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Retraction

Retracted: Enterprise Management Performance Evaluation Model Using Improved Fuzzy Clustering Algorithm in IoT Networks

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Li and L. Ma, "Enterprise Management Performance Evaluation Model Using Improved Fuzzy Clustering Algorithm in IoT Networks," *Security and Communication Networks*, vol. 2022, Article ID 9607303, 11 pages, 2022.

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Research Article

Enterprise Management Performance Evaluation Model Using Improved Fuzzy Clustering Algorithm in IoT Networks

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Enterprise core competence is closely related to enterprise management performance, and it is important to evaluate enterprise management performance. However, the current enterprise management performance evaluation model has the problems of high eigenvalues of sample data, low cumulative contribution and correlation, high error rate in the calculation of business management performance evaluation index weights, low evaluation accuracy, and long evaluation time. Therefore, the enterprise management performance evaluation model using improved fuzzy clustering algorithm in Internet of things (IoT) networks is proposed. First, in the IoT architecture, the enterprise management performance evaluation index system is established by using the balanced scorecard theory. Second, the evaluation index system is reduced in dimensionality by combining principal component analysis and kernel-independent component analysis, the fuzzy C-mean clustering algorithm based on the objective function is designed, and finally, the improved fuzzy clustering algorithm is obtained to establish the enterprise management performance evaluation model, the reduced evaluation index system is input, and the evaluation results are output. The results show that the sample data eigenvalue of this model is low. The maximum error rate of weight calculation is 2.3%, the accuracy is always more than 95%, and the average value of evaluation time is 0.57 s, which effectively realize enterprise management performance evaluation in IoT networks.

1. Introduction

With the development of China's economy, the government has given a lot of support and helped to the development of enterprises. However, in order to win a certain living space in the fierce environment, enterprises need to constantly improve their competitiveness, explore and innovate, and forge ahead [1, 2]. The development speed of today's society has exceeded that of any previous period. In such a living environment, enterprises are facing unprecedented challenges and competitive pressure. Enterprises need to enhance their comprehensive strength and improve their technical level is the only way for enterprises to survive, the first step of which is to improve the management level of enterprises. Talents play a very important role in the development and growth of enterprises. Therefore, the core work of improving enterprise management level is talent management [3, 4]. IoT refers to the real-time collection of any object or process requiring monitoring and connection and interaction through various information sensors, RFID technology, global positioning system, infrared sensors, laser scanners, and other devices and technologies, and using IoT to collect enterprise management information can lay a solid foundation for subsequent enterprise management performance evaluation. At present, the development of IoT technology has accelerated, and enterprise management performance has gradually become an internal factor of enterprise economic growth, which directly affects its competitiveness. In order to enhance competitiveness, it is necessary to improve enterprise management performance [5]. Enterprise performance management is produced under this background. Its main purpose is to strengthen the refined management of enterprises, improve the work enthusiasm and initiative of employees, and promote the healthy development of enterprises [6]. Moreover, it is also convenient for corporate leaders to understand the actual situation within the enterprise and provide reference for improving competitiveness.

Aiming at the important research topic of enterprise management performance evaluation, Fallahpour et al. [7] combined a new fuzzy modification of the analytic hierarchy process called fuzzy preference programming (FPP) and VlseKriterijumska optimizacija I kompromisno resenje (FVIKOR) to evaluate enterprise management performance. FPP is used to calculate the weight of each dimension and its criteria, language variables are used to collect enterprise performance scores in a fuzzy environment, and the FVIKOR method is used to evaluate the overall performance under enterprise management attributes. This model can effectively evaluate enterprise management performance. However, it has the problem of taking a lot of evaluation time. Li et al. [8] from the four aspects economic benefits, public services, management, and development potential constructed the relevant evaluation system by using the balanced scorecard theory and determined the weight of each index by using the comprehensive evaluation method, which combines entropy weight method and analytic hierarchy process. Combined with the weight calculation results, the BP neural network is used to construct the enterprise management performance evaluation model, so as to realize the enterprise management performance evaluation. The model has better evaluation effect. However, the evaluation accuracy decreases due to the incomplete index system. Zhou et al. [9] evaluated the enterprise product reputation more objectively and comprehensively by establishing the enterprise product reputation evaluation index system and combining the grey theory and fuzzy analysis method to evaluate the enterprise product reputation. This model can reduce the evaluation error rate caused by subjective factors, but it has the problem of high error rate in the calculation of evaluation weight. Li et al. [10] proposed an attribute reduction model of high-dimensional data based on partial correlation analysis and factor analysis. According to the attribute weights calculated by various weighting methods, multiple evaluation score vectors corresponding to the evaluated object are obtained. Combined with quadratic combination weighting and Spearman consistency test, the final score vector is determined, and the evaluation object is graded by the fuzzy c-means algorithm. This model can effectively realize the decision-making of high-dimensional data attribute reduction, complex system evaluation scoring, and cluster analysis. However, this method has the problem of low evaluation accuracy. Chen et al. [11] discussed the effectiveness evaluation system of management policy from the perspective of social computing. Based on the data obtained from the questionnaire, they used the method of factor analysis to obtain the indicators of the survey data and established a new evaluation model based on the observation indicators. The model can effectively evaluate management policies. However, the generalization effect of the characterization stability of these models is poor, and the evaluation accuracy needs to be improved. The improved fuzzy clustering algorithm belongs to the unsupervised learning algorithm, which has better effect of data mining and knowledge discovery and can accurately divide the categories of data sets.

In order to solve the problems of the above model, this paper proposes an enterprise management performance evaluation model using improved fuzzy clustering algorithm in IoT networks. The contributions of this paper are as follows: (1) Enterprise management performance evaluation is a fuzzy problem. The improved fuzzy clustering algorithm can solve this fuzzy problem precisely, and a comprehensive evaluation index system is established to improve the fairness of performance evaluation. (2) Combining principal component analysis (PCA) and kernel-independent component analysis (KICA), some indicators can be used to describe the characteristics of the whole data. This can reduce the complexity of fuzzy clustering and improve the efficiency of enterprise management performance evaluation. (3) The dimensionality of the enterprise management performance evaluation index system is reduced, so as to reduce the problem of the decline of evaluation accuracy due to the high complexity of the data. The improved fuzzy clustering algorithm is used to establish the enterprise management performance evaluation model and output the evaluation results.

2. Methodology

2.1. Data Set. An industry A-share listed enterprise is taken as the experiment object, and two companies, which are recorded as G1 enterprise and G2 enterprise, are selected. G1 enterprise is a professional human resource service provider for foreign financial institutions and economic organizations. As a professional integrated human resource solution provider, G1 enterprise has been providing a full range of human resource solutions for various organizations and enterprises, promoting the rapid growth of Chinese and foreign enterprises' business in China and helping domestic and foreign talents to continuously enhance their value. G2 enterprise has been deeply engaged in the human resource service industry, covering employment management, staffing agency, commercial outsourcing, and other services, and will continue to create value through services, products, and technology to create a valuable intelligent human resource service ecology, empowering organizations and industry development. A total of 2000 evaluation index data sample data in G1 and G2 enterprises are selected as experimental sample data, and these data are cleaned and deweighted, and 80% data were used as a train set and 20% data as a test set. This paper's model is used to evaluate the management performance of two enterprises. The evaluation grades include five categories: excellent, better, good, medium, and poor.

2.2. Enterprise Management Performance Evaluation Index System. IoT networks are information carriers based on the Internet and traditional telecommunication networks. It enables all ordinary physical objects that can be independently addressed to form an interconnected network, realizes the ubiquitous connection between things and people, and realizes the intelligent perception, identification, and management of things and processes through various possible network accesses. Therefore, this paper collects enterprise data with the support of the IoT architecture, which can lay a solid foundation for the subsequent construction of enterprise management performance evaluation index system. The enterprise data collection architecture based on IoT is shown in Figure 1.

There are two problems to be considered in the design of enterprise performance evaluation system: the selection of performance indicators and the design of management indicators. Therefore, to establish a good performance index system, we need to follow the principle of giving priority to quantitative indicators and supplemented by qualitative indicators; the principle of less but better; the principle of testability; the principle of independence and difference; and the principle of goal consistency. Therefore, according to the characteristics of enterprise management performance evaluation, this paper uses the balanced scorecard theory to establish the enterprise management performance evaluation index system. The evaluation index system is shown in Table 1.

Analysis of Table 1 shows that the enterprise management performance evaluation index system is composed of criterion layer and target layer, and the criterion layer is composed of multiple target layers. The financial standards layer includes return on net assets, net interest rate on sales, return on cost, asset turnover rate, cost reduction rate, asset utilization rate, and interest earned multiple; the customer criterion layer includes customer loyalty, customer satisfaction, market share, customer profitability, customer maintenance rate, and new customer ratio; the internal process criterion layer includes new product R&D cycle, new product launch ratio, after-sales service efficiency, internal communication frequency, product qualification rate, production capacity utilization rate, and new product sales revenue ratio; and the learning and innovation criteria layer includes employee retention rate, number and cycle of innovative products, annual patent applications, annual training investment rate, information feedback and processing rate, and R&D cost investment rate. The use of enterprise management performance evaluation index system can accurately describe the factors affecting enterprise management performance evaluation and improve the accuracy of follow-up evaluation.

2.3. Dimensionality Reduction of Evaluation Index System. PCA-KICA dimensionality reduction [12] is used to process the data of enterprise management performance evaluation index system, which can not only extract the main data from the high-dimensional enterprise management evaluation index data [13, 14] but also approximate the original data.

The mathematical model of PCA-KICA dimensionality reduction processing enterprise management evaluation index data is as follows:

$$\Phi\colon X^d \longrightarrow F, \tag{1}$$

where the mapping is Φ; the dimension of data sample of enterprise management evaluation index X^d is d.

Using Φ to map X^d into the featured space F. Let the sample matrix X of enterprise management performance evaluation index data be a $d \times N$ matrix, and the number of samples is N. The expression equation is as follows:

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ x_{d1} & x_{d2} & \cdots & x_{dN} \end{pmatrix}, \tag{2}$$

where X is the centralized sample matrix to facilitate dimension reduction and error comparison [15] and improve the dimension reduction effect of enterprise management performance evaluation index data samples. The specific steps of PAC-KICA dimensionality reduction processing enterprise management evaluation index data are as follows:

Step 1. Normalize X with

$$\overline{X} = QX\lambda, \tag{3}$$

where Q is the inverse of the square root of the sample variance matrix of X; and λ is the constant.

Step 2. Obtaining the eigenvalues of sample covariance matrix $\overline{X}$ to get $\gamma_1, \ldots, \gamma_N$ and the corresponding enterprise management performance evaluation index eigenvector matrix $A = (a_1, \ldots, a_N)$ as well as the descending order $\gamma_1, \ldots, \gamma_N$.

Step 3. Determine the number of principal elements m according to the contribution rate of principal elements of PCA and solve the first m principal elements as

$$\alpha_m = \frac{\gamma_m}{\gamma_1 + \cdots + \gamma_N}, \tag{4}$$

$$S = \frac{\sum_{i=1}^{m} \gamma_i}{\sum_{i=1}^{N} \gamma_i}, \tag{5}$$

$$X_{\text{PCA}} = A_m^T \overline{X} = A_m^T QX\lambda, \tag{6}$$

where α_m is the contribution rate of the m main X_m variance; S is the cumulative contribution rate of $X_1, \ldots, X_m$; A_m^T is the transpose of the eigenvector construction matrix of the first m principal components; and X_{PCA} denotes the data sample matrix of new enterprise management performance evaluation index established by the first m principal components after PCA dimensionality reduction.

Step 4. Whitening treatment X_{PCA} with the following equation:

$$\overline{X}_{\text{PCA}} = PIX_{\text{PCA}}, \tag{7}$$

where P is the whitening transformation matrix; $\overline{X}_{\text{PCA}}$ is the whitened X_{PCA} enterprise management performance evaluation index data matrix; and I is the unit matrix.

Step 5. According to different KICA algorithms, select the kernel function $K(r_i, r_j)$, $i, j \in m, i \neq j$; determine the

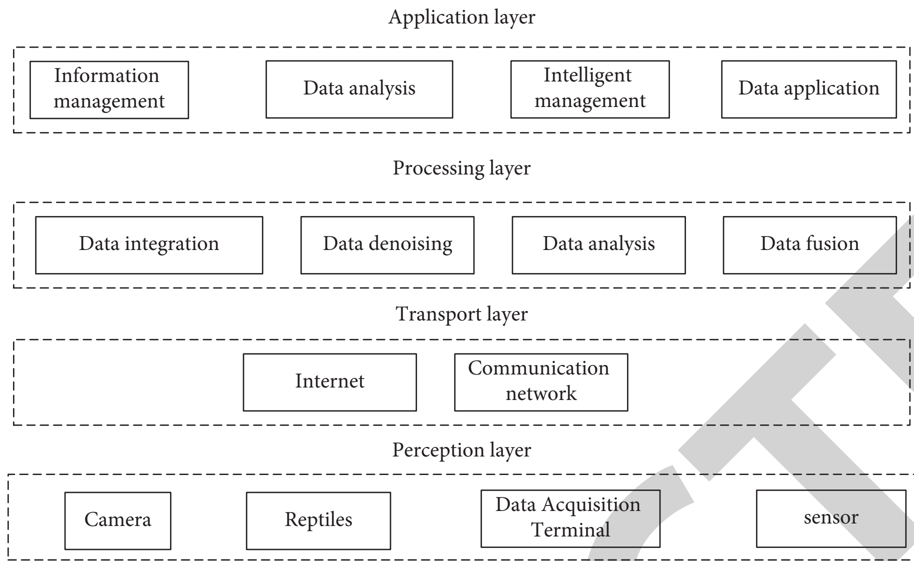

Figure 1: Enterprise data collection architecture based on IoT networks.

Table 1: Enterprise management performance evaluation index system.

Criterion layer	Target layer
The financial	Return on net assets Net interest rate on sales Return on cost Asset turnover rate Cost reduction rate Asset utilization rate Interest earned multiple
The customer	Customer loyalty Customer satisfaction Market share Customer profitability Customer maintenance rate New customer ratio
The internal process	New product R&D cycle New product launch ratio After-sales service efficiency Internal communication frequency Product qualification rate Production capacity utilization rate New product sales revenue ratio
Learning and innovation	Employee retention rate Number and cycle of innovative products Annual patent applications Annual training investment rate Information feedback and processing rate R&D cost investment rate

contrast function $A'(W)$, and through the minimization of $A'(W)$, seek the unmixing matrix W in turn [16, 17].

Step 6. W is used to estimate the original enterprise management performance evaluation index data.

$$\widehat{X} = W\overline{X}_{\text{PCA}} = WPIX_{\text{PCA}}, \tag{8}$$

where $\widehat{X}$ is the estimated value of the original enterprise management performance evaluation index data.

2.4. Enterprise Management Performance Evaluation Model. The enterprise management performance evaluation model using improved fuzzy clustering algorithm is shown in Figure 2.

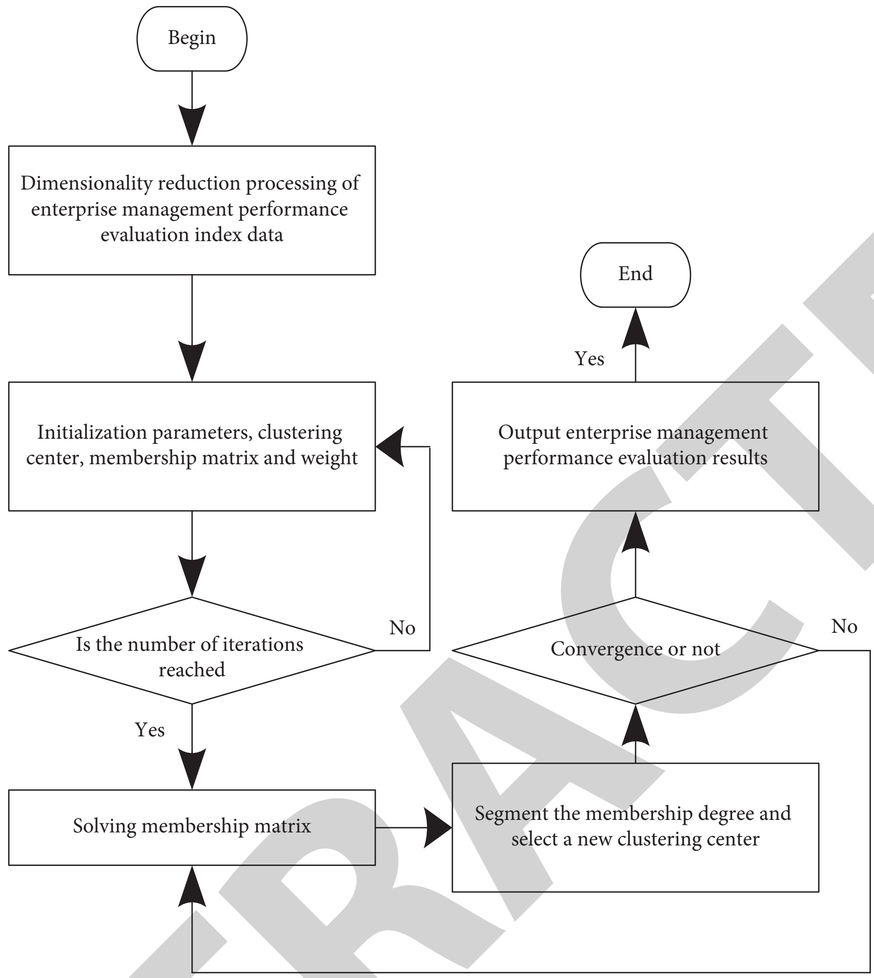

Figure 2: Enterprise management performance evaluation model.

Figure 2 shows that the dimension of enterprise management performance evaluation index data is reduced, the parameters of improved fuzzy clustering algorithm are initialized, and the clustering center, membership matrix, and evaluation index weight are determined. When the specified number of iterations is reached, solve the membership matrix; otherwise, execute the previous step. After solving the membership matrix, we need to segment the membership and select a new clustering center. In the case of convergence, output the enterprise management performance evaluation results; otherwise, re-solve the membership matrix until convergence is achieved to realize the enterprise management performance evaluation.

PCA-KCIA dimensionality reduction is used to process the enterprise management performance evaluation index data. By improving the fuzzy clustering algorithm, the evaluation index data after dimensionality reduction is clustered to obtain the enterprise management performance evaluation results [18, 19]. The improved fuzzy clustering algorithm is a fuzzy c-means clustering algorithm based on the objective function. Based on the learning of the training samples of the enterprise management performance evaluation index data after unmarked dimensionality reduction, it obtains the internal properties and laws of the data and improves the flexibility of the clustering results. The data set of enterprise management performance evaluation indicators after dimensionality reduction is $\widehat{X}$, segment $\widehat{X}$ into category c, and the corresponding c category center is C. The affiliation of each sample $\widehat{x}_{i'}$ to category i' is $u_{i'j}$. The objective function, namely the enterprise management performance evaluation model, is as follows:

$$J = \sum_{i'=1}^{c} \sum_{j=1}^{m} u_{i'j}^{\theta} \omega_{i'j} \left\| \widehat{x}_j - C_{i'} \right\|^2, \tag{9}$$

where m is, after dimensionality reduction, the number of data samples of enterprise management performance evaluation indicators; θ denotes the membership factor; and $\omega_{i'j}$ is the sample weight of enterprise management evaluation index data.

The iterative equations of $u_{i'j}$ and $C_{i'}$ are as follows:

$$\begin{aligned} u_{i'j} &= \frac{1}{\sum_{t=1}^{c} \left(\left\| \widehat{x}_j - C_{i'} \right\|^{2/\theta-1} / \widehat{x} \left\| \widehat{r}_j - C_t \right\|^{2/\theta-1} \right) d\left(l_\tau, l_{\tau'}\right)}, \\ C_{i'} &= \frac{\sum_{i'=1}^{c} \sum_{j=1}^{m} \left(\widehat{x}_j u_{i'j}^{\theta} \omega_{i'j} \right)}{\sum_{i'=1}^{c} \sum_{j=1}^{m} u_{i'j}^{\theta} \omega_{i'j}}, \end{aligned} \tag{10}$$

where t is the iteration time; and $d(l_\tau, l_{\tau'})$ is the weighted Minkowski distance between enterprise performance evaluation grade l_τ and $l_{\tau'}$.

After updating the current mean vector, repeat the above steps. The conditions for the end of the algorithm are as follows:

$$\max_{i'j}\left\{\left|u_{i'j}^{t+1}\omega_{i'j}^{t+1} - u_{i'j}^{t}\omega_{i'j}^{t}\right|\right\} < \varepsilon, \tag{11}$$

where ε is the error threshold.

The relative value of $\omega_{i'j}$ is updated by clustering error with the following equation:

$$\begin{aligned} E_{i'j}^{t} &= \sum_{i'=1}^{c}\sum_{j=1}^{m} d_{i'}^{t}\left[J^{t}(\hat{r}_j) - Y^{t}(\hat{r}_j)\right], \\ \beta^{t} &= \mu \frac{E_{i'j}^{t}}{1 - E_{i'j}^{t}}, \\ {\omega'}_{i'j}^{t} &= \ln \frac{1}{2\beta^{t}}, \end{aligned} \tag{12}$$

where $Y^t(\hat{r}_j)$ is the original clustering result; $J^t(\hat{r}_j)$ is the clustering result of the enterprise management performance evaluation model in equation (9); $E_{i'j}^{t}$ is the relative error between $J^t(\hat{r}_j)$ and $Y^t(\hat{r}_j)$; β^t is the regulatory factor; ${\omega'}_{i'j}^{t}$ is the updated sample weight; and μ is the correction factor.

When the continuous iteration $u_{i'j}$ is unchanged, i.e., $u_{i'j}$ is at the optimal state, it indicates that the clustering process has converged to the local minimum of J to obtain the final classification of enterprise management performance evaluation results [20].

2.5. Experimental Index

Data Sample Eigenvalue and Cumulative Contribution. The lower the eigenvalue and the higher the cumulative contribution in the dimensionality reduction process of index data samples, the better the processing effect of evaluation sample data.

Correlation. It is used to measure the dimensionality reduction effect of the data samples of each evaluation index at the enterprise management performance target level of this model. The closer the correlation is to 1, the better the dimensionality reduction effect of the data samples. The equation for calculating this index is as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 (y_i - \overline{y})^2}}, \tag{13}$$

where x_i, y_i refers to different experiment sample data, and $\overline{x}, \overline{y}$ refers to the average value of the experimental sample data of x_i, y_i.

Error Rate for Calculation of Index Weights. The equation for this indicator is as follows:

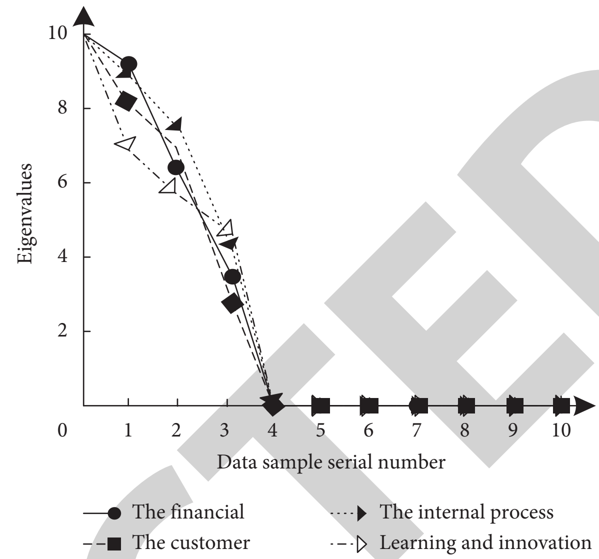

Figure 3: Eigenvalues of data samples for each criterion layer evaluation index.

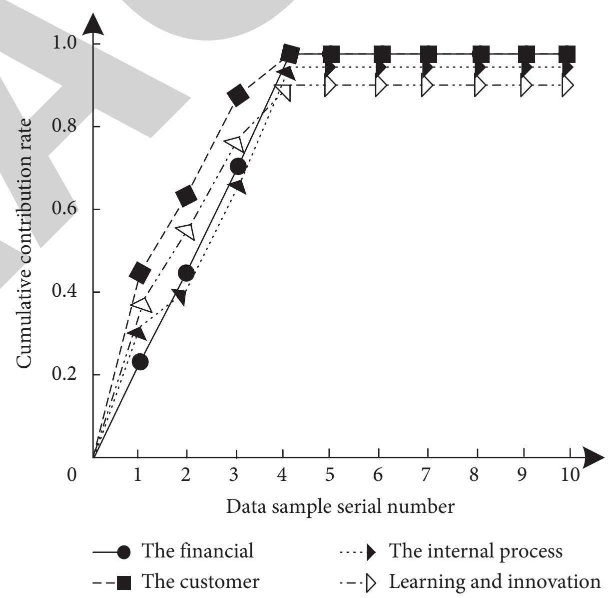

Figure 4: Cumulative contribution rate of data samples for each criterion level evaluation index.

$$e = \frac{|r_1 - r_2|}{r_1} \times 100\%, \tag{14}$$

where k_1 refers to the number of evaluation events and r_2 is the number of events with accurate evaluation results of enterprise management performance obtained by different methods.

The evaluation accuracy as an index is calculated using equation (15):

$$z = \frac{k_2}{k_1} \times 100\%, \tag{15}$$

where k_1 is the number of evaluation events and r_2 denotes the number of events for which accurate evaluation results of

Table 2: Correlation test results.

Target layer	Correlation
Return on net assets	0.976
Net interest rate on sales	0.982
Return on cost	0.993
Asset turnover rate	0.995
Cost reduction rate	0.989
Asset utilization rate	0.979
Interest earned multiple	0.981
Customer loyalty	0.975
Customer satisfaction	0.993
Market share	0.994
Customer profitability	0.988
Customer maintenance rate	0.986
New customer ratio	0.985
New product R&D cycle	0.999
New product launch ratio	0.992
After-sales service efficiency	0.991
Internal communication frequency	0.993
Product qualification rate	0.983
Production capacity utilization rate	0.982
New product sales revenue ratio	0.981
Employee retention rate	0.987
Number and cycle of innovative products	0.986
Annual patent applications	0.995
Annual training investment rate	0.996
Information feedback and processing rate	0.998
R&D cost investment rate	0.983

Table 3: Enterprise management performance evaluation index weights.

Criterion layer	Weights	Target layer	Weights
The financial	0.479	Return on net assets	0.327
		Net interest rate on sales	0.116
		Return on cost	0.062
		Asset turnover rate	0.343
		Cost reduction rate	0.052
		Asset utilization rate	0.042
		Interest earned multiple	0.058
The customer	0.128	Customer loyalty	0.147
		Customer satisfaction	0.025
		Market share	0.301
		Customer profitability	0.412
		Customer maintenance rate	0.092
		New customer ratio	0.023
The internal process	0.206	New product R&D cycle	0.084
		New product launch ratio	0.174
		After-sales service efficiency	0.452
		Internal communication frequency	0.086
		Product qualification rate	0.098
		Production capacity utilization rate	0.032
		New product sales revenue ratio	0.074
Learning and innovation	0.187	Employee retention rate	0.073
		Number and cycle of innovative products	0.086
		Annual patent applications	0.271
		Annual training investment rate	0.328
		Information feedback and processing rate	0.153
		R&D cost investment rate	0.089

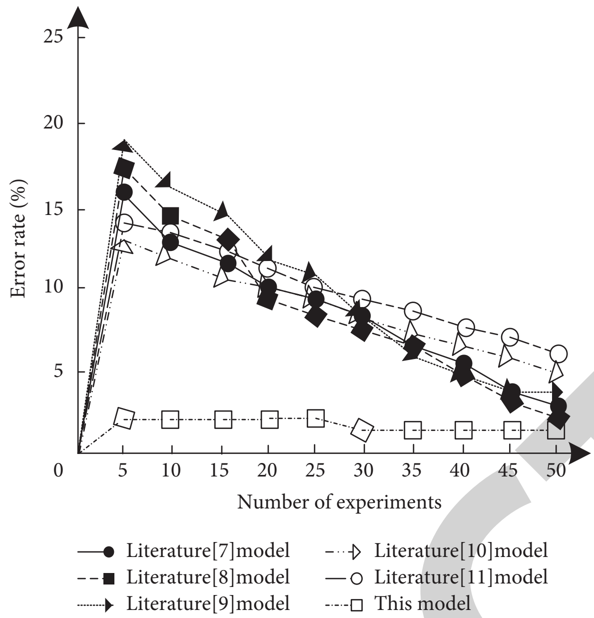

FIGURE 5: Comparison of the error rate of weight calculation.

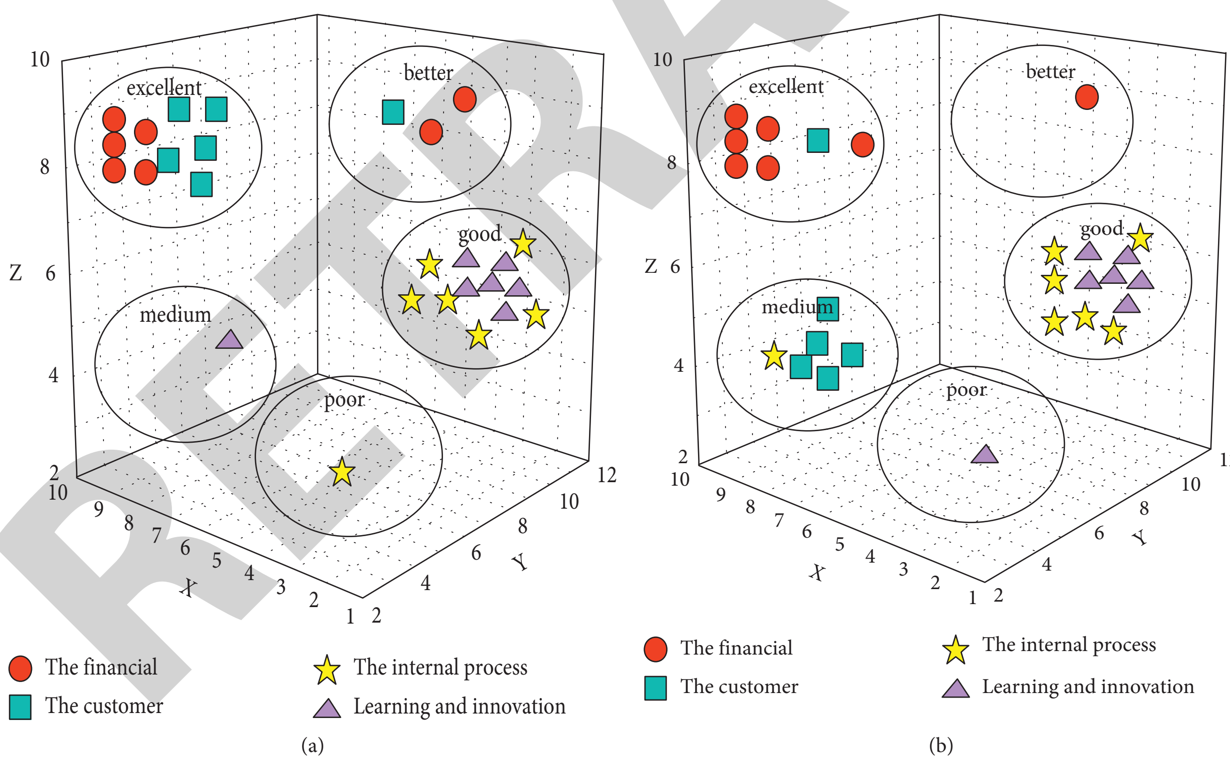

FIGURE 6: G1 and G2 enterprise management performance evaluation results. (a) Results of G1 enterprise management performance evaluation. (b) Results of G2 enterprise management performance evaluation.

enterprise management performance were obtained by different methods.

Evaluation time refers to the time to complete the enterprise management performance evaluation. The higher the index, the higher the evaluation efficiency.

3. Results and Discussion

Taking G1 enterprise as an example, the dimensionality reduction model is used to process the enterprise evaluation index data samples, and the eigenvalues and cumulative

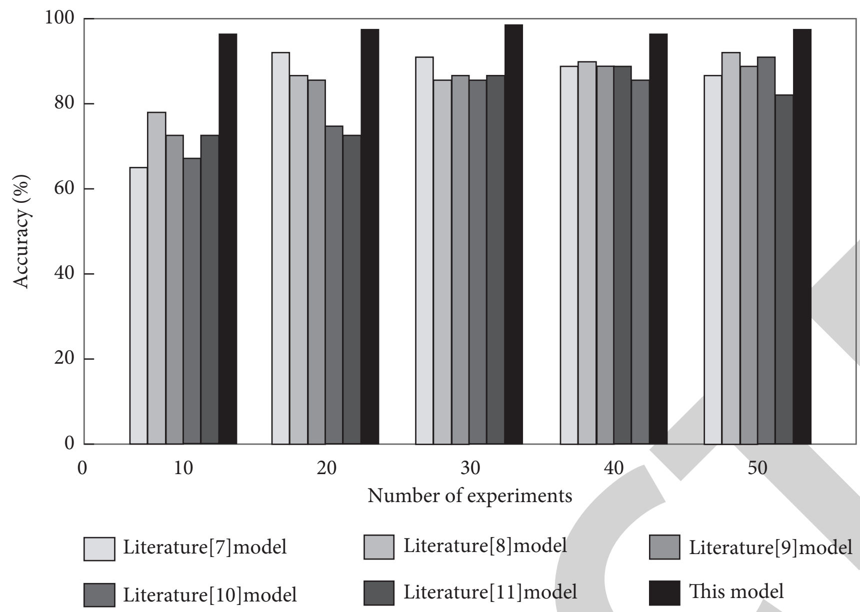

Figure 7: Comparison of enterprise management performance evaluation accuracy.

contribution rate of the evaluation index data samples at each criterion level in the dimensionality reduction process are shown in Figures 3 and 4, respectively.

According to the standard that the cumulative contribution rate exceeds 0.8, the number of principal components of enterprise management performance evaluation index data samples can be determined. According to the data in Figures 3 and 4, when the serial number of the evaluation index data samples of the four criteria layers is 4, the characteristic values of the evaluation index data samples of each criteria layer are reduced to 0, and when the serial number of the evaluation index data samples of each criteria layer is 4, the cumulative contribution rate exceeds 0.8, indicating that the first four data samples can represent all the data samples of each criteria layer, effectively realizing the dimensionality reduction of the enterprise management performance evaluation index data samples.

The correlation between the original data and the estimated data is used as the index to measure the dimensionality reduction effect of each evaluation index data sample of the enterprise management performance target layer of this model. The closer the correlation is to 1, the better the dimensionality reduction processing effect of data samples is, and the test results of the correlation of the target layer evaluation index data samples are processed by the model in this paper and are shown in Table 2.

According to the data in Table 2, the model in this paper can effectively reduce the dimension to deal with the data samples of evaluation indicators at the target level of enterprise management performance, and the correlation of dimension reduction of evaluation indicators at each target level fluctuates between 0.975 and 0.999, with an average correlation of 0.988, which is very close to 1. This shows that this model has high dimensionality reduction accuracy of enterprise management performance evaluation index data samples.

The actual values of enterprise management performance evaluation index weights are shown in Table 3.

Taking the models in [7], [8], [9], [10], [11] and the model in this paper as experimental models, this paper compares the calculation error rate of enterprise management performance evaluation index weight of these five models. The comparison results are shown in Figure 5.

Analysis of the data in Figure 5 shows that the maximum error rate of enterprise management performance evaluation index weight calculation of the model in [7] is 17.1%, that in [8] is 78.5%, that in [9] is 18.2%, that in [10] is 12.5%, and that in [11] is 14.1%. Compared with these methods, the maximum error rate of enterprise management performance evaluation index weight calculation in this model is 2.3%, which is the lowest among the six models, indicating that these methods can be used to accurately calculate the enterprise management performance evaluation index weight.

This paper calculates the weight of enterprise management performance evaluation indicators and obtains the G1 and G2 actual enterprise management performance evaluation results. The actual evaluation results are shown in Figure 6.

Taking the models in [7], [8], [9], [10], [11] and the model in this paper as experimental models, this paper compares the accuracy of enterprise management performance evaluation of these five models, and the comparison results are shown in Figure 7.

According to the data in Figure 7, the accuracy of enterprise management performance evaluation of the model in [7] is 65%–90%, that in [8] is 78%–92%, that in [9] is 73%–92%, that in [10] is 66%–91%, and that in [11] is 70%–88%. Compared with these models, the accuracy of enterprise management performance evaluation of this model is always more than 95%, which can realize the accurate evaluation of enterprise management performance.

Table 4: Comparison of enterprise management performance evaluation time.

Experiments number	Evaluation time (s)					
	Literature [7] model	Literature [8] model	Literature [9] model	Literature [10] model	Literature [11] model	This model
10	1.36	0.96	1.67	1.55	1.35	0.46
20	1.25	0.69	1.36	1.26	0.88	0.68
30	1.25	0.85	1.47	1.47	0.96	0.54
40	1.41	0.94	1.56	1.17	0.74	0.47
50	1.56	1.02	1.34	1.26	1.23	0.69
Average value	1.37	0.89	1.48	1.34	1.03	0.57

Taking the models in [7], [8], [9], [10], [11] and the model in this paper as experimental models, this paper compares the enterprise management performance evaluation time of these five models. The comparison results are shown in Table 4.

Analysis of the data in Table 4 shows that the average time of enterprise management performance evaluation of the model proposed in [7] is 1.37 s, that in [8] is 0.89 s, that in [9] is 1.48 s, that in [10] is 1.34 s, and that in [11] is 1.03 s. Compared with these models, the average time of enterprise management performance evaluation of this model is 0.57 s, which is the lowest among the six models. This shows that this method can quickly get the results of enterprise management performance evaluation, and the overall efficiency is higher.

4. Conclusion

In order to fully understand the situation of enterprises and find the problems existing in enterprise management in time, it is necessary to study the enterprise management performance evaluation model based on improved fuzzy clustering algorithm in IoT networks. The experimental results show that the sample data characteristic value of this model is low, the cumulative contribution is high, and the correlation degree is close to 1. The results shows that this model can effectively evaluate enterprise management performance, help enterprise managers understand the internal situation of enterprise management, accurately find out the internal problems of the enterprise, address them in time, enhance the effect of enterprise management, and promote the development of the enterprise. In the future, it is also necessary to continuously test the evaluation model in empirical research, scientifically revise the evaluation index system, update the evaluation index weight according to the market environment, and obtain a better ideal evaluation model.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest with any financial organizations regarding the material reported in this manuscript.

References

[1] Q. Yang, Y. Wang, and Y. Ren, "Research on financial risk management model of internet supply chain based on data science," *Cognitive Systems Research*, vol. 56, no. 8, pp. 50–55, 2019.

[2] S. Patel, "Nonlinear performance evaluation model for throughput of AQM scheme using full factorial design approach," *International Journal of Communication Systems*, vol. 33, no. 8, Article ID e4357, 2020.

[3] Y. Wang, Z. Wen, and J. Dong, "The city-level precision industrial emission reduction management based on enterprise performance evaluation and path design: a case of Changzhi, China," *The Science of the Total Environment*, vol. 734, Article ID 139350, 2020.

[4] T. Kruse, A. Veltri, and A. Branscum, "Integrating safety, health and environmental management systems: a conceptual framework for achieving lean enterprise outcomes," *Journal of Safety Research*, vol. 71, pp. 259–271, 2019.

[5] E. Kongar and O. Adebayo, "Impact of social media marketing on business performance: a hybrid performance measurement approach using data analytics and machine learning," *IEEE Engineering Management Review*, vol. 49, no. 1, pp. 133–147, 2021.

[6] M. Xu, S. Liu, Z. Xu, and W. Zhou, "DEA evaluation method based on interval intuitionistic Bayesian network and its application in enterprise logistics," *IEEE Access*, vol. 7, Article ID 98277, 2019.

[7] A. Fallahpour, K. Y. Wong, S. Rajoo, and A. Mardani, "An integrated fuzzy carbon management-based model for suppliers' performance evaluation and selection in green supply chain management," *International Journal of Fuzzy Systems*, vol. 22, no. 2, pp. 712–723, 2020.

[8] Y. Li, S. Huang, C. Yin, G. Sun, and C. Ge, "Construction and countermeasure discussion on government performance evaluation model of air pollution control: a case study from beijing-tianjin-hebei region," *Journal of Cleaner Production*, vol. 254, Article ID 120072, 2020.

[9] L. Zhou, B. Liu, Y. Zhao, and Z. Jiang, "Application research of grey fuzzy evaluation method in enterprise product reputation evaluation," *Procedia CIRP*, vol. 83, pp. 759–766, 2019.

[10] J. Li, Y. Sun, L. Gong, N. Chai, and Y. Yin, "Multiattribute fuzzy decision evaluation approach and its application in enterprise competitiveness evaluation," *Mathematical Problems in Engineering*, vol. 2021, no. 1, Article ID 8867752, 11 pages, 2021.

[11] L. Chen, X. Yuan, G. Zhang, Q. Guo, W. Liu, and S. Zhang, "The study for public management policy utility evaluation and optimization system under the framework of social computing perspective," *IEEE Intelligent Systems*, vol. 35, no. 2, p. 1, 2020.

[12] H. Zhang, J. Liu, L. Chen, N. Chen, and X. Yang, "Fuzzy clustering algorithm with non-neighborhood spatial information for surface roughness measurement based on the reflected aliasing images," *Sensors*, vol. 19, no. 15, Article ID 3285, 2019.
[13] Y. Gao, D. Wang, J. Pan, Z. Wang, and B. Chen, "A novel fuzzy c-means clustering algorithm using adaptive norm," *International Journal of Fuzzy Systems*, vol. 21, no. 8, pp. 2632–2649, 2019.
[14] S. Zhou, X. Xu, Z. Xu, W. Chang, and Y. Xiao, "Fractional-order modeling and fuzzy clustering of improved artificial bee colony algorithms," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 11, pp. 5988–5998, 2019.
[15] F. Zhao, Z. Zeng, H. Liu, R. Lan, and J. Fan, "Semisupervised approach to surrogate-assisted multiobjective kernel intuitionistic fuzzy clustering algorithm for color image segmentation," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 6, pp. 1023–1034, 2020.
[16] S. Lata, S. Mehfuz, S. Urooj, and F. Alrowais, "Fuzzy clustering algorithm for enhancing reliability and network lifetime of wireless sensor networks," *IEEE Access*, vol. 8, Article ID 66013, 2020.
[17] D. Tan, W. Zhong, C. Jiang, X. Peng, and W. He, "High-order fuzzy clustering algorithm based on multikernel mean shift," *Neurocomputing*, vol. 385, no. 8, pp. 63–79, 2020.
[18] W. Zang, Z. Wang, D. Jiang, and X. Liu, "A kernel-based intuitionistic fuzzy C-means clustering using improved multi-objective immune algorithm," *IEEE Access*, vol. 7, Article ID 84565, 2019.
[19] L.-Q. Li, X.-L. Wang, Z.-X. Liu, and W.-X. Xie, "A novel intuitionistic fuzzy clustering algorithm based on feature selection for multiple object tracking," *International Journal of Fuzzy Systems*, vol. 21, no. 5, pp. 1613–1628, 2019.
[20] D. M. Vargas and V. Mújica, "Superpixels extraction by an Intuitionistic fuzzy clustering algorithm," *Journal of Applied Research and Technology*, vol. 19, no. 2, pp. 140–152, 2021.