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Economic Transaction Model Innovation and Algorithm Optimization Enabled by Blockchain Technology

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Abstract The study explores the innovation of economic transaction model in the framework of blockchain technology and optimizes the key algorithms in the transaction. The study integrates the advantages of traditional sharing contracts and smart contracts to construct a blockchain model for sharing economic transaction innovation mode. Based on the feature selection method of chi-square test and feature correlation, the gated recurrent unit (GRU) is combined with the support vector machine (SVM) algorithm to form a detection model for abnormal blockchain transactions. For the Practical Byzantine Fault Tolerance (PBFT) consensus mechanism in the economic model, the study proposes a node pre-prepared layered consensus protocol to optimize it, and introduces a reputation model to rank nodes in terms of their reputation value, enhance the node's ability to defend itself against Sybil's witch attack, and improve node's motivation. The research results show that the anomaly detection model based on feature selection can effectively realize the accurate detection of transaction anomalies, and the detection performance of the GRU-SVM model improves the F1 score by 1.11% in the feature subset than in the full feature dataset. The improved PBFT consensus algorithm has significant improvement over the original PBFT algorithm in terms of algorithmic complexity, communication complexity, and throughput, which effectively guarantees the security of sharing economy transactions.

Index Terms blockchain, GRU, SVM, chi-square test, PBFT consensus algorithm, economic transaction mode

I. Introduction

Based on the macro context of the global financial system, the digital economy has gradually become more and more important. The reason lies in the fact that the digital economy has optimized the operational procedures in cross-border payments, asset management, etc., and has had a profound impact on the traditional financial system [1], [2]. As a result, the rise of the digital economy has provoked traditional financial institutions, such as central banks, to explore the emerging digital economy, triggering a profound rethinking of the transaction model of the digital economy [3]. As an electronic asset based on decentralized network and cryptography principles, the digital economy has unique functions such as value storage and medium of exchange, which makes it has become a research hotspot in the field of economics [4]-[6]. Reviewing the development history of the digital economy, it can be concluded that no matter from the initial exploration of Bitcoin to the formation of today's diversified digital currency market, every step of its development is a collision and fusion of economics theory and practice [7]-[9]. The rise of the digital economy not only highlights its technical advantages such as decentralization, anonymity and security, but also opens up new transaction modes and value transmission methods in the economic field [10], [11].

Blockchain technology is a secure, transparent and efficient distributed ledger system, as well as a new type of Internet protocol [12]. Its core principles are decentralization, data inerrancy, cryptography, consensus mechanism, data structure and smart contracts, which have the characteristics of openness, anonymity and security, and can promote the innovation and digital transformation of various industries [13]-[15]. Based on blockchain technology, decentralized economic transactions can be realized, empowering digital currencies and forming a new type of economic transaction mode, realizing the value flow of Internet assets. And once the physical assets can be digitally converted, the value flow based on blockchain technology can also be realized, and this is the blockchain economic transaction [16]-[20]. Compared with the traditional economy, platform economy, Internet economy and other economic transaction modes, the blockchain economy has changed in the medium of transaction, transaction mode, business model and profitability, subverting the characteristics of the previous economic transactions [21]-[24]. From the current practice, blockchain economic development faces certain bottlenecks, but it can make up for some of the defects of the current stage of the economic transaction mode, representing the direction of future economic development [25], [26].

With the development of the digital economy era, the application of digital currency and blockchain technology in financial transactions is becoming more and more widespread, and the impact it brings is also more and more far-reaching. Literature [27] integrates the theory of transaction cost economics and blockchain technology to construct a financing model for startups, which effectively solves the information asymmetry and other problems in the process of entrepreneurial financing, and is conducive to the establishment of a more effective and decentralized financing transaction model. Literature [28] shows that blockchain technology can effectively control the business risks of both parties to the transaction and improve information transparency, thus reducing the cost of interaction between economic agents, so that the brokerage agent in the process of financial transactions can obtain high-quality contract execution. Literature [29] constructs a three-principle value creation model for business transactions, which can solve many economic transaction problems including information storage, consensus generation and governance, and provides a solid theoretical foundation for the innovation of economic transaction model based on blockchain technology. Literature [30] describes the specific impact of financial technology and blockchain technology intervening in digital banking and financial services, and the technology promotes the digital transformation of the economic transaction model to a certain extent. Literature [31] emphasizes that blockchain technology plays an important role in regulating the development of the circular economy, and it promotes the transition and transformation of economic transactions to the circular economy to achieve sustainable economic development. Literature [32] utilizes the principles of blockchain technology to innovate the digital economic management model of enterprises, and through the construction of an evaluation model, it is found that this innovative transaction model has a positive impact in the e-commerce activities of enterprises. Literature [33] assessed the willingness of cryptocurrency transactions based on blockchain technology from the perspective of customers, and promoted the development of fintech technology by continuously strengthening the degree of customer trust in the blockchain economic transaction mode. It can be seen that in the era of digital economy, blockchain-enabled economic transaction mode change has a wide range of application scenarios.

By analyzing the new characteristics of economic transactions under blockchain, this paper elaborates the practical needs and possibilities of realizing the innovation and development of economic transaction mode with the assistance of blockchain technology. In view of the problem of breach of contract in the process of sharing economy transaction, this paper combines the advantages of traditional sharing contract and blockchain smart contract, embedded in the process of sharing economy transaction, and constructs a decentralized sharing economy transaction innovation model. Through the communication link, the data obtained from the bottom layer perception is transmitted to the blockchain cloud platform, and the data encrypted storage, analysis and intelligent diagnosis are utilized, combined with the smart contract triggering condition function, to realize the smart contract classification based on the sharing economy transaction scenarios, which is used for the subsequent credit evaluation of the nodes in the blockchain. Considering the lack of blockchain technology regulatory system and regulatory technology, the feature selection method based on chi-square test and feature correlation is proposed, and the gated recurrent unit and support vector machine are integrated to construct the GRU-SVM blockchain transaction anomaly detection model. Based on the traditional practical Byzantine fault-tolerant consensus algorithm, a layered consensus is proposed in the pre-preparation stage to improve the protocol, and a node reputation model is designed for evaluating the quality of participating nodes' behaviors to ensure the security and efficiency of the sharing economy transaction model. The effectiveness of the transaction anomaly detection model is verified using Ellipticc++ dataset and Elliptic dataset, and the optimization effect of the improved practical Byzantine fault-tolerant consensus algorithm is analyzed in the form of simulation experiments.

II. Characterization of blockchain economy transactions

Compared with the traditional economy, platform economy, Internet economy and other economic transaction modes, the blockchain economy has changed in the medium of exchange, transaction mode, business model and profitability [34], subverting the previous economic exchange has characteristics, this paper will next analyze the prominent characteristics of the blockchain economy from the aspects of its pass-through transaction, decentralized transaction, business model and so on.

II. A.Warrant transactions

Currency is the medium of exchange of value and an important basis for economic transactions to function. In the blockchain economy, the medium of value is the pass, which is the form of expression of rights and interests recorded in the blockchain ledger, and it is also an important basis for the blockchain economy to be able to function properly. For example, the game coins and points obtained by game players through online recharging belong to the pass, and the existence of the pass realizes the flow of value between various blocks. Under the blockchain economy, users can obtain the corresponding amount of passes by trading digital assets, such as virtual assets created by users under blockchain technology, such as game equipment, digital traces and other virtual assets. Users can also obtain certain amount of passes by contributing to the construction of the blockchain credit system according to the incentive mechanism of the blockchain. Passes can exist independently, and blockchain technology can also exist independently, but the existence of the pass economy can realize the circulation of wealth between different blocks in the blockchain network, and it is the foundation and guarantee for the decentralized transaction mode of blockchain economy to be carried out and realized.

II. B.Decentralized transactions

Blockchain technology is a decentralized distributed ledger technology, and the economic transactions carried out under this technology also have decentralized characteristics. Each user has its own independent block, and the third-party trading platform no longer exists, users can directly conduct transactions by matching the corresponding users through functional block search. At the same time, different users can communicate with each other through the private chain, and the blocks with similar user needs will gradually form a community-like group through the continuous establishment of the private chain, and then form a coalition chain. Communityization of blocks can make the coalition chain and private chain more autonomous, help users meet their own needs efficiently and reduce transaction costs to the greatest extent possible.

II. C.Business model innovation

With the continuous maturity of blockchain technology, blockchain technology has attracted great attention from relevant research fields, and they continue to explore the specific application of blockchain technology and its integration with traditional industries, and the “blockchain+” business model innovation has gradually emerged. The “blockchain +” business model has the characteristics of blockchain decentralization, de-trust, transparency and invisibility, which subverts the business model of traditional industries, and allows users and consumers to realize the independence and autonomy of data assets, and to have the right to handle and flexibly use their own data assets. The innovation of blockchain technology for business model not only fits with the concept of blockchain creation, but also can help the real economy to rapidly integrate into the digital economy.

In general, the economic transaction mode based on blockchain technology has gradually come into the public's view, providing users with new transaction modes. Under the blockchain economy, pass trading has become the basis of the blockchain economy, and in the decentralized trading mode, the traditional business model has been innovated and different enterprises and users can make the data valuable and gain revenue through labor in this economic mode, breaking the limitations of the Internet platform enterprises on the users and non-platform enterprises, and making the market development more energetic and dynamic. The Internet platform is more dynamic and dynamic for market development.

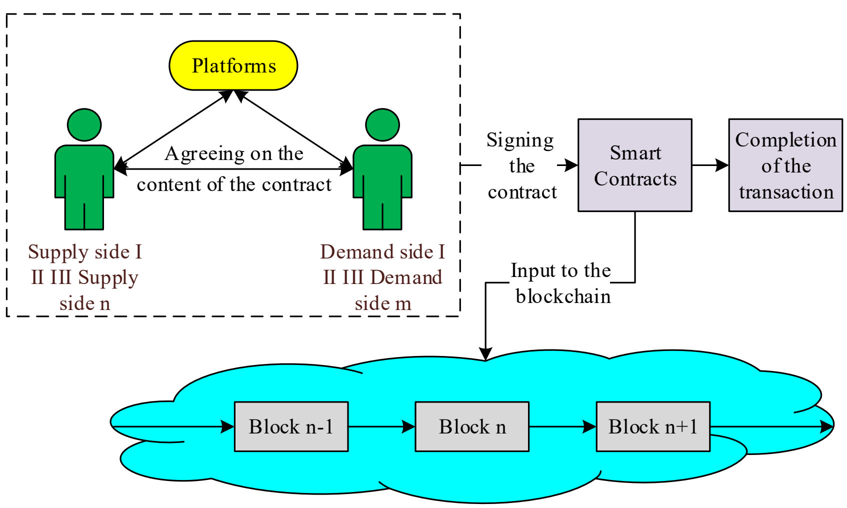


Figure 1: Sharing economic trading intelligent contract block chain model

III. Blockchain economic transaction model framework

III. A. Smart Contract Framework Model for Sharing Economy Transactions

A smart contract is a computerized protocol for informationally disseminating, verifying, or enforcing contracts. It is a mutual agreement between two or more parties to do or not to do something in exchange for something, without mutual trust between them, the contract is defined by the code, and is executed completely automatically, without intervention and without being able to intervene. Aiming at the problem of breach of contract in the sharing economy transaction process, this paper combines the advantages of traditional sharing contract and smart contract, embedded in the sharing economy transaction process, to construct a decentralized innovative sharing economy transaction model, the framework of which is shown in Figure 1.

III. B. Smart Contract Trigger Model

III. B. 1) Smart Contract Trigger Functions

The sharing economy transaction process mainly involves the transfer of the right to use the actual item and the transaction of services between people. Through the configuration of system monitoring equipment, GPS positioning technology, audio and video monitoring and other direct real-time monitoring of the location and “health” of the items, and monitoring of whether the language and actions of the people are excessive. Through the communication link, the data obtained from the bottom layer perception is transmitted to the blockchain cloud platform. Through encrypted data storage, analysis and intelligent diagnosis, smart contracts are used for decision-making and execution. Based on the sharing economy transaction scenario and smart contract classification, the smart contract trigger condition function is constructed.

Construct the smart contract trigger condition function. Let the smart contract function be $Operation(S)$, the value of this function is determined by the weighted average of the three functions of the transaction cost agreement, the transaction rule agreement, and the transaction affiliation agreement, and set the weights to be μ_1, μ_2, and μ_3, respectively, and the value of the transaction cost contract is S_f, the rule contract value is S_r, the subsidiary contract value is S_o, and the overall contract function is:

$$Operation(S) = \mu_1 S_f + \mu_2 S_r + \mu_3 S_o \tag{1}$$

Transaction fee agreements are mainly concerned with the payment of fees and are considered to be in breach of contract if the difference between the outcome of the transaction and the actual prediction is greater than a certain threshold. Let the maximum deviation threshold be α, then the transaction fee agreement threshold difference can be expressed as:

$$\left|Contract(S_f) - Actual(S_f)\right| = \alpha \tag{2}$$

That is, when the condition that triggers the fee contract is the following equation, it will trigger the smart contract to execute automatically:

$$Triggercondition(S_f) > \alpha \tag{3}$$

The trading rules agreement mainly involves the trading process of both parties to infringement of life, property and other issues, the rules contract S_r contains material class, service class two categories. For the material class sharing transactions, through the system detection equipment, GPS positioning, audio and video devices for real-time monitoring, its content involves the stability of the parts, positional conditions and other changes, let the need to monitor the parts of a total of i, the contract value of S_{r-Ki}, corresponding to i of the parts triggered by the damage threshold of β_i, a single part triggered by the execution of the contract conditions are:

$$Triggercondition(S_{r-Ki}) = \left|Contract(S_{r-Ki}) - Actual(S_{r-Ki})\right| > \beta_i \tag{4}$$

For the service class transaction, a total of j items such as sound, vibration and other external environments are detected by intelligent speech recognition keywords, and the contract value is S_{r-Mj}, corresponding to the j item triggering condition threshold of γ_j, then a single part triggers the contract execution condition:

$$Triggercondition(S_{r-Mj}) = \left|Contract(S_{r-Mj}) - Actual(S_{r-Mj})\right| > \gamma_j \tag{5}$$

Transaction subsidiary agreements involving other than fees, transaction process life property, a total of k impact factors, the contract value is denoted as S_o, the corresponding k item trigger response threshold is δ_k, then a single component triggers the contract execution condition:

$$Triggercondition(S_{ok}) = \left|Contract(S_{ok}) - Actual(S_{ok})\right| > \delta_k \tag{6}$$

The smart contract is executed in accordance with the pre-set contract terms. When the above penalty conditions are met, the smart contract will execute the relevant rewards and penalties one by one and record the transaction records and its results in the blockchain for credit assessment and traceability.

III. B. 2) Smart Contract Execution Process

The smart contract is event-driven, and the corresponding rules are jointly formulated by multiple parties. When inputting data and related transactions, the contract state machine will determine whether it meets the pre-set conditions, and if it exceeds the pre-set conditions, it will respond to the contract code to automatically execute the corresponding records and results, and output the results of the execution to the user and record them in the block.

IV. Blockchain anomalous transaction detection model

The rapid development of blockchain technology has subverted the traditional economic transaction mode. This paper proposes an innovative sharing economic transaction mode based on blockchain technology, but due to the lack of regulatory mechanism and the lack of regulatory technology of blockchain technology, many risks or criminal behaviors are easily derived in the process of economic transactions. Therefore, improving the effect of blockchain abnormal transaction detection will play a positive role in promoting the healthy development of sharing economic transactions. This chapter proposes a feature selection method based on chi-square test and feature correlation for screening feature subsets, and on this basis, it is applied to blockchain abnormal transaction detection through algorithmic models.

IV. A. chi-square test

The principle of the chi-square test is based on the Pearson chi-square statistic [35], and the size of the p-value is inferred from this by comparing the gap between the theoretically expected frequency distribution and the actual observed frequency. The larger the amount of data involved in the chi-square statistic, the better, and when the amount of data is large enough, the results of the judgment will not be greatly biased. When the amount of data involved in the statistical sample is less than 40, the expected frequency of each cell must be greater than 5, the calculated chi-square value can be used to test the judgment, otherwise the chi-square value is invalid, the judgment is not accurate. When the sample size involved in statistics is greater than 40, the expected frequency of each cell needs to be greater than 1, the chi-square test judgment is accurate enough. When for the data volume is extremely large data mining, for all of the above problems do not lead to a large deviation of the results. In the case of different test groups, the chi-square test can be used to test multiple results for multiple groups of categorical variables without conflict.

From the above analysis, it can be concluded that the mathematically defined formula for correlation analysis of factors using chi-square test is shown in (7):

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\frac{\left(f_{ij}^o - f_{ij}^e\right)^2}{f_{ij}^e} \tag{7}$$

Where: r - the number of rows in a linked table.

c - the number of columns of the concatenated table.

f_{ij}^o - observed frequency.

f_{ij}^e - the expected frequency.

The formula for f^e -expected frequency is shown in (8):

$$f^e = \frac{RT}{n} * \frac{CT}{n} * n = \frac{RT * CT}{n} \tag{8}$$

Where: RT - the sum of the row observation frequencies.

CT - the sum of the column observation frequencies.

In this paper, the chi-square test is applied in the test of the overall data of the sharing economic transactions, the data volume, and the expected frequency of each cell is generally greater than 1, so the conditions applicable to the chi-square test can ensure the accuracy of the chi-square test results of the relevance of the subset of features of the economic transaction data.

First of all, the null hypothesis that the irrelevance of the two variables between the factors is established, calculate the degree of deviation between the observed frequency and the expected frequency that is, the residuals, but the residuals of the value of both positive and negative numbers, after adding each other, the sum of the offset is 0. Therefore, it is necessary to take the square of the residuals before summing up, to get rid of positive and negative numbers of the offset. In addition, it is also necessary to consider the relative amount of residuals, for the same size of the residuals, when the expected frequency is larger, it appears smaller, when the expected frequency is smaller, it appears larger. For this reason, it is also necessary to square the residuals, divide by the expected frequency, and finally sum them. The results from this normalization of the residuals are used to determine the strength of the factorial correlation of the two variables. When the degree of deviation between the calculated observed frequency and the expected frequency is large after standardization, the calculated value is large, then the previously proposed null hypothesis is rejected, and it can be judged that the two variable factors are correlated; when the degree of deviation between the calculated observed frequency and the expected frequency is small after standardization, the calculated value is small, then it cannot be rejected the previously proposed null hypothesis, and it can be judged that the two variable factors have no correlation relationship.

By deriving the chi-square statistic from the above formula, it can be seen that if the expected and observed frequencies are the same, the chi-square statistic is the smallest, which is 0, and it can be deduced that these two variables are completely independent and do not have any correlation relationship. If the difference between the expected frequency and the observed frequency is larger, the larger the cardinality statistic can be obtained, and the higher the degree of correlation.

In addition to this, determining whether two factors are correlated through the chi-square test relies on the degrees of freedom, which are expressed in terms of how many measures worthy of constraining the data in the cross-tabulation are needed to describe the expectation. Simply put, the degree of freedom of the chi-square test is calculated as follows: the two factors are subtracted from 1, and multiplied together on this basis. For example, if a set of factors in a chi-square test has two combinations of a and b members, then their cross-tabulation has $a*b$ cells. If the calculations were performed without any restrictions, $a*b$ cells would describe all the variables. However, when calculating the expectation, the sum of each member variable is the same as the previous expectation, so it is necessary to subtract the number of members of each of the two sets of factors, i.e., $a*b-a-b$. It can be noted that there is another constraint that the expected value of all rows and the expected value of all columns in a cell are always the same. Therefore, it is necessary to add 1 to the previous calculation. i.e., the final calculation of the degrees of freedom is $a*b-a-b+1$, which simplifies to $(a-1)*(b-1)$.

After finding the chi-square statistic and the degrees of freedom between the factors, the p-value of the chi-square statistic can be obtained, and when the p-value is greater than the pre-set critical value or less than or equal to the value of the level of significance, it is thus determined that there is a correlation between the factors.

IV. B. Pearson's correlation coefficient

Pearson's correlation coefficient, a value between -1 and 1, tends to be 1 or -1 when the linear relationship between the two variables increases.When one variable increases and the other increases, they are positively correlated and the correlation coefficient is greater than 0. If one variable increases and the other decreases, they are negatively correlated and the correlation coefficient is less than 0. If the correlation coefficient is equal to 0, it indicates that there is no linear correlation between them. Pearson's correlation coefficient is calculated as:

$$\begin{aligned}\rho_{X,Y} &= corr(X,Y) = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} \\ &= \frac{\operatorname{cov}(X,Y) E\left[(X-\mu_X)(Y-\mu_Y)\right]}{\sigma_X \sigma_Y}\end{aligned} \tag{9}$$

IV. C. Anomaly Detection Model

IV. C. 1) GRU-SVM modeling

Gated Recurrent Units (GRUs) have been shown to be effective in anomaly detection [36]. GRUs can identify potential correlations between data from time-series data, quickly mine long-term and short-term dependencies, improve detection performance, and help users infer the root cause of detected anomalies.GRUs retain the advantages of original sequence processing and time-series dependency capture, and solve the gradient vanishing and gradient explosion The problem of Support Vector Machines (SVMs) are used to solve binary classification problems, overcoming the dimensionality catastrophe and linear indivisibility problems. The dataset is studied and most of the features have a clear difference between illegal and legal behaviors and can be well classified. Based on the excellent features of GRU, here in this paper, the original network features of GRU are retained, and the SVM classifier is incorporated into the GRU network, and a detection method using the SVM classifier in a neural network is proposed. A GRU-SVM model is constructed, i.e., a GRU as an input and SVM as a classifier model, in which SVM is utilized instead of Softmax function for data input prediction, and the structure of GRU-SVM model is shown in Figure 2.

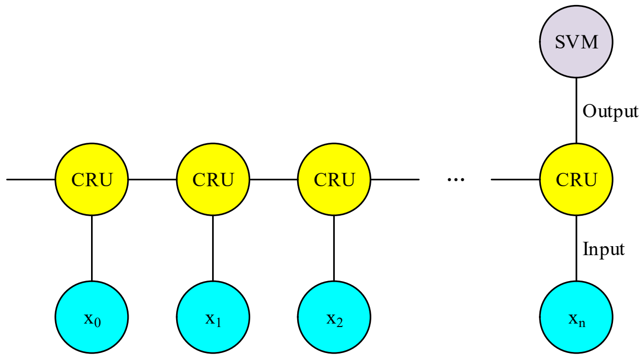


Figure 2: GRU-SVM model

IV. C. 2) GRU-SVM model construction

In this experiment, 182 features were used as model inputs and the parameters were learned through the gating mechanism of the GRU, and the reset gating signal and update gating signal were computed as follows:

$$z_t = \sigma\left(W_Z \cdot \left[h_{t-1}, x_t\right]\right) \tag{10}$$

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \tag{11}$$

where t denotes the current time step, W_r denotes the weight matrix of the reset gate, W_Z denotes the weight matrix of the update gate, x_t is the input vector, h_t is the t th time step output matrix, and h_{t-1} is the output matrix of the $t-1$ th time step. σ denotes the sigmoid function for:

$$\sigma = \frac{1}{1+e^{-x}} \tag{12}$$

The new memory $\tilde{h}_t$ generated by the GRU at the current time step, called the candidate hidden state, is computed as follows:

$$\tilde{h}_t = \tanh\left(W \cdot \left[r_t \times h_{t-1}, x_t\right]\right) \tag{13}$$

where W denotes the hidden state weight matrix and the final output h_t of the current time step is computed as follows:

$$h_t = \left(1 - z_t\right) \times h_{t-1} + z_t \times \tilde{h}_t \tag{14}$$

where z_t represents the reset gating signal in the GRU and r_t represents the update gating signal in the GRU.

With the introduction of SVM as the last layer, these parameters are also learned by optimizing the objective function of SVM. In this model, instead of using the cross-entropy function to measure the network loss, the GRU-SVM uses the loss function of the SVM to measure the network loss:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \max\left(0, 1 - y_i'\left(w^T x_i + b_i\right)\right) \tag{15}$$

Equation (15) is called the L1-SVM unconstrained optimization problem, however, this function is not differentiable, and the optimization process is performed on the L1-SVM, from which its variant L2-SVM can be obtained, and Equation (16) is the L2-SVM, which is differentiable and more stable than the L1-SVM:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} \max\left(0, 1 - y_i'\left(w^T x_i + b_i\right)^2\right) \tag{16}$$

Therefore the model is constructed using the L2-SVM loss function, for prediction, for each classification, the decision function $f(x) = sign\left(wx + b\right)$ produces a vector of scores, using the function $predicted_{class}$ for each x, to go on to produce a predicted categorical label y, and this function will return the index of the highest score in the vector of predicted classes that gives the classification result:

$$predicted_{class} = \arg\max\left(sign\left(wx + b\right)\right) \tag{17}$$

The steps of the GRU-SVM model are shown below:

(1) Input the dataset features $\{x_i \mid x_i \in R_m\}$ into the GRU model.

(2) Initialize the learning parameter weights and biases with arbitrary values, and tune the learning parameters by training.

(3) Based on the input features x_i and their learning parameter values, the cell state of the GRU is calculated.

(4) In the final input layer, the decision function of SVM is utilized to compute the prediction of the model.

(5) Calculate the loss case of the neural network using the formula, i.e., L2-SVM.

(6) Optimization is performed to minimize the loss function, and the weights and biases are adjusted for the losses calculated in the optimization, and the optimization algorithm uses the Adam optimizer.

(7) The process is repeated until the neural network reaches the desired accuracy or the highest accuracy after which the trained model is ready for binary classification of the given data.

IV. D. Experimental results and analysis

IV. D. 1) Experimental data

The Elliptic dataset contains 203769 nodes (transaction entities) and 234355 edges, and the nodes carry timestamp information.The Elliptic dataset has 49 time-steps of data transaction information.Of the 203769 transaction entities, 4679 transactions are labeled as category 1 (illegal), 41078 transactions are labeled as category 2 (legal), and the remaining data is labeled as unknown, in order to be able to compare the distribution of each category of data more clearly, according to the time step above the distribution of the 3 categories of data is shown in Fig. 3, in which category 1 is illegal transactions, category 2 is legal transactions, and category 3 is unknown transactions. There are 167 dimensions of features for each transaction, of which 93 features are original features (including time-step features, this feature is not involved in training) and 74 features are aggregated features.Elliptic++ dataset adds 15 feature dimensions on the basis of Elliptic dataset as enhanced features. Considering that the dataset transaction detection is a task closely related to time, this paper adopts time slices as the basis for dividing the training and testing sets, using an effective 80:20 training-testing split, with time steps from 1 to 39 for training and from 40 to 49 for testing.

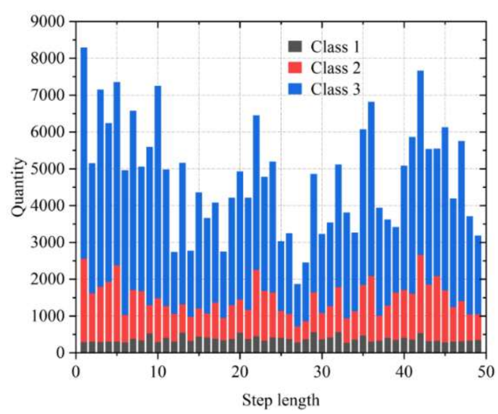


Figure 3: Data distribution of 3 types based on time step

IV. D. 2) Experimental parameterization and evaluation criteria

The experiments were conducted using Python version 3.11.2 and the classification algorithm used default parameters. In this paper, precision rate, recall rate and F1 score are used as the performance evaluation indexes of the classification algorithm. The specific formulas are as follows:

$$\text{Precision}=\frac{TP}{TP+FP} \tag{18}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{19}$$

$$\text{F1}=\frac{2\text{PrecisionRecall}}{\text{Precision+Recall}} \tag{20}$$

where TP denotes the number of true examples, FP denotes the number of false positive examples, and FN denotes the number of false negative examples.

IV. D. 3) Analysis of experimental results

(1) Comparison of classical detection models

In order to verify the detection performance of this paper's algorithm, on the Ellipticc++ dataset, this paper compares the GRU-SVM algorithm with the classical machine learning models (e.g., LR, KNN, MLP) and neural network models (e.g., BiLSTM) of the integrated algorithms (e.g., RF, CatBoost, LightGBM, etc.), and the results are shown in Table 1. As can be seen from the table, the performance of the GRU-SVM algorithm is the best among all the compared algorithms, with precision, recall and F1 score of 98.49%, 95.61% and 94.78%, respectively, which are improved by 5.26%, 2.39%, and 2.89%, respectively, compared with the LightGBM model with the next best performance, which fully demonstrates that the GRU-SVM algorithm in this paper has a better detection effect.

Table 1: Comparison of classic test models

Model	Precision/%	Recall/%	F1/%
LR	32.67	70.52	44.71
KNN	51.37	65.67	57.64
MLP	59.71	64.08	61.85
XGBoost	91.09	72.41	80.65
RF	96.99	71.83	82.43
LightGBM	93.23	93.22	91.89
CatBoost	94.45	72.63	82.05
ResNet-32	86.14	72.61	78.81
RRFU	94.61	71.05	81.29
BiLSTM	72.17	23.32	35.24
GRU-SVM	98.49	95.61	94.78

(2) Comparison of models before and after using feature screening

In order to compare the effect of feature screening on the performance of the detection model, this part conducts experiments on feature selection. First, the chi-square value is calculated for the features of Ellipticc++ dataset, and the experimental results are shown in Figure 4. From the experimental results, it can be seen that the chi-square values of seven features, Local_feature_15, Aggregate_feature_51, Aggregate_feature_67, out_txs_degree, fees, num_output_addresses, and out_BTC_min, are low, so these features need to be removed to get the feature subset subset1.

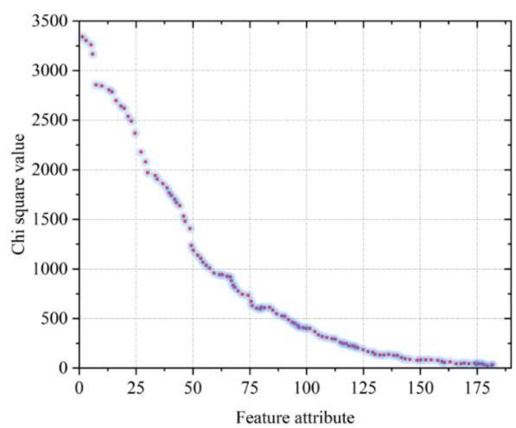
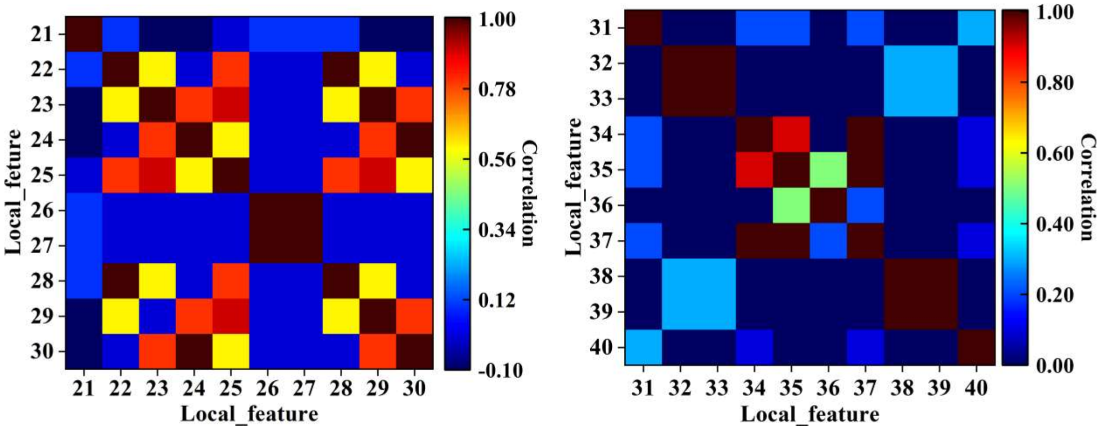


Figure 4: Chi square value under chi square test

Second, feature relevance analysis is performed on the feature subset subset1. Since the feature subset subset1 has 175 dimensional features, it is not convenient to show the correlation heatmaps of all features, so the correlation heatmaps of some features are selected as shown in Fig. 5. Figure (a) shows the correlation heat map of 10 features from Local_feature_21 to Local_feature_30, which shows that the correlation of Local_feature_26 and Local_feature_27, Local_feature_24 and Local_feature_30 are all 1. In order to reduce the interference of redundant features, therefore the features Local_feature_26 and Local_feature_30 are deleted. Figure (b) shows the correlation heat map of the 10 features Local_feature_31~Local_feature_40, it can be seen that 3 pairs of these features have correlation of 1. Therefore, the correlation of the 4 pairs of features Local_feature_32, Local_feature_34, Local_feature_35, and Local _feature_38 which are 4 features. By a similar method, feature pairs with feature relevance of 1 are identified, one of the features in the feature pair is retained, and at the same time, the other features in the feature pair are deleted, and in turn, 35 original features (Local_feature) are deleted to obtain the feature subset subset2. On the basis of the feature subset subset2, by analyzing the relevance of the aggregated features (Aggregate_feature), and then deleting the aggregated features 15, the final feature subset subset subset3 is obtained.



(a) Local_feature_21~30 (b) Local_feature_31~40

Figure 5: The correlation heat diagram between feature

Since the three models, GRU-SVM, LightGBM and RF, perform better, subset1, subset2 and subset3 are input into these three models for detection, and the above feature subsets are labeled as C, CL, and CLA, respectively, and the detection results are shown in Table 2. As can be seen from the data in the table, the detection performance all decreased, while the detection performance of the GRU-SVM model increased in the F1 score on the full feature dataset, sunbset1, subset2, and subset3 in that order, with an overall increase in precision and recall.GRU-SVM achieved the best detection performance, with the precision, recall, and F1 scores of 99.03%, 96.28%, and 95.32%. In addition, GRU-SVMCLA achieves an average improvement of 0.71%, 0.67%, and 0.54% over the full feature dataset in precision, recall, and F1 score, respectively, while saving about 25% in training time.

Table 2: Feature selection test model comparison

Model	Precision/%	Recall/%	F1/%
RF	96.99	71.83	82.43
RFC	95.83	70.81	82.16
RFCL	95.74	70.53	82.11
RFCLA	95.03	69.89	81.94
LightGBM	93.23	93.22	91.89
LightGBMC	92.96	93.08	90.74
LightGBMCL	92.71	92.87	90.05
LightGBMCLA	92.13	92.54	89.78
GRU-SVM	98.49	95.61	94.78
GRU-SVMC	98.32	95.64	94.93
GRU-SVMCL	98.58	95.77	94.99
GRU-SVMCLA	99.03	96.28	95.32

To further demonstrate the effectiveness of the feature selection proposed in the article, experiments are conducted on the Elliptic dataset and the results are shown in Figure 6. The dataset labeled as CLA after two-layer feature selection can be seen from the figure that the detection performance of the two models, RF and LightGBM, decreases by 0.31% and 2.20% in the feature subset than in the full feature dataset in terms of the F1 scores, respectively, while the detection performance of the GRU-SVM model improves by 1.11% in the feature subset than in the full feature dataset in terms of the F1 scores. And the precision and recall of the GRU-SVMCLA model are improved, and the detection effect is improved after feature selection. The experimental results show that the method based on two-layer feature selection achieves better results in anomaly detection in the above two datasets. Meanwhile, compared with the full-feature dataset, the chi-square test can remove the feature variables that have nothing to do with the target variables, and the Pearson correlation coefficient can remove some of the features of the strong correlation feature pairs, which reduces the interference of the redundant features and shortens the training time, so that the model can improve the classification effect and the detection efficiency.

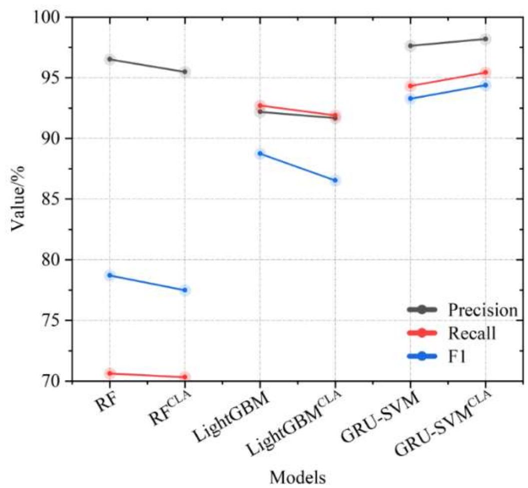


Figure 6: Feature selection test model comparison

V. Improvement of Practical Byzantine Fault-Tolerant Consensus Algorithm

Consensus algorithm directly affects the efficiency of blockchain economic transactions, and the design of a secure and high-performance consensus algorithm is an important link to further improve the sharing economic transaction model in this paper, which is of great significance to promote the innovation of blockchain economic transaction model. Practical Byzantine Fault-Tolerant Consensus Algorithm (PBFT) effectively solves the problem of malicious nodes sending error messages to disrupt the system operation in distributed systems, and has been widely adopted in federated blockchain, but there are some problems that arise from its direct application in blockchain systems, such as poor node expandability, inability to be directly applied to larger node network environments as well as higher communication complexity. Therefore, this chapter focuses on improving the above problems of PBFT consensus algorithm.

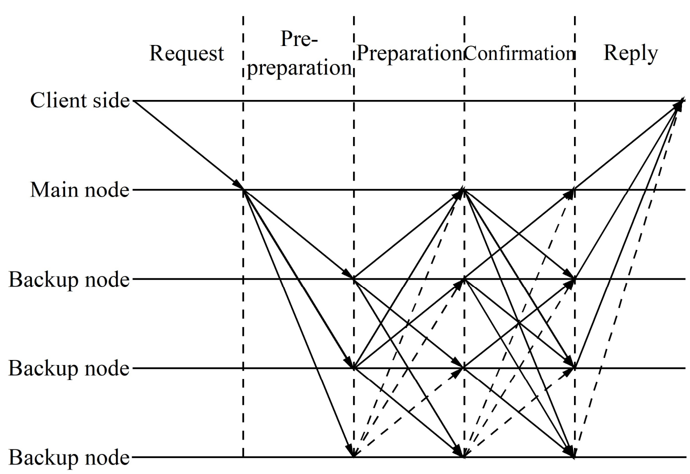


Figure 7: PBFT consistency protocol execution process

V. A. Improving the design of the PBFT distributed trust mechanism

The essence of PBFT consensus algorithm is a state machine copy replication algorithm [37], in order to ensure that the nodes reach a consensus within the distributed system, three kinds of protocols are needed to satisfy the security and activity of the algorithm, namely, the consistency protocol, the checkpointing protocol and the view replacement protocol. The consistency protocol as the core protocol of PBFT consensus algorithm, the execution order is divided into 5 steps as shown in Fig.7. The consistency protocol contains 5 nodes, which are divided into 1 client node, 1 master node and 3 backup nodes from top to bottom, among which the bottom backup node is Byzantine node. Vertical line represents the process demarcation line, horizontal line represents each node, arrow line represents the message broadcast sent from one node to another node, dashed arrows represent the error message or non-delivery of the message from the malicious node.

The consistency protocol of PBFT is a relatively efficient and secure consensus algorithm, but there is still room for improvement and optimization of the concurrent operations of node's message transmission and backup node consensus. Each node needs to broadcast its own message to other nodes, which causes the communication delay and complexity to be too high, and each operation has to go through three stages (pre-preparation, preparation and submission) to reach consensus. Therefore, this study proposes a node pre-preparation layered consensus to optimize the protocol, the improved TM-PBFT pre-preparation phase node broadcast execution flow is shown in Figure 8. In the request phase, the client transmits information to the master node and distributes it. In the pre-preparation phase, the nodes are grouped, and the dashed arrow lines in the figure represent the master nodes of other subgroups that are not drawn.

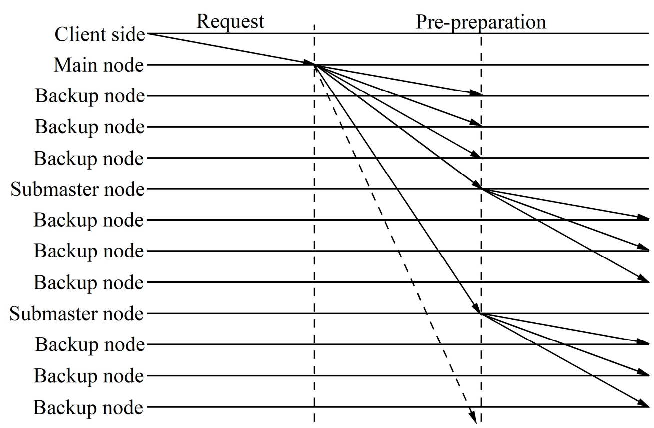


Figure 8: Execution of node broadcasting in pre-preparation phase of TM-PBFT

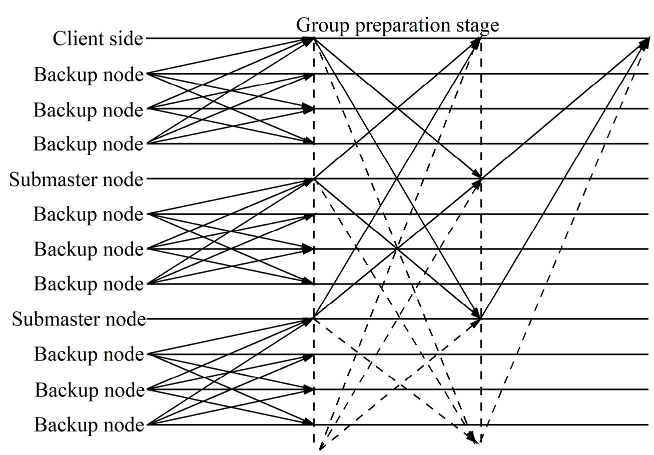


Figure 9: Flow of node consensus in the preparation phase of TM-PBFT

Each node in PBFT needs to broadcast its own message to other nodes, which will cause a large number of message transmissions, the amount of transmitted data can be reduced by compressing, merging and filtering messages, so as to improve the efficiency of the network. A group concurrent consensus mechanism is introduced in the preparation phase to enable nodes to process requests in parallel.The node consensus flowchart for the preparation phase of TM-PBFT is shown in Fig. 9. In the figure, the solid arrows represent the nodes broadcasting consensus after the pre-preparation phase. The dashed arrows represent the false information of malicious nodes that suffered from Sybil witch attack or the nodes that don't perform broadcasting.By dividing the preparation phase of the traditional PBFT algorithm into three parts and grouping the master nodes into concurrent consensus, the inefficiency of the primitive Byzantine fault-tolerant algorithm is effectively solved, and the complexity of the two-by-two confirmation of the consensus between the nodes is reduced from $O(n^2)$ to $O(\log n)$.

V. B. Reputation model design

Let the initial reputation score R_{init} of each node joining the blockchain be 50, nodes with less than 40 points R_{bad} do not participate in the consensus, and the node with the highest reputation score $R_{\max}$ is 100, and it will not be increased again when it reaches 100 points.

The increase or decrease of node reputation score is determined by a combination of factors, such as node robustness, node input cost, communication success rate, the number of votes among nodes and the number of rounds of participation in consensus.

Node robustness evaluation: Before each node joins the blockchain system to participate in the consensus, it evaluates its own stability and arithmetic power, eliminates junk nodes, and prevents the Sybil witch attack, the evaluation indexes are transaction throughput T_t and responsiveness R_b, and the formula for node robustness evaluation N_r is (α_1, α_2 is the evaluation coefficient):

$$N_r = \alpha_1 T_t + \alpha_2 R_b \tag{21}$$

Node input cost: nodes joining the blockchain system need to submit a corresponding proportion of margin P_n as a confidence voucher based on the above evaluation results, the amount of margin is inversely proportional to N_r, but does not affect the node reputation score evaluation, if the sum of all nodes' margins is P_{Sum}, the impact of the node's margins on the node's reputation score P is:

$$P = \left(\frac{P_n}{P_{Sum}}\right) \cdot N_r \tag{22}$$

Communication Success Rate: the confidence of the node increases with each successful communication, the total communication success rate C is the number of communication successes C_{suc} divided by the total number of communications C_{sum}, which is calculated as follows:

$$C = \frac{C_{suc}}{C_{sum}} \tag{23}$$

Number of votes between nodes: with n nodes, V_{ij} represents the votes of node i for node j, and V_j represents the total number of votes for node j, the formula for calculating the number of votes between nodes is as follows:

$$V_j = \sum_{i=0}^{n} V_{ij}, V_{ij} = 0,1 \tag{24}$$

Participation in consensus rounds: when node n participates in the first i rounds of consensus and is not labeled as a Byzantine node, the reputation score of $(i+1)$ rounds is not affected by the recession function. When node n has not participated in the previous i rounds, the following recession function $f(n)$ is used (θ is the recession index and s is the total consensus rounds of the node), and the formula for calculating the number of rounds of consensus participation is as follows:

$$f(n) = \theta(s-i) \tag{25}$$

Combined with the above multi-level factor considerations, the mechanism of increasing and decreasing reputation scores can be derived, while the election of the master node is positively correlated with the node reputation scores, and the node reputation scores R_i are computed as follows (β_1, β_2, β_3, β_4, and β_5 are the node reputation weights, respectively):

$$R_i = R_{init} + \beta_1 N_r + \beta_2 P + \beta_3 C + \beta_4 V_j - \beta_5 f(n), R_i \in [0,100] \tag{26}$$

V. C. Theoretical and experimental analysis

The algorithm is simulated using Python and compared with the original consensus algorithm, in terms of fault tolerance, node reputation value, communication complexity, and throughput. The experimental environment is Windows 10 operating system, the system memory is 16GB, and the CPU is Intel(R)Xeon(R)Gold6148CPU@2.40GHz2.39GHz processors.

V. C. 1) Algorithm Fault Tolerance Analysis

Let the total number of nodes be N, the number of malicious nodes be m, the number of faulty nodes be s, the number of Byzantine nodes be $f = m + s$, and the number of nodes in the system that are able to function properly be $N - f$. The fault tolerance of the improved algorithm and the original PBFT consensus algorithm is essentially the same. Assuming that Q nodes agree on a message during the consensus process, then consensus is considered reached.

When f Byzantine nodes in the system do not participate in the consensus process, then the consensus protocol should ensure that the remaining $N - f$ honest nodes reach consensus as shown in the following equation:

$$Q \le N - f \tag{27}$$

When there are Byzantine nodes participating in the consensus, there is a guarantee that the number of honest nodes in the system should exceed the number of Byzantine nodes:

$$N - f - f > f \tag{28}$$

Therefore, from equation (28), we can get $N > 3f$, so N should be at least greater than or equal to $3f + 1$, so that it can be guaranteed to be secure and active in the blockchain system.

V. C. 2) Node reputation values

Assuming that there are 30 nodes in total, which contain 9 Byzantine nodes. 4 consensus phases with 30 rounds of consensus in each phase, at the end of each phase, the reputation value of the node is updated and the result is shown in Fig. 10. It can be obtained:

(1) After the end of consensus phase 2, honest nodes and Byzantine nodes can be identified by the size of the reputation value of the nodes, so as to ensure the security and stability of the whole blockchain system in the subsequent operation.

(2) In consensus phase 1, the reputation values of nodes numbered 7, 10, 17, and 26 all exceed the threshold value of 0.5. These nodes are not detected by the system mainly because their initial reputation values are lower than those of other malicious nodes, and they are not eligible to become master nodes and supervisory nodes. However, it is only after consensus phase 1, when they are assigned to the appropriate roles, that the system starts to record them. As the consensus process proceeds, malicious nodes will be recorded by the system one by one, and eventually the consensus success rate will reach its highest value.

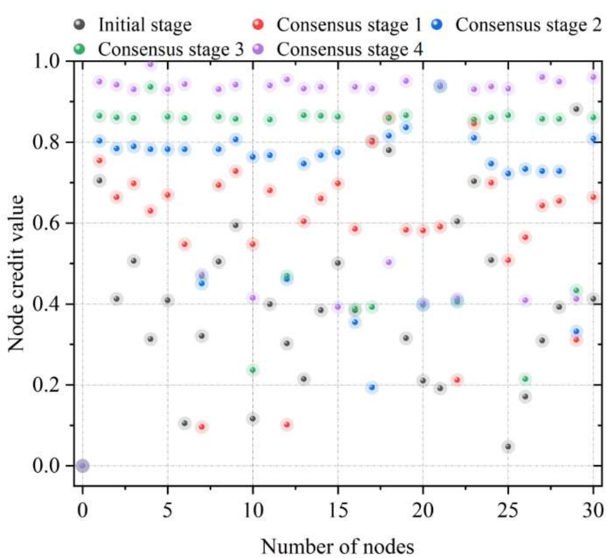


Figure 10: Node credit value distribution

V. C. 3) Communication complexity

The PBFT consensus algorithm is a network-wide broadcast through the nodes for the transmission of information, which will substantially consume the communication resources in the system. Communication overhead as one of the indicators of algorithm efficiency, improving the algorithm can improve the consensus efficiency and reduce the waste of communication resources. In the original PBFT consensus algorithm, the whole network broadcast communication is required in the preparation phase and confirmation phase, and each node needs to communicate N^2 times in this process, and the number of communications required to complete a consensus is $2N^2+2N+1$, which will bring a larger burden to the communication network when the number of nodes is large.

Neglecting the additional communication complexity brought to the system by the process of node classification and voting, the communication complexity of the original PBFT consensus algorithm and the improved algorithm in the consensus process are analyzed and compared, and the results are shown in Fig. 11. The total number of communication times of the CPBFT consensus algorithm in the consensus process is $2N^2-3$, which is a small enhancement compared with the PBFT consensus algorithm. The improved algorithm TM-PBFT is to reduce the number of consensus nodes involved in the consensus process by dividing the nodes in the system into roles. Nodes are divided into consensus nodes, supervision nodes, backup nodes, these three types of nodes due to the different roles they play, the functions they serve are also different, supervision nodes and backup nodes do not participate in the consensus process, and only supervise the nodes and vote on the reputation value. Assuming that all nodes have carried out the verification of relevant data, each round of consensus of TM-PBFT consensus algorithm contains the election, consensus, and reputation value updating phases of the master node, and the total number of communications is $2N_1+2N_1+N+2N$, and the total communication complexity will be reduced to linear order.

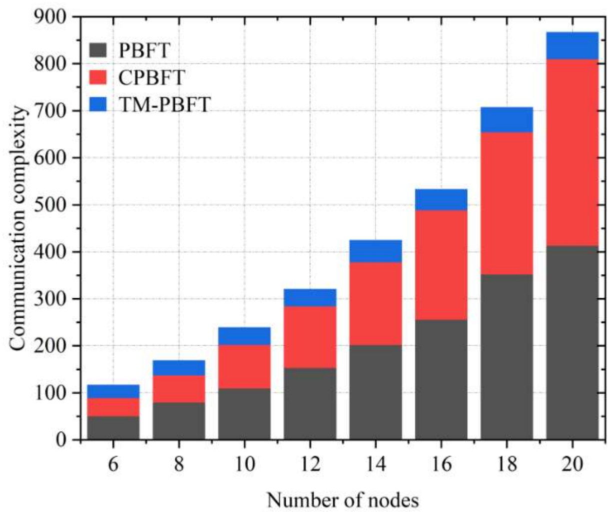


Figure 11: Comparison of communication complexity for different algorithms

V. C. 4) Throughput

The throughput of a system is the number of transactions processed per unit of time in the system, and the ability of the system to process transactions depends on the size of the throughput, the larger the throughput, the higher the ability to process transactions, and vice versa. The formula for calculating throughput is as follows:

$$TPS=\frac{transactions_{\Delta t}}{time} \tag{29}$$

Where $transactions_{\Delta t}$ is the number of transactions processed by the system during the consensus process and $time$ is the time taken by the system to process the transaction. The throughput of the improved algorithm and the original PBFT consensus algorithm are compared in the same time with the same number of nodes. To better compare the throughput of the improved algorithm and the PBFT algorithm, the relative growth rate of their throughput is calculated using equation (30):

$$E=\frac{TPS_{TM-PBFT}-TPS_{PBFT}}{TPS_{PBFT}}\times 100\% \tag{30}$$

Where TPS_{PBFT} is the throughput of PBFT and $TPS_{TM-PBFT}$ is the throughput of the TM-PBFT algorithm, the comparison results are shown in Fig. 12. It can be seen from the figure that when the number of nodes is 40. The relative growth rate of throughput is -23.79%, which is negative, indicating that the throughput of the improved algorithm at this time is less than the throughput of the original consensus algorithm. And when the number of nodes is increasing, the relative growth rate of throughput also shows a growing trend, when the number of nodes is 50 and later, the relative growth rate is positive. It indicates that the throughput of the TM-PBFT algorithm in this paper is larger than that of the original PBFT algorithm, and with the increase of the number of nodes, the gap between the throughput of the TM-PBFT algorithm and that of the PBFT algorithm is widening.

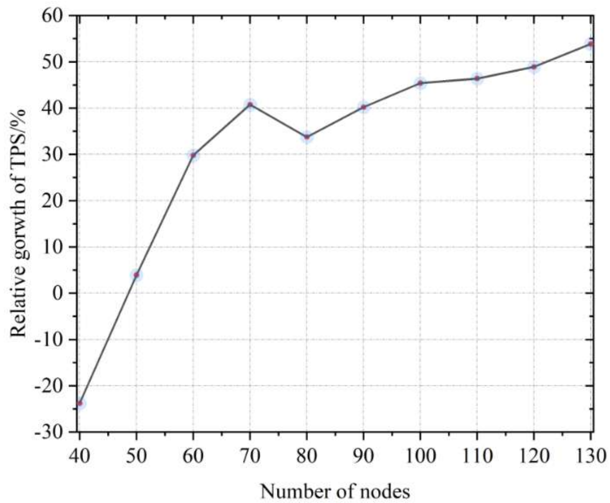


Figure 12: Node throughput ratio

VI. Conclusion

This paper explores how to realize the innovative development of economic transaction mode with the assistance of blockchain technology and optimize the key algorithms in the transaction process. The GRU-SVM model is constructed for blockchain transaction anomaly detection, and the original practical Byzantine fault-tolerant consensus algorithm is optimized to enhance the security and efficiency of blockchain economic transaction mode. Experiments and simulations are conducted in the dataset to verify the effectiveness of the method in this paper, and the results show that:

(1) The precision, recall and F1 score of GRU-SVM on the full feature dataset are 98.49%, 95.61% and 94.78%, respectively. While the index values on the feature subset after two-layer feature selection are 99.03%, 96.28% and 95.32%, respectively. Compared with the full feature dataset, the GRU-SVM model can achieve more advanced detection performance on the feature subset. It shows that this paper utilizes the chi-square test and Pearson correlation coefficient for feature selection, which has a significant enhancement effect on the detection performance of the GRU-SVM model. The model is utilized to accurately detect anomalies in blockchain transactions so that they can be handled in a timely manner.

(2) The total communication number of the improved practical Byzantine fault-tolerant consensus algorithm (TM-PBFT) is $2N_1 + 2N_1 + N + 2N$, which has a significant reduction compared with the original PBFT algorithm and CPBFT algorithm. And after the number of nodes exceeds 50, the throughput of TM-PBFT consensus algorithm is larger than that of PBFT consensus algorithm, and the throughput gap between the two shows a gradually increasing trend. It shows that the optimization of the original PBFT algorithm in this paper is effective.

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