peer can act as a public bulletin board between an external electricity market or grid and the aggregator, exchanging information about the power supply, electricity prices, etc. However, decisions are still decentralized and made by individuals with no centralized control node.

Once such blockchain-enabled aggregators are established, DERs can freely choose to participate in an aggregator. As time changes, they can also select another aggregator.

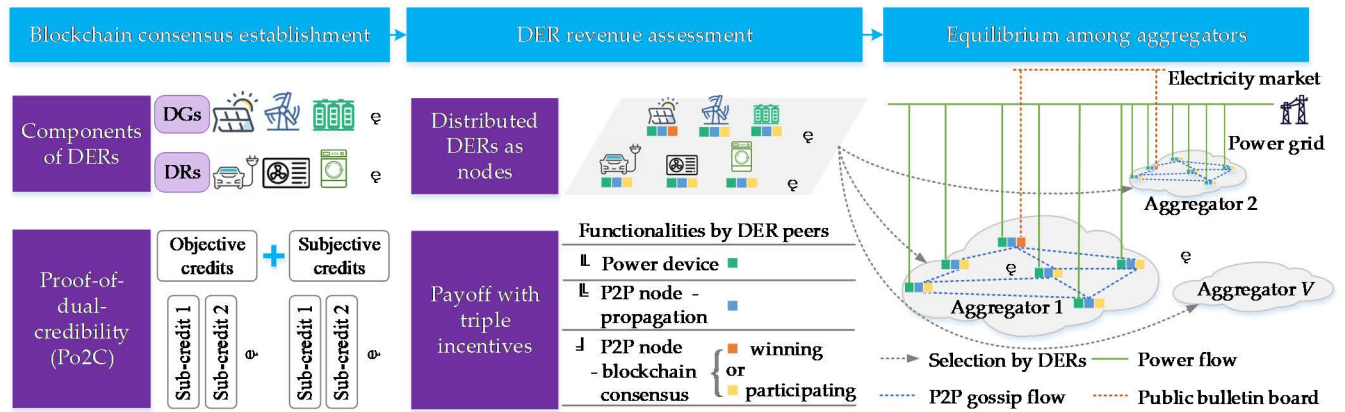


FIGURE 1. Framework for the components and selections of DERs among blockchain-enabled decentralized aggregators.

For one time interval, a DER can select only one aggregator to participate with its power supply sold entirely to it. Naturally, each DER can be seen as a rational and profit-driven individual to maximize its payoff. Thus, the Nash equilibrium among aggregators can be analyzed as an evolutionary game with stability.

B. Po2C CONSENSUS

The organization of P2P nodes is related to the consensus adopted in a blockchain. Many consensus mechanisms have bloomed in the past decade for different applications. A summary of the two most widely adopted consensus paradigms in various blockchains, i.e., BFT and proof-of-concept (PoX), is provided in Table. 1.

BFT consensus protocols, e.g., PBFT and Paxos, are widely adopted in blockchains for government and corporate affairs. This type of protocol may award a first-mover advantage for adopters, e.g., PFBT applied in Hyper-Ledger Fabric [29]. In some energy-related blockchains, e.g., energy trading transactions, as aforementioned, it can also be adopted by default. However, for these BFT protocols, a fully connected topology among consensus nodes and a leader-peer hierarchy with three-way handshakes are necessary. This leads to a communication complexity of $\Theta(n^2)$, where n is the total number of nodes in a network [16].

TABLE 1. Two typical consensus paradigms in P2P networks.

Paradigm	BFT	PoX
Merits	Deterministic agreement guaranteed Low processing latency	Low communication complexity Good network scalability
Demerits	High communication complexity Low scalability	Limited consensus finality High processing latency
Typical applications	Small-scale network with centralized admission control	Large-scale network with decentralized self-regulation

In the past few years, with the advent of the Nakamoto protocol in Bitcoin, also known as PoW, various PoX-based protocols have rapidly emerged. In each consensus round of a PoX-based protocol, nodes prove that they have a particular capability, usually by competing to perform a complex but easily verifiable task, and the winning node obtains credit. In contrast to BFT-based protocols, P2P nodes accept the received block proposal following the longest-chain rule after they verify the validity of the block. Since no all-to-all messaging phase in three-way handshakes is needed, a PoX-based protocol may have a complexity of $\Theta(n)$, much smaller than the $\Theta(n^2)$ complexity in BFT [16].

As shown in Table 1, the BFT paradigm may not be suitable for aggregating DERs that are widely distributed and have a large population. The PoX-based paradigm is a more appropriate solution but needs to overcome several aspects. The first is the high degree of electricity depletion and computation intensity in the traditional PoW protocol. The second is the ability to handle subjective deceptions and objective errors. Unlike financial applications such as virtual currency, DERs may suffer from unintentional and uncontrollable errors and deviations in forecasts, fluctuations, etc. [30], which are often neglected in most existing PoX-based protocols for DERs. Thus, in the PoX-based paradigm, a Po2C consensus is organized as follows.

In PoX-based protocols, each node should prove to what extent it can contribute and win in a consensus round, e.g., the hash rate in crypto mining. In the proposed Po2C, the required proof is determined by a dual credibility rate, which considers two types of credits regarding objective and subjective uncertainties. For example, prediction deviations between planned and actual powers are inevitable for some DERs, and thus it belongs to the objective type. As another example, as a P2P node, a DER may randomly tamper with the message that it propagates, at which point this uncertainty is of the subjective type. Four typical kinds of uncertainties are categorized in Table 2. Other types can be incorporated by adding more sub-credits.

TABLE 2. Typical kinds of uncertainties with sub-credits and coefficients.

Uncertainty kind	Feature	Typical case	Sub-credit	Sub-coefficient
Objective	Power device	Prediction deviations	$C_{it}^{\text{obj},1}$	$\varphi_v^{\text{obj},1}$
	P2P node	Communication failures	$C_{it}^{\text{obj},2}$	$\varphi_v^{\text{obj},2}$
Subjective	Power device	Revocation of scheduled outputs	$C_{it}^{\text{sub},1}$	$\varphi_v^{\text{sub},1}$
	P2P node	Malicious tampering of messages	$C_{it}^{\text{sub},2}$	$\varphi_v^{\text{sub},2}$

Thus, for DER node i , its dual-credibility rate C_{ivt} when selecting aggregator v at time interval t is represented as

$$C_{ivt} = \varphi_v (C_{it})^T \quad (1)$$

in which

$$\varphi_v = \left[\varphi_v^{\text{obj},1} \quad \varphi_v^{\text{obj},2} \quad \varphi_v^{\text{sub},1} \quad \varphi_v^{\text{sub},2} \right] \quad (2)$$

$$C_{it} = \left[C_{it}^{\text{obj},1} \quad C_{it}^{\text{obj},2} \quad C_{it}^{\text{sub},1} \quad C_{it}^{\text{sub},2} \right] \quad (3)$$

where φ_v and C_{it} are vectors representing coefficients and credits, $\varphi_v^{\text{obj},1}$, $\varphi_v^{\text{obj},2}$, $\varphi_v^{\text{sub},1}$ and $\varphi_v^{\text{sub},2}$ are sub-coefficients in aggregator v , $C_{it}^{\text{obj},1}$ and $C_{it}^{\text{obj},2}$ are the objective sub-credits for DER node i at time interval t , $C_{it}^{\text{sub},1}$ and $C_{it}^{\text{sub},2}$ are the subjective sub-credits for DER node i at time interval t .

While values of φ_v can be given, C_{it} are updated based on their credits in dealing with uncertainties at each consensus round as follows

$$C_{it}^{\text{obj},x} = C_{i(t-1)}^{\text{obj},x} + \eta^{\text{obj}} \varepsilon_{i(t-2)}^{\text{obj},x} \quad (4)$$

$$C_{it}^{\text{sub},x} = \begin{cases} C_{i(t-1)}^{\text{sub},x} + \eta_h \left| \log C_{i(t-2)}^{\text{sub},x} \right| & \text{if } i \in \Omega_h \text{ at } t \\ \eta_m C_{i(t-1)}^{\text{sub},x} & \text{if } i \in \Omega_m \text{ at } t \end{cases} \quad (5)$$

where x refers to the index of 1 and 2 in respective sub-credit, η^{obj} is a penalty factor in the objective credit, $\varepsilon_{it}^{\text{obj},x}$ is the occurring rates of prediction deviations and communication failures for DER i at time interval t , η_h and η_m are a reward factor and a penalty factor, respectively, and Ω_h and Ω_m are the set of honest nodes and malicious nodes.

Regardless of the aggregator chosen by DER i , its values of C_{it} in (4)–(5) are utilized in a tamper-evident manner by a blockchain. The logarithmic and linear forms in (5) can control the rate of growth or decline in subjective credits, respectively, while the cumulative effect of historical credit decreases over time.

C. WINNING PROBABILITY OF DERs IN Po2C

Unlike the classical PoW protocol, which runs decryption that has great computational resource demands, the Po2C protocol uses the dual-credibility rate to directly represent the willingness and capability of any DER that can contribute to the blockchain. After updating the quantified credits in the last consensus round, DERs in the same blockchain need to compete for the right of book-keeping in the next round. The necessary processes for a PoX-based protocol,

i.e., ability proving, P2P propagating, and transaction verifying, are adapted as follows.

Most BFT-based and PoX-based protocols need to find a leader node as the first step in initiating a consensus round. The probability for a node to win as a leader is proportional to the ratio between its stake and the overall stakes in the whole network in PoX-based protocols. The Po2C protocol reduces the waste of solving the hash function in PoW by directly quantifying each node's dual-credibility rate, which does not affect this probability. Thus, the probability of DER i successfully winning as a leader in aggregator v at time interval t , i.e., p_{ivt}^{leader} , can be estimated as

$$p_{ivt}^{\text{leader}} = C_{ivt} / \sum_{j=1}^{N_{vt}} C_j \quad (6)$$

where N_{vt} is the total number of DERs in aggregator v at time interval t , and j is also a DER number.

Then, DER nodes propagate information to neighboring nodes and hope to be confirmed. Caused by the efficiencies of P2P networks and lags among geographically dispersed DERs, the propagation delay is nonnegligible. Based on an empirical fitting curve for a P2P network in the PoW protocol, the average propagation time is determined by the sum of a round-trip delay and a block verification delay [24]. This propagation delay for aggregator v at time interval t , i.e., τ_{vt} , can be modeled as

$$\tau_{vt} = a/N_{vt} + b \quad (7)$$

where a and b are the coefficients reflecting the round-trip and verification properties in a P2P network, respectively.

The incidence rate at which a valid block is orphaned by propagation delay, i.e., $r(\tau_{vt})$, can be modeled by a Poisson process from a network-level probability [16]

$$r(\tau_{vt}) = 1 - e^{-\tau_{vt}\rho_v} \quad (8)$$

where ρ_v is the mean of the Poisson distribution in aggregator v , whose value is fixed by the average block arrival rate in the P2P network.

At the end of each round, the probability that DER node i can ultimately win the consensus in aggregator v at time interval t , i.e., p_{ivt}^{win} , can be derived as

$$\begin{aligned} p_{ivt}^{\text{win}} &= p_{ivt}^{\text{leader}} [1 - r(\tau_{vt})] \\ &= C_{ivt} \cdot e^{-(a/N_{vt}+b)\rho_v} / \sum_{j=1}^{N_{vt}} C_j \end{aligned} \quad (9)$$

D. INCENTIVES FOR DERs WITH Po2C CONSENSUS

DERs in blockchain-enabled aggregators can earn incentives from the perspectives of both supplying energy as power nodes and supporting transactions as consensus nodes. The latter includes participating in consensus and in the propagation of data. The three types of incentives are described below.

1) Power supply incentives. They are used to reward the successful supply of electricity and are similar to

traditional aggregators. They can be modeled by a power supply function of DERs and the probability of being identified in the aggregator.

- 2) Consensus winning incentives. They are assigned for the particular node in (8) that wins the book-keeping right in a consensus round. They are also the only incentives that a blockchain provides to nodes in most PoX-based protocols. For DERs with higher dual-credibility rates, there is also a higher chance of gaining this type of incentive.
- 3) Data propagation incentives. Because most nodes cannot be rewarded for winning, a propagation incentive is introduced to not only encourage DERs to keep P2P transactions active but also attract DERs to select this aggregator. As mentioned above, the communication complexity of a PoX-based protocol is $\Theta(n)$. Thus, this type of incentive is linearly related to the DER numbers within the aggregator.

A DER resource hopes to schedule the largest amount of power supply as it can within the maximum limits it can provide. Meanwhile, the aggregator is likely to have a contract with an external power market that binds the total amount. The aggregator can determine powers that DERs can supply according to Po2C values. An allocation function of the power that DER i can supply when it selects to participate in aggregator v at time interval t is

$$P_{ivt} = P_{it}^{\max} - f(v, P_{it}) \quad (10)$$

in which

$$f(v, P_{it}) = \begin{cases} 1 & \text{if } \sum_{i=1}^{N_{vt}} P_{ivt} \leq P_{vt}^{\max} \\ \frac{C_{ivt}^{-1}}{\sum_{j=1}^{N_{vt}} C_{jv}^{-1}} \left(P_{vt}^{\max} - \sum_{i=1}^{N_{vt}} P_{ivt} \right) & \text{if } \sum_{i=1}^{N_{vt}} P_{ivt} > P_{vt}^{\max} \end{cases} \quad (11)$$

where P_{ivt} is the power that DER i can schedule to supply when it selects aggregator v at time interval t , $f(v, P_{it})$ is the utility factor for DER i in aggregator v at time interval t , P_{it}^{\max} is the predicted maximum power that DER i can supply at time interval t , and P_{vt}^{\max} is the total amount of power that aggregator v should supply at time interval t .

Some customized types of DERs, e.g., electric vehicles, energy storage devices, and temperature-controlled loads, can also be utilized in (11) with more constraints, e.g., as in [32].

Therefore, for one DER, by simultaneously being a power provider, a consensus-winning node, and a communicating peer, it can expect a comprehensive payoff, described as

$$\mathbb{E}[R(v, P_{ivt})] = \alpha_{vt} P_{ivt} + \beta_v \lambda_t P_{ivt}^{\text{win}} + \gamma_{vt} \lambda_t z_{ivt} \quad (12)$$

in which

$$\lambda_t P_{it} = \alpha_{vt} \sum_{i=1}^{N_{vt}} P_{ivt} + \beta_v \lambda_t + \gamma_{vt} \lambda_t \sum_{i=1}^{N_{vt}} z_{ivt} \quad \forall v \in V \quad (13)$$

$$0 < \alpha_{vt} < \lambda_t \quad \forall v \in V \quad (14)$$

$$\gamma_v^{\max} = \gamma_{vt} \sum_{i=1}^{N_{vt}} z_{ivt} \quad \forall v \in V \quad (15)$$

where $R(v, P_{ivt})$ is the payoff when DER i selects aggregator v and provides P_{it} at time interval t , λ_t is an external market clearing price at time interval t , α_{vt} is a price that rewards power supply in aggregator v at time interval t , β_v and γ_{vt} are the given rates in the market clearing price that rewards consensus leader winning and P2P propagation in aggregator v , respectively, γ_v^{\max} is the maximum rate to a market clearing price that rewards all the P2P gossips, and z_{ivt} is the number of nodes that DER i gossips to in blockchain-enabled aggregator v at time interval t .

To focus on how DERs select among multiple aggregators and the feasibility of changing their selections, biddings of aggregators and locational differences in an electricity market are not introduced. Thus, a unified external market clearing price for all aggregators is given as known. Equation (13) ensures that the benefits received by an aggregator from the external electricity market are fully shared by DERs in it. In (12)–(15), P_{it}^{\max} , λ_t , β_v , and γ_v^{\max} are taken as parameters instead of variables, while α_{vt} and γ_{vt} are constrained variables. In the last term of (12), the propagation incentive is linearly positively correlated to z_{ivt} since the complexity of the PoX-based protocol is $\Theta(n)$.

III. SELECTION GAME AMONG AGGREGATORS

This section studies how DER individuals select a specific aggregator that they prefer. The equilibrium process of DERs in multiple aggregators is organized as an evolutionary game with additional evolutionary stability.

A. GAME DYNAMICS OF DERs AND AGGREGATORS

DERs seek to select one aggregator by comparing its expected payoffs in different aggregators, and it is rational to regard the selection with the highest payoff as better. This process differs from the traditional noncooperative game that analyzes how players behave through static solution concepts, in which no individual has a unilateral incentive to change their behaviors [33]. Evolutionary game theory is suitable for describing the dynamics in these DERs and blockchain-enabled aggregators.

From the perspective of the evolutionary game, DERs can be taken as one single large-populated, well-mixed species in the aggregator. Their rates of reproduction, i.e., fitness, are translated as payoffs that each DER individual tries to maximize [34]. The game dynamics can model how DER individuals change their strategy for selecting aggregators and finally achieve stability.

The evolutionary game dynamics for DERs to select an aggregator at time interval t can be mathematically defined with the 4-tuple $G_t = (I, V, \Omega_t, \{R(v, P_{it}; \Omega_t)\}_{v \in V})$ as follows.

- 1) $I = \{1, 2, \dots, i, \dots, I\}$ is the finite population of DER individuals.

- 2) $V = \{1, 2, \dots, v, \dots, V\}$ is the finite set of aggregators, which represent the strategies that are available for DERs to select.
- 3) $\Omega_t \equiv \{(\omega_{1t}, \omega_{2t}, \dots, \omega_{vt}, \dots, \omega_{Vt}) \mid \sum_{v=1}^V \omega_{vt} = 1, 0 \leq \omega_{vt} \leq 1\}$ is the vector of population states at time interval t , where ω_{vt} indicates the proportion of the DER population selecting aggregator v at time interval t . Relationships of $\sum_1^V N_{vt} = I$ and $\omega_{vt} = N_{vt}/I$ hold.
- 4) $R(v, P_{it}; \Omega_t)_{v \in V}$ is the set of each DER payoff in each aggregator with different population states, in which each value can be calculated by (12).

The classical replicator dynamics (RD) is suitable to interpret this proposed noncooperative aggregator selection dynamics [35]. It describes how DER individuals, called replicators, make rational decisions by observing and transferring to aggregators that presently provide a higher payoff. For an arbitrary aggregator, the rate of changing the selection strategy by the population of DER individuals is called the per capita growth rate, which can be derived from the difference between the expected payoff and the population's average payoff [36]. The dynamics for the evolution of the population states of aggregators $\forall \omega_{vt} \in \Omega_t$ can be organized as an ordinary differential equation as a replicator equation, $\forall v \in V, \forall t$:

$$\dot{\omega}_{vt} = \omega_{vt} [R(v, P_{it}; \Omega_t) - \bar{R}(\Omega_t)] \quad (16)$$

in which

$$\bar{R}(\Omega_t) = \sum_{v \in V} [\omega_{vt} R(v, P_{it}; \Omega_t)] \quad (17)$$

where $\dot{\omega}_{vt}$ is the per capita growth rate of aggregator v at time interval t and $\bar{R}(\Omega_t)$ is the average payoff of a DER selected at random, i.e., the mean payoff of the whole population.

The naive evolutionary logic determines that a DER individual switches to the candidate strategy only if its payoff is higher than the payoff of its current strategy. Thus, a more straightforward way to interpret (16) and (17) is as follows.

- 1) A scenario where $\dot{\omega}_{vt} > 0$: The fitness (i.e., payoff) from selecting v is above average; then, DER individuals will change their selections to aggregator v , leading to the dynamics where the ω_{vt} for aggregator v will increase in the population;
- 2) A scenario where $\dot{\omega}_{vt} < 0$: Based on the same logic, the dynamics are opposite those in Scenario I, so the ω_{vt} for aggregator v will decrease;
- 3) A scenario where $\dot{\omega}_{vt} = 0$: There is no evolutionary motivation for corresponding DERs to change their selected aggregators.

The flowchart for the game among DERs to select aggregators is shown in Figure 2. In (16), the per capita growth rate of aggregator v is considered to be the difference between a random interaction and the whole set of DERs if aggregator v is selected. The average payoff in (13) is depicted by reproducing selection strategies through all the aggregators, which is determined by the payoffs and the population proportion in

each aggregator. Features of DER individuals in a blockchain environment, i.e., autonomous, noncooperative, etc., can be fully retained in the evolutionary dynamics in (16) and (17). According to the theory of dynamic systems, trajectories in (16) leave the interior of Ω_t invariant as well as each of its faces [37].

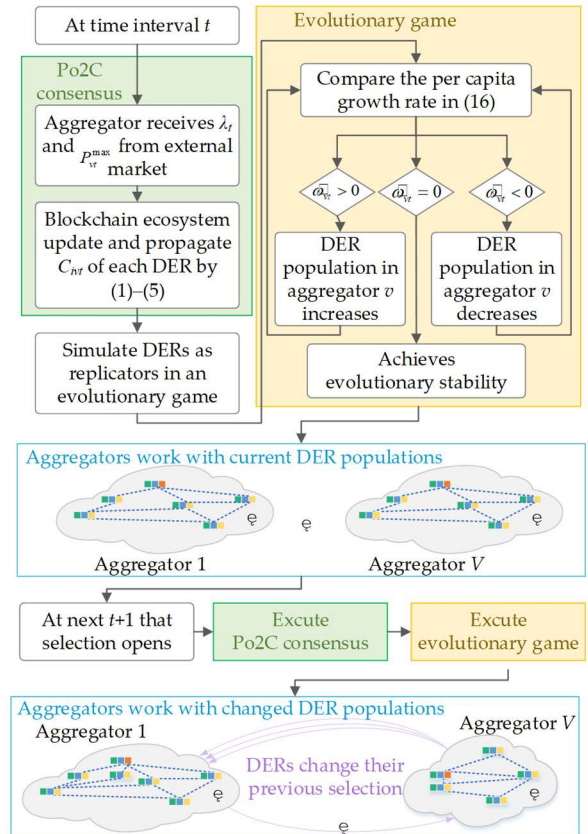


FIGURE 2. Flowchart for the game of DERs selecting among multiple aggregators.

B. EQUILIBRIUM WITH EVOLUTIONARY STABILITY

The stabilization of this dynamical system is analyzed considering that the payoff of a DER depends on the selections of other DERs. Considering all the replicator equations in the whole DER population, an evolutionarily stable strategy (ESS) for the replicator dynamics is reached, which means that none of the populations will evolve. A fixed point is defined for the ESS such that the scenario with $\dot{\omega}_{vt} = 0$ for $\forall v \in V$ is satisfied. It is often described as a Nash equilibrium (NE) with additional ESS properties [38]. To obtain the NE of this game, $G_t = \langle I, V, \Omega_t, R(v, P_{it}; \Omega_t)_{v \in V} \rangle$, there are two necessary theorems, i.e., the *theorem for NE* and the *theorem for the ESS*, and their definitions need to be stated [39].

Theorem for NE. The replicator equation for an evolutionary game satisfies the following: i) a stable fixed point is in NE and ii) a convergent trajectory in the interior of the strategy space evolves toward NE.

The definition of NE is as follows. A population state $\Omega_t^* = (\omega_{1t}^*, \omega_{2t}^*, \dots, \omega_{vt}^*, \dots, \omega_{Vt}^*)$ is the NE state of this

evolutionary game G if the following inequality holds

$$(\Omega'_t - \Omega_t^*)^T [\mathbf{R}(v, P_{it}; \Omega'_t) - \mathbf{R}(v, P_{it}; \Omega_t^*)] \leq 0 \quad \forall \Omega'_t, \Omega_t^* \in \Omega_t \quad (18)$$

where Ω'_t represents all the feasible states for population states and $\mathbf{R}(v, P_{it}; \Omega'_t)$ and $\mathbf{R}(v, P_{it}; \Omega_t^*)$ are the vectors for payoffs of aggregator v in population state sets Ω'_t and Ω_t^* , respectively.

The *theorem for NE* is the application of the traditional folk theorem in evolutionary game theory. NE is determined by the fixed point of the replicator dynamics. Next, the stability of the NE state, i.e., the ESS, is further explored with the generalization form of evolutionary games.

Theorem for the ESS. For the whole population of DERs: i) Ω_t^* is an ESS if and only if $\mathbf{R}(v, P_{it}; \Omega_t^*) > \mathbf{R}(v, P_{it}; \Omega_t)$ for all $\omega_{vt} \in \Omega_t$ that are sufficiently close but not equal and ii) ESS Ω_t^* in the interior of Ω_t is a globally asymptotically stable fixed point of the replicator equation.

The ESS is defined as follows. Population state $\Omega_t^* = (\omega_{1t}^*, \omega_{2t}^*, \dots, \omega_{vt}^*, \dots, \omega_{Vt}^*)$ is an ESS of this evolutionary game G where there is a neighbor that is sufficiently close but not equal to Ω_t^* if

$$(\Omega'_t - \Omega_t^*)^T [\mathbf{R}(v, P_{it}; \Omega'_t) - \mathbf{R}(v, P_{it}; \Omega_t^*)] = 0 \quad \forall \Omega'_t, \Omega_t^* \in \Omega_t \quad (19)$$

For an arbitrary aggregator v , assume that there is another population state ω'_{vt} that attempts to intrude upon ω_{vt}^* by attracting a fringe of DER individuals to switch. Based on (19), this ω'_{vt} could be an ESS if the following inequality holds

$$\mathbf{R}(v, P_{it}; \omega'_{vt}) - \mathbf{R}(v, P_{it}; \omega_{vt}^*) \geq 0 \quad (20)$$

where $\mathbf{R}(v, P_{it}; \omega'_{vt})$ and $\mathbf{R}(v, P_{it}; \omega_{vt}^*)$ are the payoffs for DER i with power P_{it} in aggregator v when aggregator v 's population states are ω'_{vt} and ω_{vt}^* , respectively.

The implications from (18) to (20) demonstrate that the RD ends up in NE, and not just any NE state but an ESS. Proofs based on the Lyapunov function for these two theorems can be found in [37], [39].

C. AGGREGATOR SELECTION PROCEDURE BY DERs

The procedure for evaluating DER aggregator selection strategy evolution is given in Table 3. It begins by assuming that each DER individual occasionally selects one aggregator at random. By comparing this payoff with the average payoff, each DER determines whether it needs to change the aggregator it currently selects. If so, the DER switches to a certain aggregator in the next iteration. When there are more than two blockchain-enabled aggregators, which is very likely, a random switch choice is less efficient. A more efficient switch choice considering multiple simultaneous comparisons based on a probabilistic criterion is proposed as follows

$$\rho_{i,v \rightarrow u,t}(k) = \omega_{it} \max[\mathbf{R}(u, P_{it}) - \mathbf{R}(v, P_{it}), 0] \quad (21)$$

where k is the iteration number, $\rho_{i,v \rightarrow u,t}(k)$ is the probability of DER i in aggregator v switching to aggregator u for time interval t in iteration k , and K is the maximum number of iterations to find equilibrium.

Criterion (21) is adapted from the pairwise comparisons for proportions, i.e., a proportional imitation rule [40], which is widely used in population games. In particular, DER individuals imitate strategies with a higher payoff with a probability that is proportional to the expected payoff obtained by switching to another aggregator.

The final result of evolution is that every DER individual uses a strategy with its highest payoff. The algorithm of this evolutionary game is solved locally by DERs, in which the relevant parameters they obtained and the choices they finally made are secured by the blockchain. The main advantage of the blockchain environment also includes the utility of being truthful and open records of information. General underlying technologies for blockchains, e.g., cryptographic data structures, datagram transfer protocols, and distributed ledger storage, are off-the-shelf technologies and thus are not covered here.

TABLE 3. Algorithm of the selection game.

Equilibrium of the Aggregator Selection Strategy for DERs Following Game Dynamics
<i>Initialization for parameters and functions</i>
Initialize DER types and initial dual-credibility rate values, aggregator number V
Define functions (1) to (19) with parameters
Initialize time interval t , iteration number k
Initialization for DER individuals in aggregators
for DER $i \in \mathcal{I}$ do
Randomly select one aggregator $v \in \mathcal{V}$ to initiate
end for
<i>Loop for time intervals</i>
for time interval $t \in \mathcal{T}$ do
Loop for obtaining equilibrium in each time interval
while $\hat{\omega}_{vt}$ has not converged and iteration $k < K$ do
for DER $i \in \mathcal{I}$ do
Calculate expected payoff $\mathbb{E}[\mathbf{R}(v, P_{it})]$ by (12)
Calculate the average payoff $\bar{\mathbf{R}}(\Omega_t)$ by (17)
Determine whether to switch to aggregator $u \in \mathcal{V}$ by (21)
end for
end while
return Ω_t^*
Renew dual-credibility rate values by (1)
$t \leftarrow t + 1$
end for

IV. CASE STUDY

A. SETTINGS FOR CASES AND COMPARISONS

Numerical simulations are conducted to evaluate DER selection behaviors considering different credit values in Po2C and different numbers of aggregators. Free selection is open for DERs at every time interval in the blockchain environment for case studies.

Two cases, i.e., $I = 4,000$ DERs and $V = 2$ aggregators in Case A and $I = 10,000$ DERs and $V = 4$ aggregators, are considered separately. For DERs, the initial $C_{it}^{\text{obj},x}$ and $C_{it}^{\text{sub},x}$ are both set to 1 for all DERs for $t = 0$ and $t = -1$, in which

the latter complements the historical values [41]. The rated power of DERs P_i^{\max} is set from $U(5, 25)$ with a unit of kW, which is a very common range for distributed photovoltaics, electric vehicles, flexible loads, etc. [42]. The expected outputs of P_{it}^{\max} are then sampled from $U(0.4P_i^{\max}, P_i^{\max})$. For objective uncertainties, the probability for inevitable errors in DER outputs and communication failures, i.e., $\varepsilon_{it}^{\text{obj},1}$ and $\varepsilon_{it}^{\text{obj},2}$, is set as the normal distributions of $N(0.5P_{it}^{\max}, 2^2)$ and $N(0.02, 0.01^2)$. For subjective uncertainties, the probability that DER i behaves maliciously, i.e., $i \in \Omega_m$ at t , is assumed to fit a gamma distribution of $\Gamma(3, 2)$ with a unit of % [43].

For aggregators, parameter settings are as follows. P2P-propagation-related parameters $a + b$ and ρ_v are set to 1,000 and 2, respectively [35]. The values of P_{vt}^{\max} in different cases will be given along with simulations. The external market clearing price λ_t is shown in Table 5 [44]. The empirical distribution of z_{ivt} fits a power-law distribution with an exponent value of 1.2 [45]. The default parameters in each aggregator, including penalty factors in (2) and (4)–(5) as well as unit prices for rewards in (12), are listed in Table 6. The rules for setting penalty factors in (2) is explained as follows. First, from the perspective of trustiness, which is encouraged by blockchains, the objective uncertainties are less hostile than subjective uncertainties, so that the values of $\varphi_v^{\text{obj},1}$ and $\varphi_v^{\text{obj},2}$ should be both less than $\varphi_v^{\text{sub},1}$ and $\varphi_v^{\text{sub},2}$. Second, as power devices, DERs are more prone to power fluctuations or revocations than communication failures or tampering, and the latter two have more impact on the operation of P2P networks, thus $\varphi_v^{\text{obj},2}$ and $\varphi_v^{\text{sub},2}$ should be greater than $\varphi_v^{\text{obj},1}$ and $\varphi_v^{\text{sub},1}$, respectively. Adjustments will be specified in comparisons

TABLE 4. External market clearing prices (unit: \$/mwh).

t	1	2	3	4	5	6	7	8	9	10	11
λ_t	39	35	32	31	31	33	36	45	50	54	59

TABLE 5. Default values for other parameters in each aggregator in Cases A and B.

Case	A			B			
	$v=1$	$v=2$ when $0 \leq t \leq 9$	$v=2$ when $t \geq 10$	$v=1$	$v=2$	$v=3$	$v=4$
$\varphi_v^{\text{obj},1}$	0.1	0.1	0.1	0.2	0.1	0.1	0.2
$\varphi_v^{\text{obj},2}$	0.5	0.5	0.5	1.0	0.5	0.5	1.0
$\varphi_v^{\text{sub},1}$	1.0	1.0	1.0	5.0	2.0	2.0	5.0
$\varphi_v^{\text{sub},2}$	5.0	5.0	5.0	6.0	4.0	4.0	6.0
η^{obj}	0.5	0.5	1.0	1.0	0.5	0.5	1.0
η_h	0.05	0.05	0.05	0.1	0.1	0.1	0.05
η_m	0.5	0.5	2.0	2.0	2.0	2.0	1.5
β_v	0.03	0.03	0.05	0.03	0.15	0.15	0.15
γ_v^{\max}	0.2	0.2	0.3	0.1	0.1	0.3	0.1

Simulations are conducted by Jupyter Notebook on the Anaconda platform with an Intel Core i7 CPU at 2.4 GHz with 8 GB of memory. The maximum number of iterations is set to $K = 1,000$.

B. EVOLUTIONARY ANALYSIS FOR AGGREGATOR SELECTIONS

Because NE has a significant effect on the proposed framework and the results for Q1 and Q2, Q3 is answered first by verifying the theoretical analysis of the game dynamics. In this subsection, to observe the evolution with different parameters, the P_{vt}^{\max} values in aggregators are large, i.e., no curtailment is triggered in (11).

Case A with two aggregators is first observed. The initial DER populations in each aggregator are set to (75%, 25%), (50%, 50%), and (10%, 90%). The iteration processes of DER populations in each aggregator at $t = 1$ are depicted in Figure 3. The ESSs at $t = 1$ in all three simulations are approximately 66% and 34%. This shows that the equilibrium results are not significantly correlated with the initial distributions. This indicates the feasibility of launching the proposed framework that allows free selections of DERs among aggregators.

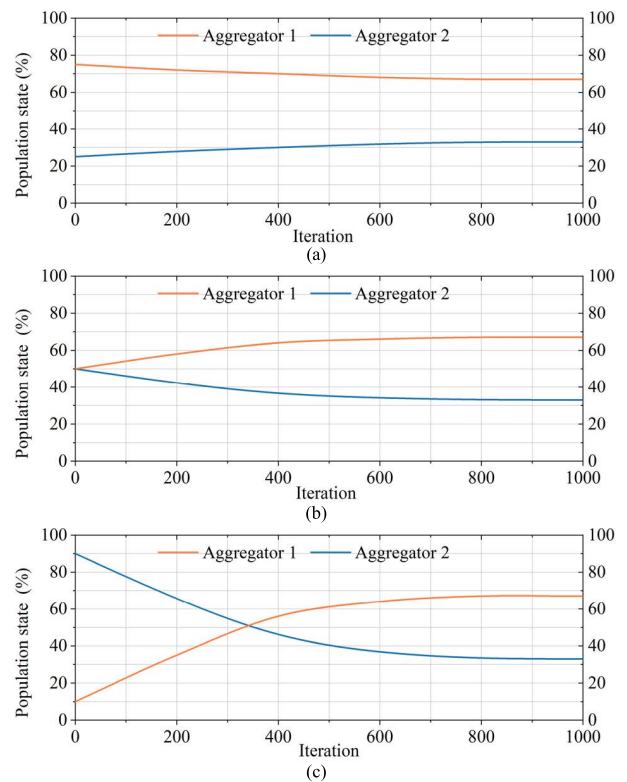


FIGURE 3. Iterations of population states for the two aggregators in Case A at $t = 1$ with different initial populations as follows: (a) (75%, 25%); (b) (50%, 50%); and (c) (10%, 90%).

DER selection strategies continue to evolve. Figure 4 takes $t = 9$ and 10 as examples. When parameters in aggregators remain unchanged, population states change from (66%, 34%) at $t = 1$ in Figure 3(a) to (82%, 18%) at $t = 9$ in Figure 4(a). The ESS point may change due to the accumulation of credit values and the fluctuation of powers. At the very next time interval in Figure 4(a), i.e., $t = 10$, the aggregator $v = 2$ increases the ratios of incentives for being P2P nodes,

i.e., β_v and γ_v^{\max} . As shown in Figure 4(b), the situation in which many DERs selecting aggregator $v = 1$ changes immediately, and the ESS point becomes (43%, 57%). This is most likely because with a limited total incentive, the larger the number of DERs, the less incentive for propagation that individuals can share, and the probability of winning consensus decreases. Once the aggregator $v = 2$ with a smaller number of DERs raises the values of β_v and γ_v^{\max} , DERs are more likely to receive an increase in the total payoff. As seen from the slope fields in Figure 4(c) and Figure 4(d), the fact that each DER strategy is the one whereby no individual has a unilateral payoff to change its selection is consistent with the theoretical analysis of NE. This shows that this framework is able to help the free selections for DERs with an obtainable ESS point when an electricity market requires openness.

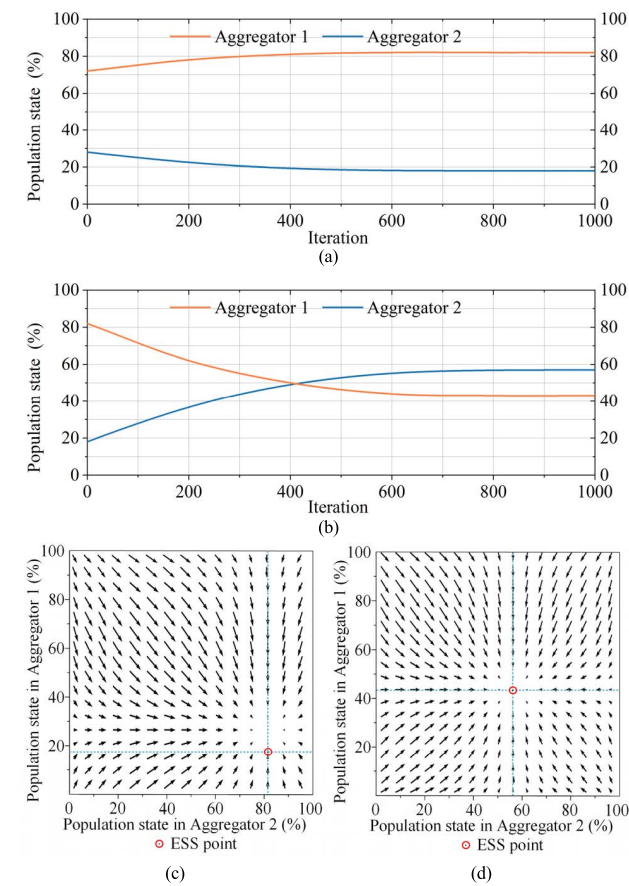


FIGURE 4. Iterations and equilibrium for replicator dynamics in Case A with 2 aggregators at different time intervals: (a) population states at $t = 9$; (b) population states at $t = 10$; (c) slope fields at $t = 9$; (d) slope fields at $t = 10$.

Case B with 4 aggregators is simulated to further test the generality. As mentioned above, the initial population distributions do not affect the NE results. Thus, initial population states can be set as random. Figure 6 depicts the evolution processes in DER population states and per capita growth rates at the next time interval. Since aggregator $v = 3$ sets a higher ratio of incentives for propagation, i.e., γ_v^{\max} , its population grows and exceeds aggregator $v = 2$ whose other

parameters are the same, despite the lower initial distribution. Generally, changes in per capita growth rates in Figure 6(b) converge to zero in a process consistent with Figure 6(a). This indicates that when the number of aggregators with different parameters increases, the framework still obtains feasible solutions in the proposed algorithm for the evolutionary game.

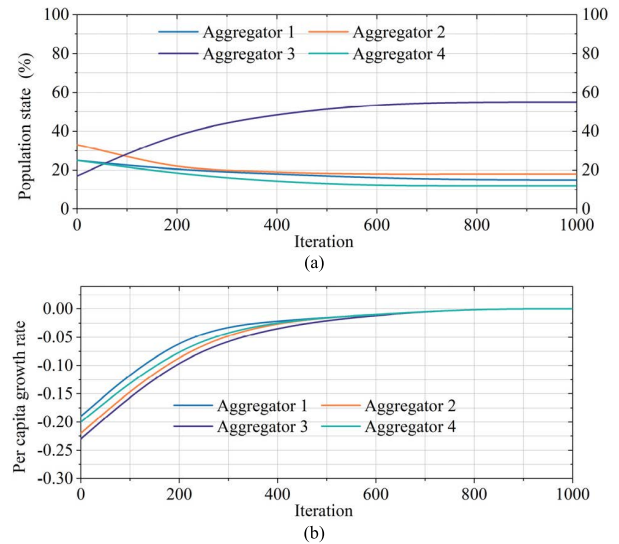


FIGURE 5. Evolution of DER selection strategies among aggregators in Case B with 4 aggregators at $t = 1$: (a) population states and (b) per capita growth rates.

Figure 3 to Figure 5 show that the evolution processes of aggregators' selection always converge before the maximum iteration. The time consumed for the cases in this and the following subsections are summarized in Figure 6. The solution time fluctuates between 72 s and 113 s when $V = 2$. It increases to between 135 s and 164 s when V increases to 4. Although the time consumed increases with the number of aggregators, it is still in a reasonable range. This indicates that the game dynamics and the proposed algorithm are suitable for analyzing the evolutionary process of DERs for their selections among aggregators.

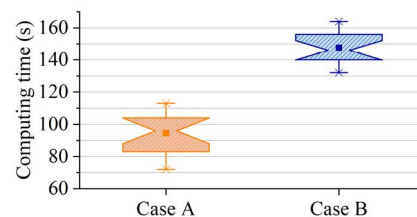


FIGURE 6. Distributions of time consumed by the algorithm for the selection game in Case A and Case B with multiple time intervals.

C. PERFORMANCE WITH DIFFERENT CONSENSUSES AND INCENTIVES

After showing that the evolutionary processes of selection are not a barrier to the proposed framework, to

answer Q1 and Q2, more comparisons are analyzed, focusing on the consensus and incentives. Case A with constrained P_{vt}^{\max} is taken as the environment for this subsection.

First, consensus protocols are compared, while the triple-incentive payoff function and game dynamics in the framework remain unchanged. Using different values for sub-coefficients $\varphi_v^{\text{obj},1}$ and $\varphi_v^{\text{obj},2}$ in aggregator $v = 1$, DER populations in the two aggregators are shown in Figure 7. When aggregator $v = 1$ treats the objective and subjective uncertainties equally, i.e., changes its Po2C with $\varphi_v^{\text{obj},1}$ equal to $\varphi_v^{\text{sub},1}$ and $\varphi_v^{\text{obj},1}$ equal to $\varphi_v^{\text{sub},2}$, the DERs in aggregator $v = 1$ regularly decrease. When aggregator $v = 1$ adjusts its $\varphi_v^{\text{obj},1}$ and $\varphi_v^{\text{obj},2}$ to 0, i.e., the objective uncertainties are disregarded, DERs in aggregator $v = 1$ increase conversely. To distinguish it from Po2C, this consensus that does not measure objective uncertainties is referred as Po1C here. By accommodating uncontrollable objective uncertainties in a consensus, it is beneficial to attract a larger population of DERs in one aggregator.

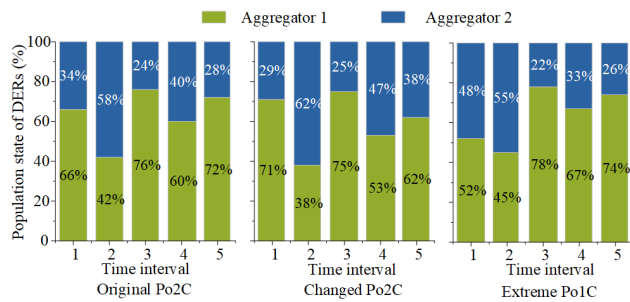


FIGURE 7. Population states of DERs after selections with cumulative power limits at each time interval in Case A, while $\varphi_{v=1}^{\text{obj},1} = 0.1$ and $\varphi_{v=1}^{\text{obj},2} = 5$ in original Po2C, $\varphi_{v=1}^{\text{obj},1} = 1.0$ and $\varphi_{v=1}^{\text{obj},2} = 5.0$ in changed Po2C, and $\varphi_{v=1}^{\text{obj},1} = \varphi_{v=1}^{\text{obj},2} = 0$ in Po1C, respectively.

Corresponding to the adjustment in the consensus and the resulting changes in DER populations in Figure 7, total power outputs in aggregators change as well. The reduction in (11) is only for the preschedule, and if the actual output exceeds it, it is still retained in the cumulative measurement. Moreover, because the impact of a power surplus can be removed by curtailment for aggregators, the shortage affects their performance in the external market.

The prescheduled and actual cumulative powers are shown in Figure 8. In general, cumulative powers are largely close to the prescheduled powers in each aggregator, regardless of the variations in the DER population. This demonstrates the validity of the proposed framework. The overall differences using the original Po2C with $\varphi_{v=1}^{\text{obj},1} = 0.1$ and $\varphi_{v=1}^{\text{obj},2} = 1.0$ are the smallest across aggregators and time intervals. The details are analyzed as follows.

For aggregator $v = 1$ in Figure 8(a), the increase in the power deficit is more evident with Po1C, which may be caused by not having enough DERs to select it. Meanwhile, the fluctuation in the power differences in Figure 8(a)

improves compared to the case where $\varphi_{v=2}^{\text{obj},1} = 1.0$ and $\varphi_{v=2}^{\text{obj},2} = 5.0$ but is more severe than in the case where $\varphi_{v=2}^{\text{obj},1} = 0.1$ and $\varphi_{v=2}^{\text{obj},2} = 5$. For aggregator $v = 2$, as shown in Figure 8(b), as the population of DERs grows with Po1C, the power deficit continues to decrease, but the surplus is higher. This may be because DERs with more objective uncertainties prefer to choose the Po1C consensus.

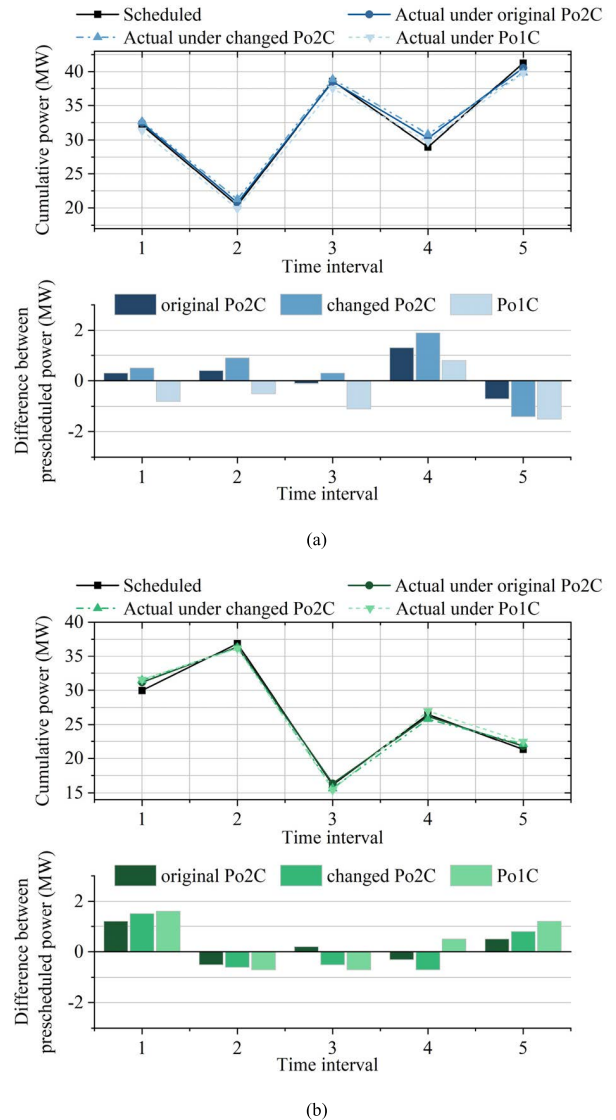


FIGURE 8. Prescheduled vs. actual cumulative powers and corresponding differences with different consensus after selections at each time interval in Case A for (a) aggregator $v = 1$ and (b) aggregator $v = 2$.

In addition, prescheduled cumulative powers also affect the population states. The higher the value is, the more DERs that choose it, e.g., for aggregator $v = 1$ at time interval $t = 3$ and for aggregator $v = 2$ at time interval $t = 2$. This is probably because of the lower power that will be curtailed by (11). However, for aggregators, because external electricity markets will evaluate their deviations, it is not

recommended to look for a single increase in the proportion in Figure 7 but rather to combine the differences in Figure 8.

Relationships between DER populations and cumulative powers can be further observed by comprehensive observations in both Figure 7 and Figure 8. Comparisons within the aggregator itself show that if one aggregator overemphasizes the penalty for objective uncertainties, i.e., using a Po2C with higher $\varphi_v^{\text{obj},1}$ and $\varphi_v^{\text{obj},2}$ for credits, an insufficient DER population will result, instead exacerbating the bias in cumulative powers. Comparisons among aggregators suggest that when the prescheduled cumulative power of an aggregator is limited, not all DERs select the aggregator that places less emphasis on objective credits. This is also the reason why the populations in NE are not disproportionately large in Figure 7.

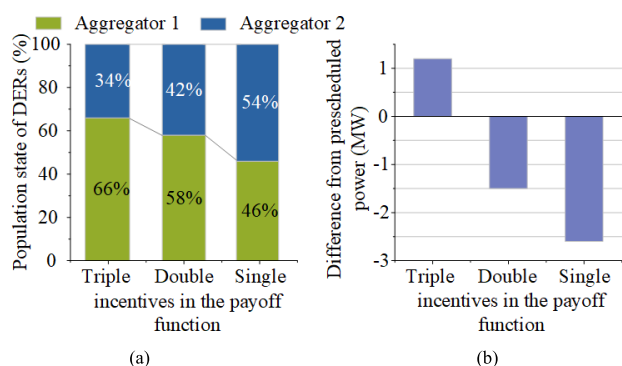


FIGURE 9. Comparisons of different numbers of incentives in Case A with 2 aggregators at time interval $t = 1$: (a) population states in two aggregators and (b) differences between prescheduled and actual cumulative powers.

Second, different incentives are removed in the payoff for aggregator $v = 1$, while Po2C and game dynamics remain. The payoff function (12) with triple incentives is replaced by double incentives that reward both power supply and consensus leader winning and a single incentive that rewards power supply only. Figure 9 shows the corresponding population states and differences in cumulative powers. The performance of aggregator $v = 1$ shows that if the P2P propagation incentive is discouraged, the number of DERs in it decreases, and a shortage emerges. If the incentive for the leader to win is further removed, greater deviations will exist in the aggregated power outputs. In particular, they are unfavorable shortages that cannot be curtailed in the way that power surplus can. This indicates that considering the need for consensus and data propagation in the blockchain ecosystem, a comprehensive payoff function helps the organization of aggregators.

V. CONCLUSION

This study focuses on providing a decentralized framework for aggregating DERs, in which DER individuals can freely and dynamically select the aggregators they participate in and achieve dynamic equilibrium. While the blockchain

ecosystem provides necessary transparency and security, a Po2C consensus protocol for the P2P network is proposed, in which quantitative models are separately given for objective credits and subjective credits. The dual properties of DERs as power nodes and information nodes are also considered in an incentive model. The game dynamics for DER selection among multiple aggregators are studied, and then, an algorithm using pairwise comparisons is proposed to find equilibrium. Simulation results show that the proposed framework effectively enables DERs to organize themselves autonomously with evolutionary stability. The proposed consensus is fully decentralized and thus does not require centralized control from aggregators.

When focusing on consensus and game dynamics, the interaction between aggregators and electricity markets or power grids is simplified. Moreover, most electricity markets currently only allow DERs to change selections at the end of a trading day, which is simplified in the simulation by allowing them to change after each time interval. In future studies, the bidding processes of decentralized aggregators in electricity markets can be further modeled, and market clearing prices as variables determined by the bilevel equilibrium can be investigated. Along with the bidding processes, more detailed models for uncertainties, e.g., RES production profiles, different load shift ratios, various failures for communications, can be further introduced. In addition, the optimization of parameters in the consensus for various components of DERs is also an important issue that is worth studying in future work.

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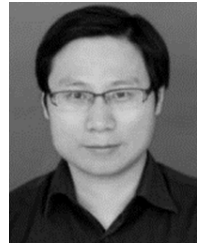
ZHENYA JI (Member, IEEE) received the B.Eng. and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 2009 and 2018, respectively. She was a Visiting Student with Rheinisch-Westfälische Technische Hochschule Aachen, Germany, from 2012 to 2013. She has been a Lecturer at Nanjing Normal University, since 2018. Her research interests include charging strategies for electric vehicles, electric vehicle adoption policies, and modeling of integrated energy systems.



HAO LI received the B.Eng. degree in electrical engineering from the Xi'an University of Posts and Telecommunications, Shaanxi, China, in 2021. He is currently pursuing the master's degree with Nanjing Normal University. His research interests include charging strategies for electric vehicles and the coordination for distribution networks and transportation networks.



YOUQING BAO (Member, IEEE) was born in Zhenjiang, China, in 1987. He received the Ph.D. degree from Southeast University (SEU), Nanjing, China, in 2016. He has been working as a Faculty Member at Nanjing Normal University (NJNU), since 2015. His current research interests include power system operation and scheduling, power demand side management, and the frequency control of the power systems.



ZHONG CHEN (Member, IEEE) received the M.S. and Ph.D. degrees from the School of Electrical Engineering, Southeast University, China, in 2002 and 2006, respectively. He is currently a Professor with the School of Electrical Engineering, Southeast University. His research interests include electric vehicle, renewable energy, and integrated power system operation and control.

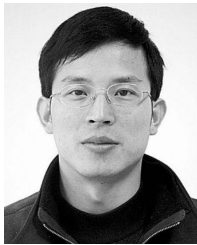


ing, and novel wireless power transfer systems.

WEI WANG (Member, IEEE) received the B.S. degree in electrical engineering and automation from Jiangnan University, Wuxi, China, in 2011, and the M.S. and Ph.D. degrees in electrical engineering from Southeast University, Nanjing, China, in 2013 and in 2017, respectively. He currently works as an Associate Professor with the School of Electrical and Automation Engineering, Nanjing Normal University. His research interests include integrated energy systems, energy harvesting,



ZIQI ZHANG received the B.S. degree from the College of Electrical Engineering, Wuhan University, China, in 2016, and the M.S. degree from the School of Electrical Engineering, Southeast University, China, in 2019, where he is currently pursuing the Ph.D. degree. His research interest includes integration of electric vehicle into modern power systems.



energy systems, energy internet, smart charging management for electric vehicles, and wireless charging technology.

XUELIANG HUANG (Member, IEEE) received the Ph.D. degree in electrical engineering from Southeast University, Nanjing, China, in 1997. He was a Visiting Scholar at Tokyo University, Tokyo, Japan, from 2002 to 2004. He is currently a Professor with the School of Electrical Engineering, Southeast University. He is also the Chief Director with the Jiangsu Key Laboratory of Smart Grid Technology and Equipment, China. His research interests include integrated multi-



YE RUI received the B.S. and M.S. degrees from the Nanjing Institute of Technology, China, in 2011 and 2015, respectively, and the Ph.D. degree from the School of Electrical Engineering, Southeast University, China, in 2022. He is currently a Researcher with Beijing East Zhongtong Technology Development Company Ltd. His research interest includes integration of electric vehicle into modern power systems.

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