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• **Supplementary File** •

A Reputation-based Blockchain Scheme for Sustained Carbon Emission Reduction

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Appendix A The basic architecture of the RBETS model

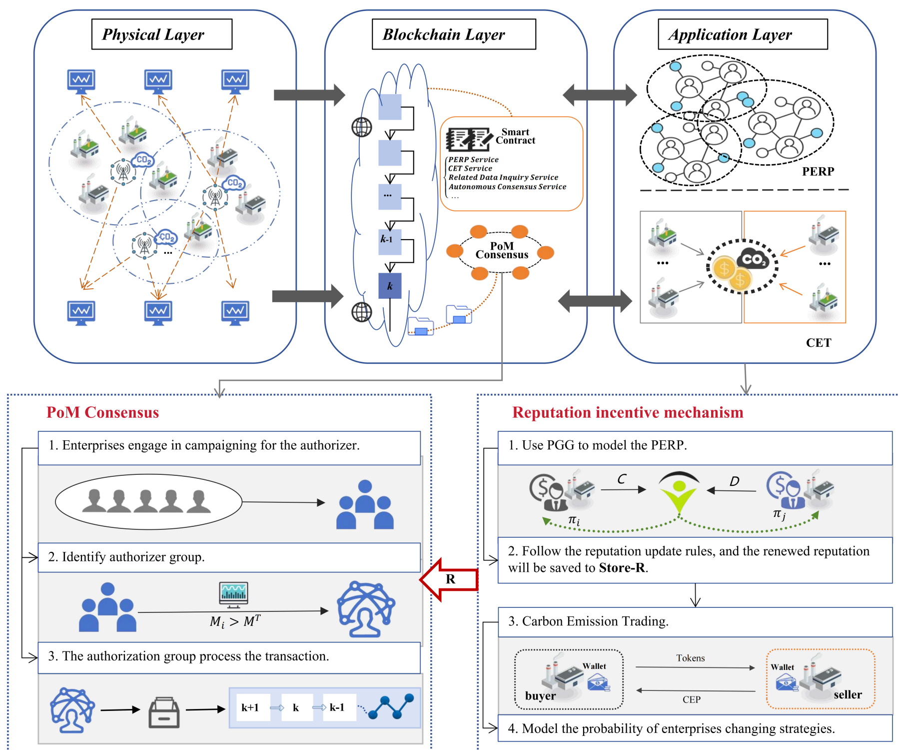

Figure A1 The basic architecture of RBETS.

The basic architecture of the RBETS model is shown in Figure A1, which is divided into the following three layers:

(1) Physical layer. At the bottom of RBETS is the physical layer, where numbers of computing and communicating entities from legitimate enterprises construct the hardware infrastructure of the system. In the traditional ETS, the government agency acts as a central role for Monitoring, Reporting, and Verification (MRV) of the system. Here, we use distributed physical nodes and smart sensor devices to take the place of the previous centralized structure.

(2) Blockchain layer. In this layer, blockchain serves distributed and interconnected emission enterprises through a peer-to-peer network [1, 2]. Hardware entities from the enterprise can be divided into lighting nodes and full nodes, which maintain and undertake the RBETS. The emitters are the lighting nodes in RBETS, which can not only invest in PERP and trade Carbon Emission Permit (CEP) but also download blocks to check their behavior records from the blockchain. The miners are full nodes, which are responsible for updating and providing data, transaction validation, and maintaining the ledger. Smart contracts provide various types of flexible consensus services. With smart contracts, both sides of the CEP transaction can trade at less cost and time, which makes it possible for the enterprises involved in the collaboration to be free from the impact of third-party conflicts and centralized control. All the data generated are then collected and packaged into blocks, i.e. stored as a ledger in the blockchain

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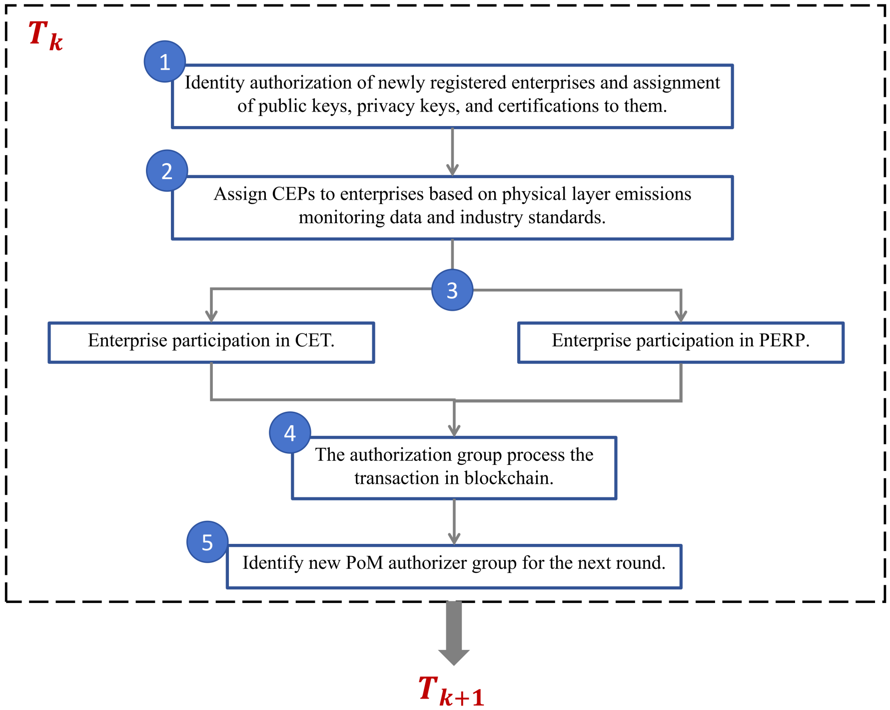

Figure A2 The basic architecture of RBETS.

network in distributed ways. Finally, the consensus protocol achieves the consistency of the stored ledger without the supervision and management of central nodes, while also ensuring the ledger is tamper and corruption resistant.

(3) Service layer. The service layer provides a simple operational interface for general enterprise users. The participants only need to get the required services and don't care about the underlying implementation of the blockchain. The service layer consists of two main modules, i.e. CET and PERP. Each module contains several small interfaces for information queries, sufficient to meet the basic needs of these enterprise users.

Remark A.1. In strict terms, the application layer also includes the authorization group service, where enterprises could take part in the candidate authorizers in blockchain. The workflow of the proposed scheme is shown in Figure A2 and the notations used in this letter are shown in Table A1.

Appendix B The supplement for Reputation incentive mechanism

Appendix B.1 Reputation update rules

At the initial moment, the reputation value is a random value that is taken uniformly from the interval $[0, R_{max}]$. Without loss of generality, we let the maximum reputation value $R_{max} = 10$. Once decision is made by player i in a PGG group g, it will trigger the smart contract to automatically update its reputation value R_i^t following the update rules, i.e. when $s_{i,g}^k = 1$,

$$R_i^t = \begin{cases} R_i^t + 0.2 & \text{if } s_{i,g}^{k-1} = 0, \\ R_i^t + 0.1 & \text{if } s_{i,g}^{k-1} = 1, \\ R_{max} & \text{if } R_i^{t-1} = R_{max}, \end{cases} \tag{B1}$$

or when $s_{i,g}^k = 0$

$$R_i^t = \begin{cases} R_i^t - 0.2 & \text{if } s_{i,g}^{k-1} = 1, \\ R_i^t - 0.1 & \text{if } s_{i,g}^{k-1} = 0, \\ 0 & \text{if } R_i^{t-1} = 0, \end{cases} \tag{B2}$$

where $s_{i,g}^{k-1}$ denotes the strategy of player i in PERP group g in the T_{k-1}.

Remark B.1. It is specified that when the player's reputation falls below a certain value σ, that is the player will be deprived of the right to participate in CET when $R_i \leqslant \sigma$. In this case, if the current actual carbon emissions of the player exceed the limit, the excess part will be punished according to 3 times of the market price. Thereafter the player can only actively participate in PERP until when it can enter the CET again when $R_i \geqslant \sigma$.

Appendix B.2 Reputation-based CET

For simplicity, the time index t and k are omitted in the following presentation. Within the time gap T_k, $\mathcal{D} \subset \mathcal{N}$ is the set of emitters with demand for trading in the system. According to the different requirement, emitters can be divided into buyers

Table B1 Notations in this letter

Notation	virtual meaning	Notation	virtual meaning
i	The index of a specific enterprise	k	The index of a specific time gap
T_k	The kth time gap	$\mathbb{S}$	The set of strategy of player in PGG group
g_i, g_j	The PGG group initiated by player i,j	d_i	The number of player i' total neighbors
t	The current time	R_i^t	The reputation of player i at the current time
R_{max}	The maximum reputation value	R_i^{k-1}	The reputation of player i last updated in T_{k-1}
$n_{g_j}^k$	The total number of collaborators of the group g_j in T_k	s_{i,g_j}^k	The strategy of player of the group g_j in T_k
π_{i,g_j}	The payoff of player i from group g_j	π_i^k	The total payoff of player i in T_k
γ	The fluctuation of the decision adopted by the strategy	M	The concept of motivation in expectancy theory
E	The concept of expectancy in expectancy theory	V	The concept of valence in expectancy theory
I	The concept of instrument value in expectancy theory	$E_{A_i^k}$	The expected payoff of player i in T_k
M_i	The motivation of player i	M^T	The motivation threshold
N_{qe}	The final candidate authorizers	N_{ce}	The number of applicants
N_{mq}	The minimum candidate authorizers	$\bar{M}$	The average motivation value of all applicants
r	The synergy factor	ρ_c	The cooperation density

$\mathcal{B} = \{1, 2, ..., N_b\}$ and sellers $\mathcal{S} = \{1, 2, ..., N_s\}$, where N_b and N_s are the numbers of buyers and sellers, respectively, $\mathcal{D} = \mathcal{B} \cup \mathcal{S}$, $\mathcal{B} \cap \mathcal{S} = \varnothing$. The transaction process of the trading system is as follows:

1) Step 1. Submit Transaction Request. At any moment in the gap T_k, emitters are permitted to submit transaction requests to the miners in their area. For either buyers or sellers, the submission information should include the demand to be traded, the bid price of each CEP, and the adaptation parameter for the forthcoming iteration of the auction. The selected miner receipt request from the emitter and checks its reputation to label it. Orders from emitters that meet the reputation requirement will be packed into the transaction pool, which include buyer requests $\mathbb{B} = \left\{B_1, B_2, ..., B_{N_b'} \mid N_b' \leqslant N_b\right\}$ and sellers requests $\mathbb{S} = \left\{S_1, S_2, ..., S_{N_s'} \mid N_s' \leqslant N_s\right\}$. In the set of $\mathbb{B}$, $B_i = \{d_{i,b}, p_{i,b}, \triangle u_{i,b}, R_{i,b}\}$ denotes the information set of buyer i, in which $d_{i,b}, p_{i,b}, \triangle u_{i,b}$, and $R_{i,b}$ ($R_{i,b} = R_i^{k-1}$) represent the CEP demand, bidding price per CEP, adaptation parameter for forthcoming auction iteration, and reputation of buyer i, respectively. Similarly, in the set of $\mathbb{S}$, $S_j = \{d_{j,s}, p_{j,s}, \triangle v_{j,s}, R_{j,s}\}$ denotes the information set of seller j, in which $d_{j,s}, p_{j,s}, \triangle v_{j,s}$, and $R_{j,s}$ ($R_{j,s} = R_j^{k-1}$) represent the available CEP quantity, expected price per CEP, adaptation parameter, and reputation of seller j , respectively.

2) Step 2. Transaction Matching. Orders in the transaction pool will trigger matching smart contracts on the blockchain, curbing node greed through the priority-value-order mechanism and the internal penalty mechanism. Specifically, valid bids from carbon sellers will be assigned priority values. The priority of carbon sellers depends on the bids submitted in the auction and reputation, the priority value of seller j can be derived from the following

$$P_{s,j} = \frac{1}{\triangle q}\rho(R_j - \bar{R}) + \frac{1}{\triangle p}(1-\rho)(\bar{S} - p_{j,s}), \tag{B3}$$

where ρ is the adaptation parameter, $\triangle q$ and $\triangle p$ are the gaps between the maximum and minimum values of reputation and bid among sellers, respectively. $\bar{R}$ and $\bar{S}$ represents the mean value of all sellers' reputation and bids, i.e.

$$\bar{S} = \frac{\sum_{h=1}^{N_s'} p_{h,s}}{N_s'}, \bar{R} = \frac{\sum_{h=1}^{N_s'} R_h}{N_s'}. \tag{B4}$$

It is evident that the bid is a favorable factor for preference when the seller's bid is below the mean value. Certainly, the higher the reputation, the higher the priority.

The buyer's bid will also be assigned a priority value that is positively correlated with their bid. In such a case, the buyer with the highest bid has the highest priority. In addition, we refer to the setting of [3, 4]. The internal penalty mechanism classifies the buyers into high, medium, and low levels based on their reputation in proportions of x%, y%, and z% ($x + y + z = 100$), which determines the additional fees. The additional fees is used to pay to miners to reward them after the auction, which is a%, b% and c% ($a < b < c$) of the total transaction amount, respectively.

In contrast to previous studies, this letter conducts auctions centered on sellers in order to reward enterprises for their efforts to reduce emissions.

First, the auction starts in order of the seller's priority from the largest to the smallest. For the focal seller j, the buyer i with the highest priority in the order pool is selected first, and the auction follows the following two rules:

(i) $if\ p_{i,b} \geqslant p_{j,s},\ p_{i,j} = \dfrac{p_{i,b} + p_{j,s}}{2}$;

(ii) $if\ p_{i,b} < p_{j,s},\ i = i+1$,

where $p_{i,j}$ denotes the final transaction price of buyer i and seller j.

In order to increase the attractiveness of the market, we apply a dynamic double iterative auction that enables the market to obtain a higher possible percentage of winning bids. Specifically, when the seller has matched the last buyer and still hasn't sold out, it will wait for the next round of auction. Within the new round of auction, buyers and sellers will follow the adaptation parameters to raise or lower the price. Until the last seller is sold out or all buyers have met their demand, the auction of the T_k time period ends.

3) Step 3. Process Transaction. The system will automatically trigger the smart contract to query the wallet addresses and CEP accounts of both buyers and sellers. The transaction amount will be charged from the buyer's wallet to the seller'. Meantime, the seller will transfer the corresponding CEP amount to the buyer's CEP account. Besides, the unsold CEP of sellers will be retained at a loss rate of 20% until T_{k+1}. Buyers who fail to purchase enough CEP will be penalized for the excess at 3 times of the market price. Setting up this penalty mechanism will effectively control greedy bids from enterprises, as well as incentive the enterprises to strive to improve their reputation.

Table C1 Functional comparison among PoW, PoA, PoT, AND PoM.

Consensus Protocol	Main Strategy	Energy Consumption	Incentive Compatibility	Matthew effect
PoW	Competing to solve Hash puzzles	High	Low	Strong
PoA	Voting for block signers	Low	Middle	Weak
PoT	Selecting validators based on trust value	Low	Middle	Strong
PoM	Authorizer group with high motivation	Low	High	Weak

Appendix C The supplement for PoM Consensus

Appendix C.1 Predict the motivation of emitters with reputation

The expectancy theory is also known as “Valence-Means-Excpectancy” theory [5], which is an incentive theory introduced to model the relationship between needs and goals. The formula measures the needs gained by paying one unit of effort, which can be used to quantify the motivation of individuals. To maximize M, Vroom constructed an implementation model, which is represented in

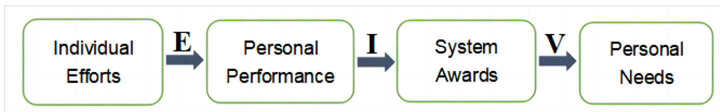

Figure C1 Expectation-incentive implementation model.

In RBETS, the ultimate goal is to incentivize emitters to actively participate in carbon reduction. In other words, we aim to motivate enterprises to actively participate in the PERP collaboration. Expectancy theory assumes that individuals are thoughtful, rational beings. It is reasonable to assume that assigning blockchain bookkeeping tasks to enterprises with high work potential will accelerate the efficiency and ensure the stability of the system. In addition, selecting enterprises that positively invest as authorized miners could serve as an incentive for these enterprises to contribute to sustained emission reduction. Therefore, we will calculate the motivation of enterprises for the PERP, and then the enterprises with high motivation value are selected as the authorizers. The system labels enterprises with a reputation for the purpose of incentivizing them to reduce emissions. However, individual enterprises are selfish, as they actively participate in PERP only try to get a high reputation to enhance their priority in the trading market, and then to get the larger gain. The larger the valence is, the more attractive the priority to them.

From the perspective of the expectancy theory, the personal performance of enterprises' individual efforts is reputation. It is further obtained that the system reward is the priority of the enterprise in the trading market, and the corresponding valence is the gain it wants to obtain from the market. Thus, the motivation for player i to be active on PERP can be obtained by the following formula

$$M_i^k = 1 \times \frac{R_i^{k-1}}{R_{max}^{k-1}} \times \frac{{E_A}_i^k}{{E_A}_{max}^k}, \tag{C1}$$

where 1 denotes $E = 1$ (we set enterprises to actively participate in PERP will necessarily enhance their reputation). In other words, the predicted probability that player i perceives an active investment to obtain personal performance (Reputation) is 1. Due to the priority-value-order mechanism, the players' transaction priority can be considered to be proportional to their reputation ranking. Since we set that the priority of enterprises within T_k in the trading market is determined by their reputation within T_{k-1}, the perceived probability of player i can be considered as $I = R_i^{k-1}/R_{max}^{k-1}$. ${E_A}_i^k$ represents the expected payoff of player i in the CEP trading market, i.e.

$${E_A}_i^k = d_i \times p_i, \tag{C2}$$

where ${E_A}_{max}^k$ represent the highest expected payoff among all players. It is noted that there is no distinction between buyers and sellers here since CEP transactions are beneficial for both buyers and sellers. Obviously, the more gain an enterprise tries to earn from the trading market, the more valuable the organizational reward (trading priority) is to it. Thus, the valence V can be measured as ${E_A}_i^k/{E_A}_{max}^k$.

Remark C.1. It is noted that individuals tend to expect fair and just rewards for achieving their goals in the expectancy theory. Rewards can be multifaceted, either on the material or spiritual level. In this letter, we consider only the material level of the transactional profits of improved reputation to the enterprise.

Appendix C.2 Consensus Protocol Analysis

In this subsection, a simple comparison among the PoM, PoW [6], PoA [7], and PoT [8]. The results are presented in Table C1.

Different consensus protocols generally adopt different strategies. In PoW, users compete for the rights to generate blocks by solving computational puzzles, which perform well in terms of system security and robustness but consume high energy consumption. PoT selects the block signer by considering the users' trust value as a social evaluation criterion. In PoA, an open election framework was designed for users to be voted as signers for block generation, as well as be disqualified from the voting process. In PoM, the model of the autonomous consensus process based on the expectation theory is built. Then, for the balance between incentive level and decentralization, a dynamic authorizer group mechanism is developed that can derive the computable threshold for block data authorizer qualification. Since PoA, PoT, and PoM are not required to mine, they all have low computing energy consumption and relatively high performance.

Besides, PoW allows any nodes contributing computing power to generate blocks competitively, which is irrelevant to the application scenario resulting in low incentive compatibility. PoA and PoT consider the reputation and social evaluation of users in the system, which improves the incentive compatibility of consensus protocols to some extent. In PoM, all users are encouraged

Table D1 Information of Buyers.

Buyers	R	Demand of CEP	Price	Adaptability Parameters	R Level	Price Priority
A	8.2	48 units	142	2	High	3
B	7.4	34 units	158	3	Middle	1
C	5.2	52units	153	1	Low	2
D	4.1	49units	140	2	Low	4

Table D2 Information of Sellers.

Emitting enterprise	R	CEP Amount	Price	Adaptability Parameters	Priority Rank
a	8.7	35 units	152	2	2
b	9.2	29 units	160	2	1
c	7.9	12units	141	1	4
d	8.1	18units	157	3	3
e	7.2	14units	142	2	5
f	6.3	9units	138	1	6

to participate in the bookkeeping. It couples with trading through reduction motivation assessed by the expectancy theory, which greatly improves the incentive compatibility of ETS. Furthermore, the expectancy theory is applicable to all collective work incentive efforts, which ensures the scalability of PoM.

Moreover, it is noted that the accumulation of the computing power of PoW and the trust value of PoT will cause a heavy Matthew effect [9] after a long run. The random voting rules of PoA weaken the Matthew effect. For PoM, it maintains a dynamic group of authorizers by updating the number of authorizers and dividing the time slice in each round, which avoids working time and continuous block generation constraints, i.e. weaken the Matthew effect.

Appendix D Case Study and Numerical Simulation

Environment: the proposed scheme is deployed on Hyperledger Fabric 2.x, and uses the Java language to customize smart contracts to perform the CET transaction process. The configuration is as follows: Deploy a general channel in Fabric, and set 2 leagues to represent different areas; Configure 10 user certificates to represent enterprises; Set 2 orderers and 3 peer nodes to implement functions for users. In addition, MATLAB is used to verify the consensus protocol, and the PGG is iterated forward in accordance with the Monte Carlo simulation (MCS) procedure.

Appendix D.1 Case Study

In this subsection, we present a simple case study with reference to the data setup in [3, 4] to demonstrate the process of CEP transactions. Parameters are first defined: $x = 30, y = 30, z = 40, a = 5, b = 10, c = 15, \rho = 0.7$, and the market price of CEP unit price $p = 155$.

There are four enterprises A $\sim$ D which try to purchase CEP in the market. They need 48 units, 34 units, 52 units, and 49 units of CEP, respectively. And they have bids of 142, 158, 153, and 140 and acceptable iterative adaptation parameters of 2 , 3, 1, and 2, respectively. According to the previous settings, the rank of reputation and bid priority of the enterprises are calculated respectively. As can be seen, the reputation level of these enterprises are High, Medium, Low, and Low, respectively. So they will pay $5\%, 10\%, 15\%$, and 15% of trading volumes as additional fees to reward miners in the forthcoming transactions. Table D1 lists the basic information of these four enterprises.

Meanwhile, six enterprises a $\sim$ f are selling CEP in the market. They generally conform to the regularity that the higher the reputation is, the higher the amount of CEP is available for sale, and the higher the bid price is. That is because the rules for reputation updates of enterprises are accumulated, the higher the reputation of an enterprise means that it is more active in the PERP, the more CEP can be sold inevitably. Enterprises with high reputations hold an absolute advantage in the trading market, which results in a high probability of greedy bids. As well, we calculate the priority size of these sellers according to Eqs. (B3)(B4) and sort them. Table D2 lists the basic information of these six enterprises.

Then, the auction starts with the seller as the center, in order of preference from largest to smallest. Here, we specify that a seller is allowed to sell CEPs to multiple buyers, as well as a buyer is allowed to purchase CEPs from multiple sellers. The auction follows the auction rules in B.2, which will be executed automatically by smart contracts The final auction results are summarized in Table D3, which shows there are seven transactions waiting to be further processed. For instance, transaction (a$\rightarrow$B) indicates the transaction between seller a and buyer B.

As shown above, the high-priority seller b has no successful transactions due to high bids, while the low-priority e and f are both sold out. On the other hand, buyers A and D with low bids have unmet demand. Buyers A and D have an unmet volume of 46 and 49, respectively, so the corresponding fine amounts are 21390 and 22785. Meanwhile, the successfully matched orders in Table 5 will be required to pay an additional fees for rewarding authorized enterprises. As we mentioned previous, this fees is charged by the buyers to penalize them for their negative attitude toward the reduction efforts. Based on the buyer's reputation level, we can calculate that the additional fees paid by A, B, and C are 14.8, 527, and 1163.25 respectively. Obviously, the additional fees is a sizeable amount, which will motivate enterprises to strive to improve their reputation by actively contributing for sustained emissions reductions.

Appendix D.2 Numerical Simulation

Appendix D.2.1 *Setup*

We assume that the carbon emissions of enterprises at the initial moment satisfy normal distribution, $c_i \sim N\left(\mu, \sigma^2\right)$, where $\mu = 2000$, $\sigma^2 = 100$. Set the total number of legitimate emitting enterprises $N = 1000$. In any PERP, they have half cooperative

Table D3 Matching Results.

Trading Pair	Transaction Volume	Sold Price
a→B	34	155
a→C	1	152.5
c→C	12	147
e→C	14	147.5
f→C	9	145.5
d→C	16	154
d→A	2	148

and half defection strategies. The experiment is simulated with an NW small world network and according to the MCS procedure for 1000 iterations forward. Furthermore, there may exist some simulations that have a little amplitude of fluctuations which need to carry out statistical averages. Thus, the fluctuations can be hopefully removed from the final results. In this letter, 10 independent runs are performed for each set of parameter setups. Thus, the current choices of simulation parameters are enough to assure the reliability of simulations. Cooperation density ρ_c (cooperation level) is defined as the proportion of cumulative cooperative behavior of all individuals in a round, which is calculated as follows

$$\rho_c = \frac{\sum_{i=1}^{N} n_{g_i}}{\sum_{i=1}^{N} d_i + 1}. \tag{D1}$$

As described earlier, players in the network are emission enterprises with reputations. And we specify that when an enterprise's reputation falls below a threshold σ, it will not be allowed to participate in the trading market. Here, we let $\sigma = 2$.

Previous studies [10] have shown that when the payoff of player i from a cooperative strategy is higher than that from a defection strategy, the following conditions must be satisfied

$$r > d_i + 1. \tag{D2}$$

Let the mean degree of all nodes be d. In the NW small world network, each node connects k edges to its closest k ($N \gg k > 1$) nodes and adds an edge with probability p between the randomly selected $Nk/2$ pairs of nodes.

In this case, the connectivity of each node may be k, k+1, ..., k+N−1, with the corresponding probability $C_{N-k-1}^{0} p^0 (1-p)^{N-k-1}$, $C_{N-k-1}^{1} p^1 (1-p)^{N-k-2}$, ..., $C_{N-k-1}^{N-1} p^{N-k-1} (1-p)^0$. Therefore, the average degree of all nodes is

$$d = \sum_{x=0}^{N-k-1} (k+x) C_{N-k-1}^{x} p^x (1-p)^{N-k-1-x}. \tag{D3}$$

Accordingly, if we intend to turn cooperation into an advantageous strategy for the system, the synergy factor r must be satisfied as follow

$$r > \sum_{x=0}^{N-k-1} (k+x) C_{N-k-1}^{x} p^x (1-p)^{N-k-1-x}. \tag{D4}$$

Here, we set $k = 2$. Accordingly, we can calculate $d = 5$, from which we can set r>5 in the following simulation.

Appendix D.2.2 *Dynamical Evolution of Cooperation*

Figure D1 compares the change process of cooperation density between considering the reputation and without reputation considerations when $r = 6$. When reputation is not taken into account, the selection intensity of an enterprise is constant and the strategy changes only when the payoff of the selected neighbor is far higher than it. However, when considering the reputation in the selection intensity, the selection strength varies with reputation. Players with low reputations are quite likely to change their strategy due to being discriminated against in the CET, while players with high reputations will stick to the cooperative strategy due to being granted high priority in the CET. As a result, the cooperation density of the whole group will grow rapidly. Since the setup of simulation satisfies Eq. (E2), the game evolution will eventually reach a steady state. According to Figure D1, the network reached a stable state when it reaches roughly 300 iterations, while the typical Fermi's rule iteration to roughly 900 times reaching stability. The experimental results further validate the enhancing effect of reputation on players' cooperative behavior, as mentioned [11].

Appendix D.2.3 *PoM Consensus Protocol Analysis*

First, the enterprise's motivation value is determined by three factors: expectancy, valence, and instrument value. Based on the analysis in C.1, the enterprise's motivation value can be calculated, and the number of enterprises with a motivation value greater than 0.5 in each iteration and plot them in Figure D2. It can be seen that the overall trend of the number increases as the iterations move forward. This is because, at the beginning of the experiment, the data are randomly generated, where the motivation value calculation involves no connection between reputation and transaction amount. Thus, enterprises with high reputations are likely to have low transaction demand. However, as the iterate forward, the performance of PERP directly affects the reputation accumulation and the transaction amount. Reputation gradually has a positive relationship with the transaction amount. Figure D3 shows the distribution of motivation values for enterprises with values greater than 0.5 when iterating to 624 iterations (arbitrarily chosen).

Then, the correlation between the determination of the motivation threshold and the number of authorized candidate nodes is investigated. Here, we chose the data when the iteration reaches 1000 times, which is stable and reliable according to the evolutionary results in D.2.2. By solving Problem 1, i.e. when the Jain's fairness is maximized, the optimal motivation threshold and the number of candidate nodes can be obtained. From Figure D4, we can see that the motivation threshold decreases with the increasing number of candidate nodes. Jain's fairness reaches the maximum at a fixed number of candidates $N_{qe} = 17$. Then, the optimal motivation threshold can be got ($M_T = 0.73$).

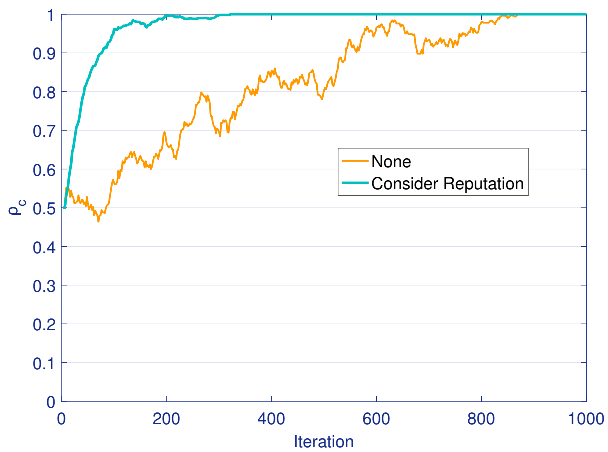

Figure D1 Consider the effect of reputation on the evolution of the game ($r = 6$).

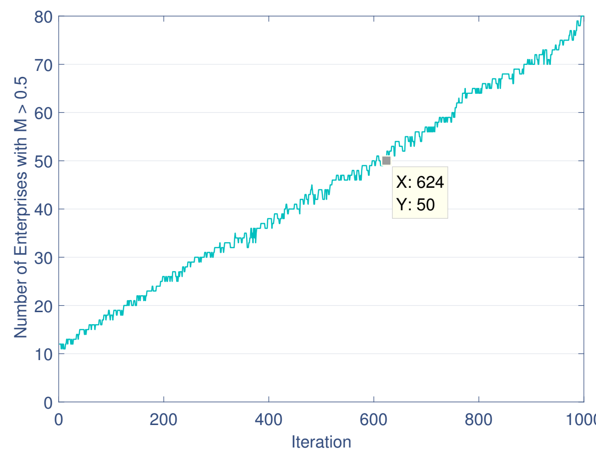

Figure D2 The trends in the number of enterprises with motivation value greater than 0.5.

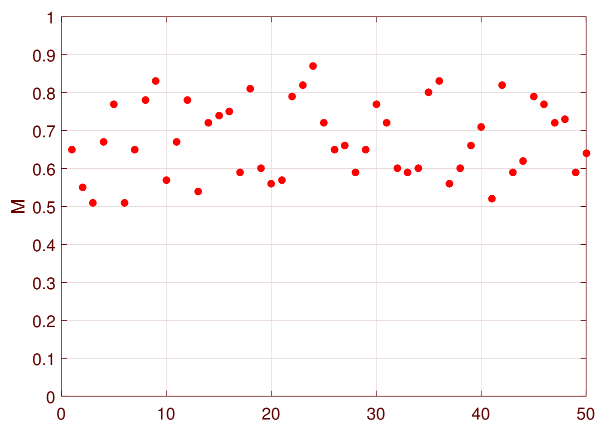

Figure D3 The distribution of the motivation values for the 50 enterprises.

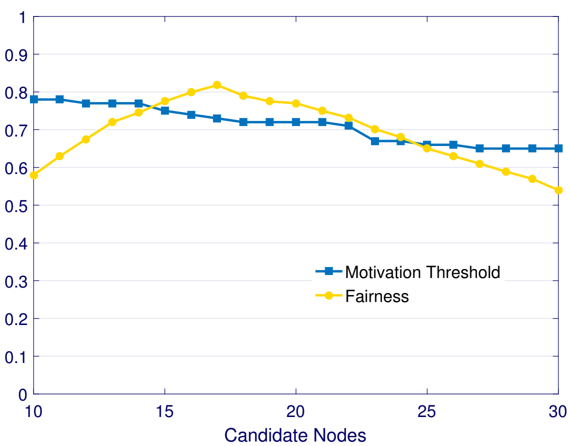

Figure D4 The determination of the optimal number of candidates and motivation threshold.

Appendix D.2.4 *Comparison with other work*

(1) Comparison of emission reduction efficiency of RBETS with other solutions

The traditional ETS [12,13] generally discusses only the impact of the cap-and-trade mechanism on enterprises' production and operation decisions and carbon emissions, but the results suggest that enterprises tend to purchase carbon allowances from the CET only when the low-carbon processing cost outweighs the potential opportunity benefits. In the reputation-based ETSs, e.g., the BD-ETS proposed in [3] and the proposed permissioned blockchain enabled ETS in [4], a certain high level of reputation is also required for purchasing carbon allowances successfully, which somewhat enhances the enthusiasm of enterprises to participate in carbon reduction work. In RBETS, the public cooperative behavior of emission reduction among enterprises is considered and the incentive role of reputation is further strengthened, which maximize the emission reduction efficiency of the system.

We specify that when an enterprise invests an amount of 1 unit cost in the cleaning project, its emissions will be reduced by 0.1 unit. The mean carbon emissions of enterprises are used to measure the reduction efficiency of a system; the more obvious a decrease in carbon emissions, the higher the reduction efficiency of a system is. In this case, an enterprise that invests cost c only can receive $0.1c$ unit of CEP benefit fixed. However, we consider climate as a typical global public good in RBETS, which call on enterprises to cooperate with each other. As a player in PGG, enterprises can not only initiate their own PERP but also participate in a PERP initiated by a neighboring enterprise, which has a high positive externality and will greatly improve environmental resources. Therefore, enterprises will obtain CEP benefits of much more in a high probability than $0.1c$ units at the same investment cost of c. Figure D5 records the average carbon emissions of these enterprises for each round, as well as compares the effectiveness of the RBETS and other solutions in reducing emissions. At the early stage of the iteration, the number of cooperative players in RBETS is quite small, and the efficiency of carbon emission reduction is not very different from that of other solutions. As the iteration moves forward, the number of cooperative players grows or even all cooperate. Accordingly, the efficiency of emission reduction reaches its maximum, and the gap between other solutions and RBETS becomes larger and larger with the iteration.

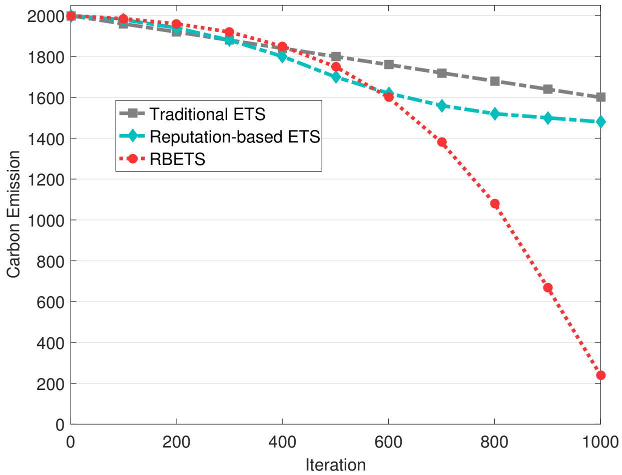

Figure D5 Consider the effect of PERP on emission reduction efficiency.

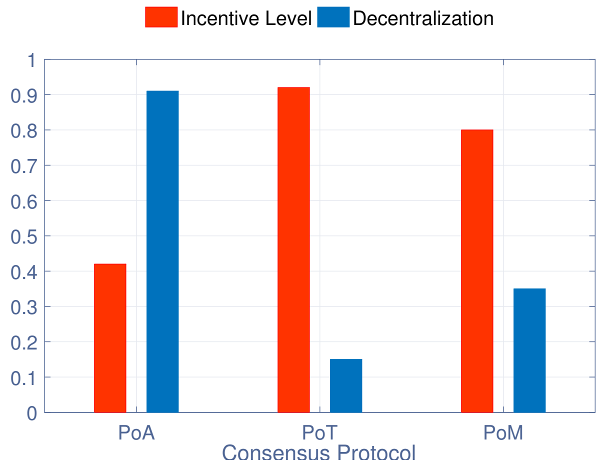

Figure D6 The incentive level and decentralization comparison among PoA, PoT, and PoM.

(2) Evaluation and comparison of PoM with other consensus protocols

PoA and PoT protocols are evaluated and compared. Figure D6 shows the comparison results for incentive level and decentralization, in which PoM achieved a good balance between PoA and PoT. PoA grants equal authorizer rights to blockchain nodes, whereas PoT selects only a few nodes with high credit as authorizers. The PoM protocol sets a sensible motivation threshold, allowing certain candidates whose motivation values exceed the threshold for becoming authorized candidate nodes. As a result, PoA can enable high decentralization while having a low incentive level, whereas PoT can achieve a high incentive level while having low decentralization. In contrast, PoM achieves a favorable balance between the decentralization and the incentive level by introducing a motivation threshold determination algorithm and a dynamic authorizer group mechanism.

Remark D.1. As explained above, the designed priority-value-order mechanism and the internal penalty mechanism perform well in CET, and the proposed scheme further improves the CEP market process. Meanwhile, the high emission reduction efficiency of RBETS is verified through comparison with other solutions. In addition, compared with PoA and PoT protocols, PoM consensus protocol achieves a good balance between the incentive level and the decentralization.

Remark D.2. Some future research challenges and works in the future. On one hand, the RBETS should be applied in extensive practice to further optimize the details of smart contracts and consensus protocol. On the other hand, there is a growing interest in controlling and reducing carbon emissions in the power system. It is necessary to build a decentralized market model for microgrids that integrates the electricity and the carbon trading solution, further considering the cost of carbon trading as one of the optimization objectives.

References

1 Zhong S, Huang X. Special focus on security and privacy in blockchain-based applications. Sci China Inf Sci, 2020, 63(3): 1-2.
2 Bao Z, Tang C, Lin F, et al. Rating-protocol optimization for blockchain-enabled hybrid energy trading in smart grids. Sci. China Inf. Sci, 2023, 66(5): 159205.
3 Hu Z, Du Y, Rao C, et al. Delegated proof of reputation consensus mechanism for blockchain-enabled distributed carbon emission trading system. IEEE Access, 2020, 8: 214932-214944.
4 Muzumdar A, Modi C, Vyjayanthi C. A permissioned blockchain enabled trustworthy and incentivized emission trading system. J. Clean. Prod, 2022, 349: 131274.
5 Wabba M A, House R J. Expectancy theory in work and motivation: Some logical and methodological issues. Hum. Relat, 1974, 27(2): 121-147.
6 Xiao Y, Zhang N, Lou W, et al. A survey of distributed consensus protocols for blockchain networks. IEEE Commun. Surv. Tutorials, 2020, 22(2): 1432-1465.
7 Naumoff A. Why blockchain needs ‘proof of authority’ instead of ‘proof of stake’. 2017. https://cointelegraph
8 Zou J, Ye B, Qu L, et al. A proof-of-trust consensus protocol for enhancing accountability in crowdsourcing services. IEEE Trans. Serv. Comput, 2018, 12(3): 429-445.
9 Merton R K. The Matthew effect in science: The reward and communication systems of science are considered. Science, 1968, 159(3810): 56-63.
10 Xu C, Zhao Y, Zhang J F. Decision-implementation complexity of cooperative game systems. Sci China Inf Sci, 2017, 60: 1-18.
11 Xia C, Ding S, Wang C, et al. Risk Analysis and Enhancement of Cooperation Yielded by the Individual Reputation in the Spatial Public Goods Game. 2017, 11(3): 1516-1525.
12 Chen W, Chen J, Ma Y. Renewable energy investment and carbon emissions under cap-and-trade mechanisms. J. Clean. Prod, 2021, 278: 123341.
13 Wang S, Wan L, Li T, et al. Exploring the effect of cap-and-trade mechanism on firm’s production planning and emission reduction strategy. J. Clean. Prod, 2018, 172: 591-601.