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Dynamic Game Model for Ranking Bitcoin Transactions Under GSP Mechanism

GUANGHUI YAN, (Senior Member, IEEE), SHAN WANG, ZHIFEI YANG, AND YI ZHOU
School of Electronic and Information Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China

Corresponding author: Shan Wang (0218649@stu.lzjtu.edu.cn)

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ABSTRACT Bitcoin is the first and most successful Blockchain system so far. In the Bitcoin system, miners use transaction attached fees as a driving force to mine a new block and package transactions, while users compete by bidding transaction fees for faster confirmation. Considering the particularity of Bitcoin trading system, we take time series into consideration to analyze the transaction rules of Bitcoin system from the perspective of multiple cycles and establish a dynamic game model related to time under Generalised Second Price(GSP) mechanism, and also confirm the model's superiority on saving users' fees, compared with the static game model. Also, we propose the quantification of the user experience quantified by calculating the price difference between the transactions uploaded by the same user within adjacent times, making the transaction process of the Bitcoin system no longer the final say of the transaction price. The dynamic game model shows that there is a perfect Bayesian game equilibrium solution in the payment decision, so there is no incentive for users to change the attached fee, and the whole system is maintained stably. In addition, we verify the dynamic game model from computational experiment. Firstly, it is proved that with the help of revenue discount, the cost saving of the dynamic model is generally higher than that of the static model. Then the user's revenue under the dynamic model is showing an upward trend, and the transactions order under the dynamic model is more stable than that under static model, which can be illustrated mathematically and computationally that the proposed dynamic game model in this paper will help all transactions be processed more efficiently in a uniform pipeline.

INDEX TERMS Blockchain, bitcoin, user liveness, Generalized Second Price auction.

I. INTRODUCTION

Blockchain is a novel application model that combines the uniqueness and innovation of computer technology. Blockchain technology has attracted intensive research interests and witnessed phenomenal development in recent years [1], [2]. The first and most successful blockchain system so far is widely known as Bitcoin.

Under a mechanism named ''mining'', the miner who succeeds in the consensus competition gets the right to confirm his/her chosen transactions and record them into the new block. And the miner will get paid of the block reward and transaction fees [6], [7]. Block reward accounted for the vast majority of the miners' earnings in the early days of the system, but the transaction fees begin to play the key role as the economic incentive to stimulate miners contributing their computing power so as to confirm transactions.

Therefore, a critical demand in the individual-level for bitcoin users to optimize their transaction fees emerges, and also in the system-level for Bitcoin blockchain to consummate its transaction ranking mechanism, with the aim of reducing the exaggerating transaction fees and improving the system efficiency. At present, the vast majority of Bitcoin transactions are processed in the order defined by the ''rank-by-fee'' mechanism, and the payment rule defined by the ''pay-it-bid'' mechanism, which is known as ''Generalized First Price (GFP)''. That is, the transactions with higher attached fees will be packaged first and users need to pay their declared fees. The GFP mechanism was the original design for Sponsored Search Auction(SSA) since 1998, and this simple rule will lead users to pay unnecessarily high fees to maintain the desired ranking of their transactions. However, it is possible that the attached fees would reach or even exceed the trading

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bitcoins, especially in micro-payment scenarios. With this in mind, the exorbitant transaction fees resulting from the GFP mechanism will render the system uneconomical for micro payments [3], [12]. Furthermore, the GFP mechanism has been proved to be unstable in many scenarios, due to the dynamic environment, which may force inefficient investments in gaming [8]. And in 2002 GFP had been replaced by the Generalized Second Price (GSP) mechanism due to its inefficiency and high volatility shown in the market practice. From the research perspective, it is better to model the transaction ranking problem with the game-theoretic analysis [9]. In literature [13], Li *et al.* proposed a transaction ranking standard based on GSP mechanism from the perspective of game theory, and verified its advantages over GFP mechanism in saving user expenses. However, the author only considered the ordering of static single-round trading, ignoring the dynamic multi-round trading. Compared with the static game model, the dynamic model has strong continuity, timeliness and expansibility, and has the ability to carry adjustment and renovation out independently. Therefore, we propose a dynamic game model of bitcoin transaction ranking based on GSP mechanism.

Based on the single-round static game model in literature [13], from the perspective of leading a dynamic game, a payment model and a revenue model are respectively established to analyze the Bitcoin transaction pricing problem under GSP mechanism. This paper considers the ranking of transactions from the perspective of successive rounds, and takes the user transactions in the previous round into consideration of the bidding in the next round, so as to optimize the continuity and enhance the independent adjustment ability of the model.

Compared with the static game model, the main work of this paper is as follows:

1) On the basis of the existing static game model under GSP mechanism, we take time series into consideration, compare with traditional sorting method and static game model, to analyze the transaction rules of Bitcoin system from the perspective of multiple cycles and establish a dynamic game model related to time under GSP mechanism, and also confirm the model's superiority on saving users'fees, compared with the static game model.
2) Also, we propose the quantification of the user experience in this paper quantified by calculating the price difference between the transactions uploaded by the same user within adjacent times, which makes the transaction process of the Bitcoin system no longer the final say of the transaction price, thus improving the probability of small transactions to get higher ranking and alleviating the transaction pressure to a certain extent.
3) And we also raise a parameter named revenue discount, user revenue under the dynamic model increases with the growing of revenue discount value, finally approach and surpass the revenue under static model.
4) In addition, we verify the dynamic game model from computational experiment. The experimental results show that with the help of revenue discount, the cost saving of the dynamic model is generally higher than that of the static model. Then the user's revenue under the dynamic model is showing an upward trend, and the transactions order under the dynamic model is more stable than that under static model, which can be illustrated mathematically and computationally that the proposed dynamic game model in this paper will help all transactions be processed more efficiently in a uniform pipeline.

The rest of this paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 establishes the dynamic game model under GSP mechanism, which is mainly considered from two aspects:parameter specification and the payment model. Section 4 conducts computational experiments to validate our theoretical models and analysis. Section 5 summarizes this paper.

II. LITERATURE REVIEW

Currently, there are only a limited number of efforts devoted to understanding the transaction confirmation game in Bitcoin systems. Lavi *et al.* [14] argued that Bitcoin's current fee market based on the GFP mechanism does not extract revenue well for miners when blocks are not congested. Also, according to Houy [9], if transaction fees are totally determined by a decentralized market and the maximum block size is not constrained, transaction fees will eventually go to zero and miners will not have the sufficient incentives to keep mining, and hence to keep Bitcoin viable. Li *et al.* [13] proposed a static game model under the GSP mechanism to analyze the transaction pattern of Bitcoin system. The GSP mechanism has achieved a lot in theoretical research, and its superiority has been amply proved. Bidding users commit to maintain their transaction current positions unchanged with a small cost difference. The first economic analysis of GSP is formulated by Edelman *et al.* [8] and Varian [15], and they proposed the Locally Envy-Free Equilibrium and the Symmetric Nash Equilibrium for the GSP with complete information, respectively.

Therefore, considering the applicability of GSP mechanism in maintaining the transaction packaging and verification in Bitcoin system, as well as its advantages proven in both theoretical researches and practical performance, it can be shown that employing the GSP model to replace the currently adopted GFP model is a timely and meaningful research innovation [13].

III. DYNAMIC GAME MODEL BASED ON GSP

This section introduces the payment model of Bitcoin system as the first part of dynamic game model under the GSP mechanism. The detailed process is as follows.

First, new transactions pending for confirmation with associated fees are submitted by users, and they will enter the memory pool and remain in an unconfirmed state. Then,

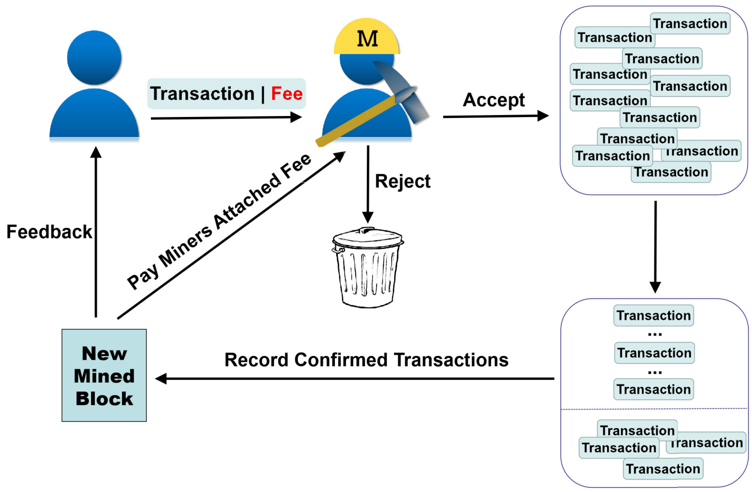

FIGURE 1. **Process of the Bitcoin transaction confirmation.**

miners scan the relevant information of these unconfirmed transactions, and select a group of preferred transactions ranked in top positions as their mining basis. Miners who successfully obtain the right in packaging selected transactions from their memory pools will upload them to the new block.

In the Bitcoin system, all information regarding each transaction will be broadcasted in public as soon as it is submitted, which includes size, fee, input amount, output amount, address, and submission time, etc. After each block is mined, we are free to access the information of confirmed transactions in the block, which means the auction results are public information. Besides, Bitcoin transactions are basically transfer transactions. As the transfer amount is public information, we can then consider that the transaction's value is also public information. As such, we study the Bitcoin transaction confirmation game in the incomplete-information setting.

The basic process of the Bitcoin transaction confirmation is shown as Figure1.

A. PARAMETER SPECIFICATION

The relevant parameters of the model are set as follows. Suppose that the miner's memory pool has a trading capacity of N, the total number of trading users is K, and each user submits only one transaction pending for confirmation. In the Bitcoin system, active users contribute a lot to maintain the high-quality sustainable development of the system. As shown in literature [3], with the market price of Bitcoin plummeting, many users chose to quit the Bitcoin system, resulting in a significant reduction in the market size of Bitcoin and a significant decline in the revenue of the system. This indicates that the level of user activity will affect the long-term benefits of the system, so the following model should be designed with user engagement in mind. It is reasonable to assume that users who have a better experience in the transaction are more willing to continue to participate in the following Bitcoin trading. In the SSA market, the quantification of the user experience is measured by the "quality score". The concept of quality score was first used in the advertising, the higher the quality score, the more prominent the advertisement is, so as to encourage the quality advertising content [17]. Analogously, this paper proposes a variable α used to mark the liveness of users in the Bitcoin system, which makes the transaction process of the Bitcoin system no longer the final say of the transaction price, thus improving the probability of small transactions to get higher ranking and alleviating the transaction pressure to a certain extent.

In [18]–[20], quality score is implicitly assumed to be an independent variable that is exogenously assigned by search engines, and remains unchanged in repeated SSA auctions. Inspired by the quality score formulation in online ad auctions [17], we formulate the following function to calculate the user i's liveness at time t:

$$\alpha_i^t = \frac{s_i^t \cdot d_i^t + f_i}{s_i^{t-1} \cdot d_i^{t-1}} \tag{1}$$

where,s is the sum of accumulated transaction costs of transaction i up to time t, d is the cumulative number of transactions, and f is the price paid by transaction i at time $t(s \geq f)$. The greater the gap between the cost of transaction i at time t and that at time $t-1$, that is, the better the user experience is in a deal, the higher the user is willing to continue to participate in the trading process, and the stronger the user's enthusiasm will be. In other words, the greater the liveness value α will be.

Besides, in Bitcoin system, transaction fees are calculated based on the kilobyte size of the transaction, and due to the limited block size, which restricts on the number of transactions that can be recorded to each block. Therefore, the transaction size should be taken into account when analyzing the transaction ordering problem. As mentioned above, we use

TABLE 1. List of notations.

Notation	Definition
N	Capacity of memory pool
K	Total number of trading users
M	The block size
f_i	Transaction fee of user i
s_i^t	The sum of accumulated transaction costs of transaction i up to time t
d_i^t	The cumulative number of transaction i up to time t
α_i^t	The liveness of user i at time t
$f_i^{\prime}$	Weighted transaction fee of user i
m_i	Size of transaction i
p_i	Transaction payment of i
ρ	Revenue discount in representing the loss degrees of user revenue
W	User revenue
U_i	The expected revenue of user i
$f(t)$	Continuous probability density function with time t as the random variable
p_i	The payment of user i in the bidding game
b_{k+1}	The fee submitted by the last user whose transaction occupies the $(k+1)$th position

the weighted fee $f_i^{\prime}$ calculated by compound factors to rank these transactions, including the transaction fee f_i, the block size m_i, the user liveness α_i. The more active the user, the more willing they are to pay for the transaction, and the smaller the transaction, the more they have to pay to ensure that the transaction is successfully packaged. It should be noted that different formulations can be established according to the specific design targets, and they will not influence the correctness of the following analysis [16].

Based on the above discussions, we first assign each transaction a number i according to the descending order of their weighted valuations $f_i^{\prime}$ and establish the formula of $f_i^{\prime}$:

$$f_i^{\prime} = \frac{\alpha_i \cdot f_i}{m_i} \tag{2}$$

The higher the weighted fee, the higher the transaction rank. Miners pack deals into new block in the order of ranking until the block is full. If there are more than one trade with the same weighted fee, the trade is randomly selected for packaging: $f_1^{\prime} > f_2^{\prime} > \cdots > f_n^{\prime}$.

Bitcoin users concern about whether their transactions can be packaged successfully. If transaction i meets the following inequality, it is considered that transaction i is strictly included in the block, where M is block size:

$$\sum_{k=0}^{i} m_k < M$$

The revenue discount ρ is designed to represent the different degrees of loss of user benefits with the influence of marginal transactions. Common transactions are strictly included in the block, so the revenue loss can be neglected, while marginal transactions need to use Segwit to properly adjust the transaction size so that it can be squeezed into the block, and the loss of size indirectly leads to the loss of user income. The revenue discount is designed as follows according to different degrees of loss:

$$\rho_i = \begin{cases} 1, & \sum_{k=0}^{i} m_k \leq M \\ \dfrac{M - \sum_{k=0}^{i-1} m_k}{m_i}, & \sum_{k=0}^{i-1} m_k < M < \sum_{k=0}^{i} m_k \\ 0, & \sum_{k=0}^{i-1} m_k \geq M \end{cases} \tag{3}$$

B. PAYMENT MODEL

For any participant i, and for the remaining user k who did not upload the transaction, the bid price p_i increases with the revenue W_i (Otherwise, users will choose to lower the price in order to gain more, which is not conducive to the stability of the trading system); then, if the benefit of i is lower than that of j, that is $W_i < W_j$, it has to be explained that there is no relationship between bid price and revenue with the result of $p_i > p_j$ (Otherwise some people will imitate others to increase their own income). The next step is the establish process of formula p_i.

Set a payment parameter $q(k, b_{k+1}, W)$, so that when the user's revenue is W, there is no difference in the revenue at location k and $k-1$:

$$d_{k-1} \cdot (W - q(k, b_{k+1}, W)) = d_k \cdot (W - b_{k+1}) \tag{4}$$

Then,

$$q(k, b_{k+1}, W) = W - \frac{d_k}{d_{k-1}}(W - b_{k+1}) \tag{5}$$

Let $q(k, s, W) = q(k, b_{k+1}, W)$, where b_{k+1} is the fee submitted by the last user whose transaction occupies the $(k+1)$th position. This equation holds when $s = b_{k+1}$, i.e. the cumulative transaction cost of the transactions after i is the current transaction itself.

Next step is the proof that the equation $p(k, s, W) = q(k, s, W)$ holds for any parameter, that is q is the exact payment when there are k participants and the accumulative transactions cost is s with the revenue W.

1) According to the above analysis, there must be a minimum revenue value W_{min}, which makes $W_{min} \geq b_{k+1}$ (Otherwise, some of the remaining k users are bound to drop out of the following game due to the excessive low benefit). Therefore, when the revenue of some users is less than W_{min}, they can choose to quit the trading.
2) Next is the discussion on the circumstances of $W \geq W_{min}$. Assuming that there is revenue of a user is $W \geq W_{min}$, then the maximum cost paid by the user with revenue W is equal to the maximum cost of all users, that is, $p_{max} = \max(p_i \mid 0 < i \leq k)$. And then assuming that the revenue W_0 of user i is the minimum, then the payment $p_i(k, s, W_0)$ of user i is the maximum cost, that is $p_i = p_{max}$. Without loss of generality, it can be assumed that there are many users choose to submit fees equal to p_i or less than p_i.

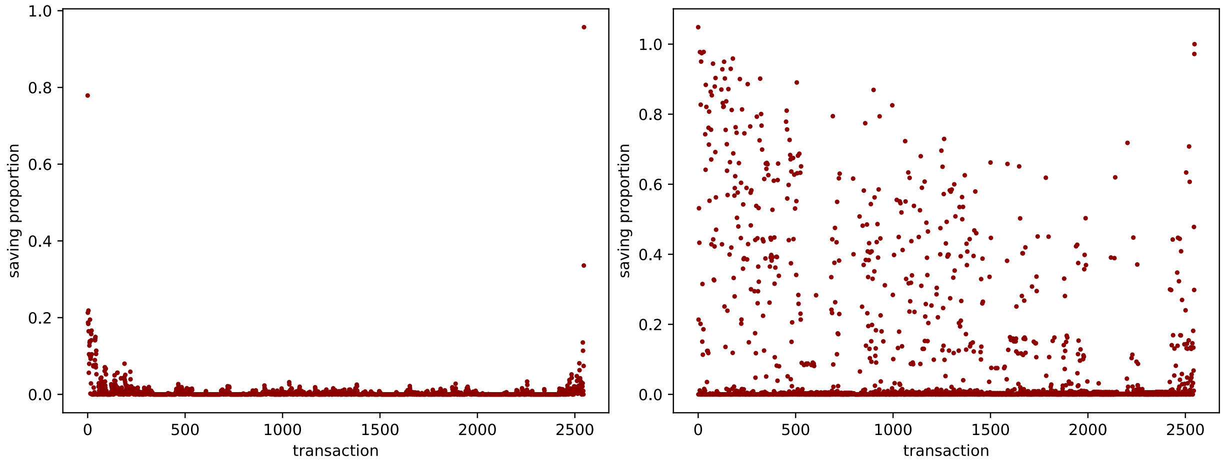

FIGURE 2. Comparison on saving proportion of static and dynamic game model.

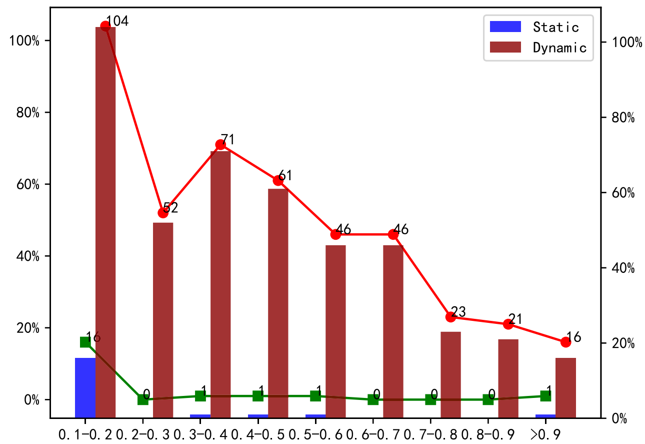

FIGURE 3. Comparison of the saving ratios under static and dynamic game model.

3) And then to consider what will happen when many users choose to submit for p_i or less. Assuming that some users will choose to pay their own fees when the revenue is W_0. User i with revenue W_0 will continue to participate in the following game. The next thing to note is that the payment is the highest for the user of W_0.
   a) First of all, assume that user i is not the participant with highest payment, and let parameter $l < k-1$, user i gets the position l with a certain probability. Consider any continuous process $R^t \sim R^t_{l+2}$ in the game, in which the user with the highest transaction cost is the user who submits the transaction at R^t_{l+2} (The bid increases with time, the later the bid is submitted, the higher the price will be, which is determined by GSP), so at this time, the position the user gets is $l+2$, and the bid is p_{l+2}, and user i will be one of the remaining $l+1$ members. In the later bidding process, user i can get position l with a certain probability.
   b) Next is the consideration on variable $p_i(l+1, b_{R^t_{l+2}}, W_0)$. Some users' bidding price will be lower than p_i. Taking user j as an example to select the highest revenue W', and there must be $W' > W_0 \geq b_{l+2}$ and also $q(l+1, s_{l+2}, W') \leq p_i(l+1, b_{R^t_{l+2}}, W_0)$, so we can get:
$$p_i \geq q$$
Thus,
$$p(l+1, s_{l+2}, W_0) \geq q(l+1, s_{l+2}, W') > q(l+1, s_{l+2}, W_0) \geq b_{l+2}$$
From which we can see that the user i with the minimum revenue pays highest. And also $p(l+1, s_{l+2}, W_0)$ of user i is higher than $q(l+1, s_{l+2}, W_0)$ of user j, so $q(W_0)$ is the best choice.

4) The following is the discussion on p. The revenue of user i with position $l+1$ is $\alpha_{l+1}(W_0 - b_{l+2})$, and with position l is $\alpha_l(W_0 - b_{l+1})$. According to the previous analysis, we know $p_i > q_j$ and $W_0 < W'$, then there is:
$$\begin{aligned}\alpha_l W_0 - p_{l-1} &< \alpha_{l+1}(W_0 - p_l)\\ &= \alpha_l(W_0 - q(l+1, b_{R^t_{l+2}}, W_0))\end{aligned}$$
Supposing the payment is $p_i - \epsilon$, and the probability of other users bidding between $(p_i - \epsilon, p_i)$ decreases with the decrease of the p_i, and finally approaches 0. The revenue is $\alpha_k(W_0 - p_{k+1})$ when the payment is $p_i - \epsilon$, and the revenue is $\alpha_{k-1}(W_0 - p_i(k, s, W_0)) < \alpha_k(W_0 - p_{k+1})$ when choosing p_i, which would make $p_i - \epsilon$ the best price for i, but that would violate the original assumption, so p_i is the best choice.
On the basis of the above analysis, the equation $p(k, s, W) = q(k, s, W)$ is true in any case, and formula 5 can be successfully deduced in reverse. Finally, when there are k users participating in the game, user i needs to bid $p(k, b_{k+1}, W)$ with occupying the kth position and earning W:
$$p(k, b_{k+1}, W) = W - \frac{d_k}{d_{k-1}}(W - b_{k+1}) \qquad (6)$$

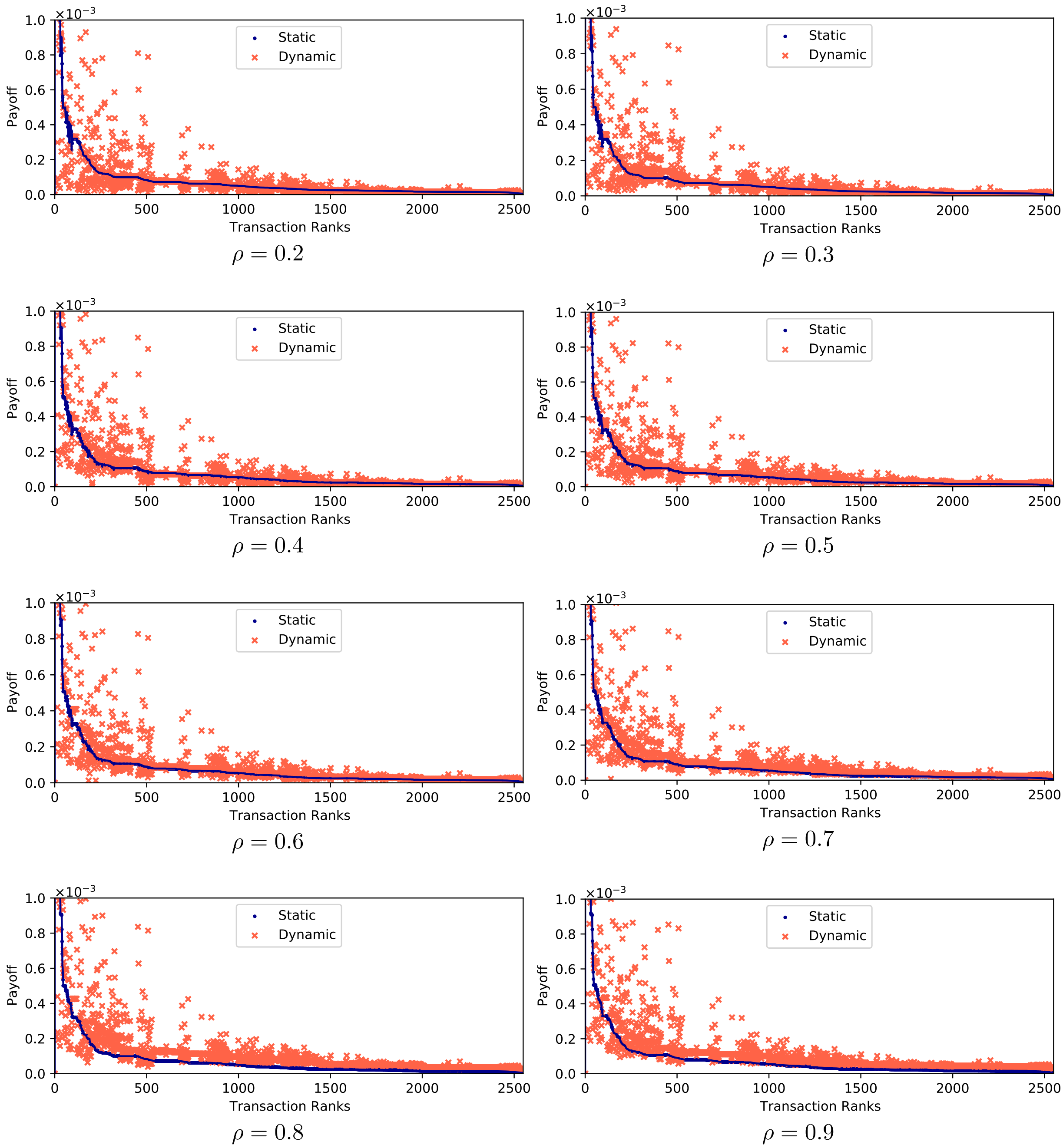

FIGURE 4. Comparison of payoff u_i for the static and dynamic game model under different values of ρ.

When the GSP dynamic game model is used as the user payment reference, the calculation formula of user income is as follows. The discount level of the difference between the user's weighted bid cost and the user's actual payment is taken as the consideration of user's revenue in the game.

$$\begin{aligned} u_i &= \rho_i \cdot (f_i' - p_i) \\ &= \rho_i \cdot (\frac{\alpha_i \cdot f_i}{m_i} - p_i) \\ &= \frac{M - \sum_{k=0}^{i-1} m_k}{m_i} \cdot (\frac{\alpha_i \cdot f_i}{m_i} - p_i) \end{aligned} \tag{7}$$

And the revenue function for participant i is selected randomly, resulting in the expected revenue is used as the basis for the decision. In this paper, the expected revenue function of user i is designed as follows, a continuous density function $f(t)$ that is positive everywhere on $(0, \infty)$:

$$\begin{aligned} U_i &= \int_0^\infty u_i \cdot f(t) d(t) \\ &= \int_0^\infty \rho_i \cdot (f_i' - p_i) \cdot f(t) d(t) \end{aligned} \tag{8}$$

When user i bid p_i, the model reaches a perfect Bayesian equilibrium. At this time, there is no incentive for users to

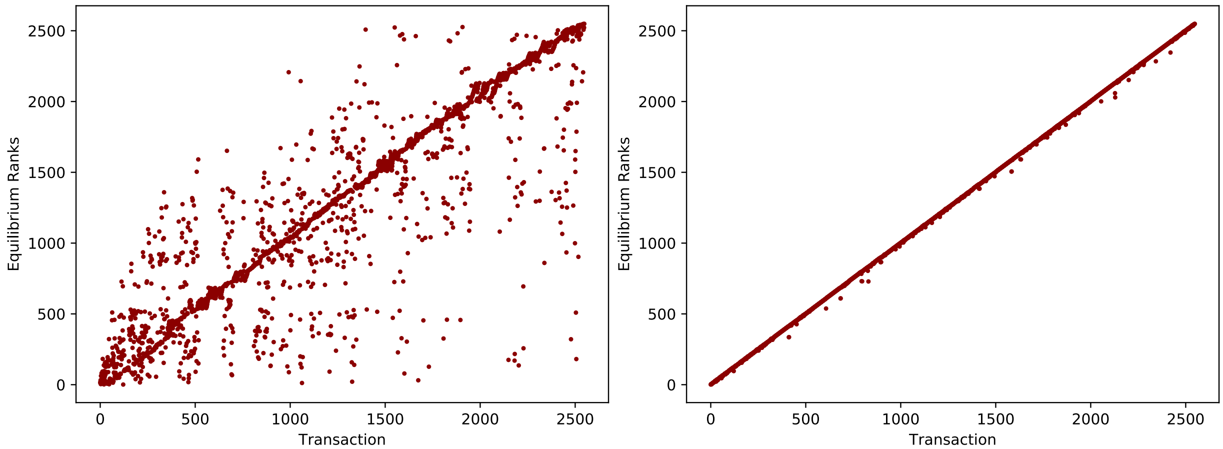

FIGURE 5. Comparison on change of transaction order under the static and dynamic game model.

change the transaction price, and the whole system will be maintained in a stable condition.

IV. COMPUTATIONAL EXPERIMENTS

This paper aims to establish the dynamic game transaction model of bitcoin system based on GSP mechanism, then compare it with the static game model proposed by literature [13]. We choose the same real transactions in block #567948 as the contrast experiments as the dataset of our experiments. This block was mined at 04:13 PM on March 20, 2019, and it is a full block with the size of 1,258,958 bytes.

As shown in figure 2, the left one is the static model in literature [13] saving 5.12% of transaction costs for all users, while the dynamic model established in this paper saves 6.15%, and the transaction saving ratio is shown in the right photo. And by comparison, it is found that the bidding rate d_k/d_{k-1} is included in the consideration of each bidding round in the dynamic game model, which makes the whole transaction process flow in layers of nested, and has more capacity of undertaking and self-adjustment.

Figure 3 shows more specifically the comparison of the two models' saving ratios at each stage where the probability of payment savings are greater than 0.1%. The number of users in the dynamic game model is 104 when the probability of payment saving is between 0.1% and 0.2%, while the number in the static interval is only about 10. The higher the saving probability is, the lower the number of users will be. But on the whole, about 424 users can save 0.1% to 0.9% of the transaction cost submitted by the static game model with the help of the dynamic game model, and the transaction cost saving probability of 16 users exceeds 1%. Even under ideal conditions, the proportion of saved payment for users will be up to 97.74%.

Figure 4 shows that user revenue under the dynamic model increases with the increase of revenue discount ρ value. In the range of [0, 1], different ρ values lead to different user revenue, and with the increase of ρ, the revenues are on the rise.

The payoff under dynamic model is obviously lower than that under static model when the ρ value has little influence. However, with the gradual increase of ρ, the payoff under the dynamic model gradually increases, among which, the transactions at the top of the ranking have a large increase, while the transactions at the bottom of the ranking surpass the payoff under the static model.

As can be seen from formula 7, the more active the user with a better trading experience is, that is, the higher the value of α is, the more willing the user is to pay a higher price to continue to participate in the following transactions. Then the accumulated number of transactions d will also increases, so that such user will gain a higher income in the long run under dynamic game model.

Figure 5 shows the changes in the order of transactions. The order of abscissa represents the Bitcoin transaction sequence under the existing sorting mechanism, the ordinate on the left is the new order of transactions under the static model, and on the right is the new order under the dynamic model.

The left one is the change of transaction orders under the static game model, among which 99.76% ranking positions have changed, with the minimum change range of 1, accounting for 0.39% of the total trading volume. At the same time, 5.06% of transaction position changes are limited to 10, which can be concluded that the overall change of the transactions under the static model is obvious, but the original ordering trend is not affected, floating up and down in a small range from the original position.

The right one is the change of transaction orders under the dynamic game model, among which 78.46% ranking positions have changed, with the minimum change range of 1, accounting for 33.23% of the total trading volume. At the same time, 97.72% transaction position changes are limited to 10, which can be concluded that the positions change stably, almost consistent with the original order under the dynamic game model.

By comparing the above two modes, it can be seen that the dynamic game model can maintain the transaction in the original state to a greater extent than the static game model. Therefore, the dynamic game model is not only better than the static game model in the degree of user cost saving, but also in maintaining the transaction positions unchanged.

V. CONCLUSION

Considering the particularity of Bitcoin trading system, we take time series into consideration, compare with traditional sorting method and static game model, to analyze the transaction rules of Bitcoin system from the perspective of multiple cycles and establish a dynamic game model related to time under GSP mechanism, and also confirm the model's superiority on saving users' fees, compared with the static game model.

Also, we propose the quantification of the user experience in this paper quantified by calculating the price difference between the transactions uploaded by the same user within adjacent times, which makes the transaction process of the Bitcoin system no longer the final say of the transaction price, thus improving the probability of small transactions to get higher ranking and alleviating the transaction pressure to a certain extent.

And under the influence of the new raised parameter revenue discount, user revenue under the dynamic model increases with the growing of revenue discount value, finally approach and surpass the revenue under static model.

Our proposed dynamic game model shows that there is a perfect Bayesian game equilibrium solution in the payment desicion, so there is no incentive for users to change the attached fee, and the whole system is maintained stably. In addition, we verify the dynamic game model from computational experiment. Firstly, it is proved that with the help of revenue discount, the cost saving of the dynamic model is generally higher than that of the static model. Then the user's revenue under the dynamic model is showing an upward trend, and the transactions order under the dynamic model is more stable than that under static model, which can be illustrated mathematically and computationally that the proposed dynamic game model in this paper will help all transactions be processed more efficiently in a uniform pipeline.

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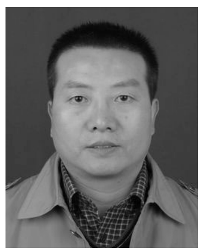
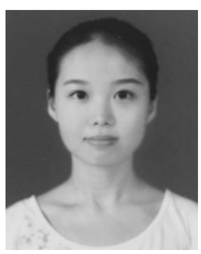


GUANGHUI YAN (Senior Member, IEEE) was born in 1970. He is currently pursuing the Ph.D. degree. He is also a Professor and a Ph.D. Supervisor. His main research interests include database theory and systems, the Internet of Things engineering and application, data mining, complex network analysis, and so on. He is a member of the China Computer Federation (CCF).



SHAN WANG was born in 1995. She is currently pursuing the master's degree in computer application technology with Lanzhou Jiaotong University. Her main research interest includes blockchain technology.

ZHIFEI YANG was born in 1980. He is currently pursuing the Ph.D. degree in blockchain technology and artificial intelligence with Lanzhou Jiaotong University.

YI ZHOU was born in 1994. He is currently pursuing the master's degree in computer application technology with Lanzhou Jiaotong University. His main research interests include data mining and complex networks.