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An IoT-driven intelligent risk management framework integrating neural networks and system modeling for multi-project and supply chain environments

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Abstract In the context of increasing complexity and volatility in enterprise project operations and financial systems, this study proposes an integrated risk management framework combining Internet of Things (IoT) technologies, BP neural networks, and data-driven modeling approaches. The research addresses risk identification and control in multi-project management environments by constructing a resource conflict risk evaluation model based on neural networks, utilizing Garson sensitivity analysis to rank risk factor significance. For financial operations, an IoT-enabled inventory pledge financing model is developed to mitigate fraud and market fluctuation risks through real-time monitoring and intelligent data processing. Empirical analysis of operational risk loss data from banks and financial institutions is conducted using SPSS and the Peak Over Threshold (POT) model. Value at Risk (VaR) and Expected Shortfall (ES) are applied to quantify high-loss risks across categories such as internal fraud, external fraud, employee error, and IoT system failures. The study further implements a multi-layered embedded management system and proposes algorithmic enhancements for clustering and optimization in resource allocation. Results demonstrate that integrating IoT and neural networks significantly improves risk visibility, early warning capability, and systemic stability in both marketing and financial domains.

Index Terms biomechanics, internet of things, deep learning, BP neural networks, risk management

I. Introduction

In order to prevent and control risks from the system and process management, a strong marketing risk management system has been built through the deployment of marketing risk management; Enhance the capacity to recognize marketing risks, completely recognize significant marketing risks, and guarantee that no significant risk incidents transpire by examining risk factors and developing and refining appropriate countermeasures; To make sure that no human risk event happens, increase the oversight and inspection of professional management and internal control management [1], [2]. In order to ensure the safe operation of the sales system, adapt to the new market situation and risk control needs, realize the transformation of development mode and healthy and sustainable development in the current fierce market competition, and comprehensively enhance the core competitiveness of the enterprise, it was necessary to identify and analyze risks in the business process in a timely manner. This allowed for the discovery of internal control defects, the reasonable determination of risk response strategies, and the control of risks within an acceptable range [3], [4]. For this reason, information technology is essential for risk management in proactive early-warning marketing [5].

As the business activities of enterprises become more and more project-based, the number of projects as the carrier of enterprise profits in enterprises is increasing. In the same period, enterprises are required to manage multiple implemented projects [6], [7]. Enterprises are beginning to face such challenges: Originally, only a single project is in progress, and only a simple and easy way of single project management can be used to complete the project objectives [8], [9]. Now, due to the gradual expansion of the scale and the increase of the number of projects, enterprises need not only to ensure that the objectives of each single project can be achieved, but also to systematically manage multiple projects to ensure that the organizational strategic objectives can be achieved [10], [11]. Traditional single project management focuses too much on the performance of a single project and cannot effectively coordinate multiple projects [12], [13]. The survival of an enterprise and the realization of its strategic objectives depend on the successful implementation of these multiple projects within its scope. In order to better solve these complex enterprise multi project problems, project group management came into being. Therefore, how to manage the risk of resource conflict in project group management is a problem worthy of attention [14], [15].

By merging the resource sharing relationship between the subprojects inside the project group, this study uses the project group as the research object and examines the possible resource conflict risk factors in the project group's resource management. To give businesses new ideas and ways to manage project group resource conflict risks, develop a project group resource conflict risk indicator system, create a project group resource conflict risk assessment model using the BP neural network algorithm, analyze the significance of different risk factors using the Garson sensitivity analysis method, and suggest project group resource conflict risk response strategies based on the significance of risk factors [16], [17].

II. Methodology

II. A. Risk financing marketing mode based on IoT

Prepayment and accounts receivable financing are not the same as the inventory pledge financing mode of supply chain finance. The collateral circulation is what makes it special. As a result, this mode's risk control point is the efficient supervision of the collateral, which also makes it flawed in that it cannot prevent the risk of fraud and collusion between SMEs and third-party logistics companies, as well as the risk of price fluctuations on the collateral due to market risk [18]. In view of the above analysis, this paper uses the visual tracking function of the Internet of Things to monitor the pledged goods in real time to achieve full process control, which can prevent false pledge and other operational risks; With the help of the data analysis and processing function of the Internet of Things technology, the market price of the pledged goods is intelligently analyzed and managed. The data processing function of the Internet of Things technology can quickly follow the market price and make a later prediction to avoid the risk of price fluctuation caused by similar competition in the market. All parties involved in supply chain finance can effectively share any type of information created during the operation of inventory pledge financing through the IoT' information sharing feature, which lowers the risk associated with information asymmetry in the business development process. In light of the aforementioned functions, this study develops an Internet of Things-based inventory pledge financing mode, as illustrated in Figure 1, in conjunction with the supply chain finance inventory pledge financing mode's commercial features.

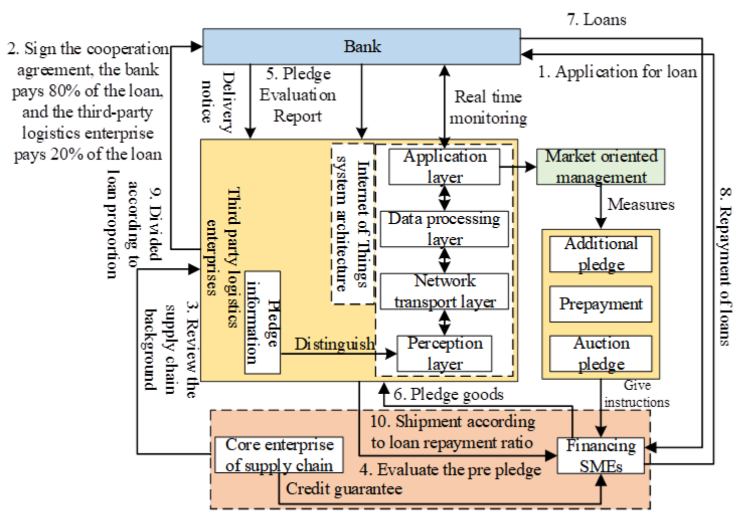

Figure 1: Inventory pledge financing mode based on internet of things technology

The application for funding SMEs' inventory pledge loan business will be approved if both parties can agree. The third-party logistics company first embeds all of the pledged items in electronic tags as part of the business development process. Then, using the Internet of Things system's perception layer (RFID technology), it intelligently monitors the pledged items, keeping track of their location and quantity. Following the network transmission layer's summary of the collected data in the database, the cloud computing platform's data processing layer examines the data and, based on the findings, provides the appropriate operating instructions. If the market price of the pledged property is tracked and the future trend is predicted, the data processing layer will analyze the disposal result of the pledged property according to the market price obtained under the initially set pledge rate of the business, and give corresponding instructions, such as adding the pledged property, prepayment or auctioning the pledged property. Lastly, the application layer provides the funding SMEs with the appropriate instructions. The Internet of Things application layer is used to communicate all information to all supply chain finance participants during the development of the complete loan business, enabling real-time sharing of all financing business data. The visual real-time tracking of the pledged products has enhanced the oversight and operational capabilities of logistics companies in the Internet of Things-based inventory pledge finance mode. Real-time data sharing enhances the bank's regulatory ability to lower capital risk, and it facilitates the efficient transmission of correct and up-to-date warehouse information across all stakeholders, increasing the transparency of financing business development. Figure 2 illustrates how the new model's "four streams in one".

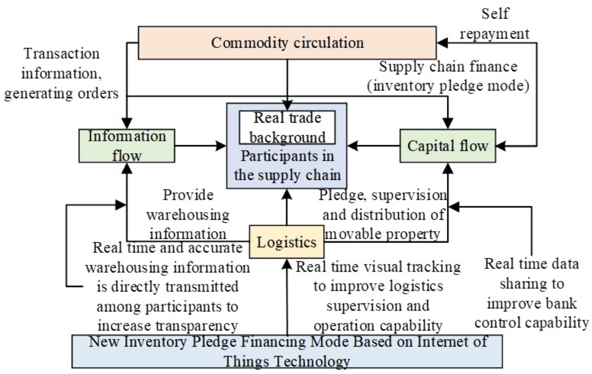

Figure 2: "Four flow in one" under the new mode

II. B. Construction of project group resource conflict risk management model

By importing the characteristic data in the sample data from each neuron node in the input layer by the external environment, the BP neural network propagates information. The data is then transmitted to the hidden layer neuron's receiving end via the weight connection between the input layer and the hidden layer neuron. Inside the secret layer, the information is triggered. Following transformation, the activation function is passed into the output layer via the link between the neurons in the hidden and output layers. At this point, the expected output data from the sample data is compared with the values produced by the comparison model. If there is a large gap between the two values, the next stage is the reverse adjustment of the error. The error is allocated to each neuron of the previous layer according to the proportion of the connection weight value, and is transmitted from the output layer to the input layer through layer-by-layer transmission. The error data accumulated by neurons of each layer is used to guide the update of the connection weight value. The basic computing unit of BP neural network is called neuron. Multiple neurons are connected together to form a network structure. Neurons and neurons are regenerated by linking weights, mimicking the way the human brain receives signals to transmit neurotransmitters. Both the neuron's structure and its method of data processing are straightforward and easy to understand. Through the connection weight value for summation and summary, the neuron receives the signal output from the neuron of the upper layer of the neural network. The activation function transforms the inner portion of the neuron, and the newly generated signal is then transmitted through the connection weight value. Figure 3 illustrates how it operates.

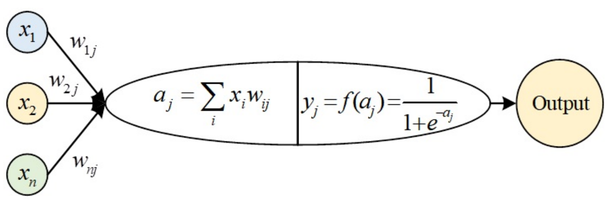

Figure 3: Working mechanism of neurons

However, a single neuron can only process a certain amount of data; to process complicated data, several neurons can be connected in parallel to create a network structure. Combining network structure and the BP algorithm, the BP neural network is a composite computing model that primarily consists of two steps: Forward propagation, where sample data is input and the output value is obtained by utilizing initial weight and threshold value; and back propagation, which compares the difference between the expected and actual values and distributes the error to each neuron along the neural network structure in reverse to correct the connection weight. After the implementation of a forward propagation and a reverse propagation, it means that a training is completed. The training is repeated for many times. When the model can successfully extract the relationship between the data, and the model output value is very small from the expected value, the model training is completed. After several trainings, the learning phase is finished when the neural network output's error between the actual and expected values converges to a specific range. Figure 4 illustrates how it operates.

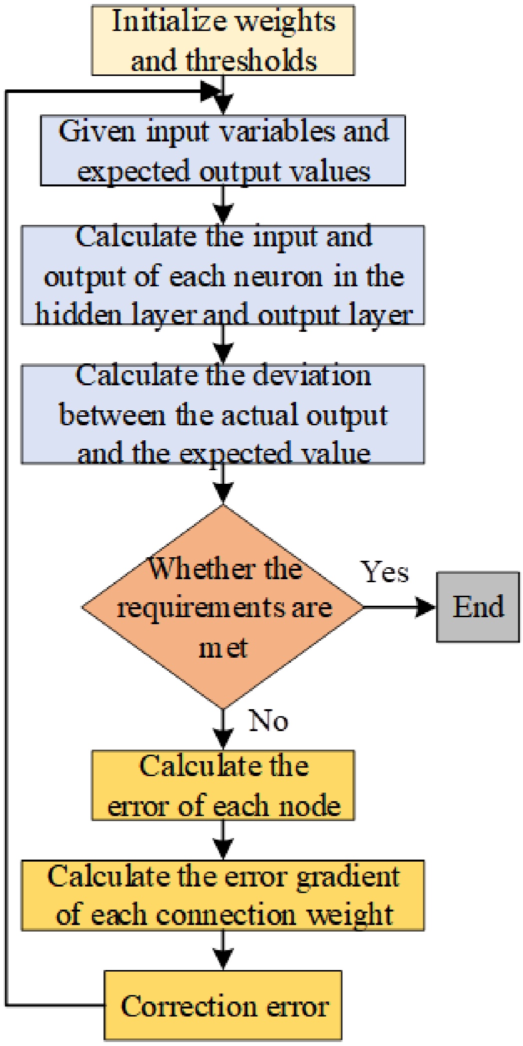

Figure 4: Working mechanism of BP neural network

BP neural network is a simulation model based on network structure, which has a high sensitivity to network structure, and corresponding network structure should be selected for different problems. For BP neural network, the input layer is usually a layer to reflect the feature set of the problem. The output layer should also be a layer, which represents the information we expect to obtain. Therefore, hidden layers can be distinguished. The higher the complexity of the problem, the more difficult it is to summarize the nonlinear relationship between the data. Therefore, neural networks with complex network structure and many hidden layers should be selected for processing. However, the more layers the internal neurons have, the more complicated the calculation will be, the more training time will increase, and the speed of error convergence will be correspondingly reduced. Therefore, the number of hidden layers is an important parameter to change the performance of neural networks. It is found that the ability of single hidden layer BP neural network is sufficient to complete the mapping from m dimension to n dimension of any data. One is to use empirical formula to calculate the number of nodes in the input layer and output layer of the network. The common empirical formula is as follows:

$$\begin{aligned} m &= \sqrt{n+l+a} \\ m &= \tfrac{n+l}{2} \\ m &= \log_2 n \end{aligned} \tag{1}$$

where m, n, l respectively represents the number of nodes in the hidden, input and output layers, and a is a constant in the (0,10) interval. The other is to set the hidden layer nodes to a number randomly for training, and determine the final number of hidden layer nodes according to the error convergence. In view of the difference in the results calculated by each empirical formula of the first method, the second method spends too much time randomly setting hidden layer nodes for training, so this paper adopts the method of combining the two methods. The first step is to use the above formula to calculate the range in which the neurons in the hidden layer determined by the empirical formula should be distributed. The second step is to take the values in this range in turn to form different BP neural network models. Several groups of sample data sets are used to test the fitting performance of the model. The regression evaluation index is used to determine which value the number of neurons in the hidden layer is set to to make the model achieve the best performance. This paper needs to establish a neural network model to evaluate the risk value of resource conflict in the project group, so the number of neurons in the output layer is determined to be 1.

II. C. System design of multitask embedded management system

You can display the user configuration interface with relatively little system resources by using the Web as the interface. When configuring, users can directly configure data via the web page. Following Web page configuration, the data stream reaches the configuration management layer, which is primarily in charge of uniformly processing the data, establishing the format of the data stream, and forwarding the data to the subsequent step in accordance with the messages sent by the w curve layer. The data stream sent by the configuration management layer has two directions: One is directly sent to the Linux driver layer, and the other is sent to the specific protocol module. This layered design scheme is mainly conducive to the refinement of functional modules and the expansion of functional modules in the future, including preparing for the later system testing.

The multitask embedded management system is designed according to the principle of layering. The advantage of this is that each functional module can be better divided, and the later function expansion and bug finding can be simple and easy. The management system is divided into two layers. The top layer is the Web layer, and the bottom layer is the configuration management layer.

The configuration management layer sits between the system resources and the management media, as seen in Figure 5. It is in charge of how the system resources and management media interact. Users can interact with the system in a variety of ways thanks to the management interfaces that are provided by the management media. The center of the entire management system is the management core. In order to allow the management media to grow as needed, it is in charge of giving them a single interface. The management module is in charge of overseeing both the protocol and functional modules. It follows instructions from the management core to run and stop. In addition, the management module is responsible for interacting with the Linux driver, so that the configuration data of the top management media can reach the protocol module and driver module. In the requirement analysis, it is mentioned that we should fully understand the user's requirements for the product, which means that our product should first be easy to use for the user. Therefore, we have designed a Web interface for the user interface at the upper layer, which is a graphical interface (GUI), compared with the previous command line. The advantages of the graphical operation interface are simple and easy to use, and the operation efficiency of the product is high. Users do not have to remember obscure command parameters. Click the corresponding button directly with the mouse. After the user clicks the corresponding button after configuring the data, the user configured data must be transferred to the driver layer in a way. This requires that a configuration management layer be built at the lower layer of the W music layer. Its role is to provide an interface for the upper layer of W music and complete the interaction between W music and drivers and applications.

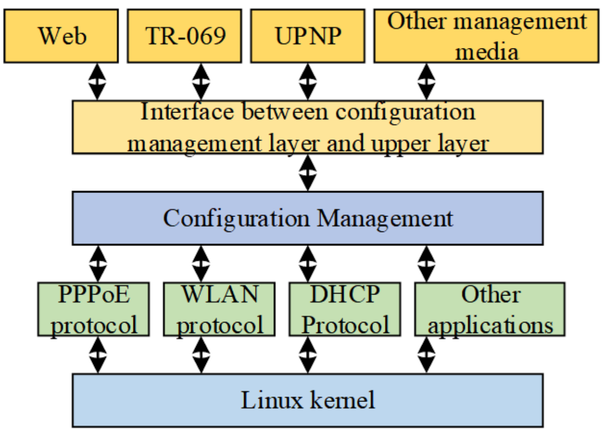

Figure 5: Overall architecture of multi task embedded management system

III. Experiments

III. A. Performance analysis of risk financing marketing model based on IoT technology

Sample data of operational risk loss cases of banks and other financial institutions that conducted supply chain financial inventory pledge financing business from 2010 to 2016 were gathered for this paper from public disclosure information provided by the CBRC, the People's Bank of China, the National Audit Office, portal websites, magazines published by financial regulators, and other authoritative media outlets. The gathered data is categorized and subjected to preliminary analysis in accordance with the identification and analysis of operational risk in Chapter IV. Table 1 displays the findings.

Table 1: Inventory pledge financing (unit: 10,000 yuan)

Operational risk loss category	Number of lost samples	Average value	Intermediate value	Maximum	Minimum value	Skewness	Kurtosis	J-B value
Internal fraud	100	2366.25	2356.7	6542	26	1.99	6.15	104.6
External fraud	76	3066.99	3055	7383	32	1.76	7.08	67.16
Loss and damage of pledge	47	1555	1531	3452	23	0.68	5.99	20.23
Operation error of employees	23	853	721	2466	10	1.78	10.05	51.6

The sample data was processed descriptively by SPSS, and the Q-Q diagram of sample data of various loss events was obtained as shown in Figure 6.

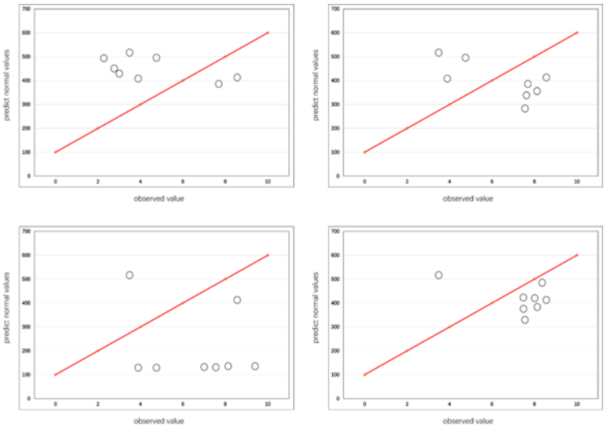

Figure 6: Q-Q chart of sample data of various loss type events of operational risk

The data points in the Q-Q chart exhibit an upward curving shape rather than a straight line when looking at the sample data Q-Q of different kinds of operational risk loss occurrences in the inventory pledge financing model. As shown in Figure 6, as a result, it can be concluded that the operational risk loss sample data that was gathered has a thick tail distribution. Each operational risk loss event's estimated mortar value and 10,000 loss distribution are estimated using the POT model, and the best threshold is tested and determined using the chi square goodness of fit approach.

It is evident from Table 2's results that, when the confidence level is set at 99.9%, the operational risk's high loss characteristics—that is, "no cry, no cry"—are highlighted by the VI and ES values of all kinds of loss events. However, there is a sizable numerical disparity across the different kinds of loss events. With a VaR of 91,451,800 yuan and an ES of 174,545,600 yuan, external fraud has the highest loss value. Internal fraud is the second. The ES value is 118,136,600 yuan, and the VaR is 67,306,400 yuan.

Table 2: Loss category event of operational risk.

Operational risk loss category	Internal fraud	External fraud	Loss and damage of pledge	Operation error of employees
VaR (99.9%)	6730.64	9145.18	3096.35	1373.86
ES (99.9%)	11,813.66	17,454.56	5247.85	2584.13

III. B. Risk measurement analysis based on IoT

The methodical and intelligent administration of the identification is the primary goal of the Internet of Things-based inventory pledge financing approach developed in this research. We gathered the loss data resulting from the system risks of financial institutions like Ping An Bank when executing the financial business of the Internet of Things and made the necessary modifications by consulting the pertinent facts in other literature and market research. Lastly, Table 3 displays the initial examination of loss data for every kind of Internet of Things-based inventory pledge financing strategy.

Similarly, SPSS software is used to obtain the Q-Q diagram of the risk loss data of the Internet of Things system to determine whether it presents a fat tailed distribution. The results are shown in Figure 7. It can be determined that the sample data follows a thick tailed distribution.

Table 3: Preliminary analysis of operational risk loss data of inventory pledge financing mode based on Internet of Things technology (unit: 10,000 yuan)

Operational risk loss category	Number of lost samples	Average value	Intermediate value	Maximum	Minimum value	Skewness	Kurtosis	J-B value
Internal fraud	100	2366.25	2356.7	6542	26	1.99	10.05	225
External fraud	50	3204.06	3050	7386	30	1.3	3.56	9.95
Loss and damage of pledge	24	1682.97	1526	3450	26	1.75	3.68	8.44
Risks of IoT system	16	91.35	876	2450	11	1.76	7.05	9.45
Operation error of employees	23	859.96	721	2466	10	1.86	5.33	11.55

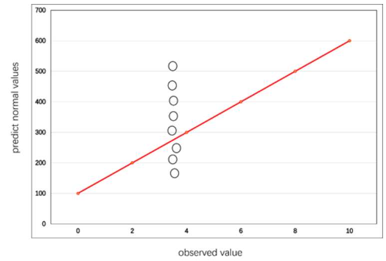

Figure 7: Q-Q diagram of risk sample data of IoT system

Table 4: Training results of hidden layer neuron regulation quantity

Number of hidden layer neurons	RMSE	R2
10	0.02477	0.99227
11	0.02458	0.99243
12	0.02499	0.99216
13	0.02447	0.99246
14	0.02468	0.99226
15	0.02457	0.99237
16	0.02471	0.99233
17	0.02495	0.99216
18	0.02477	0.99225
19	0.02507	0.99212
20	0.02465	0.99235
21	0.02485	0.99222
22	0.02467	0.99231
23	0.02488	0.99222
24	0.02517	0.99203
25	0.02435	0.99254
26	0.02508	0.99212
27	0.02533	0.99296
28	0.02466	0.99238
29	0.02480	0.99225
30	0.02478	0.99226

III. B. 1) Verification of neural network group resource conflict risk assessment model

The question setting of this questionnaire includes the basic information of the consulted personnel and the setting of questions related to resource conflict risk. According to the statistical results of the questionnaire, 75.65% of the respondents to the questionnaire have more than 5 years of experience in the field of project group management, and more than 67.87% of the respondents said that they frequently participate in the management practice of parallel implementation of multiple projects. In conclusion, it can be considered that the results of this survey are reliable, and the interviewees have rich experience in resource conflicts during project implementation. Before model training, it is necessary to use several groups of data to try to run the model to determine the optimal parameters of the model [10]. In order to build a network with the best performance, next, train all networks of 10 to 30 hidden layer neurons to determine the number of hidden layer neurons. Two important indexes of regression evaluation indexes are selected as the ruler to evaluate the network fitting performance. The first index is root mean square error (RMSE), which can express the difference between the model output value and the real value. The second indicator is the coefficient of determination R2. The value of R2 is between 0 and 1. When R2 is close to 1, the model fitting effect is good; On the contrary, when it is close to 0, it indicates that the model fitting effect is poor; When the result is 1, the model prediction is very accurate. The training results of hidden layer node adjustment quantity are shown in Table 4.

It can be observed that when the number of neurons in the hidden layer is within the range of [11], [12], the decision coefficient R2 of the BP neural network is above 0.99, indicating that the learning ability of the BP neural network is strong at this time, and the numerical range determined by the empirical formula has good fitting ability. When the number of neurons in the hidden layer is 25, the value of the determination coefficient R2 reaches the maximum value of 0.99254 in the overall test, and the value of the root mean square error RMSE reaches the minimum value of 0.02435 in the overall test, indicating that 25 is the best number of neurons in the hidden layer. At this time, the BP neural network has the best fitting ability, so the structure of the BP neural network model established in this paper is 19-25-1 [13], [14]. The sample data set collected in this study includes 20 groups of sample data, which are divided into two groups: Training samples and test samples. The training sample data is set as 16 groups, and the test sample data is set as 4 groups. As for the learning rate of the model, this paper sets a control group, selects 0.5, 0.1 and 0.01 as the learning rate of BP neural network for observation, and the results of 1000 iterations are shown in Figures 8–10.

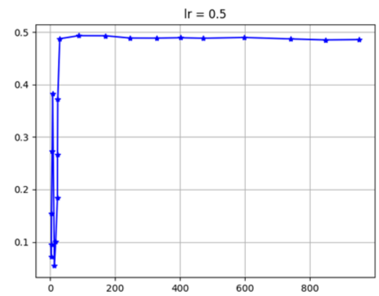

Figure 8: Error change chart when learning rate is 0.5

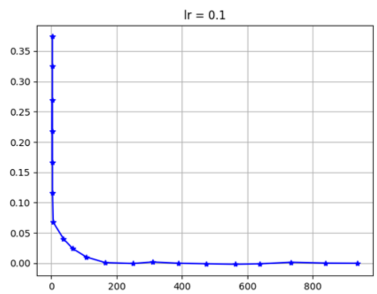

Figure 9: Error change chart when the learning rate is 0.1

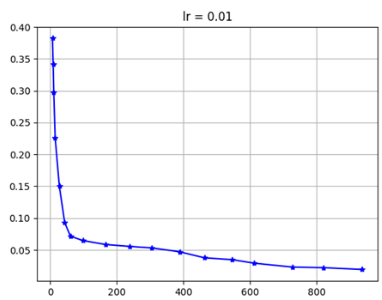

Figure 10: Error change chart when the learning rate is 0.01

The figure shows that when the learning rate is set to 0.5, the model's error rapidly decreases over the first few iterations. However, after around 20 iterations, the model's error no longer converges and instead begins to increase. Consequently, the model's error cannot converge when the learning rate is 0.5. The model performs well overall when the learning rate is set at 0.01. Although the error keeps decreasing, it does so slowly, and after 1000 cycles, the error is still higher than 0.01. More iterations and training time are needed to get the model to fulfill the requirements. When the learning rate is 0.1, the convergence rate of the model error is very fast and the error almost coincides with 0 when the iteration is 1000 times. Therefore, in order to save the training time and complete the model training efficiently, the learning rate of the model is set to 0.1 [13], [14]. It is found that although the error is still declining after 500 iterations of the model, the rate of decline is extremely slow [15], [16]. In order to avoid affecting the fitting ability of the model due to excessive training, the number of training iterations of the model is set to 500. The Dropout method is used to optimize the model, and the freezing parameter is set to 0.5. The error of the training model is shown in Figure 11.

Figure 11: Error change chart of model training

It can be seen from the figure that the error between the output value of the project group resource conflict risk assessment model and the expected output is getting smaller and smaller after training. The error of the model decreases rapidly from the initial 0.368. After 436 iterations, the error has converged to the minimum error range of 0.001, which has met the requirements of model accuracy. Therefore, it can be shown that the established project group resource conflict risk assessment model has good nonlinear mapping ability, and the nonlinear mapping relationship in the sample data used for training has been extracted and stored in the network structure [17], [18]. Next, the model will be validated using the four groups of validated sample data to check the generalization ability of the model. The results of model validation are shown in Table 5 and Figure 12.

Table 5: Model verification results

Sample data	True value	Model output	Error percentage (%)	R2	RMSE
1	0.604	0.587	−2.14		
2	0.633	0.625	−0.45		
3	0.567	0.574	0.55		
4	0.464	0.475	2.36		
				0.980	0.008

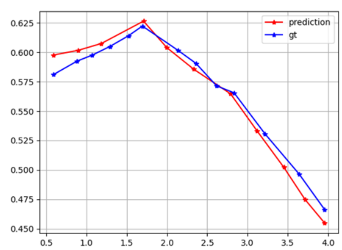

Figure 12: Comparison between expected value and model output value

It can be seen from the table that the relative error is between [−2.14%, 2.36%], the maximum relative error percentage is 2.36%, the minimum relative error percentage is −0.45%, and the average prediction accuracy is 98.615%. The value of root mean square error RMSE is 0.008, which is very close to 0, and the value of determination coefficient R2 is 98%. The model has good generalization ability [19], [20]. This shows that, within the allowable range of error, the project group resource conflict risk assessment model, with its strong nonlinear fitting ability, greatly weakens the impact of subjective factors, can accurately obtain the overall resource risk results of the project group, provides reliable decision support for the project group managers, and is conducive to better implementation of resource management for the project group [21]–[23].

IV. Conclusion

This research presents a comprehensive, intelligent risk management model that integrates IoT-based data systems with neural network-driven predictive modeling to address operational and resource conflict risks in modern enterprises. The proposed

IoT-enabled inventory pledge financing model enhances real-time monitoring and fraud prevention while mitigating market-driven collateral value fluctuations. Experimental results based on SPSS and POT modeling confirm the presence of fat-tailed loss distributions in both traditional and IoT-based operational risk scenarios. The BP neural network model effectively quantifies project resource conflict risks, with Garson analysis providing critical insights into the relative impact of risk factors. Furthermore, the implementation of a multi-task embedded management system enhances system modularity, user configurability, and information flow. The integration of intelligent technologies and biological computing principles into enterprise risk management represents a step forward in developing proactive, resilient, and sustainable business ecosystems. Future work will explore dynamic feedback models and expand real-time deployment of these intelligent frameworks in large-scale enterprise environments.

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Conflict of interest:

The author declares no conflict of interest.

References

[1] Karmanov, M. V., Kiseleva, I. A., Kuznetsov, V. I., & Sadovnikova, N. A. (2021). Marketing strategies: models for assessing efficiency and risk level. *Revista Turismo Estudos e Práticas-RTEP/UERN,* (01), 1–9.

[2] Araz, O. M., Choi, T. M., Olson, D. L., & Salman, F. S. (2020). Role of analytics for operational risk management in the era of big data. *Decision Sciences, 51*(6), 1320–1346.

[3] Byun, C. G., & Ha, H. H. (2020). An Exploratory Study on Successful Factors of Entrepreneurial Marketing in Start-up. *Asia-Pacific Journal of Business Venturing and Entrepreneurship, 15*(2), 183–192.

[4] Cross, S. N., Gustafsson, A., Pechmann, C., & Winterich, K. P. (2022). Responsible research in business and management (RRBM) and the journal of public policy & marketing: connected through impact. *Journal of Public Policy & Marketing, 41*(1), 51–53.

[5] Bangsawan, S., Haseeb, M., & Ms, M. (2020). A product of social mission, sustainable entrepreneurial and marketing orientation: enhancing social entrepreneurial self-efficacy in Indonesian education sector. *Journal of Security and Sustainability Issues, 10*(October), 163–178.

[6] Guo, C. The Setting and Dynamic Adjustment Mechanism of Law Majors Facing the Development of Regional New Economy. *Journal of Combinatorial Mathematics and Combinatorial Computing, 120*, 43–50.

[7] Njeri, G. B. (2021). Influence of credit management on financial performance of dairy marketing cooperatives in Kenya. *International Journal of Accounting, Finance and Risk Management, 6*, 10–15.

[8] Morrish, S. C., & Jones, R. (2020). Post-disaster business recovery: An entrepreneurial marketing perspective. *Journal of Business Research, 113,* 83–92.

[9] Sharma, P., Leung, T. Y., Kingshott, R. P., Davcik, N. S., & Cardinali, S. (2020). Managing uncertainty during a global pandemic: An international business perspective. *Journal of Business Research, 116,* 188–192.

[10] Rosário, A., Moniz, L. B., & Cruz, R. (2021). Data science applied to marketing. *Journal of Information Science and Engineering, 37*(5), 1067–1081.

[11] Dhameria, V., Ghozali, I., Hidayat, A., & Aryanto, V. (2021). Networking capability, entrepreneurial marketing, competitive advantage, and marketing performance. *Uncertain Supply Chain Management, 9*(4), 941–948.

[12] Xu, Y., Tao, Y., Zhang, C., Xie, M., Li, W., & Tai, J. (2022). Review of digital economy research in China: a framework analysis based on bibliometrics. *Computational Intelligence and Neuroscience, 2022*(1), 2427034.

[13] Wang, K. The construction of fuzzy prediction model of stock price rise and fall based on machine learning technology. *Journal of Combinatorial Mathematics and Combinatorial Computing, 120*, 125–136.

[14] Behera, R. K., Bala, P. K., Rana, N. P., & Kizgin, H. (2022). Cognitive computing based ethical principles for improving organisational reputation: A B2B digital marketing perspective. *Journal of Business Research, 141*, 685–701.

[15] Sodhi, R. S., & Bapat, D. (2020). An empirical study of the dimensions of entrepreneurial marketing. *Academy of Marketing Studies Journal, 24*(1), 1–7.

[16] Azadegan, A., Ojha, D., & Ogden, J. A. (2022). Benefiting from supplier business continuity: The role of supplier monitoring and buyer power. *Industrial Marketing Management, 106*, 432–443.

[17] Eggers, F., Niemand, T., Kraus, S., & Breier, M. (2020). Developing a scale for entrepreneurial marketing: Revealing its inner frame and prediction of performance. *Journal of Business Research, 113*, 72–82.

[18] Ahmed, W., & Huma, S. (2021). Impact of lean and agile strategies on supply chain risk management. *Total Quality Management & Business Excellence, 32*(1–2), 33–56.

[19] Kieras, T., Farooq, J., & Zhu, Q. (2021). I-SCRAM: A Framework for IoT Supply Chain Risk Analysis and Mitigation Decisions. *IEEE Access, 9,* 29827-29840.

[20] Nozari, H., Edalatpanah, S.A. (2023). Smart Systems Risk Management in IoT-Based Supply Chain. In: Garg, H. (eds) Advances in Reliability, Failure and Risk Analysis. *Industrial and Applied Mathematics*. Springer, Singapore.

[21] Meng, L. (2021). Using IoT in Supply Chain Risk Management, to Enable Collaboration between Business, Community, and Government. *Smart Cities, 4*(3), 995-1003.

[22] Kuashuai Peng, Guofeng Yan. A survey on deep learning for financial risk prediction[J]. *Quantitative Finance and Economics, 2021, 5*(4): 716-737. doi: 10.3934/QFE.2021032

[23] Huang, J., Chai, J. & Cho, S. Deep learning in finance and banking: A literature review and classification. *Front. Bus. Res. China 14*, 13 (2020).