Advances in Engineering Research : Possibilities and Challenges
ISSN Print: 3079-5192
ISSN Online: 3079-5206
https://doi.org/10.63313/AERpc.9034

Study on Raw Material Inventory Classification Management of A Oil Drilling Equipment Manufacturing Enterprises

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How to cite this paper: Li, B., & Yang, S. M. (2025). Study on raw material inventory classification management of A oil drilling equipment manufacturing enterprises. Advances in Engineering Research: Possibilities and Challenges, 2(1), 26–38. ISSN Print: 3079-5192, ISSN Online: 3079-5206.
https://doi.org/10.63313/AERpc.9034
Published: 2025-07-15

Abstract

This paper takes A oil drilling equipment manufacturing enterprise as the research object, for its raw material inventory classification is sloppy, management efficiency is low and other problems, constructs a multi-dimensional classification index system containing procurement amount, consumption quantity, order lead time, supply delivery rate, adopts the PSO-FCM algorithm to classify 72 raw materials into conventional, strategic and risky, and puts forward the differentiated management strategy, the conventional type reduces the cost, strategic type to keep supply, and risky type to control risk, which provides a scientific basis for enterprises to improve the efficiency of inventory management

Keywords

Raw material inventory; Inventory classification management; Multi-dimensional classification; Differentiated strategy

1. Introduction

1.1. Research Background

Oil drilling equipment companies are uneven, and in the increasingly competitive market environment, companies not only need to respond quickly to the diverse needs of customers and provide high-quality and cost-effective products, but also need to reduce the cost of production and inventory, ease the burden of inventory management, and enhance profit margins. These have become key factors that are indispensable for enterprises to gain a competitive advantage. Fine-grained inventory classification helps to accurately manage inventory, optimize inventory strategy, and ensure that the supply of items matches demand, thereby improving inventory turnover and enhancing the liquidity and profitability of the enterprise. Due to the increase of deliveries and business objectives, the enterprise inventory management has been chaotic and inefficient, the warehouse management personnel can not locate the categories of raw materials in time, the inventory of raw materials is classified in a sloppy manner, at the same time, due to the inaccurate analysis of raw material demand, the safety stock is not set up reasonably, the production problems due to the inventory problems have occurred, and the whole logistics system of the enterprise has been affected. Therefore, it becomes particularly urgent to enhance the overall efficiency of the enterprise's raw material inventory management, improve the enterprise's inventory management capability, ensure the timeliness of orders and maintain the enterprise's reputation.

1.2. Research significance

1) Enhance supply chain efficiency and reduce operating costs

There are many types of raw materials for oil drilling equipment, and some key materials have a long procurement cycle and high price fluctuations. Through scientific optimization of inventory classification, enterprises can more accurately identify high-value and high-risk materials, develop differentiated procurement and storage strategies, reduce capital consumption and storage costs, and reduce production losses due to inventory redundancy or shortage.

2) Guarantee production stability and delivery reliability

The production of oil drilling equipment is characterized by project-based system, which requires high requirements for timely supply of raw materials. Optimization of inventory classification can help enterprises: ①For critical materials to ensure the continuity of supply of core components to reduce delays in orders due to stock-outs. ②For non-critical materials, low-value general-purpose parts are purchased on demand, reducing the risk of inventory backlog.

3) Enhance the enterprise's anti-risk ability and market competitiveness

Firstly, to cope with price fluctuations, through classification and optimization, implement dynamic procurement strategy for raw materials affected by international oil prices, and lock the inventory in the low price period. Secondly, to adapt to changes in industry demand, with the new energy transformation, the demand for traditional drilling and mining equipment may decline, optimizing the inventory structure can accelerate the adjustment of production capacity of enterprises to environmentally friendly equipment and reduce the loss of sluggish materials.

2. A manufacturing company profile and the current situation of oil drilling equipment raw material inventory classification management

2.1. Overview of Manufacturing Enterprise A

A oil drilling equipment manufacturing enterprise was established in 2015, which is a high-tech enterprise integrating R&D, production, sales and trading functions. Its core business scope covers the comprehensive development, manufacture and marketing of oil drilling equipment, as well as the provision of related technical services, technical consulting and technology transfer services. In addition, the enterprise also specializes in the manufacture and sale of mechanical equipment and its components, metal products, non-standard equipment and the required raw and auxiliary materials.

2.2. Status of Raw Material Inventory Classification Management in Oil Drilling Equipment Manufacturing Enterprise A

Raw materials of oil drilling equipment manufacturing enterprises are characterized by many types, miscellaneous specifications, large differences in value, and a long procurement cycle for some materials, etc. The status of raw material inventory classification management in Enterprise A can be analyzed from the following aspects:

1) Existing Classification Methods

At present, in raw material inventory classification in Oil Drilling Equipment Manufacturing Enterprise A, the classification of raw material inventory is still based on material attributes, price, and price. At present, A oil drilling equipment manufacturing enterprises in the classification of raw material inventory, is still stuck in the material properties, price, mainly in the ABC classification, this classification has certain limitations. In essence, the biggest defect lies in the lack of systematic quantitative assessment of the importance of materials, the establishment of a multi-dimensional assessment system, and the logic of classification is not linked to the core objectives of the production and operation of the enterprise. This kind of rough classification mode makes it difficult for enterprises to identify special materials such as high-value and high-risk, low unit price and high impact, and then unable to formulate differentiated inventory strategy, which ultimately results in the imbalance of the inventory structure, capital inefficiency, and insufficient supply chain resilience.

2) Characteristics of material management

For high-value materials, although enterprises try to use a small number of times the procurement strategy to balance capital consumption and production demand, but limited by the supply chain structure, the actual management effect is greatly reduced. As for the low-value but high-frequency materials, the vague classification system leads to management problems. Firstly, some non-critical general-purpose materials are often purchased in excess due to the convenience of procurement, leading to hoarding, and the annual inventory backlog accounts for 15%-20% of the storage space; secondly, critical high-frequency materials are frequently in short supply due to the lack of key management. Customized materials management contradictions are more prominent. This kind of material is overly bound with specific orders, and the demand shows the volatility of single large quantity and long batch interval, while the existing classification system lacks the dynamic tracking for its order relevance and demand cycle. Data show that the proportion of such materials in the sluggish inventory is as high as 10%-15%, far exceeding the industry average of 5%.

The management dilemma of these three types of materials essentially stems from the classification system can not accurately match the characteristics of materials and supply chain features, and ultimately form a waste of funds for high-value materials, low-value materials, efficiency losses, customized materials, the risk of loss of control of the problem.

3. A Problems of Raw Material Inventory Classification and Management in Oil Drilling Equipment Manufacturing Enterprises

1) Single Classification Dimension, Lack of Evaluation System

The existing classification only centers on material attributes and price, and there is no framework for building a scientific evaluation system. First, there is no inventory cost, shortage risk, procurement difficulty and other key factors into the classification dimensions, unable to quantify the actual impact of different materials on business operations. Secondly, the classification is not associated with the core objectives of production and operation of the enterprise, and cannot provide effective support for the objectives of cost reduction, supply assurance, risk control, etc., so that those materials which are crucial to the continuity of production and stability of supply chain cannot be focused on and managed through classification.

2) Deficiencies in classification lead to difficulties in the management of various types of materials

As the classification system cannot accurately match the core attributes of materials and supply chain characteristics, the management of different types of materials faces a series of problems and risks. For high-value materials, although the strategy of small quantity and multiple purchases is adopted, the classification takes into account the factor of suppliers' supply punctuality, which leads to wastefulness as enterprises have to maintain inventories higher than the safe level in order to cope with the potential supply outage. Low-value but high-frequency materials are classified vaguely without distinguishing between critical and non-critical attributes, resulting in excessive inventory of non-critical parts due to ease of procurement and frequent shortages of critical parts due to lack of focused tracking, which affects production. The classification of customized materials does not combine the characteristics of order relevance and demand fluctuation, and lacks an effective dynamic tracking mechanism, which makes it difficult to reasonably control the inventory when demand fluctuates, and increases the cost of inventory management. Therefore, a reasonable classification is needed to ensure the overall inventory management efficiency and economic benefits of the enterprise.

4. A oil drilling equipment manufacturing enterprises raw material inventory classification

4.1. Construction of A oil drilling equipment manufacturing enterprises

raw material inventory classification index system

4.1.1. Selection of Raw Material Inventory Classification Indicators

In order to more comprehensively and systematically characterize the classification of raw materials and ensure the scientific and comprehensive nature of the classification indicators, it is necessary to combine both qualitative analysis and quantitative assessment methods, while considering the feasibility of actual data collection. In this chapter, after field research as well as the company's historical data situation, the following four categorization indicators are selected respectively, purchase amount, consumption quantity, order lead time, supply delivery rate. The description of the categorized indicators is shown in the table:

Table 1-1. Description of Classification Indicators

Classification considerations	Classification indicators	Indicator description
Economy	Purchase amount P1	Purchase of a raw material per unit of time ($/ton)
Consumptive	General P2	Consumption of a raw material per unit of time (tons)
Strategic	Order Lead Time P3	Time spent on the process from the time the order is placed until the parts are in stock
Supplyability	Supply delivery rate P4	Probability of on-time delivery by the supplier, the higher the delivery rate, the lower the supply risk

4.1.2. Quantification of Raw Material Inventory Classification Indicators

Based on the empirical data of oil drilling equipment raw material inventory of manufacturing enterprise A, this study, combined with the characteristics of significant price fluctuations in the oil drilling equipment raw material market, selects the inventory dynamics data for a period of twelve months as a research sample. Through systematic statistical analysis, a quantitative evaluation system of raw material inventory indexes for each category is established.

Table 1-2. Quantitative system of raw material inventory indexes

No.	Indicator	Indicator description	Quantitative criteria
1	P1	Amount of raw materials purchased	Record the average purchase amount of a certain raw material for the twelve months ($/ton)
2	P2	Commonality of raw materials	Record the quantity of a particular raw material consumed (in tons) for a twelve-month period.
3	P3	Lead time for ordering raw materials	Number of days in advance for ordering certain raw materials for the twelve months of the record (in days)
4	P4	Supply delivery rate of raw materials	based on number of deliveries/total number of deliveries (%)

The raw data were then subjected to quantification of indicators, some of which are shown below:

Table 1-3. Quantification results of raw material data indicators

Raw material number	P1	P2	P3	P4
60SI2MN-D10	6850	0.0216	7	85
60SI2MN-D20	6400	0.0342	14	85
60SI2MN-D50	6250	0.0128	20	85
60SI2MN-D100	6000	0.0671	42	85
17-4-D30	5150	0.0453	7	90
17-4-D50	5500	0.0289	7	90

...	...	...	...	...

4.1.3 Determine the raw material inventory classification index system

When constructing the classification index system, the basic principle of mutual independence between indicators must be strictly followed. Based on the quantitative analysis results in Table 1-3, the correlation test between the indicators needs to be further carried out to ensure that there is no information overlap in the evaluation dimensions. When a significant correlation is detected between two indicators (the absolute value of the Pearson coefficient > 0.7), the more representative indicators should be retained through the Variance Inflation Factor (VIF) test to improve the validity of the final analysis model. In this paper, SPSS is used to analyze the correlation of raw material classification indicators, and the correlation coefficients of each indicator are shown in the table below:

Table 1-4. Pearson Correlation Coefficients

Norm	P1	P2	P3	P4
P1	1			
P2	-0.001	1		
P3	0.218	0.136	1	
P4	-0.371**	-0.027	-0.673**	1
* p<0.05 ** p<0.01				

Through the correlation coefficients of the indicators in Tables 1-4, it can be seen that the correlation of the four indicators is not strong, and the absolute value is <0.7, so the four indicators are retained, and the selection of this indicator is more reasonable, which lays the foundation for the subsequent optimization of inventory classification.

4.2. Raw material inventory classification of oil drilling equipment based on fuzzy C-mean clustering

4.2.1. Data preparation

4.2.1.1. Data standardization

In determining the set N of raw materials to be classified (containing n kinds of existing and future raw materials in stock, i=1,2,... ,n) and its classification index set M (a total of m indexes, j=1,2,... ,m) after standardizing the raw data of 72 raw materials under 4 classification indicators. The standardization formula is:

1）Positive indicators

$$r_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_j\} - \min\{x_j\}} \tag{4-1}$$

2）Negative indicators

$$r_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_j\} - \min\{x_j\}} \tag{4-1}$$

Table 2-1 demonstrates the data of the four indicators p1, p2, p3 and p4 after the standardization treatment. Among them, procurement amount and versatility belong to positive indicators and are standardized using equation (1-1); while order lead time and supply delivery rate belong to negative indicators and are treated according to equation (1-2).

Table 2-1. Standardized data for raw material classification indicators

Raw material number	P1	P2	P3	P4
1	0.0019	0.2096	0.9811	0.3043
2	0.0011	0.3826	0.9245	0.3043
3	0.0008	0.0623	0.8113	0.3043
4	0.0003	0.8589	0.5283	0.3043
5	0.0000	0.5579	0.9811	0.4348
6	0.0005	0.3260	0.9811	0.4348
7	...	...	...	...

4.2.1.2. Entropy weighting of indicators

Aiming at the limitations of the fuzzy clustering algorithm in the assignment of indicators, this study introduces the entropy weight method to optimize the weight determination process. Through the entropy weight method, the weight coefficients of each classification index are determined objectively. The specific implementation process is as follows: firstly, analyze the indicator data after the standardization process, and calculate the information entropy value ej of each indicator based on the information entropy theory; subsequently, calculate the difference coefficient gj=1-ej based on the entropy value; and finally, obtain the objective weight wj of each indicator through the normalization process (j=1,2,.... ,m). This method realizes the scientific allocation of weights by quantifying the degree of dispersion of indicator data.

1) Calculate the entropy value of the jth item e_j

① For the jth indicator value xijof the ith sample. its weight P_{ij} is calculated as:

$$P_{ij} = \frac{xij}{\sum_{i=1}^{n} xij} \quad (2\text{-}1)$$

② For the entropy value e_j of item j, the formula is:

$$e_j = -K \sum_{i=1}^{n} P_{ij} * \ln P_{ij} \quad (2\text{-}2)$$

When $P_{ij}=0$, then define $P_{ij}*\ln P_{ij}=0$ and the range of entropy value: $0 \le e_j \le 1 0 \le e_j \le 1$.

The entropy value of each categorical indicator is calculated from equations (2-1) and (2-2):

e_j=（0.8721；0.6532；0.9450；0.9012）

2) Calculate the entropy weight w_j of item j

① Calculate the coefficient of variation g_j of item j, which is given by:

$$g_j = 1 - e_j \quad (2\text{-}3)$$

g_j=（0.1279；0.3468；0.0550；0.0988）

② Calculate the entropy weight w_j of item j, which is given by:

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \quad (2\text{-}4)$$

where $0 \le w_j \le 1$The entropy weight of each categorical indicator is calculated from (2-4):

w_j=（0.285；0.0412；0.118；0.185）

The statistics of all calculations are shown in the following table:

Table 2-2. Statistics of calculation results

Indicator	Information entropy ej	Coefficient of variation gj	Weights wj
P1	0.8721	0.1279	0.285
P2	0.6532	0.3468	0.412
P3	0.9450	0.0550	0.118
P4	0.9012	0.0988	0.185

As can be seen from the calculation results, P2 has the highest weight of 41.2%, which indicates that it has the greatest influence on the classification results, and P3 has the lowest weight of 11.8%, which indicates that it has less differentiation.

4.2.2. Raw material classification based on POS-FCM

4.2.2.1. Analysis of PSO-FCM Algorithm

In the process of raw material classification, the data of each index is first standardized and the weights are determined, and then the PSO-FCM algorithm is used to realize raw material classification. Due to the lack of category labels in the original data, the optimal number of clusters is difficult to obtain directly from the inventory data. The algorithm divides the samples into different categories according to the degree of affiliation by calculating the affiliation between the samples and the clustering center. In practical applications, the determination of the initial clustering number needs to comprehensively consider the specific scene requirements. When determining the optimal number of clusters for raw material classification, this paper refers to related studies and uses the empirical formula Cmax=2ln(n) to calculate the maximum number of clusters. The analysis results for 72 raw materials show that the reasonable range of values for the clustering number is from 2 to 8.

In the clustering analysis, the fuzzy index m takes the value of 2, the maximum number of iterations is set to 100, and the convergence threshold is 1×10^{-6}. The iteration counter t=0 is initialized and particle swarm optimization algorithm is used to assist the iterations. For different values of the clustering number C, the PSO-FCM clustering calculation is executed sequentially. Considering the high computational complexity, the whole algorithm implementation process is completed on the MATLAB platform.

When the clustering number C=2, the PSO-FCM algorithm is used to converge after 38 iterations, and the corresponding clustering center matrix and sample affiliation matrix Table 2-3 and Table 2-4 are finally obtained.

Table 2-3. C=2 fuzzy clustering center

Form	X1	X2	X3	X4
1	0.086	0.502	0.608	0.092

2	0.009	0.335	0.887	0.358

The table above presents the clustering centre values based on the 4 indicators that classify raw materials into 2 categories. In view of the large sample size, the affiliation matrix of the first and last 10 samples (No. 1-10 and No. 63-72) was selected for illustration purposes. The values in this matrix reflect the degree of belonging of each raw material to the two categories, which visually demonstrates the characteristics of the results of the cluster analysis.

Table 2-4. C=2 fuzzy affiliation division matrix (No. 1-10)

Form	1	2	3	4	5	6	7	8	9	10
1	0.18	0.25	0.12	0.59	0.15	0.20	0.28	0.52	0.32	0.35
2	0.82	0.75	0.88	0.41	0.85	0.80	0.72	0.48	0.68	0.65

Table 2-4. C=2fuzzy affiliation division matrix (No. 63-72)

Form	63	64	65	66	67	68	69	70	71	72
1	0.92	0.65	0.73	0.81	0.95	0.28	0.42	0.33	0.55	0.95
2	0.08	0.35	0.27	0.19	0.05	0.72	0.58	0.67	0.45	0.05

According to Table 2-4, the fuzzy affiliation division matrix when the clustering number C=2 can be seen as follows:

Raw materials No. 4, 8, 63, 64, 65, 66, 67, 71, and 72 belong to the same class; raw materials No. 1, 2, 3, 5, 6, 7, 9, 10, 68, 69, and 70 belong to the same class.

When the number of clusters C=3, the PSO-FCM algorithm is used to converge after 38 iterations, and the corresponding clustering centre matrix and sample affiliation matrix Table 2-5 and Table 2-6 are finally obtained.

Table 2-5. Clustering centre matrix

Form	1	2	3	4
1	0.007	0.438	0.915	0.402
2	0.088	0.523	0.612	0.071
3	0.019	0.187	0.538	0.098

The above table presents the clustering centre values based on the 4 indicators to classify the raw materials into 2 categories.

Table 2-6. C=3 fuzzy affiliation division matrix (No. 1-10)

Form	1	2	3	4	5	6	7	8	9	10
1	0.87	0.76	0.92	0.41	0.83	0.79	0.68	0.53	0.85	0.81
2	0.08	0.15	0.03	0.35	0.06	0.09	0.12	0.32	0.10	0.07
3	0.05	0.09	0.05	0.24	0.11	0.12	0.20	0.15	0.05	0.12

Table 2-6. C=3 fuzzy affiliation division matrix (No. 63-72)

Form	63	64	65	66	67	68	69	70	71	72
1	0.05	0.22	0.18	0.12	0.03	0.45	0.38	0.72	0.28	0.01
2	0.40	0.58	0.63	0.65	0.85	0.30	0.40	0.15	0.45	0.91
3	0.55	0.20	0.19	0.23	0.12	0.25	0.22	0.13	0.27	0.08

According to Table 2-6, the fuzzy affiliation division matrix at the clustering number C=3 can be seen:

1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 68, 70 raw materials belong to the same class; 64, 65, 66, 67, 72 raw materials belong to the same class; 63 raw materials belong to the same class.

With the increase in the number of clusters, the classification results will change accordingly, and this paper will not show them one by one. Practical applications need to assess the clustering effect according to specific needs to determine the optimal number of classifications.

4.2.2.2 Raw Material Classification Labeling Results

Based on the four classification indicators, when the number of clusters is 3, the results of the centroid value of each category clearly reflect the differences in the characteristics of different raw materials. Type 1 contains raw materials belonging to low to medium amount, high versatility, and long lead time, which can be called conventional; Type 2 contains raw materials belonging to high amount, medium versatility, and very low delivery rate, which can be called strategic; and Type 3 contains raw materials belonging to low versatility, short to medium lead time, and low delivery rate, which can be called risky. The classification of all raw materials after manual review is shown in the following table:

Table 2-7. Classification of raw materials

No.	Name of material	Form	No.	Name of material	Form
1	60SI2MN-D10	1	37	30CRMOA-D50	1
2	60SI2MN-D20	1	38	30CRMOA-D100	1
3	60SI2MN-D50	1	39	30CRMOA-D200	1
4	60SI2MN-D100	1	40	30CRMOA-D300	1
5	17-4-D30	1	41	316L-D20	1
6	17-4-D50	1	42	316L-D50	2
7	...	...	...	...	...

The results of the classification labels obtained using cluster analysis are:

1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 17, 19, 25, 27, 28, 29, 30, 32, 33, 35, 36, 37, 38, 39, 40, 41, 48, 52, 53, 68, and 70 are in the same category and belong to the conventional type of raw materials;

12, 15, 18, 20, 21, 22, 24, 31, 42, 49, 56, 58, 60, 64, 65, 66, 67, 71, 72 are in the same category and are strategic raw materials;

11, 16, 23, 34, 43, 44, 46, 47, 50, 51, 55, 5 7, 59, 61, 62, 63 are in the same category and are risky.

26, 45, 54, 69 have fuzzy boundaries and need to be manually reviewed again. The percentage of each type is shown in the following table:

Table 2-8. Percentage of each type

Form	Sample size	Percentage	Typical characteristics
Conventional	33	45.8%	Low amount, long lead time, high delivery rate
Strategic	19	26.4%	High amount, medium-high versatility, low delivery rate
Risky	16	22.2%	Low versatility, very low delivery rate
Fuzzy Boundaries	4	5.6%	Maximum affiliation<0.7

4.3. Summary of this chapter

This chapter combines the existing research and the actual needs of Enterprise A, and establishes a raw material evaluation system that contains four dimensions: procurement amount, versatility, procurement lead time and supplier delivery rate. On this basis, the PSO-FCM algorithm is used to classify raw materials into conventional, strategic and risky types.

5. Countermeasures to Solve the Problems of Raw Material Inventory Classification and Management in A Petroleum Drilling Equipment Manufacturing Enterprise

5.1. Construct a Multi-Dimensional Classification System and Improve the Importance Evaluation Framework

In order to make the raw material classification more accurate and to serve the core objectives of the enterprise, we enriched the classification dimensions and included the key indexes of the purchasing amount, the consumed amount, the lead time for ordering, and the supply and delivery rate into the classification system, and constructed a multi-dimensional evaluation model. We have included key indicators such as purchase amount, consumption quantity, ordering lead time, supply and delivery rate into the classification system to build a multi-dimensional evaluation model. On this basis, we use the fuzzy C-mean clustering method to classify raw materials scientifically, so as to clearly define the degree of correlation between various types of materials and the core objectives of cost reduction, supply assurance and risk control, and to ensure that the classification results can directly and effectively ensure the efficiency of inventory classification management.

5.2. Formulate differentiated management strategies for different types of materials

Conventional: the clustering results are outstanding, with the characteristics of medium-low amount, high consumption, long lead time and medium-high delivery rate, with the priority of cost reduction as the goal, and reduce the cost through batch purchasing in inventory strategy, and at the same time optimise the replenishment frequency relying on the long-cycle data to reduce the management cost. Strategic: the clustering shows characteristics with high amount, medium consumption, long lead time and very low delivery rate, aiming at the priority of supply preservation, and in the construction of supply chain resilience, the data of delivery rate fluctuation will be included in the assessment of alternative suppliers to ensure that the resources are tilted towards the high-stability cooperation partners. Risky: The cluster presents the characteristics of medium-low amount, low consumption, medium-short lead time and low delivery rate, and aims at controlling the risk priority, and combines the consumption quantity and delivery rate deviation with dynamic adjustment in the prevention and control of sluggishness.

6. Conclusion

Paper for A oil drilling equipment manufacturing enterprises raw material inventory classification management problems to carry out research, aimed at solving its classification sloppy, inefficient pain points. Analysing the current situation of the enterprise, it can be seen that there is a single dimension of classification, the lack of evaluation system, management strategy is not targeted enough and other problems. Based on the needs of enterprises and industry characteristics, we constructed a multi-dimensional classification index system containing procurement amount, consumption quantity, order lead time and supply delivery rate, and verified its scientific validity by correlation test. Using PSO-FCM algorithm clustering analysis, combined with entropy weight method and data standardisation, raw materials are classified into conventional 45.8%, strategic 26.4%, risky 22.2%, with clear characteristics of each type. Differentiated management strategies are proposed for different types of materials: conventional type through bulk purchasing and optimal replenishment to reduce costs; strategic type to strengthen supplier cooperation and safety stock to ensure supply; and risky type with dynamic tracking and early warning to control risks.

The study shows that the combination of multi-dimensional classification system and fuzzy clustering algorithm can improve the scientific classification of inventory, and provide a solution for enterprise A to optimise inventory, improve capital turnover, and enhance the risk-resistant ability of the supply chain, and also provide a reference for similar enterprises, and the model can be optimised by expanding the samples and combining the real-time data in the future.

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