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Blockchain-Enabled Demand Response Scheme with Individualized Incentive Pricing Mode

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Abstract: Demand response (DR) can offer a wide range of advantages for electrical systems by facilitating the interaction and balance between supply and demand. However, DR always requires a central agent, giving rise to issues of security and trust. Besides this, differences in user response cost characteristics are not taken into consideration during incentive pricing, which would affect the equal participation of users in DR and increase the costs borne by the electricity retail company. In this paper, a blockchain-enabled DR scheme with an individualized incentive pricing mode is proposed. First, a blockchain-enabled DR framework is proposed to promote the secure implementation of DR. Next, a dual-incentive mechanism is designed to successfully implement the blockchain to DR, which consists of a profit-based and a contribution-based model. An individualized incentive pricing mode is adopted in the profit-based model to decrease the imbalance in response frequency of users and reduce the costs borne by the electricity retail company. Then, the Stackelberg game model is constructed and Differential Evolution (DE) is used to produce equilibrium optimal individualized incentive prices. Finally, case studies are conducted. The results demonstrate that the proposed scheme can reduce the cost borne by the electricity retail company and decrease the imbalance among users in response frequency.

Keywords: demand response; incentive pricing; Stackelberg game

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1. Introduction

Demand response (DR) has been recognized as a powerful tool to better balance supply and demand by influencing the behavior of the demand side in electrical grid [1–3]. Specifically, due to the uncertainty of renewable energy, electricity market prices and the cumulation of prediction errors [4], the pressure to ensure stable electricity supply continues to increase. When there is a shortage of electricity, DR becomes an effective alternative solution to absorb the gap between electricity supply and demand as well as to control the demand for electricity.

Various incentive mechanisms have been used in DR programs to motivate users to adapt their loads to supply availability [4–6]. An incentive-based DR program with an advanced reward system was proposed in [7] to aggregate residential demand. An effort-based reward approach was proposed in [8] for the allocation of load shedding amount in microgrids. An extended multi-energy DR scheme for an integrated energy system was established in [9] with the objective of shaving peak load and minimizing total costs. Nevertheless, the incentive prices in these studies are mostly set as constants and less on a theoretical basis. Considering the utility and elasticity of customers, an incentive-based DR model was built in [10], and the optimal incentive price was obtained by solving the model. A novel incentive pricing mechanism was proposed in [11], and the optimal pricing factor was decided by solving a two-stage Stackelberg game. These studies have provided methods of incentive pricing. However, the incentive prices offered to different users are unified, which means that the relationship between user response cost characteristics and incentive prices are not well integrated, leading potentially to increased costs for the electricity retail company.

In incentive pricing, due to the difference in user response cost characteristics, offering unified incentive prices to all users would not only make the response frequency of users significantly imbalanced, which would affect the equal participation of users in DR, but would also increase costs borne by the electricity retail company. Therefore, to decrease the imbalance and make the costs borne by the electricity retail company as low as possible, the individualized incentive pricing mode should be adopted. Considering that user behavior is time-dependent, a time-correlated user response behavior model was established in [12], and thus, the differentiated incentive mechanism was adopted. However, this model still fails to set different incentive prices for different users.

DR always requires a central agent to collect information and dispatch optimal solutions [2,13], which would give rise to issues of security and trust [14]. Hence, a secure DR scheme needs to be adopted. As a decentralized database, blockchain technology has demonstrated their potential for secure operations [15,16] due to their characteristics of security, reliability and tamper-proofing [17–19]. These features correspond with the appeal of DR and have received increasing attention in recent research. In low/medium voltage smart grids, a blockchain-based model for distributed management, control and validation of DR events was established in [20]. A privacy-preserved and incentive-compatible DR mechanism based on blockchain was developed in [21].

Despite the fact that blockchain technology has the advantages of trust and security, it is still problematic to apply it to DR. For various reasons which are explained in detail in Section 3, electricity retail companies and profit sensitive users may hold opposite attitudes regarding participation in blockchain-based solutions. Beyond this, electricity retail companies and users still face other problems. The electricity retail company adopts a profit-based model to motivate users and bears the incentive payment independently in DR; when the electricity market fluctuates wildly [22], the incentive payment may be even more. The demands of users for revenue can be met by the profit-based model, but users still expect contributions which are closely related to the reward in the blockchain environment. Thus, to successfully apply blockchain to DR, a dual-incentive mechanism considering the demands for both the revenue and contribution of users should be constructed. Blockchain contains an incentive layer, which usually encourages participants to contribute computing power [23,24] and rational operation [25]. Consequently, it is suitable for building a contribution-based model on such a platform. A blockchain-based incentive mechanism was proposed in [26]. An incentive mechanism based on blockchain was designed in [27] to provide accurate and secure services. However, the contribution of users in DR is not taken into consideration in these studies.

Aiming at promoting the secure implementation of DR, decreasing the imbalance among users in response frequency and reducing the costs borne by the electricity retail company, a secure blockchain-enabled DR scheme with individualized incentive pricing mode is proposed in this paper. The major contributions of this paper are as follows.

1. To promote the secure implementation of DR, a blockchain-based DR framework is proposed and the benefits of the use of blockchain technology are illustrated and specified.
2. Considering the difference in user response cost characteristics, an individualized incentive pricing mode is adopted and optimal individualized incentive prices are produced by solving the constructed Stackelberg game model.
3. To successfully apply blockchain technology to DR, a dual-incentive mechanism considering the demands for both revenue and contribution of users is designed.

The rest of this paper is organized as follows. Section 2 describes the system framework and the operation mechanism of the blockchain-enabled DR. Section 3 introduces the dual-incentive mechanism.

Section 4 illustrates the Stackelberg game model and its solution algorithm. Section 5 provides the results of the simulations. A conclusion is given in Section 6.

2. System Framework

2.1. System Framework Description

This paper focuses on a system which contains a single electricity retail company and multiple users. The electricity retail company purchases electricity from the electricity market and sells it to users. When there is a shortage of electricity supply, the electricity company announces a set of individualized incentive prices which contains different prices for different users, while blockchain announces contribution prices to users. Then, users decide the volume of load shedding under such a context of dual-incentive mechanism The blockchain is responsible for the analysis and calculation of these parameters collected from the electricity retail company and users. Using the Stackelberg game model, the above process was executed repeatedly until the iteration reached its upper limit. Thus, equilibrium solutions are obtained.

The electricity retail company and users execute the equilibrium solutions such as optimal incentive prices and optimal volume of load shedding to achieve optimal operations. The overall framework of the blockchain-enabled DR scheme is illustrated in Figure 1. The TOU price is given. The contribution price is agreed by the electricity retail company and the blockchain. The optimal individualized incentive prices and the optimal volume of load shedding are determined by the equilibrium solutions.

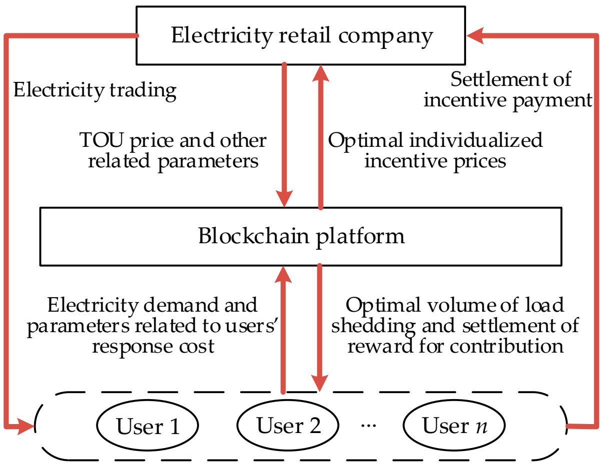


Figure 1. The overall framework of the blockchain-enabled DR scheme.

2.2. The Network of Blockchain-Enabled DR

The consortium blockchain is a "permissioned" blockchain, which is suitable for power grid and other scenarios with high authority requirements. Thus, a consortium chain is adopted to carry the electricity retail company and users under the blockchain-enabled DR. There are many consensus mechanisms for the blockchain, such as proof of work (PoW), proof of stake (PoS) and practical byzantine fault tolerance (PBFT). The PoW and PoS consensus mechanisms are used in public blockchain environments [28]; these are not suitable for the consortium blockchain adopted in this paper. The PBFT consensus mechanism, which the consortium blockchain mostly adopts, is relatively loose. It can shorten the time for consensus and shows superiority in throughput and energy consumption compared with PoW and PoS [29]. Thus, it is more suitable for DR efficiency requirements, and is utilized in this paper.

As the blockchain network is attached to nodes, the electricity retail company and users are regarded as nodes in the blockchain network. Peer-to-peer energy trading and transaction settlements can be conducted between the nodes of the electricity retail company and those of users, and verification information can be sent and fed back between all nodes. Taking user *i* as an example, the information flow between *i* and the electricity retail company, as well as other users in blockchain network, is shown in Figure 2.

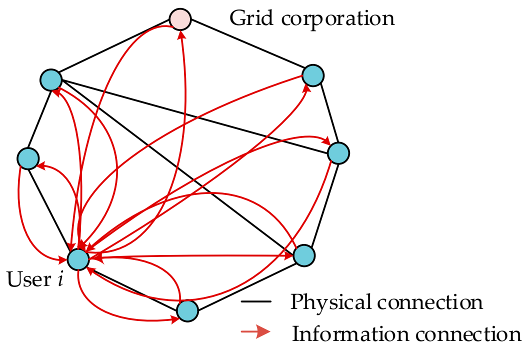


Figure 2. The information flow between user *i* and other nodes in blockchain-enabled DR network.

2.3. Operation Mode

All nodes work according to the following rules.

(1) When a certain user enters the network, relevant identity authentication is required. After the authentication is passed, a new node is formed. The blockchain returns to the user a pair of public and private keys. The public key is used as the user's account address on the blockchain, and the private key is used as a unique key to operate the account.
(2) The user broadcasts the predicted electricity demand and parameters related to response cost characteristics in the whole network, together with the public key, while also downloading other users' parameters. During each scheduling period, each user re-uploads the predicted electricity demand and updates other users' parameters.
(3) Each node creates an empty block every time interval.
(4) The blockchain checks the current operating status every time interval to determine whether the contract has been reached. If it is reached, the DR, based on a dual-incentive mechanism, is automatically conducted to obtain the equilibrium solutions, which will be broadcast to the verification nodes in the blockchain and then wait for consensus.
(5) The verification node first performs signature verification to ensure the validity of the information; the verified information then enters the waiting consensus set. After most verification nodes reach consensus, all nodes automatically execute equilibrium solutions, conduct energy trading and carry out transaction settlements.
(6) Each node forms a data block with its own information and the received transaction data using a timestamp. The block will be connected to the current longest blockchain, forming the latest block.

2.4. Security Illustration of Blockchain-Enabled DR

The security of the blockchain-enabled DR can be guaranteed by two aspects: asymmetric encryption and the consensus mechanism.

To avoid information being modified and tampered with in transmissions between the electricity company and users, a cryptographic hash function and signature are used in asymmetric encryption. PBFT consensus mechanism is used to reach consensus among the nodes composed of the electricity company and multiple users. Each node in the blockchain network acts as a primary node in turn, and the remaining nodes become backup nodes. PBFT can tolerate no more than one-third of the total number of malicious nodes in the system; therefore, there is little chance that the information and transaction records could be modified or tampered with.

However, the use of the blockchain does not mean that the final execution information is exactly correct. There are still some challenges in blockchain due to the various threats of malicious attack including intelligent contract and reply attacks. This is a focus for the improvement of blockchain technology, but is not within the scope of this paper. Relevant research can be found in [30,31].

3. Dual-Incentive Mechanism Modeling

To meet the demands of users for both revenue and contribution, a dual-incentive mechanism which consists of a profit-based model and a contribution-based model was designed.

3.1. Profit-Based Model

In the case of electricity shortages, the electricity retail company hopes to ensure economical operation as much as possible on the premise of guaranteeing an uninterrupted supply of critical loads. Therefore, a profit-based model needs to be adopted in DR to motivate users to respond to the electricity retail company. Users respond to the electricity company by load shedding for incentive revenue. The costs borne by the electricity retail company consist of the incentive payments for users, the reduced electricity purchase costs from the electricity market and loss of revenue. The revenue of users consists of incentive revenues, response costs and reduced electricity purchase costs from the electricity retail company.

3.1.1. Electricity Retail Company Modeling in DR

Incentive payments are offered by the electricity retail company to motivate users to adapt their electricity loads to supply availability. If the electricity retail company offers unified incentive prices to all users, due to the differences in users' response cost characteristics and sensitivity, the response frequency of each user will vary greatly, making it impossible for each user to have equal trading initiatives and equally participate in DR. In addition, the costs borne by the electricity retail company are not the lowest that they can be. To illustrate, the response frequency of each user can be expressed as the sum of the response times in all scheduling periods within a 24-h period. The response frequency of user i in 24-h is shown as Equation (A1) in the Appendix A.

Therefore, to motivate less frequent users to reach more frequent responses and make the costs borne by the electricity retail company as low as possible, the individualized incentive pricing mode is adopted. The incentive payments offered by the electricity retail company are expressed as follows.

$$C_{\text{grid,COM},t} = \sum_{i \in N} c_{i,\text{COM},t} P_{i,\text{LC},t}, \; N = \{1, 2, 3, \ldots, n\} \tag{1}$$

where $c_{i,\text{COM},t}$ is the individualized incentive price for user i at time interval t, whose optimal value is determined by the equilibrium solutions; $P_{i,\text{LC},t}$ is the volume of load shedding of user i at time interval t; and N is the set of users.

As the electricity retail company incentivizes users to reduce their loads, its costs for purchasing electricity will be reduced, as will its revenue from electricity sales. The price of electricity sold by the electricity retail company to users adopts TOU pricing. The reduced purchase cost from the electricity market and the loss of revenue can be expressed as follows.

$$C_{\text{grid,be},t} = \sum_{i \in N} c_{\text{be},t} P_{i,\text{LC},t} \tag{2}$$

$$C_{\text{grid,se},t} = \sum_{i \in N} c_{\text{se},t} P_{i,\text{LC},t} \tag{3}$$

where $c_{\text{be},t}$ is the electricity purchase price of the electricity retail company; and $c_{\text{se},t}$ is the TOU price at time interval t.

In conclusion, the costs borne by the electricity retail company can be expressed as follows.

$$\begin{aligned} f_{\mathrm{grid},t} &= C_{\mathrm{grid,COM},t} - C_{\mathrm{grid,be},t} + C_{\mathrm{grid,se},t} \\ &= \sum_{i \in N} c_{i,\mathrm{COM},t} P_{i,\mathrm{LC},t} - \sum_{i \in N} c_{\mathrm{be},t} P_{i,\mathrm{LC},t} + \sum_{i \in N} c_{\mathrm{se},t} P_{i,\mathrm{LC},t} \end{aligned} \tag{4}$$

3.1.2. User Modeling in DR

The main revenue of users participating in the DR program comes from the incentive payments offered by the electricity retail company. The incentive revenue of user i can be expressed as follows.

$$C_{i,\mathrm{COM},t} = c_{i,\mathrm{COM},t} P_{i,\mathrm{LC},t} \tag{5}$$

The differences in user response cost characteristics are mainly reflected in the different response costs of different users. In this paper, the response costs of user i participating in DR refer mainly to the load shedding cost, and can be expressed as follows.

$$C_{i,\mathrm{DR},t} = a_{i,\mathrm{LC}} P_{i,\mathrm{LC},t}^2 + b_{i,\mathrm{LC}} P_{i,\mathrm{LC},t} \tag{6}$$

where $a_{i,\mathrm{LC}}$ and $b_{i,\mathrm{LC}}$ are the load shedding cost coefficients of user i.

User i responds to the electricity retail company by load shedding, and thus, the electricity purchase costs from the electricity retail company are reduced. The reduced electricity purchase cost from the electricity retail company can be expressed as follows.

$$C_{i,\mathrm{RC},t} = c_{\mathrm{se},t} P_{i,\mathrm{LC},t} \tag{7}$$

3.2. Contribution-Based Model

Despite the fact that blockchain technology has the advantages of security and trust, there may be a disagreement between the electricity retail company and users over whether or not to apply the blockchain to DR. On the one hand, the security of blockchain technology has varying degrees of beneficial effects on the electricity retail company and users. The electricity retail company engages in transactions more frequently than any other user, and thus, is well placed to recognize the economic benefits from secure information, while users are not. On the other hand, certain threshold fees will be charged when the electricity retail company and users enter the blockchain network. As a result, the electricity retail company and profit sensitive users may hold opposing attitudes regarding the application of blockchain technology to DR. Additionally, the electricity retail company and users face other problems. The electricity retail company bears the incentive payment independently in DR, especially when the electricity market fluctuates wildly. A mere profit-based model can meet the demand of users for revenue, but it may not be enough to meet the demand for contributions, which is an important index by which to measure the benefits of a node in the blockchain environment.

To successfully apply blockchain technology to DR, the electricity retail company and the blockchain must reach an agreement, i.e., that the electricity retail company pays threshold fees to the blockchain for users to apply blockchain technology to DR, and correspondingly, the blockchain provides a contribution-based model to distribute incentive payments and to meet the demands of users for contributions in the blockchain environment. Consequently, a contribution-based model is designed in the blockchain environment.

Users who make contributions to the operation of the system can be rewarded by the blockchain. The reward of user i for contributions is expressed as follows.

$$C_{i,\mathrm{contrib},t} = c_{i,\mathrm{contrib}} \frac{P_{i,\mathrm{LC},t}}{P_{\mathrm{sh},t}} \tag{8}$$

where $c_{i,\text{contrib}}$ is the contribution price which is agreed upon by the electricity retail company and the blockchain; and $P_{\text{sh},t}$ is the volume of electricity shortage at time interval t.

At the end of each trading day, the cumulative contribution of user i on that day will be used as an important indicator to determine its parameters in the next trading day, such as contribution prices and transaction fees. Since the contribution of users is directly related to their rewards, some users may tamper with transaction records to increase their contributions for more rewards. It is worth noting that the proposed DR runs on the blockchain and adopts the PBFT consensus mechanism for bookkeeping under the principle of the majority. The malicious behavior of a few irrational nodes is not enough to affect the final consensus equilibrium solutions, guaranteeing the security of the transaction.

From the above, the revenue of users based on the dual-incentive mechanism is expressed as follows.

$$\begin{aligned} f_{i,t} &= -C_{i,\text{DR},t} + C_{i,\text{RC},t} + C_{i,\text{COM},t} + C_{i,\text{contrib},t} \\ &= -a_{i,\text{LC}} P_{i,\text{LC},t}^2 + (-b_{i,\text{LC}} + c_{\text{se},t} + c_{i,\text{COM},t} + \frac{c_{i,\text{contrib}}}{P_{\text{sh},t}}) P_{i,\text{LC},t} \end{aligned} \tag{9}$$

4. Stackelberg Game Modeling and Solution

4.1. Optimization Model of Electricity Retail Company

In the process of DR, both the electricity retail company and users aim to maximize their profits. The purpose of the electricity retail company is to find the optimal individualized incentive prices for users to minimize costs that must be borne by the company. The electricity retail company is in the upper layer of the Stackelberg game model, and the objective function is as follows.

$$\min f_{\text{grid},t} = \sum_{i \in N} c_{i,\text{COM},t} P_{i,\text{LC},t} - \sum_{i \in N} c_{\text{be},t} P_{i,\text{LC},t} + \sum_{i \in N} c_{\text{se},t} P_{i,\text{LC},t} \tag{10}$$

Since the electricity retail company needs to absorb the supply gap with the response of users, constraint (11) needs to be met. Constraints (12)–(13) limit the range of incentive prices and the volume of load shedding. As users are in the electricity network, the volume of load shedding needs to meet the constraints as follows, which include power balance, node power and branch power constraints. These constraints are shown as Equation (A2)–(A6) in the Appendix A.

$$\sum_{i \in N} \frac{-b_{i,\text{LC}} + c_{\text{se},t} + c_{i,\text{COM},t} + \frac{c_{i,\text{contrib}}}{P_{\text{sh},t}}}{2a_{i,\text{LC}}} \geq P_{\text{sh},t} \tag{11}$$

$$0 \leq c_{i,\text{COM},t} \leq c_{\text{COM,max}} \tag{12}$$

$$0 \leq P_{i,\text{LC},t} \leq P_{i,\text{LC},t,\text{best}} \tag{13}$$

where $c_{\text{COM,max}}$ is the upper limit of incentive price; and $P_{i,\text{LC},t,\text{best}}$ is the maximum volume of load shedding for user i; its formula is shown as Equation (15).

4.2. Optimization Model of Users

The purpose of users is to decide the corresponding optimal volume of load shedding to maximize their revenue according to individualized incentive prices, the contribution-based model and user response cost characteristics. Users are in the lower layer of the Stackelberg game model. The objective function of user i is as follows.

$$\max f_{i,t} = -a_{i,\text{LC}} P_{i,\text{LC},t}^2 + (-b_{i,\text{LC}} + c_{\text{se},t} + c_{i,\text{COM},t} + \frac{c_{i,\text{contrib}}}{P_{\text{sh},t}}) P_{i,\text{LC},t} \tag{14}$$

When the electricity retail company issues a set of individualized incentive prices, users will calculate the corresponding maximum volume of load shedding with the purpose of maximizing their revenue by the analytic method. The maximum volume of load shedding will be set as the upper limit of load shedding. The calculated maximum volume of load shedding can be expressed as follows.

$$P_{i,\mathrm{LC},t,\mathrm{best}} = \begin{cases} 0 & c_{i,\mathrm{COM},t} \leq b_{i,\mathrm{LC}} - c_{\mathrm{se},t} - \frac{c_{\mathrm{contrib},t}}{P_{\mathrm{sh},t}} \\ \frac{-b_{i,\mathrm{LC}}+c_{\mathrm{se},t}+c_{i,\mathrm{COM},t}+\frac{c_{\mathrm{contrib},t}}{P_{\mathrm{sh},t}}}{2a_{i,\mathrm{LC}}}, & c_{i,\mathrm{COM},t} > b_{i,\mathrm{LC}} - c_{\mathrm{se},t} - \frac{c_{\mathrm{contrib},t}}{P_{\mathrm{sh},t}} \end{cases} \quad (15)$$

The maximum volume of load shedding of each user will affect the costs borne by the electricity retail company, prompting the company to adjust its individualized incentive prices until an equilibrium is reached.

4.3. Solution Algorithm

According to the literature [32], it is easy to prove that the Stackelberg game model constructed in this paper has equilibrium solutions. The upper layer model of the Stackelberg game is a linear programming model, and the solver is directly used based on CPLEX platform. In each iteration, Differential Evolution (DE) [33] is applied to the mutation, crossover and selection of individualized incentive prices. The lower layer model of the Stackelberg game is a quadratic convex function, and the maximum volume of load shedding of each user for any set of individualized incentive prices can be calculated by the analytic method.

Each set of individualized incentives prices is an individual in the population. The initial population is $\boldsymbol{X}^0 = (x_1^0, x_2^0, x_3^0, \ldots, x_{np}^0)$, and np is the population size. The initialization formula of the individualized incentive prices is expressed as follows.

$$x_j^0 = \boldsymbol{ones}(1, Dim)x_{\min} + \boldsymbol{rand}(1, Dim)(x_{\max} - x_{\min}),\ j = 1,2,3,\cdots np \quad (16)$$

where Dim is the individual dimension, that is, the number of users; $\boldsymbol{ones}(1, Dim)$ is a $1 \times Dim$ matrix of ones; $\boldsymbol{rand}(1, Dim)$ is a $1 \times Dim$ matrix uniformly distributed between [0, 1].

The mutation is based on the differences between randomly sampled individuals in a contemporary population. Individuals after mutation can be expressed as follows.

$$v_j^{G+1} = x_{r1}^G + F(x_{r2}^G - x_{r2}^G) \quad (17)$$

where G is the iteration of evolution; v_j^{G+1} is the individual after mutation; x_{r1}^G is the parent basis vector; $(x_{r2}^G - x_{r3}^G)$ is the parent difference vector, and satisfies the inequality $r_1 \neq r_2 \neq r_3 \neq j$; and F is the scaling factor, which is set as 0.3 in this paper.

To maintain the diversity of the population, a binomial crossover operator is used to generate cross individuals. Individuals after crossover can be expressed as follows.

$$u_{j,k}^{G+1} = \begin{cases} v_{j,k}^{G+1}, & \boldsymbol{rand}(1,1) \leq C_{\mathrm{R}} \\ x_{j,k}^G, & else \end{cases} ,k = 1,2,\cdots Dim \quad (18)$$

where C_{R} is crossover probability.

To ensure a better individual level in the population, selection should be carried out. Individuals after selection can be expressed as follows.

$$x_j^{G+1} = \begin{cases} u_j^{G+1}, & f(u_j^{G+1}) \leq f(u_j^{G+1}) \\ x_j^G, & else \end{cases} \quad (19)$$

The flowchart for solving the equilibrium solutions of the Stackelberg game is shown in Figure 3. First, the set of individualized incentive prices is initialized according to Equation (16). Next, the analytic method is used to calculate the maximum volume of load shedding for each user under the current set of incentive prices according to Equation (15). Then, according to the objective function set in Equation (10), the volume of load shedding for each user and the costs borne by the electricity retail company under the current set of incentive prices are solved based on the CPLEX solver. Next, mutation, crossover and selection are carried out according to Equations (17)–(19) to update the set of individualized incentive prices. Finally, the above process can be repeated until the iteration reaches its upper limit $G_{\max}$ to obtain the equilibrium solutions which contain optimal individualized incentive prices, the optimal cost for the electricity retail company and the optimal response volume of each user.

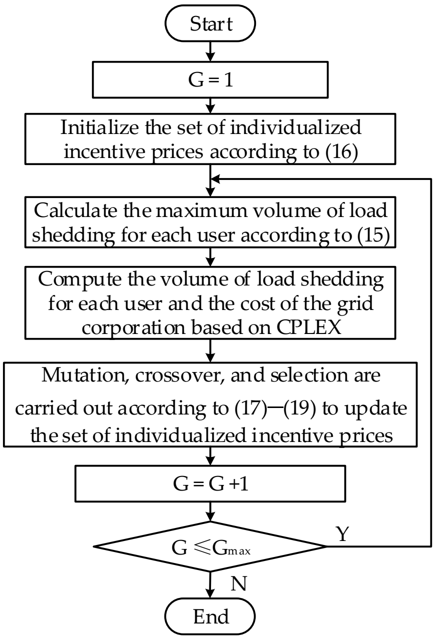


Figure 3. Flowchart of the Stackelberg game for solving the equilibrium solutions.

5. Case Studies

5.1. Parameters Setting

In this section, a 14-node, receiving-end electricity network [34] and an electricity retail company are used to verify the effectiveness of the proposed scheme. The nodes of the electricity network are renumbered, and its topology is shown in Figure A1. Take the moment when t = 18 as an example, the electricity load of each node is shown in Table A1. The predicted electricity load profile is shown in Figure A2, in which 20% of total demand at each node is considered critical.

Taking the case where all imbalances between the supply and demand are electricity shortages as an example, due to the influence of the cumulation of prediction errors on a large time scale, there is an electricity shortage on an hour time scale; its profile is shown in Figure A2. When applied to practical problems, the proposed scheme can be applied in the time period when an electricity shortage occurs.

The TOU price is provided in [35]. The $c_{i,\text{contrib}}$ is set as \$60. The $G_{\max}$ is set as 150. Assume that each node corresponds to a user and the user number is the node number. The parameters of the response costs of all users are adopted from [35], and some changes were made to accommodate for the number of users in this paper. The parameters are shown in Table A2. The research methods (equations) used in this paper and corresponding references are shown in Table 1.

Table 1. Research method description.

Equation	Based on	Equation	Based on
(1)–(5)	own elaboration	(A1)	own elaboration
(6)	[36]	(A2)–(A4)	[37]
(7)–(15)	own elaboration	(A5)–(A6)	own elaboration
(16)–(19)	[38]		

5.2. Simulation Results

According to the proposed scheme and parameter settings, the simulation results are as follows when the proposed dual-incentive mechanism is adopted in the blockchain environment. By solving the Stackelberg game model, the optimal individualized incentive prices are produced, as indicated in the box chart shown in Figure 4a. Users with higher load shedding cost coefficients, such as users 4, 5, 9 and 13, have higher response costs in response to the same load shedding compared to other users. This kind of user is only willing to participate in DR when they are motivated by higher incentive prices. Therefore, to encourage this kind of user to participate in DR, the electricity retail company needs to offer them higher incentive prices compared to those offered to other users. The relationship between user response cost characteristics and their incentive prices are well reflected.

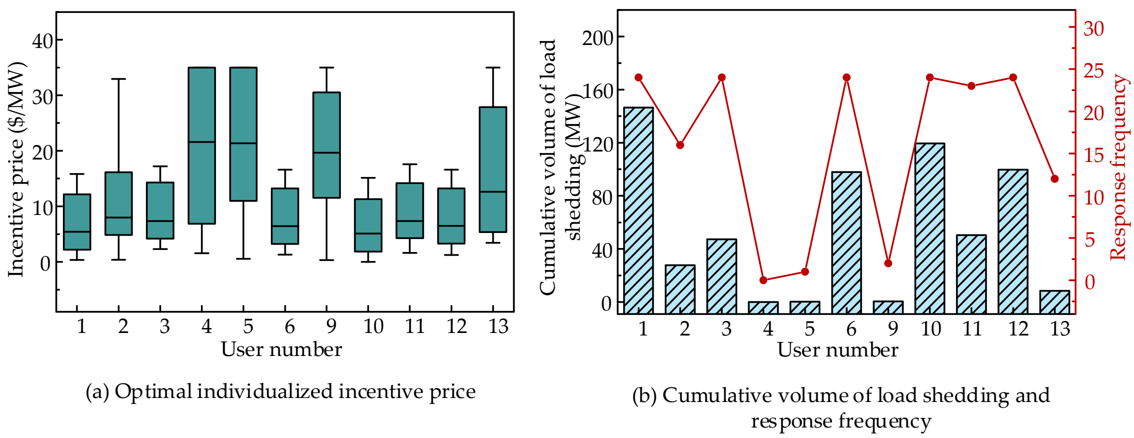


Figure 4. Equilibrium results of optimal individualized incentive price (**a**) as well as cumulative volume of load shedding and response frequency (**b**) when the proposed dual-incentive mechanism is adopted.

The cumulative volume of load shedding and response frequency of each user over a 24-h period is shown in Figure 4b. In the process of the operation, the electricity retail company expects to minimize its costs while absorbing the gap between the supply and demand. This prompts the electricity company to give priority to users with lower incentive prices when choosing response users. Consequently, users requiring lower incentive prices have a higher cumulative volume of load shedding and response frequency, while users requiring higher incentive prices have a lower cumulative volume of load shedding and response frequency, e.g., users 4, 5, 9 and 13. Take typical users 1, 2, 11, and 13 as an example; their optimal individualized incentive prices and corresponding volume of load shedding over a 24-h period are shown in Figure 5. The actual volume of load shedding and response frequency can indirectly reflect user response cost characteristics.

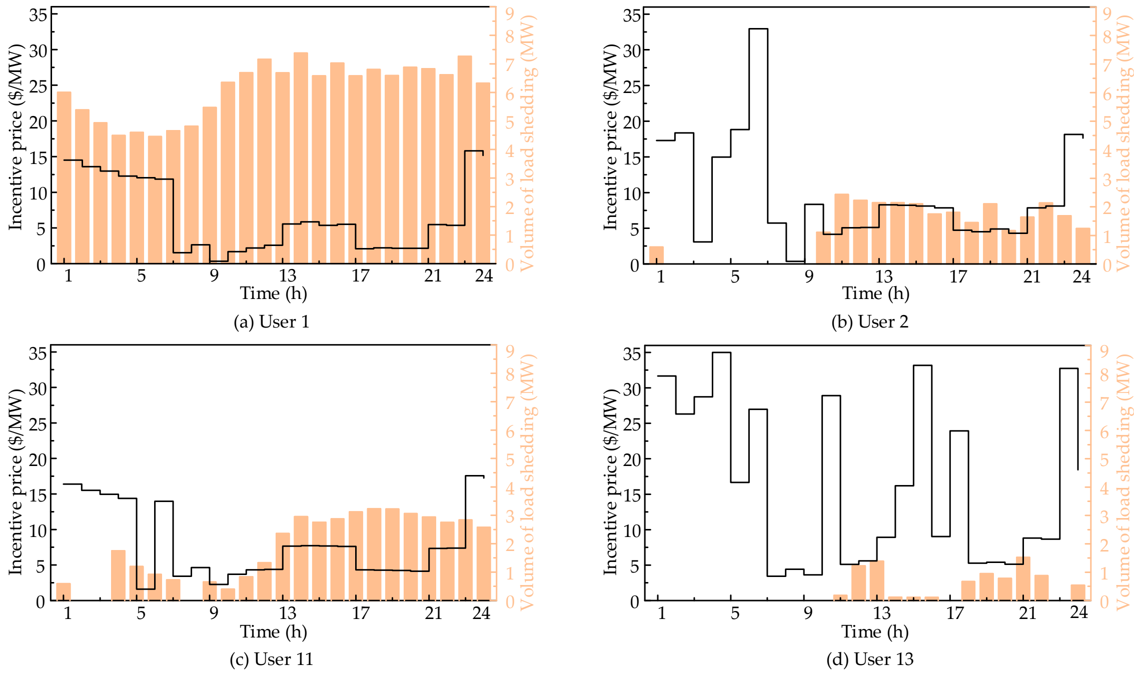


Figure 5. Optimal individualized incentive prices and corresponding volume of load shedding over a 24-h period for users 1, 2, 11 and 13.

The variation trends of the costs borne by the electricity retail company with the number of iterations in each time interval are shown in Figure 6. It can be seen from the figure that the solution results in each time interval reach convergence within 150 iterations.

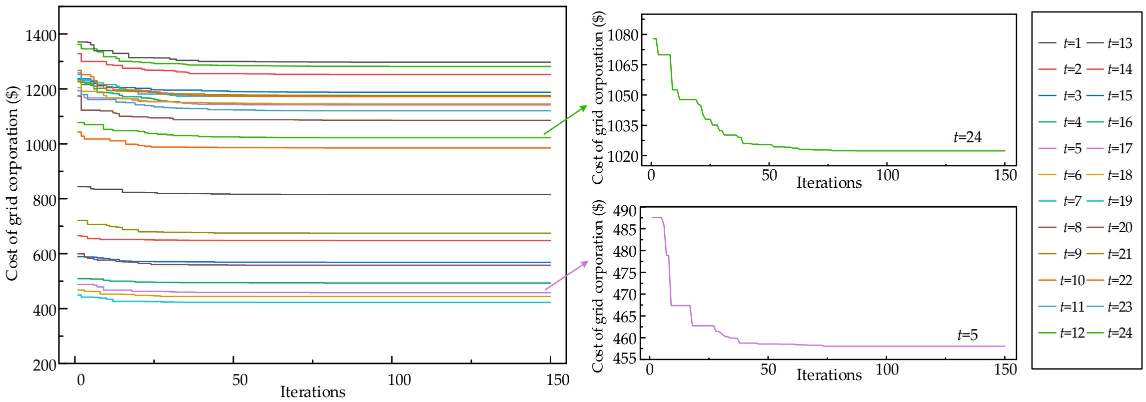
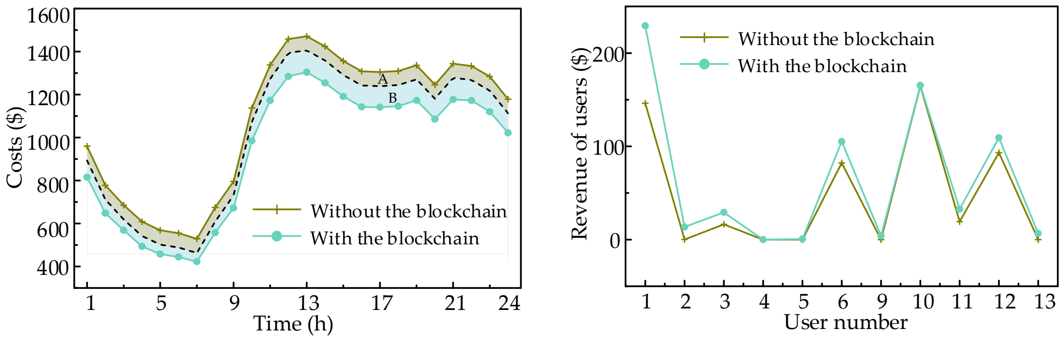


Figure 6. The variation trends of the cost borne by the electricity retail company with the number of iterations in each time interval.

5.3. Analysis on Security of Blockchain

When the DR between the electricity retail company and users does not operate in the blockchain environment, there is a possibility that the information broadcast between them may be tampered with. The probability that the information received by a node has been tampered with is shown in Table A3. There is no contribution-based model launched by the blockchain in such a case. The response of users to the electricity retail company is only motived by the incentive mechanism of the profit-based model, and individualized incentive pricing mode is adopted.

The cost profiles of the electricity retail company without and with the blockchain over a 24-h period are shown in Figure 7a. Due to the lack of both asymmetric encryption and consensus mechanisms in the absence of the blockchain, the incentive prices received by users from the electricity retail company and the volume of load shedding received by electricity retail company from users may be tempered with. The increased costs borne by the electricity retail company caused by insecure information are shown as the filled area B in Figure 7a. Due to the lack of a contribution-based model offered by the blockchain, the DR incentive payment is borne by the electricity retail company independently; these costs are shown as the filled area A in Figure 7a. This shows that the costs borne by the electricity retail company are significantly increased without the blockchain.



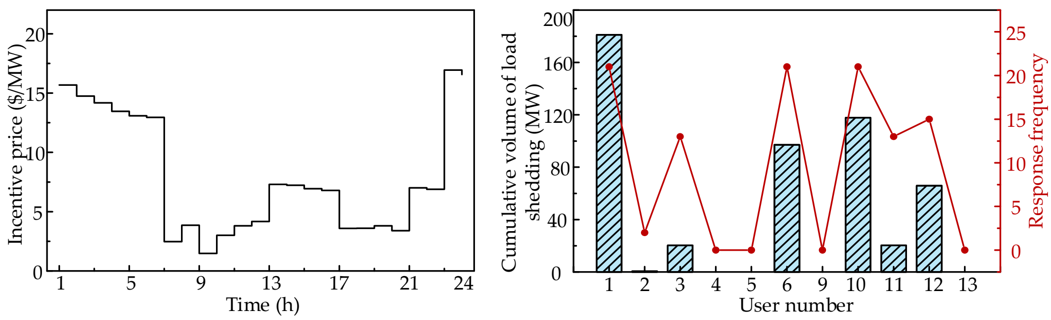
(a) Costs borne by the electricity retail company (b) Revenue of users

Figure 7. Comparison of the costs borne by the electricity retail company (**a**) and revenue of users (**b**) without and with the blockchain.

The revenue profiles of users without and with the blockchain are shown in Figure 7b. Because of the insecure information, there are slight differences between the revenues of users without and with the blockchain. The insecure information in the individualized incentive prices received by users and the volume of load shedding received by electricity retail company result in the unreliable and inaccurate revenue of users. As Figure 7 shows, the security of blockchain has varying degrees of beneficial effects for the electricity retail company and users. Therefore, the points in Section 3 support the hypothesis that the electricity retail company will regularly benefit enough to recognize the economic value of secure information, while users may not.

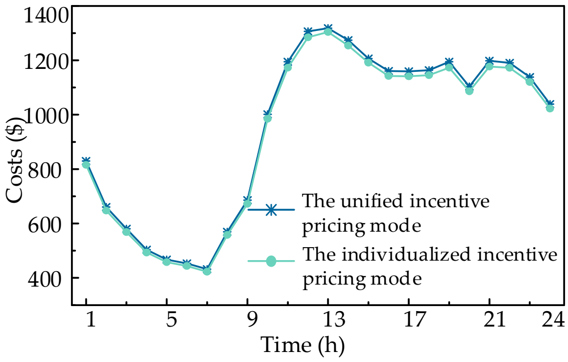
5.4. Analysis of Incentive Prices

The simulation results are as follows when a unified incentive pricing mode is adopted that offers the same incentive prices to different users. By solving the Stackelberg game model, the equilibrium results are shown in Figure 8. The optimal incentive price in each time interval is shown in Figure 8a, and the cumulative volume of load shedding and response frequency of each node over a 24-h period are shown in Figure 8b. A comparison of the costs borne by the electricity retail company and the revenue of users under the unified and individualized incentive pricing modes is shown in Figure 9.

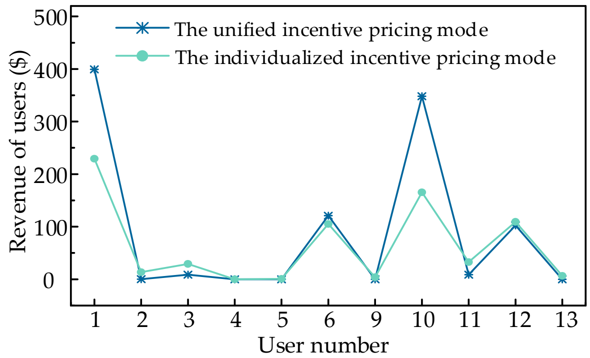


(a) Optimal incentive price (b) Cumulative volume of load shedding and response frequency

Figure 8. Equilibrium results of optimal incentive price (**a**) as well as cumulative volume of load shedding and response frequency (**b**) when the unified incentive pricing mode is adopted.



(a) Costs borne by the electricity retail company



(b) Revenue of users

Figure 9. Comparison of costs borne by the electricity retail company (**a**) and revenue of users (**b**) under the unified and individualized incentive pricing mode.

The costs borne by the electricity retail company when the individualized incentive pricing mode is adopted are lower than when a unified incentive pricing mode is adopted, because the former allows individualized incentive pricing for different users. In terms of the volume of load shedding and revenue, compared with the case when the individualized incentive pricing mode is adopted, the response situation and revenue of each user are obviously different when the unified incentive pricing mode is adopted. Users with lower load shedding cost coefficients, such as users 1, 6 and 10, have a higher cumulative volume of load shedding, response frequency and revenue. Meanwhile, users with a higher load shedding cost coefficient, such as users 4, 5, 9 and 13, are not selected by the electricity retail company to respond at any time. The response frequency and revenue of each user are imbalanced greatly when the unified incentive pricing mode is adopted, while the imbalance among users is moderately reduced when individualized incentive pricing mode is adopted.

6. Conclusions

A secure blockchain-enabled DR scheme with individualized incentive pricing mode is proposed in this paper. According to the simulation results, the main conclusions are as follows.

1. The scheme proposed in this paper can minimize the costs borne by the electricity retail company and maximize the revenue of users while absorbing the gap and maintaining the balance between supply and demand.
2. Compared with offering unified incentive prices to all users, providing individualized incentive prices for different users can significantly reduce the costs borne by the electricity retail company and moderately decrease the imbalance among users in terms of response frequency and revenue.
3. The application of blockchain technology in DR, on the one hand, can promote secure implementation and ensure that the scheduling results are reliable. On the other hand, the contribution-based model offered by blockchain reduces the incentive payments for the electricity retail company and meets the demand of users for contribution.

The proposed scheme revealed that further study in the following directions would be worthwhile.

1. Improve the contribution-based model by studying other aspects, such as contribution pricing, voting weight determination and specific influence research. Do verification on the blockchain simulation platform to capitalize upon the transactions between the electricity retail company and users.
2. Consider more market-realistic situations such as more than one electricity retail company participating in DR and a larger number of users. Explore game and solution models, which are suitable for this type of market-realistic situations.

3. Consider the potential issue with scaling the proposed scheme and simulate user opinions regarding the use of blockchain technology in DR with a more effective/convincing method, such as explainable artificial intelligence (XAI).

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Appendix A

The response frequency of user i in 24-h can be expressed as follows.

$$RF_i = \sum_{t \in T} x_{i,t} \tag{A1}$$

where, $x_{i,t}$ is the state of response of user i; If user i responses to the electricity retail company at time interval t,$x_{i,t} = 1$, otherwise, $x_{i,t} = 0$; T is the set of time intervals.

Constraints (A2)–(A4) reflect the power balance of the whole network, nodes and branches, respectively. Constraints (A5)–(A6) limit the power of branches and load nodes, respectively.

$$\sum_{i \in N} P_{i,\mathrm{S},t} - \sum_{i \in N} P_{i,\mathrm{L},t} - \sum_{i \in N} P_{i,\mathrm{LC},t} = 0 \tag{A2}$$

$$P_{\mathrm{S},t} - P_{\mathrm{L},t} + P_{\mathrm{LC},t} = B\theta \tag{A3}$$

$$P_0 = B_{b,\mathrm{e}} R_\mathrm{e} \theta \tag{A4}$$

$$\left| P_{l,m} \right| \le P_{l,m,\max} \tag{A5}$$

$$0 \le P_{i,\mathrm{LC},t} \le P_{i,\mathrm{LC},\max} \tag{A6}$$

where, $P_{i,\mathrm{S},t}$ and $P_{i,\mathrm{L},t}$ are received power and load of user i, respectively; $P_{\mathrm{S,t}}$, $P_{\mathrm{L,t}}$ and $P_{\mathrm{LC,t}}$ are vectors of received power, load and load shedding, respectively; P_0 is the vector of branch power; B and $B_{b,\mathrm{e}}$ are node susceptance matrix and node susceptance diagonal matrix, respectively; θ is the vector of node phase angle; R_e is the node-to-branch incidence matrix of electricity subsystem; $P_{l,\mathrm{m}}$ and $P_{l,\mathrm{m,max}}$ are the active power and the upper limit of the active power of branch m, respectively; $P_{i,\mathrm{LC,\ max}}$ is the upper limit of load shedding of user i related to critical load.

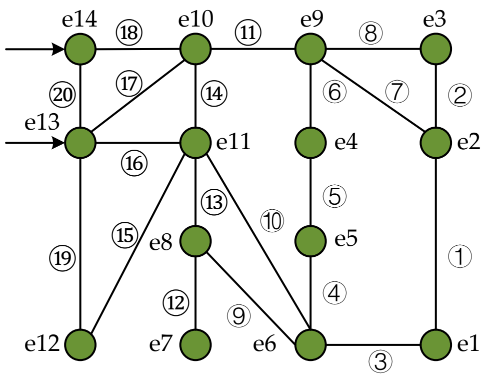

Figure A1. The topology of the 14-node receiving-end electricity network.

Table A1. The electricity load of each node at t = 18.

User Number	Electricity Demand (MW)	User Number	Electricity Demand (MW)
1	14.9	8	/
2	13.5	9	11.2
3	6.1	10	7.6
4	3.5	11	47.8
5	9	12	94.2
6	29.6	13	21.7
7	/	/	/

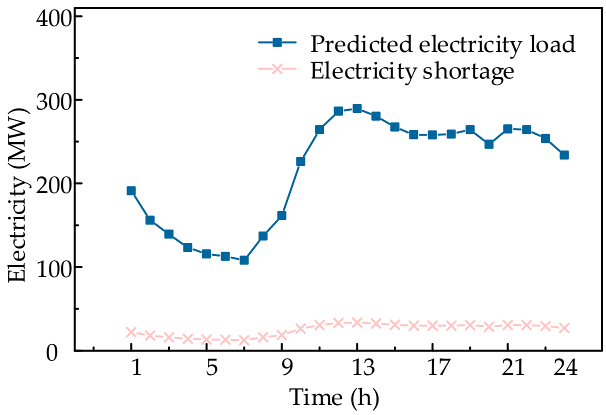

Figure A2. Profiles of predicted electricity load and electricity shortage.

Table A2. Parameters of response cost of all users.

User Number	$a_{i,\text{LC}}$	$b_{i,\text{LC}}$	User Number	$a_{i,\text{LC}}$	$b_{i,\text{LC}}$
1	0.25	36	8	/	/
2	0.25	41	9	0.25	44
3	0.25	40	10	0.25	36
4	0.25	46	11	0.25	40
5	0.25	43	12	0.25	38
6	0.25	38	13	0.25	42
7	/	/	/	/	/

Table A3. The probability that the information received by a node is tampered with.

Node Number	Probability	Node Number	Probability
1	0.8675	8	/
2	0.9035	9	0.9409
3	0.9035	10	0.9799
4	0.9035	11	0.9409
5	0.8675	12	0.9409
6	0.9035	13	0.9799
7	/	/	/

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