An Adaptive State Supervising Method for Power Data Blockchain Based on Relay Mechanism

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ABSTRACT

With the continuous advancement of Power Blockchain constructions, many domestic companies have established multiple blockchain applications such as Smart Contract, Smart Finance, Energy Cloud and so on. While blockchain is in the stage of developing, thus there exists a lot of problems on these established blockchain applications. Supervision on chain data is one of these problems and it is always difficult, in order to resolve this problem, we propose a supervising method based on relay mechanism to monitor the chain data adaptively and to detect and control the abnormal data timely. We generate the data according to the data structure of the power distribution automation system for anomaly detection. The experimental results show that the proposed supervision algorithm detects abnormal power data in time, and adaptively updates the algorithm parameters according to the changes of the data on the chain, ensuring the accuracy of the detection results, and can help the supervisory unit to supervise the data on chain.

CCS CONCEPTS

• **CCS:**; • **Information systems** → Data management systems; Database administration;

KEYWORDS

Blockchain, Relay Mechanism, Power Distribution Automation System

ACM Reference Format:
Wenhao Xue*, Cheng Yang, and Zhuofan Wu. 2022. An Adaptive State Supervising Method for Power Data Blockchain Based on Relay Mechanism. In *The 2022 4th International Conference on Blockchain Technology (ICBCT'22), March 25–27, 2022, Shanghai, China.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3532640.3532659

1 INTRODUCTION

Since 2019, State Grid has incorporated the application of blockchain technology into the key tasks of the construction of ubiquitous power Internet of Things. State Grid is actively deploying in pilot verification, platform construction, and standard systems; it has carried out pilot applications in energy finance, e-commerce, trading and other fields, and has achieved positive progress in adapting to energy changes, improving grid service levels, and optimizing the business environment [1].

At present, blockchain technology is still in its early stage [2]. Not only has it not yet formed a unified technical standard, but various technical solutions are still developing rapidly. Based on the scalability of blockchain technology, it has not yet undergone large-scale practical tests. Various blockchain applications that have been established by the State Grid may have various problems, such as non-essential data on the chain: If all the data of the State Grid blockchain are recorded as transaction records, the amount of data will grow rapidly, considering that the amount of stored data only used for reading will become larger and larger over time, and the network overhead will also increase; difficulty in on-chain data supervision: the inherent characteristics of the blockchain, "decentralization", "trust mechanism", and "anonymity" are the difficulties of supervision on chain; business problems such as inaccurate automatic status monitoring results. The traditional block chain which is shown in Figure 1 anomaly supervising method is oriented to all data on the chain, and the effective data content is low, and the excessive redundant data causes the efficiency and consumption of the abnormal monitoring algorithm. Existing energy data abnormal monitoring and supervision mostly use manual methods, and abnormal data discovery is difficult and not timely. Existing algorithms propose to monitor data through artificial intelligence algorithms, which can detect abnormal data in a timely manner and manage and control the corresponding database, ensure the safety of energy use, and facilitate enterprises to better perform power distribution scheduling. However, due to the rapid generation of power data and large changes, a large amount of new data may be generated in a short time. The existing abnormal supervising algorithms for power data only train historical data once, and the accuracy of the generated monitoring model decreases over time.

Based on the side chain relay mechanism [3], we preprocess the power data through principal component analysis (PCA), and combine the just-in-time learning algorithm (JITL) with the one-class support vector machine (One-Class SVM) regression algorithm. The chain data performs adaptive status monitoring, and detects and manages abnormal data in time. Deploy the blockchain supervision core agency on the public side chain of the blockchain that needs to be supervised, and store and monitor the core energy data on the chain. Through the monitoring algorithm we propose, we can discover the abnormality of the energy data in time, and based on the data on the chain. The algorithm parameters are adaptively updated according to changes to ensure the accuracy of the detection

ICBCT'22, March 25–27, 2022, Shanghai, China

ACM ISBN 978-1-4503-9576-2/22/03…$15.00
https://doi.org/10.1145/3532640.3532659

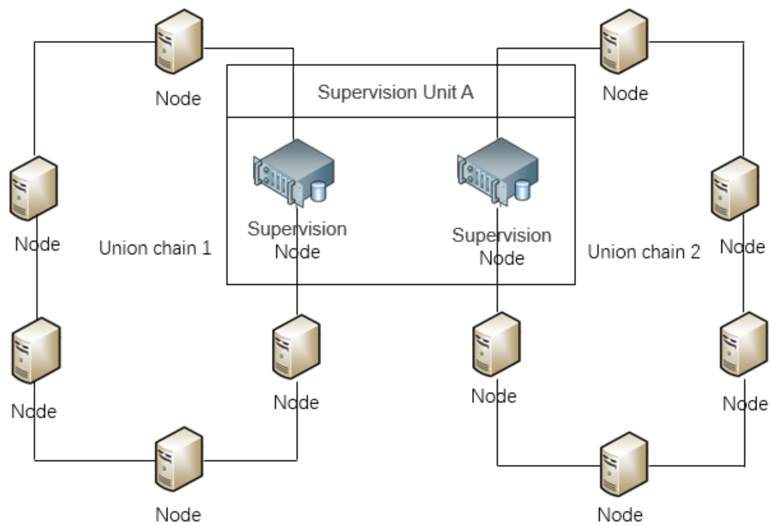

Figure 1: Traditional blockchain exception monitoring methods

results, which can help the supervisory unit to supervise the data on the chain.

Overall, main contributions of our work are listed below:

- We solve the problem of high training cost of anomaly supervising model. We separate the core data with high regulatory requirements across the chain of custody, and then streamline the data attributes through PCA, which can accurately and conveniently perform abnormal supervising.
- We solve the problem of difficulty in abnormal supervision. We introduce artificial intelligence algorithms, and the abnormality effect is significantly improved.
- The JITL framework can periodically update the training set and retrain by setting a time threshold. The effect of abnormal supervision and control is even better.

2 RELATED WORK

2.1 Blockchain

Blockchain is a new application of computer technologies such as distributed data storage, point-to-point transmission, consensus mechanism and encryption algorithm. The essence of blockchain, a distributed ledge technology, is a method of data storage, transmission and certification in a decentralized, distributed structure [3, 4].

2.2 Sidechain

Sidechain is a blockchain which is used as an extension of another block chain (main chain). Usually, the main chain maintains an asset ledger and is connected to the side chain, while in the meantime, the sidechain is connected to the main chain through a cross-chain communication protocol as an independent system. In practical use, the sidechain doesn't necessarily maintain the secondary and both chains can be each other's sidechains [5]. Whether it is the main chain or a sidechain, cross-chain technology is the key to realizing the value interconnection. One of the cross-chain technologies is the relay mechanism, which is a fusion of the sidechain and the notary schemes. The relay chain is a fully functional blockchain that can read and verify the data information of the blockchains connected to it. If a sidechain is equipped with relay mechanism, then it can be the relay chain.

2.3 Just-in-time Learning Algorithm (JITL)

The basic idea of JITL is to select the training dataset with the highest similarity from the historical database according to the current state of the data, and then use the corresponding global modeling method to construct model to obtain the output corresponding to the current state. The tradition way of training the model generally tries to include all situations, and model is often accomplished after one thorough training and the trained model will never change. On the contrary, the model built through JITL is discarded after the corresponding output is given. Classical methods are often based on global data, and get a global model, while JITL obtains a local model by selecting relevant local data, and its prediction error is relatively small [6].

3 METHOD

3.1 Structure of Power Data Supervision

There are multiple regional power data alliance chains in the existing power system. However, the consensus algorithm [7] and data structure of different blockchains are various. It is necessary to use cross-chain supervision technology to realize the supervision of the data on the chains and we use the relay mechanism. The relay mechanism aims to construct a third-party public chain to specifically carry applications, and to establish a channel between the two chains so that the two chains can interact with each other through the channel. We propose to take the public sidechain of the original alliance data chain composed of regulatory agency nodes as the public chain of custody. Through the relay mechanism,

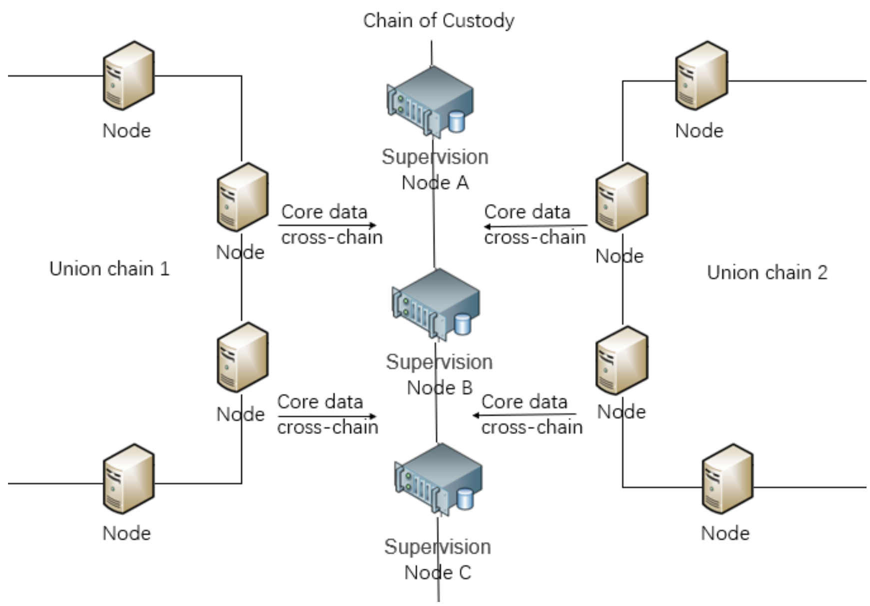

Figure 2: Relay mechanism

the core data related to the supervising algorithm on the original alliance chain are exchanged across the chain. As Figure 2 shows, the data stored on the chain of custody will be updated with the data of other alliance chains. The chain of custody operates and maintains abnormal data supervising model, and at the same time supervises the abnormal data of multiple alliance chains.

3.2 Abnormal Data Supervising Process

The abnormal data supervising model first collects the core power data on the alliance chain by the sidechain when initializing. Firstly, the sidechain uses Principal Component Analysis (PCA) to remove the redundant attributes of the power data for data reduction. Then, an abnormal supervising model is trained through an anomaly supervising algorithm. Among which, the abnormal supervising model includes PCA, JITL, and support vector machine (SVM). The model can supervise abnormal changes in data in the chain of custody for a period of time in the future. At the same time, the algorithm will retrain on the updated power data on the chain of custody and generate a new model to supervise the future data each time a fixed time has passed. The abnormal data supervising process is shown in Figure 3.

3.3 Abnormal Detection Algorithm

The abnormal detection algorithm is constructed by training the data on the chain of custody in the historical time t, and on this basis, the data in the future time Δt will be supervised for anomaly by using PCA, JITL framework [8] and SVM. The training time threshold of the JITL framework is $t + \Delta t$ and the model will be updated after each time threshold.

3.4 PCA

Principal component analysis (PCA) transforms a group of variables that may be correlated into a group of linearly uncorrelated variables through orthogonal transformation [9]. Because of the diversity of the power system data structure, PCA can convert the data in the system into structure data with limited characteristics. The reduced dimensionality of PCA is determined by the actual distribution of system data combined with historical data.

Suppose that the total dataset used for the abnormal detection algorithm has size m and each data in it has n attributes including current and voltage. The distribution of each attribute of normal data conforms to the normal distribution, and the abnormal data distribution is irregular.

We centralize these m pieces of n-dimensional power data $(x'^{(1)}, x'^{(2)}, \ldots, x'^{(m)})$ to $(x^{(1)}, x^{(2)}, \ldots, x^{(m)})$, where $\sum_{i=1}^{m} x^{(i)} = 0$.

Through orthogonal projective transformation, we get a new coordinate $\{w_1, w_2, ..., w_n\}$, where w is the stand orthonormal basis, namely $||w||_2 = 1, w_i^T w_j = 0$. This standard orthonormal basis doesn't represent the current and voltage properties of the original power data, but a combination of the corresponding current and voltage properties.

The target projection dimension is n', and the orthogonal bases of the original coordinate needs to be discarded to form a new coordinate system $\{w_1, w_2, ..., w_{n'}\}$. The projection of the sample point $x^{(i)}$ in n'-dimensional coordinate system is $z^{(i)} = (z_1^{(i)}, z_2^{(i)}, ..., z_{n'}^{(i)})^T$, where $z_j^{(i)} = w_j^T x^{(i)}$ is the j-th coordinates of $x^{(i)}$ in low dimensional coordinate system.

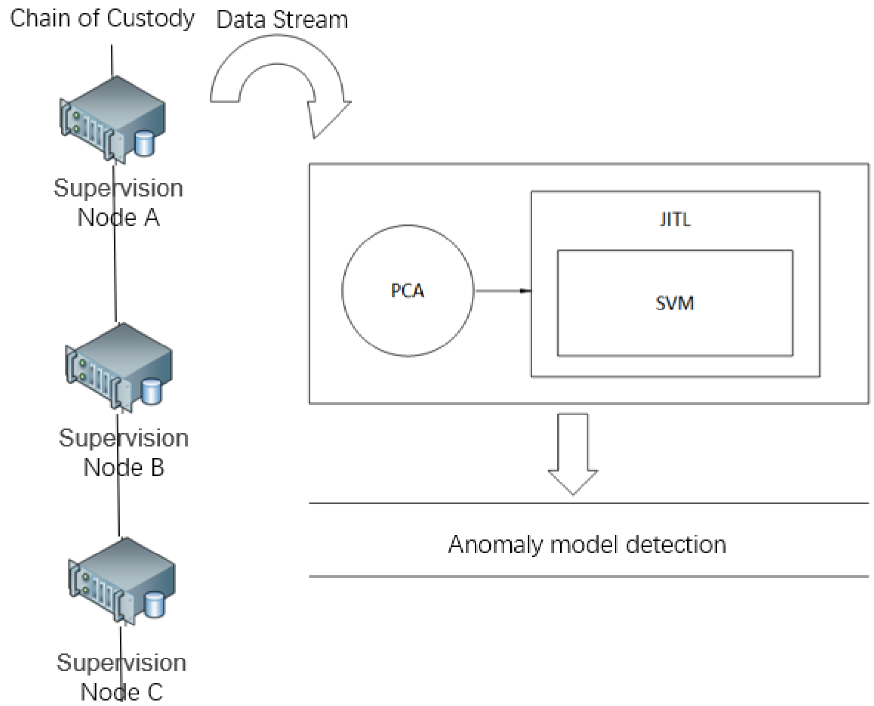

Figure 3: Abnormal data monitoring process

Assume that W is the orthogonal basis matrix, then the original data represented by $z^{(1)}$ is $\bar{x}^{(i)} = \sum_{j=1}^{n'} z_j^{(i)} w_j = Wz^{(i)}$. The optimization goal of PCA requires that all samples have the closest distance to the new orthogonal basis. The objective optimization function is as follows:

$$min \sum_{i=1}^{m} \left\| \bar{x}^{(i)} - x^{(i)} \right\|_2^2$$

With the help of conversion formula of the original dimension and the target dimension, we use the sum of squares formula, the matrix transposition formula, and the merging of similar items and matrix traces to form an optimized function, we get:

$$\sum_{i=1}^{m} \left\| \bar{x}^{(i)} - x^{(i)} \right\|_2^2$$

$$= \sum_{i=1}^{m} \left\| Wz^{(i)} - x^{(i)} \right\|_2^2$$

$$= \sum_{i=1}^{m} z^{(i)T} z^{(i)} - 2\sum_{i=1}^{m} z^{(i)T} W^T x^{(i)} + \sum_{i=1}^{m} x^{(i)T} x^{(i)}$$

$$= \sum_{i=1}^{m} z^{(i)T} z^{(i)} - 2\sum_{i=1}^{m} z^{(i)T} z^{(i)} + \sum_{i=1}^{m} x^{(i)T} x^{(i)}$$

$$= -\sum_{i=1}^{m} z^{(i)T} z^{(i)} + \sum_{i=1}^{m} x^{(i)T} x^{(i)}$$

$$= -tr\left(W^T X X^T W\right) + \sum_{i=1}^{m} x^{(i)T} x^{(i)}$$

Simultaneously, the goal of PCA can be transformed into:

$$argmin - tr\left(W^T X X^T W\right) s.t. W^T W = I$$

By using the Lagrange function, we can obtain the derivative:

$$J(W) = -tr\left(W^T X X^T W + \lambda\left(W^T W - I\right)\right)$$

$$X X^T W = \lambda W$$

3.5 JITL Framework & Single-Class SVM

Assume that the test sample x'_k is input at time k, first, calculate the similarity $\{S_{i,\ k}\}_{i=1}^{N_1}$ between x'_k and the input vector $X = \{x_i\}_{i=1}^{N_1}$ of all training samples, where N_1 is the number of samples in the training set. Then we sort $\{S_{i,\ k}\}_{i=1}^{N_1}$ from large to small, the larger the value represents the higher correlation between the i-th training sample and the training sample x'_k.

The first L training samples corresponding to the $S_{i,\ k}$ are screened out and the relevant training samples subsets $\{X_L\}$ and $\{Y_L\}$ composed from x'_k are used to train the local model.

We adapt the dataset obtained in the previous step for single-class SVM [10] training which is unsupervised and is different from SVM based on supervised learning. Practically, we uses the Support Vector Domain Description (SVDD) [11]. Assuming that all non-anomalous samples are positive, and at the same time, SVDD uses hyperspheres to divide. The algorithm obtains the spherical boundary around the data in the feature space, hoping to minimize the volume of the hypersphere, thereby minimizing the influence of abnormal point data. The optimization goal is as follows:

$$minV(r) + C\sum_{i=1} \zeta_i$$

$$\|x_i - o\|_2 \leq r + \zeta_i, i = 1, 2, 3 \ldots m$$

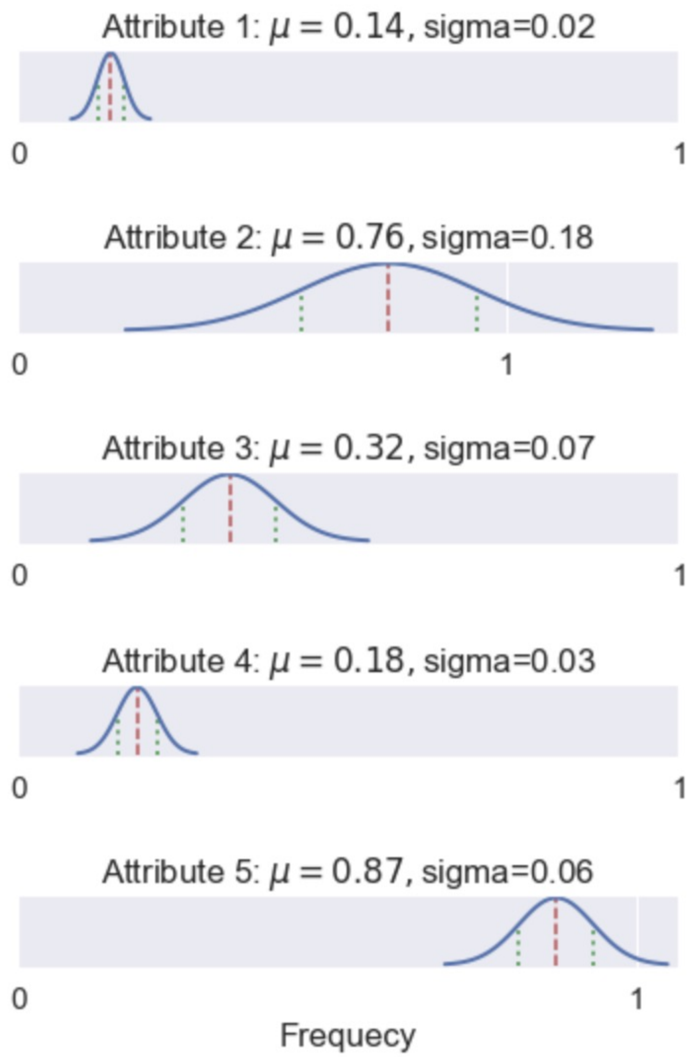

Figure 4: Attribute distribution curve

$$\zeta_i \geq 0, i = 1, 2, \ldots m$$

where V represents the volume of the target hypersphere, o represents the center of the sphere, ζ is the slack variable and C is the training penalty coefficient, which is determined according to the actual dataset.

Lagrance duality can be used to determine whether the new data point is inside the hypersphere and if the new data point is outside the hypersphere, then it is an abnormal point. By this way, we realize the detection of abnormal data on the chain within a period of time. After the training is completed, supervising the data for anomalies together with the input of new test samples will be completed simultaneously. After a fixed interval of time, the local model of the previous step will be discarded, and new local model will be updated based on the new data.

4 EXPERIMENT

4.1 Data preprocessing and PCA

We simulate and generate data based on the data tracking results of the distribution automation system to detect and trace abnormal data. A total of $m = 10,000$ pieces of data $x_1, x_2, x_3, \ldots, x_m$ are randomly generated. Each piece of power distribution data has $n = 25$ attributes $a_1, a_2, a_3, \ldots, a_n$ including power data such as current and voltage. The data value of each attribute conforms to the normal distribution, and outliers are randomly generated at random locations. The distribution curves of the first five attributes are shown in Figure 4.

PCA is used to reduce the dimension of the n-dimensional sample set $D = (x_1, x_2, x_3, \ldots, x_m)$, the expected principal component proportion threshold is $t \in (0, 1]$, and the sample set after dimensionality reduction is D'.

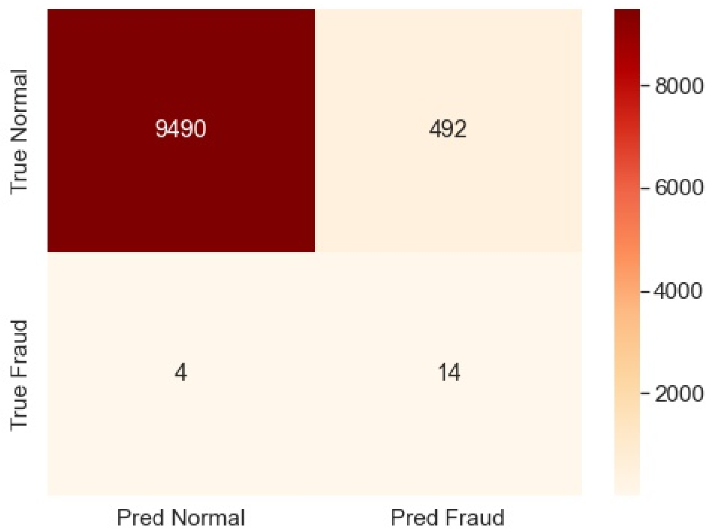

Figure 5: Examples of automated system operations

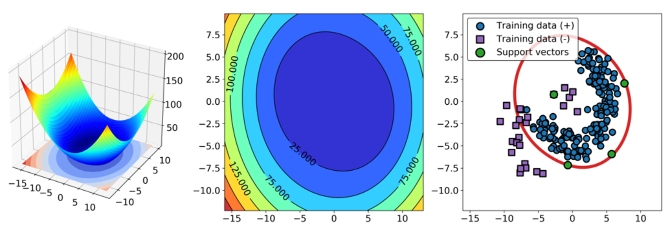

Figure 6: SVDD accurately extract abnormal data

After data centering is processed, the sample covariance matrix XX^T is calculated, and eigenvalue decomposition is performed on XX^T.

$$x_i = x_i - \frac{1}{m}\sum_{j=1}^{m} x_j$$

If n eigenvalues are $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots \geq \lambda_n$, then n' can be obtained by the following formula:

$$\frac{\sum_{i=1}^{n'} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \geq t$$

The eigenvector $(\omega_1, \omega_2, \omega_3, \ldots, \omega_{n'})$ of the maximum n' eigenvalues is normalized to form an eigenvector matrix W. For each sample x_i in the sample, it is transformed into a new sample $z_i = W^T x_i$, and the output set sample $D' = (z_1, z_2, z_3, \ldots, z_m)$ is obtained.

Table 1: Abnormal detection index of simulation experiment

Detection Index	Result
Precision	0.9997
Accuracy	0.9618
Error Rate	0.0320
F1 Score	0.9523

4.2 Method effect detection and Result

10,000 pieces of data are generated by simulating the data structure of the distribution automation system, which contain outliers with abnormal attributes. The abnormal data is detected through principal component analysis and One-Class SVM under the JITL framework. The results are shown in Figure 5. Our model has also achieved good results in precision rate, accuracy rate, error rate and F1 score which is shown in Table 1. It can be seen from Figure

6 that our SVDD hypersphere is very effective in dividing abnormal samples, and can accurately draw abnormal data hidden in normal data.

5 CONCLUSION

In view of the difficulties in data supervision on the existing chain of State Grid and the inaccurate results of automatic state monitoring, this paper designs a block chain power data adaptive state monitoring method based on the relay mechanism. Through the combination of principal component analysis, just-in-time learning algorithm framework and single-class support vector machine algorithm, the purpose of detecting and controlling abnormal data in time is achieved.

According to theoretical analysis and specific experimental simulations, it can be verified that the power data block chain adaptive state detection algorithm based on the relay mechanism proposed in this paper can detect abnormal energy data in time, and adapt to update the algorithm parameters according to the changes of the data on the chain, which has a certain engineering reference value.

ACKNOWLEDGMENTS

This work is supported by the SGEC Science and Technology Project "Research on Chain-to-Chain Supervision Technology Applicable to National Network Business Scenarios," Funding, Project No.: 1200/2021-72005B

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