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Loaning Decision for Electric Vehicles under Uncertain Electricity Price in the Blockchain Internet of Energy

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***Abstract*—This paper discusses an uncertain loaning decision problem for electric vehicles in the blockchain Internet of energy. Blockchain guarantees the security and privacy of transactions. In view of the uncertainty of electricity price, the scenario method is introduced. A new Stackelberg game model between multi plug-in hybrid electric vehicles and a loan bank is established. For each player, through the optimal solution of the loaning decision problem, the decision of each electric vehicle and the bank is obtained. Differing from the deterministic decision problem, a robust decision problem is proposed for the uncertainty of electricity price. In particular, in the loaning decision for each plug-in hybrid vehicle, a two scenario subset robust optimization method is used. A relaxation algorithm is proposed to solve the robust decision problem. The equilibrium of robust Stackelberg game model is achieved at the optimal loaning amount of all electric vehicles and the optimal loaning rate of the bank. Finally, an experiment was conducted to test the established game model in three different instances. The effectiveness and advantages of the established game model were verified by the computational results.**

Keywords-uncertain electricity price, energy trading, blockchain, robust decision problem

I. Introduction

Conventional energy management is traditionally centralized. However, under the effect of decentralized management, our power grid can realize "global village", that is, become an energy sharing network [1]. This great transformation was first attributed to the concept of Internet of energy (IoE), which came into being during the third industrial revolution. In recent years, one belt, one road, has been attracting more and more attention from IoE. IoE provides an innovative concept for power distribution, energy storage, power grid monitoring and communication in the future green cities [2]. With the increasing number of nodes and performance requirements of IOE, how to meet the growing energy demand is a huge challenge. In order to solve this problem, IOE nodes can exchange residual energy with other nodes through P2P energy transactions, such as energy transactions in electric vehicles. As a distributed energy storage device, electric vehicle is one of the important components of IOE. With the increasing number of electric vehicles, large-scale electric vehicles connected to the smart grid will not only have a profound impact on the grid architecture, but also bring new challenges to the safe and stable operation of the power system [3].

Some nodes may not be willing to participate in the transaction as energy providers due to privacy concerns [4]. In this case, the energy supply and demand between nodes are unbalanced. In addition, the traditional centralized energy transaction based on trusted third party also has problems such as single point failure and privacy disclosure [5]. Therefore, it is very important to solve the security and privacy problems in energy trading.In recent years, a blockchain technology with the advantages of decentralization, security and trust has been introduced into power trading. Blockchain is a P2P distributed ledger technology, which can execute power transactions in a decentralized, transparent and secure market environment. Literature [6] analyzes the infrastructure of energy blockchain, which can be used in information security, power trading, multi energy cooperation and other fields [7] [8]. Jeong et al [9] proposed a billing system based on the blockchain. The billing information is stored in the blockchain to prevent modification and ensure the security of the billing information. Kang et al [10] proposed a new P2P energy transaction model, which uses the alliance blockchain method to solve the privacy protection and transaction security problems of plug-in hybrid electric vehicles (PHEVs). Therefore, the use of blockchain can solve the security problem of energy transaction in the IOE node.

However, there are generally efficiency challenges in the transaction data market based on blockchain, the main reason is the delay of transaction confirmation [11]. The consensus process of blockchain increases the delay of transaction confirmation, which affects transaction efficiency and capital turnover. The buyer usually does not have enough funds to support their next transaction [12]. In order to overcome the above challenges, a flexible P2P loaning mechanism is needed to improve transaction efficiency. In [10], a digital cryptocoins named energy coins are proposed, which is used as a digital asset of energy nodes when energy transactions are conducted in the Internet of things. In order to solve the problem of insufficient energy coins, the IOT nodes in [13] can borrow energy coins from other IOT nodes, and propose an algorithm based on iterative double auction to solve the problem. In [14], a credit based payment scheme is designed to support fast and frequent energy transactions of electric

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vehicles by borrowing energy coins. It can be seen that the transaction speed can be effectively accelerated by loaning.

The study of the above-mentioned loaning problem is carried out under the assumption that the electricity price is deterministic, but in the actual loaning process, the electricity price is affected by uncertain market and human factors, and the electricity price information is uncertain. It is of great practical significance to study the decision-making of the loaning and charging of electric vehicles under the uncertain electricity price. However, as far as we know, there is no report on the decision-making of electric vehicle charging under uncertain electricity price.Scenario method is an important tool to build uncertain model in robust optimization [15], and it is widely used in uncertainty problems [16]. In [17], the optimal delay charge scheduling problem of electric vehicles is studied. Considering the change of grid price, the uncertain price is described as a set of random numbers to study the constrained stochastic optimization problem. Literature [18] studies the optimal charging strategy of the charging electric taxi, and solves the uncertain price problem by providing the price scenario of each charging time. Based on the above, we can consider using scenario to solve the problem of uncertain electricity price.

Four main contributions are as follows. Firstly, considering the uncertainty of electricity price, discrete scenario is introduced to describe electricity price. Secondly, for more than one worst-case scenario, a two scenario subset robust optimization criterion is defined and applied to the decision-making of electric vehicle loaning. At the same time, the relaxation algorithm is used to solve the problem. The robust decision-making of hybrid electric vehicle can effectively avoid the utility deterioration caused by the price fluctuation. Thirdly, a robust Stackelberg game model is established to describe the competitive decision-making of multiple PHEVs. The Stackelberg Equilibrium is realized under the optimal robust decision-making of all electric vehicles and loaning banks. Finally, simulation experiments are carried out, and the results show that the model is better than the deterministic model and the worst-case model.

II. The Descriptions of Transaction Process Based on Blockchain

In blockchain, an important transaction audit stage, node consensus process, needs to be executed before transaction records are formed into blocks. Pre select trusted nodes as energy agents [19], who collect and manage their local transactions. Some energy buyers don't have enough energy coins for frequent energy transactions. In order to solve this problem, the frequent P2P energy transactions through energy coin loaning are considered.

The following energy buyer refers to the electric vehicle that needs energy, the energy seller refers to the electric vehicle that can provide energy, the borrower refers to the energy buyer that does not have enough energy coin, and the loaning bank refers to the institution that can lend to the lender.

First, each electric vehicle has a unique identity, private key and public key, and obtains the wallet address from the authority. Use this information as a mapping list for the EV and store it in the account pool. The storage pool stores all transaction records in the energy blockchain, while the credit bank records credit based payment [14]. In the energy transaction, after the energy buyer determines the energy demand, the energy agents in the blockchain collect and summarize the data and broadcast the demand. After the energy seller determines the sales amount, the energy buyer transfers the energy coins from its wallet to the wallet address provided by the energy seller. A buyer who does not have enough energy coins can apply to the credit bank for token according to the credit grades to complete the payment. The main steps are: the borrower sends the loan request to the credit bank, the credit bank verifies the identity of the borrower, calculates the optimal loan amount and the corresponding interest rate and penalty rate, and sends the relevant loan information and the secret key and public key of the wallet to the borrower. When the borrower needs to conduct energy transaction, the energy coins in the wallet is used to complete the payment. After the credit bank checks the payment information, the corresponding energy coins in the wallet is transferred to the wallet address of the energy seller, and the balance in the wallet is updated, so the payment is completed. A new transaction is generated after payment, and then the transaction is broadcast to the energy agent for audit. Energy agents collect all transactions over a period of time and record them in blocks. Each block contains the encrypted hash value of the previous block, forming a chain. Finally, in the process of consensus, the energy agent who gives effective proof of workload will be selected as the blockchain leader. Blockchain leaders broadcast block data to other energy agents for verification and audit. Other energy agents send their audit results to each other, compare them and reply. If all energy agents agree to the block data, the block will be stored in the blockchain. At the same time, blockchain leaders can get energy coins rewards. Therefore, the blockchain not only guarantees the security and privacy of energy transactions, but also solves the problem of transaction confirmation delay through the energy coins loans of electric vehicles and credit banks, and quickly pays transaction costs.

III. The Stackelberg Game Model for PHEVs under Deterministic Electricity Price

This section studies the problem of credit decision-making in the process of frequent P2P energy transactions through energy coins loaning. Among them, the credit bank acts as the lender with enough energy coins, and the credit bank provides energy coins loans for electric vehicles. Credit bank manages and guides the charging credit behavior of electric vehicles by making and adjusting the credit policy of electric vehicles. The credit of credit bank is reflected in the borrowing price of energy coins (i.e. interest rate and penalty rate). The electric vehicle determines its borrowing behavior in the energy transaction under the guidance of a certain borrowing price given by the credit bank.

In order to solve the problem of loans between electric vehicles and the bank to get the optimal decision. It is assumed that the set of participants consisting of I PHEVs in the electricity market is denoted by $V = \{1,\ldots i,\ldots,I\}$. The satisfaction function of the i th ($i \in V$) PHEV is given by Li et al. [14] as follows:

$$u_{sat}^{i} = d_i \ln(\frac{R_i}{p_i} - Q_i^{\min} + \theta_i) \tag{1}$$

where d_i, θ_i are predefined factors. R_i is the amount of energy coin given by the credit bank to the electric vehicle EV_i. The minimum energy required by EV_i is $Q_i^{\min}$. p_i is a determined price.

The utility function of EV_i can be expressed as follows.

$$u_i = a_i[u_{sat}^{i} - \beta_i R_i t_i] - (1-a_i)\alpha_i R_i \tag{2}$$

where a_i is repayment ability of a loan. β_i is interest rate of the loan depended by the credit bank. α_i is penalty rate of the repayment delay. We consider that the relationship between the interest rate and the penalty rate is $\alpha_i = \eta_i t_i \beta_i$. Here η_i is a predefined factor and t_i is the time when the loan began.

The income of the credit bank includes the interest of the loan from EV_i and the penalty caused by its failure to repay the loan in time [20]. The cost of a credit bank is $R_i t_i c_i$. Here, c_i is the unit cost of the loan provided by the credit bank. Therefore, the economic benefit of the i th PHEV to the credit bank is defined as follows.

$$u_{bc}^{i} = \gamma_i\left(\beta_i R_i t_i - R_i t_i c_i\right) + \left(1-\gamma_i\right)\alpha_i R_i \tag{3}$$

where γ_i is predefined credit grade factor depended on EV_i 'scredit grade given by the credit bank. The credit grades are classified into different levels according to credit values. Higher credit grade brings higher γ_i.

This paper establishes the Stackelberg game, credit bank is the leader and PHEVs are the followers. The credit bank finally determines the penalty rate (i.e. α_i) for the i th PHEV, and the i th PHEV determines the best loan amount (i.e. R_i) according to the penalty rate set by the credit bank.

For a given price, the game form is defined as $G(p) = \left\{V, \{R_i\}_{i\in V}, \{\alpha_i\}_{i\in V}, \{u_i\}_{i\in V}, U\right\}$. Where V represents the set of players in the game. $\{R_i\}_{i\in V}, \{\alpha_i\}_{i\in V}$ represent the set of decisions of PHEVs and the bank respectively. $\{u_i\}_{i\in V}, U$ represent the set of utility of PHEVs and the bank respectively.

The objective functions of the game are denoted as follows.

$$\max_{\alpha_i} \sum_{i=1}^{V} u_{bc}^{i}\left(\alpha_i\right) \tag{4}$$

$$s.t., \alpha_i \geq 0 \tag{5}$$

$$\max_{R_i} u_i\left(R_i\right) \tag{6}$$

$$\text{s.t. } Q_i^{\min} p_i - \theta_i p_i < R_i < R_i^{\max} \tag{7}$$

where $i = 1, 2, \cdots I$. Equation (5) is the constraint of the bank, that is, the penalty rate is not negative. Equation (7) is the constraint of electric vehicles.

Because the price of electricity is affected by uncertain market and human factors, the price information is not completely determined. It is assumed that the price of electricity fluctuates within a certain range. As the price of electricity is an uncertain input parameter in the utility function of PHEVs, a new loaning decision problem is proposed, and a game model with uncertainty is established.

IV. Robust Stackelberg Game Model for PHEVs under Uncertain Electricity Price

Here we suppose that the electricity price of each time period fluctuates within a certain range. Considering the uncertainty of electricity price, we formulate a new robust loaning decision problem and establish a robust Stackelberg game (RSG) model for all PHEVs participated.

A. The Descriptions of Uncertain Electricity Price under Discrete Scenarios

In the real electricity market environment, the price of electricity is actually an uncertain input parameter. In the case of price uncertainty, it is necessary to solve the loaning decision problem of PHEVs again.

Here, we consider the case where an uncertain price is represented by a discrete scenario. When market participants make decisions under uncertain price, the change of price will directly affect the utility of participants. Therefore, the uncertainty of electricity price should be considered in bidding decision.

λ is a price scenario, representing a possible price fluctuation deviating from the predicted price. In the same λ scenario, the price of each PHEVe is the same. Λ is a set of scenarios with $|\Lambda|$ price scenarios, where $\lambda \in \Lambda$.

B. Robust Loaning Decision Problem for Single PHEV

Here, we use the definition of a bad scenario set. The bad scenario set is defined based on the number of bad scenarios rather than the given threshold. For simplicity, bad scenario set containing only two scenarios is considered. In addition to the worst-case scenario, the optimization criterion also considers another bad scenario. Based on the minimum maximum criterion, a 2-scenario subset robust optimization criterion is proposed. Under the discrete scenario description of electricity price, the 2-scenario subset robust optimization criterion is applied to the loaning decision problem of a single PHEV, and the 2-scenario subset robust decision problem is established. The relaxation algorithm is used to obtain the optimal solution.

The loaning decision of PHEVs and the bank will be affected by the price fluctuation, the utility function of the i th PHEV under the uncertain price is expressed as follows.

$$U_i(R_i|\lambda) = a_i[d_i \ln(\frac{R_i}{p_i^\lambda} - Q_i^{\min} + \theta_i) - \beta_i R_i t_i] - (1-a_i)\alpha_i R_i \quad (8)$$

where $U_i(R_i|\lambda)$ represents the utility of the i th PHEV under λ scenario. p_i^λ indicates the market price of the i th PHEV under λ scenario.

A 2-scenario subset of Λ is a set of two discrete scenarios coming from the scenario set Λ. Λ_2 represents a two scenario subset. The average performance of solution R_i under 2-scenario subsets can expressed as follows.

$$MP\left(R_i|\Lambda_2\right) = \frac{1}{2}\sum_{\lambda\in\Lambda_2} U_i\left(R_i|\lambda\right) \quad (9)$$

For a given solution R_i, the worst 2-scenario subset Λ_2^ω is expressed as:

$$\Lambda_2^\omega = \arg\min_{\Lambda_2\subset\Lambda} MP\left(R_i|\Lambda_2\right) \quad (10)$$

Maximize the average performance under the worst 2-scenario subset, $MMP(i)$ representing the decision problem of the i th PHEV, which is expressed as:

$$\max_{R_i} MP\left(R_i|\Lambda_2^\omega\right) \quad (11)$$

$$\text{s.t. } Q_i^{\min} p_i^\lambda - \theta_i p_i^\lambda < R_i < R_i^{\max} \quad (12)$$

$$p_i^{\min} \le p_i^\lambda \le p_i^{\max} \quad (13)$$

where $p_i^{\min}$, $p_i^{\max}$ represent the minimum and maximum electricity price. Constraint (12) represents the range of the amount of energy coin borrowed under uncertain electricity price. Constraint (13) represents the fluctuation range of electricity price.

$MMP(i)$ can be further expressed as:

$$\max_{R_i}\min_{\Lambda_2\subset\Lambda} MP(R_i|\Lambda_2) \quad (14)$$
$$\text{s.t.}(12),(13)$$

By solving the problem $MMP(i)$, we can get the solution of the i th PHEV, and solve the effect of electricity price fluctuation on utility function.

Let $ME(R_i|\Lambda_2) = -MP(R_i|\Lambda_2)$ transform it into a minimum maximum problem, rewrite $MMP(i)$ as $MEP(i)$.

$$\min_{R_i}\max_{\Lambda_2\subset\Lambda} ME(R_i|\Lambda_2) \quad (15)$$
$$\text{s.t.}(12),(13)$$

The problem $MEP(i)$ is a typical minimum maximum problem with linear constraints. The relaxation algorithm (RA) based on relaxation criteria proposed by K. Shimizu et al. [21] can be used.

The $MEP(i)$ can be transformed into $MEP1(i)$ by introducing an auxiliary variable σ.

$$\min_{R_i,\sigma} \sigma \quad (16)$$

$$\text{s.t. } ME(R_i|\Lambda_2) \le \sigma,\ \forall\Lambda_2 \subset \Lambda \quad (17)$$
$$(12),(13)$$

Λ_2 traverses every one of 2-scenario subset of Λ .Because the number of scenarios of Λ is limited , equation (17) contains a finite number of inequalities. Therefore, the solution of the problem can be obtained through the fmincon function in MATLAB.

C. The Equilibrium of Robust Stackelberg Game for PHEVs

RSG model under uncertain electricity price can be expressed as

$$G\left(p^\lambda\right) = \left\{V, \{R_i\}_{i\in V}, \{\alpha_i\}_{i\in V}, \{u_i|\lambda\}_{i\in V}, U|\lambda\right\} \quad (18)$$

$\{u_i|\lambda\}_{i\in V}$,$U|\lambda$ represent the utility set of PHEVs and the bank under uncertain electricity price.

The Stackelberg Equilibrium (SE) of RSG model will be obtained under the optimal robust solution of each PHEV and the bank. When all PHEVs and the bank reach their optimal utility, game G reaches SE. When PHEVs choose their only loaning amount, once the bank finds α_i^*, game G reaches SE. Thus SE point can be obtained by solving the optimal robust decision of $MMP(i)$.

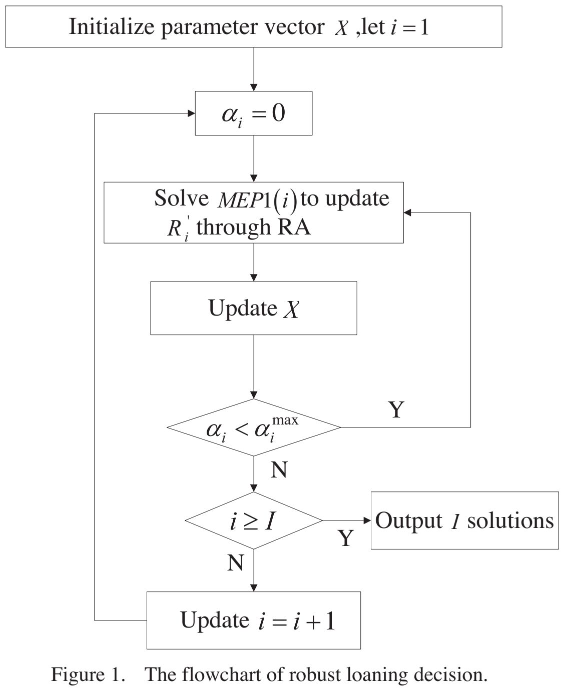

Figure 1. The flowchart of robust loaning decision.

After the solution is obtained by the 2-scenario subset method, the solution is substituted into the benefit function of the upper bank, which is repeated until the optimal solution $\left(R_i, \alpha_i\right)$ is obtained. The simplified flowchart is shown in Fig. 1, and the specific steps are as follows. For simplicity, let $X = \left(R_i, \alpha_i, u_{bc}^i, u_i\right)$

Step 1) Initialize X, let $i = 1$.

Step 2) Let $\alpha_i = 0$.

Step 3) Solve $MEP1(i)$ with RA method, and substitute the obtained R_i into the bank benefit expression. If $u_{bc}^{i'} > u_{bc}^i$, X will be updated and increase α_i; otherwise, it will not be updated and increase α_i.

Step 4) If the maximum value of α_i is not reached, go to Step 3); if the maximum value is reached, get R_i, α_i.

Step 5) If $i < I$, then $i = i + 1$; otherwise, go to Step 2).

V. Computational Results and Analysis

An experiment was conducted to investigate the performance of the established RSG model under uncertain electricity price. All models are written in MATLAB 2017A. All PHEVs and the bank parameters are from literature [14].

Within the price fluctuation range, the price scenarios are generated by the Latin hypercube sampling (LHS) program [22]. Set the number of scenarios to 20. The price fluctuation range is divided into 20 equal intervals. Then, select a sampling point randomly from each interval to form a sampling point set, and each sampling point is a price scenario.

We take five PHEVs to test RSG model. Fig. 2 shows the convergence evolution of the total economic benefits of the credit bank and the optimal lending volume of randomly selected PHEVs, respectively. After 15 iterations, the total economic benefit and the optimal loan amount of the bank converge to the optimal value rapidly.

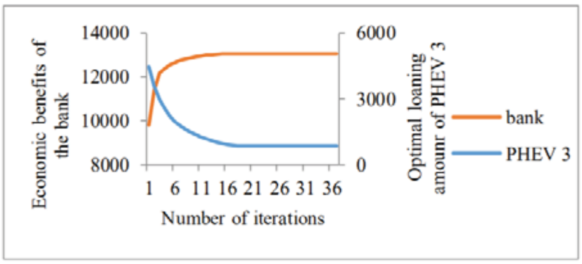

Figure 2. The iterative evolution of economic benefit and loan amount.

Fig. 3 shows the impact of credit grade factor γ_i on the bank's benefits. Compared with PHEV 3 and 4, the credit grade factors of PHEV 3 and 4 are 0.200 and 0.277 respectively. The results show that when γ_i is increased, the economic benefits of PHEV to the bank will be reduced, because PHEV with higher credit grade is more likely to repay the loan in time, resulting in less fines and reduced the bank benefit.

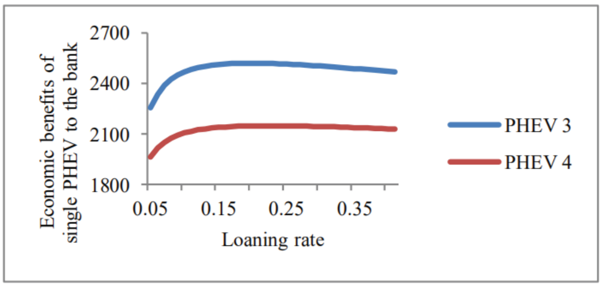

Figure 3. The influence of credit grade factors on bank efficiency.

Fig. 4 shows the effect of loan repayment ability λ_i on the benefit of PHRVs. Comparing PHEV 1 and 2, the loan repayment ability of PHEV 1 and 2 are respectively 0.187 and 0.108 , the results show that the economic benefit of PHEV will increase when λ_i is increased, because the fine amount of PHEV with higher loan repayment ability will be reduced to protect its own interests.

We compare RSG model with two possible alternative models to show the advantages of RSG model. The two alternative models under uncertain price have the same game framework as RSG model. The first model is the game model (MNG) in the mean scenario, whose decision-making problem is actually the traditional certainty problem in the mean scenario. Under the scenario of average price, the price is the average price under all possible scenarios. The second model is the worst-case robust game model (WRNG), which uses the worst-case electricity price to describe the decision-making problem.

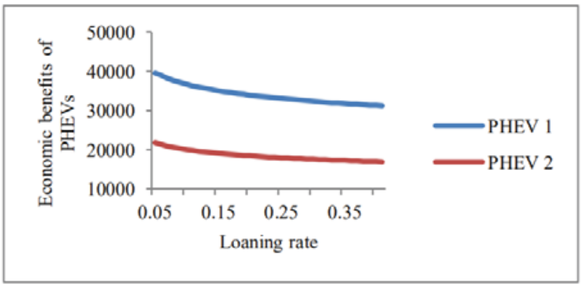

Figure 4. The influence of the ability to repay the loan on the benefit of PHEVs.

TABLE I. Comparison of Utility of PHEVs Obtained by Three Game Models in Three Cases

Case	**Average Utility of PHEVs at Equilibrium Point**		
	MNG	***WANG***	***RSG***
case 1	24706.55	24144.63	24165.92
case 2	26240.68	25646.48	25669.00
case 3	26346.70	25750.42	25773.02

In case 1, case 2 and case 3, three game models are tested, which are 5, 10 and 15 PHEVs participating in loaning decision. The average utility of PHEVs solution obtained under Stackelberg Equilibrium is recorded. The comparison of the three game models is shown in Table 1.

VI. CONCLUSIONS

In the blockchain energy Internet, this paper discusses an uncertain loaning decision between multiple electric vehicles and the bank, which ensures the transaction information security during the loan. In the case of price uncertainty, a new robust loaning decision problem for hybrid electric vehicles is proposed, which replaces the deterministic loaning decision problem. Accordingly, the robust game models of multiple PHEVs are established instead of the deterministic game models. In order to reduce the conservatism of the robust solution, the new robust loaning decision problem considers more bad scenarios than the traditional minimum maximum robust optimization problem. The numerical results show that the new robust game model is effective and efficient.

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