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A reputation-based blockchain scheme for sustained carbon emission reduction

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Climate change is a global issue that necessitates collective responsibility from all nations. Recently, a blockchain-enabled emission trading scheme (ETS) has been proposed for reducing carbon emissions to overcome the drawbacks of centralized methods [1, 2]. However, existing consensus protocols in blockchain have not been well prepared for low energy consumption and high incentive compatibility [3], which is contrary to the low carbon goal of ETS. Moreover, the phenomenon of "tragedy of the commons" is widespread in emission reduction. Regrettably, none of the existing blockchain-enabled ETS studies have taken into account the potential social cooperation among emitters [4].

In this study, we propose a reputation-based blockchain ETS (RBETS) that can serve as a sustained reduction solution. Specifically, we first design a reputation incentive mechanism to incentivize enterprises for participating in sustained emission reduction, where the process of emission reduction is modeled as a public goods game (PGG) [5] with reputation. Naturally, the enterprise's performance-driven reputation affects its treatment in the trading market, which encourages enterprises to actively participate in reduction efforts over the sustained. Then, we propose a new consensus protocol based on the expectancy theory (named proof of motivation, PoM), which builds an autonomous consensus with the character of high incentive compatibility and low computing energy consumption. Besides, a dynamic authorizer group mechanism is developed with the consideration of incentive level and decentralization, which avoids ineffective rewards and maintains certain fairness.

System model. Assuming that there are N registered enterprises in the system, an emitter i ($i \in \{1, 2, \ldots, N\}$) with an authorized identity could participate in RBETS. As participants in RBETS, they can engage in carbon emission trading (CET) and public emission reduction project (PERP), and also take part in the candidate authorizers in blockchain (more details are shown in Figure A1 in Appendix A). This study focuses on addressing two key issues in carbon emission reduction: (1) at the application level, designing an effective incentive mechanism to encourage long-term participation of enterprises in carbon emission reduction; (2) at the technical level, designing a consensus protocol with low computing energy consumption and high incentive compatibility to further improve the decarbonization of the system.

Solution. In response to the above two issues, we will address RBETS in the following two aspects.

(i) Reputation incentive mechanism. The reputation incentive mechanism consists of three parts: PERP, Store-R (virtual reputation storage), and CET, where they interact with each other and form a triangle loop.

Firstly, the enterprises in PERP follow the reputation update rules that reflect their strategic characteristics, and the renewed reputation will be saved into Store-R. Specifically, the enterprise's reputation depends on the extent to which it contributes to PERP. The payoffs of players are determined by their contributions to PERP and the return benefit of achievement, which can be regarded as a PGG. During each iteration of the Monte Carlo simulation (MCS) (expressed as a time gap T), player i may be in a PGG group g initiated by itself or by one of its neighbors. It will choose its strategy $s_{i,g}^k$ from the strategy set $\mathbb{S} = \{C, D\}$, where C and D represent cooperation and defection, respectively. The payoff function that player i from group g_j in T_k is

$$\pi_{i,g_j} = \begin{cases} \frac{rn_{g_j}^k}{d_j+1}, & \text{if } s_{i,g_j}^k = C, \\ \frac{rn_{g_j}^k}{d_j+1} - 1, & \text{if } s_{i,g_j}^k = D, \end{cases} \tag{1}$$

where g_j denotes the PERP group initiated by player j, $n_{g_i}^k$ is the total number of collaborators in the group, and d_j is the number of player j's total neighbors. r ($r \geqslant 1$) denotes the synergy factor, which is introduced due to the high positive externality. Further, the total payoff of player i obtained from the $d_i + 1$ groups in T_k can be summarized as π_i^k.

Once a 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 ($t \in T_k$). Reputation will accumulate throughout the entire time domain. Scenarios with different reputation values are distinguished here to stress the importance of cooperation, as well as to give more incentives to the cooperative players. More details of reputation update rules can be seen in Appendix B.1.

Then, the incentive effect of reputation works in CET, which shows that the higher reputation of the enterprise,

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the more popular it will likely be in CET. 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. The incentive effect of reputation operates through the priority-value-order mechanism and the internal penalty mechanism. The details of reputation-based CET are shown in Appendix B.2.

Finally, an irrational nearest neighbor selection strategy is introduced to model the probability of enterprises that change their strategies in PERP, i.e.,

$$P(s_{j,g}^{k-1} \to s_{i,g}^{k}) = \frac{1}{1 + \mathrm{e}^{(\pi_i^{k-1} - \pi_j^{k-1})/\gamma_i^k}}, \quad (2)$$

where $s_{j,g}^{k-1}$, $s_{i,g}^{k}$ denote the strategy of player j in the group g in T_{k-1} and the strategy of player i in T_k, respectively. $P(s_{j,g}^{k-1} \to s_{i,g}^{k})$ indicates the replication probability of $s_{j,g}^{k-1}$ to $s_{i,g}^{k}$. γ_i^k denotes the fluctuation of the decision adopted by the strategy during the current cooperative evolution for player i, also known as selection intensity. Previous studies usually set γ as a constant value. Whereas, according to Kurt Lewin's field theory, learning behavior is a function of the learner and the environment. In this study, the selection intensity is characterized as a function of reputation, i.e.,

$$\gamma_i^k = \frac{\alpha}{1 + \mathrm{e}^{-(R_i^{k-1} - \beta)}}, \quad (3)$$

where α and β are the adaptation parameters. R_i^{k-1} denotes the last updated reputation of player i in T_{k-1}, which plays a decisive role in the Carbon Emission Permit auction.

(ii) PoM consensus. A new consensus protocol is proposed to ensure system security and data consistency. Like most protocols, PoM chooses a part of the applicants as block authorizers, which is achieved by a motivation threshold.

Firstly, the motivation here refers to the work potential, which is derived from the expectancy theory proposed by Victor H. Vroom. Vroom argues that when individuals take a certain action, they must know that the result of the action will satisfy their needs. The expectation formula is proposed as

$$M = \sum E \times \left(\sum V \times I\right), \quad (4)$$

where M, E, V, and I represent motivation, expectancy, valence, and instrument value, respectively.

In RBETS, the ultimate goal is to incentivize emitters to actively participate in carbon reduction. We will calculate the motivation of enterprises for the PERP, and then the enterprises with high motivation value are selected as the authorizers. 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:

$$M_i^k = 1 \times \frac{R_i^{k-1}}{R_{\max}^{k-1}} \times \frac{{E_A}_i^k}{{E_A}_{\max}^k}, \quad (5)$$

where 1 denotes $E = 1$. The perceived probability of player i is considered $I = R_i^{k-1}/R_{\max}^{k-1}$, and ${E_A}_i^k$ represents the expected payoff of player i in CET. See Appendix C.1 for more detailed reasoning processes.

Then, the authorization group is identified. Within each round of the MCS, enterprises with sufficient computing resources can participate in the candidate authorizers. These applicants are required to pay a heavy deposit.

In an incentive system, the proper incentive level has a direct effect on the effectiveness of the incentive. Two conflicting considerations are present in the PoM consensus protocol. (1) The authorizers with high motivation are expected for incentive level consideration. (2) Each user is expected to have the same opportunity being authorized for decentralization considerations. Decentralization and incentive level are defined, respectively, as

$$\mathcal{D}(M_i \geqslant M^T) = \frac{N_{qe}}{N_{ce}}, \ \mathcal{M} = \frac{M^T - \bar{M}}{\bar{M}}, \quad (6)$$

where M^T, N_{ce}, and N_{qe} represent the motivation threshold, the number of applicants, and the final candidate authorizers, respectively. $\bar{M}$ indicates the average motivation value of all applicants. Problem 1 considers the trade-off between incentive level and decentralization.

Problem 1. Considering the measure of Jain's fairness, the motivation threshold and the optimal number of candidates are solved by the optimization problem:

$$\begin{aligned} \mathcal{P}1: \max_{\{N_{qe}, M^T\}} \mathcal{F}_{\mathrm{Jain}} &= \frac{(\varphi\mathcal{D} + \psi\mathcal{M})^2}{2\left((\varphi\mathcal{D})^2 + (\psi\mathcal{M})^2\right)}, \\ \text{s.t. } N_{mq} &\leqslant N_{qe} \leqslant N_{ce}, \end{aligned} \quad (7)$$

where N_{mq} represents the minimum candidate authorizers, φ and ψ are weight factors. Jain's fairness measure leads to fairness from $\frac{1}{n}$ to 1 (n is the considering item).

To show the effectiveness of the RBETS, we illustrate the case study and numerical simulation in Appendix D.

Conclusion. In this study, we established an efficient reputation-based blockchain ETS for sustained emission reduction. We first modeled the carbon emission reduction as a PGG. Based on the PGG model with reputation, we then designed an incentive mechanism to increase the efficiency of emitters for sustained emissions reduction. Furthermore, we took the reputation as a bond to design a new consensus protocol to further enhance decarbonization, which will be achieved by the decreasing consumption of computing energy and the improving incentive compatibility of current blockchain-enabled ETS.

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Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

References

1 Khaqqi K N, Sikorski J J, Hadinoto K, et al. Incorporating seller/buyer reputation-based system in blockchain-enabled emission trading application. Appl Energy, 2018, 209: 8–19

2 Jin H, Xiao J. Towards trustworthy blockchain systems in the era of "Internet of value": development, challenges, and future trends. Sci China Inf Sci, 2022, 65: 153101

3 Fu X, Wang H M, Shi P C. A survey of blockchain consensus algorithms: mechanism, design and applications. Sci China Inf Sci, 2021, 64: 121101

4 Sadawi A A, Madani B, Saboor S, et al. A comprehensive hierarchical blockchain system for carbon emission trading utilizing blockchain of things and smart contract. Tech Forecast Soc Change, 2021, 173: 121124

5 Govaert A, Ramazi P, Cao M. Rationality, imitation, and rational imitation in spatial public goods games. IEEE Trans Control Netw Syst, 2021, 8: 1324–1335