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Inventory control model based on multi-attribute material classification: An integrated grey-rough set and probabilistic neural network approach

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A B S T R A C T

Efficient and reasonable inventory control can help enterprises improve inventory management efficiency, reduce inventory cost, and ensure the full utilization of resources. Considering that there are many attributes of material, different materials have different effects on enterprises. A multi-attribute material classification model based on grey rough set and probabilistic neural network is proposed, and an inventory control strategy model based on material classification is constructed according to the characteristics of different types of material. Based on the construction of the relevant models, taking the inventory materials of sample Enterprise *A* as an example, the grey rough set algorithm is used to reduce the redundant material attributes, and the sample data of normalized reduction attributes are used to classify and discriminate the materials by probabilistic neural network. The results are simulated by MATLAB to obtain the efficient and reasonable classification of the materials of enterprises. Finally, with the sample data of different types of representative materials, a matching model of inventory control strategy based on material classification is applied in practice, and the applicability and feasibility of the model are illustrated, providing a scientific basis for enterprises to make decisions on material management and inventory control.

A R T I C L E   I N F O

Keywords:
Inventory control strategy;
Modelling;
Material classification;
Grey rough set;
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1. Introduction

Material is the premise of enterprise production. In order to ensure the production needs, enterprises should keep part of the material as a turnover inventory. However, due to a variety of reasons, enterprises generally have high inventory, resulting in inventory overstocking and waste of resources, affecting the economic efficiency of enterprises. Inventory control of enterprise materials is a hot issue in scientific management of materials as an important tactical decision-making of enterprises [1]. Its main objective is to minimize the inventory cost of materials on the premise that the needs of production and operation of enterprises are met [2].

As the premise of enterprise inventory control, material classification is the focus of enterprise procurement, production, and sales. Therefore, the basic task of inventory control is to complete the classification, storage, and safekeeping of materials through warehouses. Efficient and reasonable inventory is helpful for enterprises to expedite the flow of materials, reduce costs, ensure the smooth progress of production, and achieve effective control and management of resources [3]. Traditional enterprise inventory control focuses on the quantity control of inventory materials to optimize the single inventory cost; it even insists that its main content is to maintain a certain quantity of materials. However, as far as the content of inventory control is concerned, quantity control constitutes only one of the important items and not the whole content of inventory control. Excessive inventory and confused classification will not only engage a large amount of operating capital of enterprises, affect the turnover of capital, increase the cost of commodity inventory, waste allocation time, but also increase the market risk of enterprises. On the contrary, extremely low inventory quantity and too fine classification will affect the smooth progress of normal production and operation activities of the enterprises and waste a substantial amount of manpower, material resources, and costs, and even make the enterprises lose market opportunities. Efficient inventory control is a prerequisite for production control and job routing decision-making in a multi-objective stochastic manufacturing system [4]. Therefore, it is necessary to adopt scientific material classification and inventory control methods to ensure that enterprises establish an efficient inventory control and classification mechanism on the basis of the normal production and business operation activities. In this way, enterprises can make full use of their limited resources, implement feasible order execution and supply plan, respond quickly to market and customer demand, minimize inventory and operating cost, and improve the economic efficiency of enterprises. It is in this context that research on inventory control based on multi-attribute material classification has become a controversial topic among scholars.

2. Literature review

In order to facilitate inventory management and control, it is necessary to classify inventory materials according to certain rules. ABC classification is a classic and widely used method. However, ABC classification has the defect of single classification index in practical application. Therefore, some scholars tried improving the method from the perspective of classification index optimization based on different scenarios. For example, Xiao *et al*. (2011) proposed a loss-based classification method to overcome the cross-selling effect in ABC classification, and the profit loss of cross-effect was considered as an important rule of classification [5]. Kabir and Hasin (2013) classified the inventory materials with the multi-criteria ABC classification integrating fuzzy analytic hierarchy process (AHP) and neural network methods [6]. Šarić *et al*. (2014) concluded that the multi-criteria classification approach combined with AHP, neural network and clustering analysis was more effective than the traditional single-criteria ABC inventory classification approach in inventory control [7]. Douissa and Jabeur (2016) took ABC classification as an assignment problem, and the multi-criteria classification method PROAFTN was used to classify the inventory materials [8]. May *et al*. (2017) proposed an improved multi-criteria weighted non-linear ABC optimization method, which offered a better multi-criteria classification method for inventory materials [9]. In addition, some scholars tried improving the classification algorithm of material classification ABC. Hu *et al*. (2015), for example, adopted K-MEANS algorithm of clustering to overcome the division error in the classification boundary of the traditional ABC classification method [10]. Chen *et al*. (2008) established a multi-factor classification matrix model, in which ABC classification was combined with the complexity of the supply market and the classification criteria was expanded from three to multiple categories [11]. The above research on multi-attribute material classification provides a scientific basis for formulating inventory control strategy.

Studies on inventory control strategies are actually concerned about the timing and manner of ordering, leading scholars to formulate corresponding inventory control strategies conducive to different conditions. Typical inventory control strategy model has been widely used. For example, Strijbosch and Moors (2006) deduced the safety factor of (R, S) inventory control strategy with modified normal distribution and pointed out that the safety factor of normal distribution of general standard should be increased, otherwise, the level of customer service would be reduced [12]. Rossetti *et al*. (2013) analyzed the influence of aggregation utility of demand forecasting time on inventory control under (Q, R) inventory control strategy. The results indicated that the longer the interval was, the more stable the data performance would be. It could be easily forecasted by a simple model, but it was also easy to ignore the problem of satisfaction rate [13]. Liu (2015) adopted (s, S) strategy for class A and B materials with a stable demand for spare parts inventory control strategy, and improved the parameter calculation. The (Q, R) strategy was adopted for class C materials [14]. Liu and Jiang (2017) studied the ordering of core materials of auto parts manufacturing enterprises with the improved (Q, R) inventory control strategy [15]. It can be seen from the above analysis that different scholars have different choices of inventory control strategies. For example, the application of (Q, R) strategies needs to be specific to the actual situation.

However, in most cases, the material demand of enterprises is not always fixed and tends to exhibit a certain degree of randomicity. Zhang (2007) put forward a quantitative inventory control model under the condition of stochastic demand, according to which the optimal ordering strategy was obtained. It used stochastic demand to obtain the expected value, and then, adopted EOQ model to solve the problem to obtain the optimal order quantity with this expected value [16]. Güler *et al.* (2015) studied a stochastic demand situation where demand was influenced by price, and pointed out that demand would be influenced by both current price and reference price. The safety inventory was used as a decision variable for modelling and solving. The results showed that the optimal level of inventory increased with the increase of reference price [17]. Zhao (2016) constructed a multi-echelon inventory control model for the supply chain under stochastic demand by the application of control theory [18]. Gocken *et al.* (2017) proposed an optimization approach to find the initial inventory, reorder point and determine the optimal value of the order in a completely stochastic supply chain environment through Optimization via Simulation (OvS) approach [19]. Moreover, demand not only exhibits stochastic, but also shows the characteristics of being non-stationary. Strijbosch *et al.* (2011) studied the interaction between forecasting and inventory control under the condition of non-stationary demand, extended the research scope to non-stationary demand by using simulation method, and analyzed the cumulative effects of the optimal estimator, optimal forecasting parameters, and correct variance [20]. Rahdar *et al.* (2018) put forward a three-tier optimization model in the case of uncertain demand and lead time. That model satisfied uncertain demand and lead time by rolling plan, so as to minimize the total order cost [21]. Li *et al.* (2011) proposed the use of confidence inference to solve the problem of non-stationary demand, and confirmed that this approach was superior to the traditional approach [22].

Based on the above literature, it can be found that, for the inventory control of multi-attribute materials, such as raw materials of manufacturing enterprises or spare parts of a certain enterprise, it is generally necessary to classify materials first and then adopt corresponding inventory control strategies for different classifications. According to the current material classification methods, the multi-criteria classification method, based on ABC classification and matrix classification, is the most widely used and studied method. If multi-criteria material classification is to be carried out, the selection of classification indicators and the determination of classification grade are keys to achieving material classification.

In view of the above analysis, the following questions are raised: (1) How to select appropriate indicators for effective classification of multi-attribute materials? (2) Which material classification method is the most suitable? (3) How to propose targeted inventory control strategies for different classifications of materials? In order to answer these three questions, this paper proposes a material classification method based on rough set probabilistic neural network. This method reduces the duplication and redundancy of material attributes of the enterprise. The attribute reduction algorithm of grey rough set is adopted to reduce the attribute index of materials. The probabilistic neural network (PNN) approach is used to build the material classification model based on the reduced attributes; the probabilistic distribution of multi-Gaussian mixture of approximate data in different material classifications is used to solve the problem of material classification. On this basis, based on the classification results, from the point of view of the demand characteristics of different types of materials, an inventory control strategy model of different types of materials is proposed. Finally, an empirical analysis is carried out using a specific example. In this paper, a material classification model based on rough set probabilistic neural network and an inventory control strategy model for different materials are proposed, which are tested by practical cases. It is helpful for enterprises to improve the intellectualization, credibility, and scientific nature in material management, and has strong practical significance for inventory control and management of enterprises.

3. Inventory model building

3.1 Evaluation index system of material attributes

The traditional ABC material classification is based on the value of material (average capital occupancy), but in reality, an indicator is obviously insufficient to show the importance of material. Therefore, a set of scientific and reasonable evaluation index system of material attributes is first needed, so as to express and realize the effective classification of multi-attribute materials by quantitative indicators, such as the importance, availability, difficulty in obtaining, cost proportion, and strategic importance of materials to enterprises. With reference to the determination of material attribute indexes in the relevant literature [23-25], this paper intends to use three first-level indicators to describe the characteristics of materials, namely procurement risk, value proportion, and strategic importance; and then determine the second-level indicators. The evaluation index system of material attributes is shown in Table 1.

Table 1 Evaluation index system of material attributes

First-level Index	Second-level Index	
	Name	Serial No.
Procurement risk	Impact of supplier interruption	C_1
	Number of suppliers	C_2
	Substitutability	C_3
	Degree of difficulty in obtaining	C_4
	Product complexity	C_5
Proportion of the value	Total amount of purchase	C_6
	Proportion of total procurement expenditure	C_7
	Proportion of total cost	C_8
	Impact of fluctuations in the price of certain materials on profits	C_9
Strategic importance	Bargaining power of suppliers	C_{10}
	Influence degree of materials on product quality	C_{11}
	Losses caused by shortage of materials	C_{12}

- Procurement risk

Procurement risk mainly refers to the unexpected situations that may occur in the procurement process. It is mainly used to describe the extent of the influence of the unexpected situations encountered in the procurement process on production. The main factors influencing the risk degree of material procurement should be fully considered in determining the second-level index of procurement risk, which mainly come from two aspects: material supplier**s** and themselves [23, 26]. For suppliers, factors such as the impact of interruption of suppliers and the number of suppliers should be taken into account. For materials themselves, the substitution of materials, the difficulty of obtaining materials and the complexity of products are the important factors influencing the risk of material procurement.

- Proportion of the value

The proportion of the value mainly represents the value of materials, that is, the contribution of materials to products. In order to better assign resources and enable enterprises to attach great importance to those materials that contribute greatly to enterprises, factors such as the total amount of purchase, the proportion of total procurement expenditure, the proportion of total cost and the influence of fluctuation in the price of certain materials on profits should be fully taken into account in the process of constructing the second-level index of value proportion [24].

- Strategic importance

From the perspective of the influence of materials on production, **s**trategic importance mainly focuses on the strategic influence on production plan, and the influencing factors mainly come from suppliers and materials themselves [27]. Therefore, the strategic importance of materials is represented by three factors in this paper, namely, the bargaining power of suppliers, the influence degree of materials on product quality, and the losses caused by shortage of materials.

3.2 Classification model of multi-attribute materials

Based on the evaluation index system of material attributes established above, a material classification model based on grey rough set and PNN is proposed in this paper. Firstly, by taking the advantage of the attribute reduction of grey rough set, the important attributes in the classification and evaluation system are extracted, and the input complexity of the evaluation index system of material attributes in the classification and decision-making system is reduced. Then, inventory classification is carried out combined with the strong classification ability of PNN. This method fully combines the advantages of grey rough set and PNN, simplifies the input complexity of material classification system, reduces the complexity of sample training and machine learning in PNN approach, improves the accuracy of material classification, and achieves the purpose of better assisting enterprises to classify materials correctly and guiding enterprises to implement different inventory control strategies according to different material classification.

Grey rough set attribute reduction algorithm

In order to solve the problem of duplication and redundancy, the attribute reduction algorithm of grey rough set is proposed in this paper. Let $S = (U,A,V)$ be a multi-attribute information system, while $U = \{1, 2, \cdots, n\}$ is a non-empty finite set of objects and $n \geq 2$; $A = \{a_1, a_2, \cdots, a_m\}$ is a non-empty finite set of attributes, including the set of efficiency indexes C and the set of cost indexes D; the larger the index attribute value of set C, the better, while the smaller the index attribute value of set D, the better. Let A_c and A_d be the subscript sets of efficiency indexes and cost indexes, respectively, where $= A_c \cup A_d$, $A_c \cap A_d = \emptyset$ and $m \geq 2$. The indexes are divided into conditional attribute C_A and decision attribute D_A, and $C_A \cup D_A = A$, $C_A \cap D_A = \emptyset$, $\forall_i \in U$, $\forall_{a_j} \in A$, V represents the set of the value of indexes, and v_{ij} represents the observed value of the object i about the indicator a_j.

In the system, each index in the indicator set has different dimensions and attributes, and the type of attribute value has two forms, namely clear number and linguistic items, and the attribute value of the same attribute has the same information form. For convenience, let A_d and A_l respectively denote the attribute subset whose attribute values are clear number and the formal information of the linguistic items. $A_d = \{A_1, A_2, \cdots, A_h\}$, $A_l = \{A_{h+1}, A_{h+2}, \cdots, A_m\}$, and $A_d \cup A_l = A$; Let S_1 and S_2 be the subscript sets of attribute subsets A_d and A_l, respectively. $S_1 = \{1, 2, \cdots, h\}$, $S_2 = \{h+1, h+2, \cdots, m\}$. For attribute values, the specific description is as follows:

- If $a_j \in A_d$, then $v_{ij} = v'_{ij}, j \in S_1, i \in U$, where v'_{ij} is a real numeric value, without losing generality, here suppose $v'_{ij} \geq 0$.
- If $a_j \in A_l$, then $v_{ij} = v''_{ij}, j \in S_2, i \in U$, where v''_{ij} is a linguistic item, $v''_{ij} \in P$. Here P is a set of linguistic items, $P = \left\{P_t \middle| t = 0, 1, \cdots, \frac{L}{2} - 1, \frac{L}{2}, \frac{L}{2} + 1, \cdots, L\right\}$, where P_t represents the $(t+1)$-th linguistic item in P, and $(L+1)$ represents the number of items in P. When $L = 6$, $P = \{p_0, p_1, p_2, p_3, p_4, p_5, p_6\} = \{PP(particularly\ poor), Wo(worse), P(poor), M(medium), We(well), B(better), EW(especially\ well)\}$ when $z \geq b$, P_z is better than or equal to P_b; if P_z is better than or equal to P_b, then $max\{p_z, p_b\} = P_z$, $min\{p_z, p_b\} = P_b$; when $b = L - z$, $inv(p_z) = p_b$, where inv is an inverse operator. The specific normalized calculation formulas are respectively expressed, as shown below:

  (a) If $a_j \in A_d$, then the normalized calculation formula is as follows:

$$G_{ij}^{d}=\begin{cases}\frac{v'_{ij}-v_j^N}{v_j^P-v_j^N},i\in U,j\in S_1\cap A_c\\ \frac{v_j^P-v'_{ij}}{v_j^P-v_j^N},i\in U,j\in S_1\cap A_d\end{cases} \tag{1}$$

where

$$v_j^P=max\left[\max_{1\le i\le n}\left(v''_{ij}\right)\right],j\in S_1 \tag{2}$$

$$v_j^N=min\left[min_{1\le i\le n}\left(v''_{ij}\right)\right],j\in S_1 \tag{3}$$

(b) If $a_j\in A_l$, then the normalized calculation formula is as follows:

$$G_{ij}^{l}=\begin{cases}v''_{ij}\quad ,i\in U,j\in S_2\cap A_c\\ inv\left(v''_{ij}\right),i\in U,j\in S_2\cap A_d\end{cases} \tag{4}$$

Linguistic item G_{ij}^{l} can be converted into corresponding triangular fuzzy number G_{ij}^{TFN} that is, $G_{ij}^{TFN}=\left(G_{ij}^1,G_{ij}^2,G_{ij}^3\right)$; the calculation formula is shown thus:

$$\varphi^{TFN}=(\varphi^1,\varphi^2,\varphi^3)=\left[\max\left(\frac{t-1}{L},0\right),\frac{t}{L},\min\left(\frac{t+1}{L},1\right)\right] \tag{5}$$

$$G_{ij}^{d}=\sqrt{\frac{1}{3}\left[\left(G_{ij}^1\right)^2+\left(G_{ij}^2\right)^2+\left(G_{ij}^3\right)^2\right]} \tag{6}$$

After dimensionless processing of v_{ij}, dimensionless feature values of object behaviour can be obtained. Any two objects $f,k\in U$ on the indicator $\forall_{a_j}\in A$, grey correlation coefficient ξ_{fk}^{j}, and correlation degree ξ_{fk}^{A} of indicator set A, correlation cluster analysis can be carried out for each scheme. The calculation formula to calculate the grey correlation coefficient ξ_{fk}^{j} and correlation degree ξ_{fk}^{A} of the scheme f,k on attribute a_j and attribute set A is shown as Eq. 7.

$$\xi_{fk}^{j}=\frac{\min_i\min_j\left|x_k^j-x_i^j\right|+\theta\max_i\max_j\left|x_k^j-x_i^j\right|}{\left|x_k^j-x_i^j\right|+\theta\max_i\max_j\left|x_k^j-x_i^j\right|} \tag{7}$$

$$\xi_{fk}^{A}=\frac{1}{m}\sum_{j=1}^{m}\xi_{fk}^{j} \tag{8}$$

On this basis, grey incidence matrix between objects can be established as follows:

$$\xi=\begin{vmatrix}\xi_{11}^A & \xi_{12}^A & \cdots & \xi_{1k}^A & \cdots & \xi_{1n}^A\\ \xi_{21}^A & \xi_{22}^A & \cdots & \xi_{2k}^A & \cdots & \xi_{2n}^A\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \xi_{i1}^A & \xi_{i2}^A & \cdots & \xi_{ik}^A & \cdots & \xi_{in}^A\\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots\\ \xi_{n1}^A & \xi_{n2}^A & \cdots & \xi_{nk}^A & \cdots & \xi_{nn}^A\end{vmatrix}$$

According to the grey incidence matrix, $\xi_{fk}^{A}$is the correlation degree of the decision objects f,k on attribute set A, which represents the possibility that the object belongs to the same classification, and the best critical value can be determined by the Bayesian criterion. The specific method is as follows:

(i) C_a, C_m, and C_u respectively denote that objects f,k have a high correlation degree $AF_A^{(\alpha,\beta)}(n)$, a medium correlation degree $MB_A^{(\alpha,\beta)}(n)$, a low correlation degree $DN_A^{(\alpha,\beta)}(n)$; $E(C_{ak})$, $E(C_{mk})$ and $E(C_{uk})$ respectively denote the expected loss function, and that object f belongs to $AF_A^{(\alpha,\beta)}(n)$, $MB_A^{(\alpha,\beta)}(n)$ and $DN_A^{(\alpha,\beta)}(n)$.

The calculation formula of expected loss function is shown as Eq. 9, Eq. 10, and Eq. 11:

$$E(C_{ak}) = \delta_{aA}\xi_{fk}^{A} + \delta_{aD}\left(1 - \xi_{fk}^{A}\right) \tag{9}$$

$$E(C_{mk}) = \delta_{mA}\xi_{fk}^{A} + \delta_{mD}\left(1 - \xi_{fk}^{A}\right) \tag{10}$$

$$E(C_{uk}) = \delta_{uA}\xi_{fk}^{A} + \delta_{uD}\left(1 - \xi_{fk}^{A}\right) \tag{11}$$

where δ_{aA}, δ_{mA} and δ_{uA} respectively indicate the loss function, and that the decision makers take under a high correlation degree $AF_A^{(\alpha,\beta)}(n)$. δ_{aD}, δ_{mD} and δ_{uD} respectively indicate the loss function, and that the decision makers take under low correlation degree $DN_A^{(\alpha,\beta)}(n)$.

(ii) According to the Bayesian decision criterion, the optimal action plan needs to be selected as the action set with the minimum expected loss. The specific decision rules are as follows:

Decision rules of $AF_A^{(\alpha,\beta)}$: if both $E(C_{ak}) \leq E(C_{mk})$ and $E(C_{ak}) \leq E(C_{uk})$ are true, then $k \in AF_A^{(\alpha,\beta)}(n)$;
Decision rules of $MB_A^{(\alpha,\beta)}$: if both $E(C_{ak}) \geq E(C_{mk})$ and $E(C_{uk}) \geq E(C_{mk})$ are true, then $k \in MB_A^{(\alpha,\beta)}(n)$;
Decision rules of $N_A^{(\alpha,\beta)}$: if both $E(C_{uk}) \leq E(C_{ak})$ and $R(O_N\,|k) \leq R(O_U\,|k)$ are true, then $k \in DN_A^{(\alpha,\beta)}(n)$.

(iii) According to Bayesian reasoning, the rules for simplifying decision-making are as follows:
If $\xi_{fk}^{j} \geq \alpha$ and $\xi_{fk}^{A} \geq \alpha$, then the correlation degree of decision object f, k is high;
If $\beta < \xi_{fk}^{j} < \alpha$ and $\beta < \xi_{fk}^{A} < \alpha$, then the correlation degree of decision object f, k is medium;
If $\xi_{fk}^{j} \leq \beta$ and $\xi_{fk}^{A} \leq \beta$, then the correlation degree of decision object f, k is low;
where $\forall f, k \in U, \forall a_j \in A, 0 \leq \beta \leq \alpha \leq 1$.
The correlation degree of object f about attribute set A is divided as follows:

$$AF_A^{(\alpha,\beta)}(n) = \left\{k \in U \middle| \xi_{fk}^{A} \geq \alpha\right\} \tag{12}$$

$$MB_A^{(\alpha,\beta)}(n) = \left\{k \in U \middle| \beta < \xi_{fk}^{A} < \alpha\right\} \tag{13}$$

$$DN_A^{(\alpha,\beta)}(n) = \left\{k \in U \middle| \xi_{fk}^{A} \leq \beta\right\} \tag{14}$$

The calculation formulas of α and β are:

$$\alpha = \frac{(\delta_{aD} - \delta_{mD})}{(\delta_{aD} - \delta_{mD}) + (\delta_{uA} - \delta_{mA})} \tag{15}$$

$$\beta = \frac{(\delta_{mD} - \delta_{uD})}{(\delta_{mD} - \delta_{uD}) + (\delta_{uA} - \delta_{aA})} \tag{16}$$

Finally, based on the classification of critical values α and β, the attributes are reduced, and the reduction methods are as follows:

- $Q \subseteq C_A, IND(Q) = \{(e,w) \in U^2 | \forall a \in C_A, e \neq w, q(e,a) = q(w,a)\}$, and $IND(Q)$ divides the object U into z equivalence classifications, which is denoted as $U / Q = \{x_1, x_2, \cdots, x_z\}$;
- R is the equivalent relation in A and $r \in R$, if $IND(R) = IND(R - \{a\})$, then is reducible in R, otherwise, r is irreducible in R. If each r is irreducible, then r is independent;
- If $W \in R$ and W is independent, at the same time, $IND(W) = IND(Q)$, then, W is the reduction of U on attribute set Q.

To sum up, the problem to be solved in this paper is how to obtain the reduction scheme of all indexes through a multi-attribute reduction method based on multi-attribute information system S, attribute correlation coefficient ξ_{fk}^{j}, and correlation degree ξ_{fk}^{A}. The algorithm of attribute reduction based on grey rough set is as follows:

Step 1: Normalize the attribute index data with multiple information forms according to Eq. 1 to Eq. 6.

Step 2: Obtain the correlation degree between objects according to Eq. 7 to Eq. 8, and then establish the incidence matrix of characteristic variables.

Step 3: Obtain the optimal critical value of the correlation degree of each object according to Eq. 9 to Eq. 16 and categorize the objects accordingly.

Step 4: Reduce the attribute index according to the division of the correlation degree.

PNN material classification discriminate model

Probabilistic Neural Networks was proposed by Specht in 1990, it is a neural network suitable for classification [28]. According to Bayesian classification rules, it takes the mixed form of multi-Gaussian function to approximate the probability of data in each classification and select the one with the maximum probability value as the classification as the data belongs to. In essence, it is a parallel algorithm based on Bayesian minimum risk criterion. Therefore, based on the reduction results of material attributes, the PNN approach is used to build the classification and discrimination model of materials. This model applies Bayesian criterion to estimate the posterior classification probability $P(c_i \,/\, x)$, that is, the unknown vector x belongs to the probability of all possible classification c. According to Bayesian criterion, this probability is proportional to the product of prior probability π_i (the ratio of the unknown vector belongs to each classification) and the probability density function $f_i(x)$ (probability density function of each classification of vector), that is, $P(c_i \,/\, x) \propto \pi_i f_i(x)$, where the probability density function of classification i is as per Eq. 17:

$$f_i(x) = \frac{1}{(2\pi)^{\frac{v}{2}}\sigma^v}\frac{1}{k_i}\sum_{j=1}^{i} exp\left[-\frac{\left(x-x_{ij}\right)^T\left(x-x_{ij}\right)}{2\sigma^2}\right] \tag{17}$$

where x_{ij} is the j-th training sample belonging to classification i, k_i is the number of training samples in classification i, σ_i is the smoothing parameter, and v is the dimension of each sample. If the prior probability is unknown, it can be estimated by the occurrence frequency of each classification sample in the training set as per Eq. 18:

$$\pi_i = k_i \Big/ \sum_{j=1}^{c} k_j \tag{18}$$

If all kinds of prior probabilities are assumed to be the same and constant terms are ignored, then:

$$P(c_i \,/\, x) \propto \sum_{j=1}^{i} exp\left[-\frac{\left(x-x_{ij}\right)^T\left(x-x_{ij}\right)}{2\sigma^2}\right] \tag{19}$$

PNN can be obtained through three layer neural network: (a) the input layer accepts input vectors and formats them; (b) in the layer of radial basis neuron, the distance between the input vector and the training sample is first calculated and then multiplied by the threshold vector, calculated by the radial transfer function at last; (c) in the competitive layer, the calculation results of nodes in the first layer are accepted and the output belonging to the same classification is synthesized. Finally, the classification of unknown vectors is judged according to the size of each output result. It can be seen that PNN is obtained by combining radial basis function neural network with competitive neural network. It is a new classification tool, which considers both

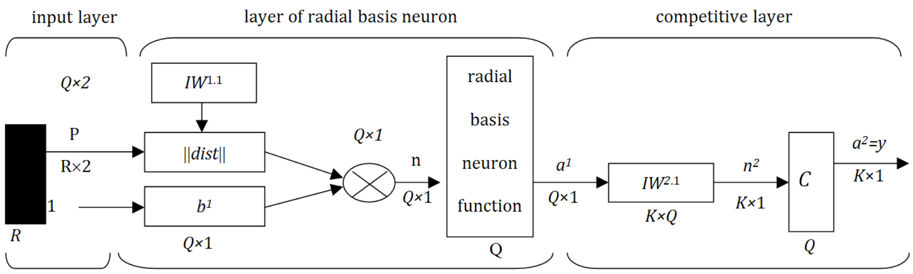

Fig. 1 The specific structure of PNN

the inhomogeneity of the input samples and the classification and pattern recognition capability of the competitive neural network. The specific structure of PNN is shown in Fig. 1.

As shown in Fig. 1, R represents the number of input vector elements; Q is the number of neurons in the second layer; P is the sample matrix of input; $\| dist \|$ represents the distance between the input vector and the weight vector; n^1 is the distance between the sample matrix of input $IW^{1.1}$ and weight matrix multiplied by the threshold b^1; a_i^1 represents the i-th element of a^1; while a^1 is the output from radial basis neuron layer, a^2 is the output from competitive layer, and $a_i^1 = radbas(\|_i IW^{1.1} - p \| b_i^1)$; $y = a^2 = compet(IW^{2.1} - a^2)$, where $radbas()$ is the radial basis function, $compet()$ is the competitive function; IW^1 is the weight matrix of the radial basis network layer; $IW^{1.1}$ is the i-th row vector of the weight matrix IW^1, IW^2 is the weight matrix of the competitive layer; module C represents the competitive transfer function, that is the maximum value of each element in its input vector n^2 is calculated, the output of neurons corresponding to the maximum value is set to 1, and the output of neurons of other classifications are set to 0. Specifically, the input weight of the first layer of the PNN network $IW^{1.1}$ is the transport matrix of the input sample P^T; after calculation by $\| dist \|$, the output vector of the first layer represents the approximation degree between the input vector and the sample vector, then multiplies with the threshold vector and is then calculated by the radial transfer function. When the input vector is approximate to the samples, all the elements corresponding to a^1 will be 1s. The weight of the second layer $IW^{2.1}$ is set as the expected value vector matrix$T$; only one element in each row vector is 1, representing the corresponding classification; the remaining elements are 0, and then the product Ta^1 is calculated. Finally, n^2 is obtained through the competitive transfer function of the second layer; the larger element is 1 and the others are 0. At this point, the PNN network can complete the classification of input vectors [29, 30].

Due to the large quantity and complexity of the materials, the classification results should be simplified as far as possible. The attributes of materials are various, and the degree of influence and importance of materials are different for different equipment. The maximum and minimum values of expert evaluation classification score D are extracted, and then the value interval is divided into four equal parts; each sub-interval corresponds to a score, equal to the scores of 1, 2, 3, and 4. Here, the materials are divided into four grades, according to the range of materials: strategic materials, bottleneck materials, general materials, and leverage materials. Among them, strategic materials mainly include materials that are of vital importance to the products or industrial processes of the enterprise. These materials often have a high supply risk, mainly because of the shortage of supply or transportation difficulties. The bottleneck type is mainly characterized by the fact that the price of the material itself may be not very expensive, but it is still difficult to obtain. The main characteristics of general materials are relatively rich supply, little influence on procurement costs, and high standardization of products. Leveraged materials are relatively simplified and shared in specifications, which have a significant influence on cost and have the characteristics of a large number of suppliers and fierce market competition.

3.3 Inventory control strategy model based on material classification

Different types of materials are suitable for different inventory control strategies. In this paper, the appropriate inventory control strategy model will be selected according to the characteristics of each kind of materials (strategic materials, bottleneck materials, general materials, and leveraged materials). Therefore, it constructs a matching model based on material classification and inventory control strategy, as shown in Fig. 2.

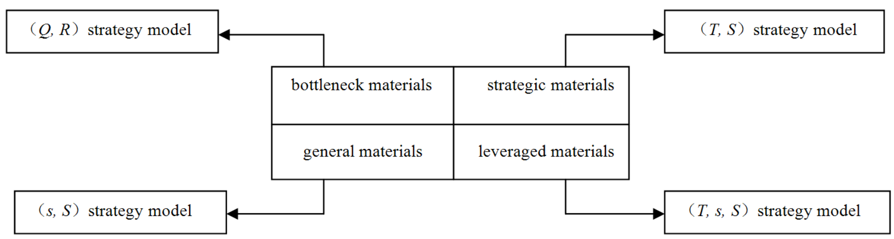

Fig. 2 Matching model of inventory control strategy based on material classification

Strategic materials – (T, S) strategy model

Strategic material has a high value, great complexity, and strong professionalism, and the supplier has great influence on it. The inventory level should be reduced as much as possible, and a good cooperative relationship should be established with the strategic material suppliers. Therefore, the (T, S) strategy model can be adopted. The inventory cycle interval of the *(T, S)* strategy is relatively long; it checks the inventory level through time T and sets the inventory to the maximum inventory level S. In the (T, S) strategy model, three parameters need to be determined: order cycle T, maximum inventory level S, and order quantity Q.

- Order cycle T

The order cycle T is a fixed value. Generally speaking, the order cycle T needs to be determined according to the consumption of materials.

- Maximum inventory level S

S should satisfy the consumption of order cycle T and the order lead time. Meanwhile, safety inventory should also be considered in order to prevent the uncertainty of demand. Assuming that the demand in order cycle and lead time is normal distribution, the mean value is μ, the standard deviation is σ, the lead time is p, the safety inventory is Iss, and the safety coefficient is k. Then, the expression of the maximum inventory level S is:

$$S = Iss + \mu(T + p) \tag{20}$$

$$Iss = k\sigma\sqrt{T + p} \tag{21}$$

- Order quantity Q

Let the inventory level at time t be It and the order quantity be Qt. From the operation process of *(T, S)* strategy model, the expression of Qt is as follows:

$$Q_t = S - I_t \tag{22}$$

However, in practice, materials are usually composed of a unit package, that is there is a minimum package unit Q_0, and the order quantity should be several times the minimum package unit. Therefore, it can be further written as follows:

$$Q_t = nQ_0 \tag{23}$$

$$n = roundup\left(\frac{S - I_t}{Q_0}\right) \tag{24}$$

where, roundup () represents the upward integer function.

Bottleneck materials – (Q, R) strategy model

Due to the low value of bottleneck materials—great complexity, strong professionalism, and high influence of suppliers on them—it is necessary to keep abreast of the inventory status of such materials, set up safe inventory, and adopt high security inventory strategy to reduce the inventory level. Therefore, the strategy model *(Q, R)* is selected in this paper. The fixed-point quantitative *(Q, R)* strategy of continuous inventory is mainly applicable to the bottleneck materials with large demand and great uncertainty, and no shortage is allowed. Once the shortage occurs, the cost of shortage is very high.

Suppose the order and purchase cost of bottleneck material i is C_{2i}, then:

$$C_{2i} = P_i \mu_{D_{it}} \tag{25}$$

where P_i represents unit price of material i; $\mu_{D_{it}}$ is the average demand of material i in time t.

The total ordering business cost $C_i{}'$ within time t can be expressed as:

$$C_i{}' = C_i \cdot \frac{\mu_{D_{it}}}{Q_i} \tag{26}$$

where C_i is the single order cost (including storage cost, travel cost, etc.); Q_i is the order quantity of material *i.*

The total storage cost of material *i* in time *t* is C_{is}, and then:

$$C_{is} = S_i \cdot t \cdot \left(\frac{Q_i}{2} + R_i - \mu_{D_{ip}}\right) \tag{27}$$

where S_i represents the storage cost of per unit material in unit time of material *i*; R_i is the order point of material *i*.

If the demand D_{ip} of material *i* in lead time is greater than the order point R_i, there will be a shortage. The average value of shortage is:

$$\int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip}) \tag{28}$$

If the shortage rate isη, the number of possible shortages in t time is $\frac{\mu_{D_{it}}}{Q_i} \cdot \eta$. If the unit cost of loss due to the shortage of material *i* is $C_{i\eta}$, then the average cost of shortage in time *t* is C_η:

$$C_\eta = C_{i\eta} \cdot \frac{\mu_{D_{it}}}{Q_i} \cdot \eta \cdot \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip}) \tag{29}$$

Therefore, the objective function namely C_{it} is the total inventory cost of material *i* in time *t*:

$$C_{it} = C_{2i} + C_i' + C_{is} + C_\eta =$$

$$P_i \mu_{D_{it}} + C_i \cdot \frac{\mu_{D_{it}}}{Q_i} + S_i \cdot t \cdot \left(\frac{Q_i}{2} + R_i - \mu_{D_{ip}}\right) + C_{i\eta} \cdot \frac{\mu_{D_{it}}}{Q_i} \cdot \eta \cdot \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip}) \tag{30}$$

The partial derivatives of the sum of Eq. 30 are respectively obtained, and the result is:

$$\begin{cases} \frac{\partial C_{it}}{\partial R_i} = S_i t - C_{i\eta} \cdot \frac{\mu_{D_{it}}}{Q_i} \cdot \eta \cdot \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip}) \\ \frac{\partial C_{it}}{\partial R_i} = \frac{S_i t}{2} - \frac{\mu_{D_{it}}\left[C_i + \eta \times C_{i\eta} \times \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip})\right]}{Q_i^2} \end{cases} \tag{31}$$

Set Eq. 31 equal to zero; then get:

$$\begin{cases} \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip}) = \frac{\eta \times C_{i\eta} \times \mu_{D_{it}} - S_i \cdot t \cdot Q_i}{\eta \times C_{i\eta} \times \mu_{D_{it}}} \\ Q_i^2 = \frac{2\mu_{D_{it}}\left[C_i + \eta \times C_{i\eta} \times \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip})\right]}{S_i t} \end{cases} \tag{32}$$

General materials – (s, S) strategy model

General materials have a low value, strong universality, and low influence from suppliers, which are suitable to adopt *(s, S)* strategy model. The *(s, S)* strategy is also known as maximum and minimum strategy. In this strategy model, four parameters need to be checked, namely inventory check time, and reorder point s, order level s, and order quantity *Q.*

- Inventory check time

The inventory level is gradually reduced with consumption, while the continuous inspection strategy does not mean to check the inventory at any time, which is not feasible in practical operation, especially for the material inventory of various manufacturers. Therefore, it is necessary to determine an inventory inspection cycle and checkpoint, which should be consistent with the production plan that is keeping in step with the material demand plan.

- Reorder point

In this strategy model, when the inventory level drops to *s* or below, the order will be issued; so the inventory of the ordering point needs to meet two consumption conditions: one is the inventory consumption in lead time, and the other is to guarantee the service level so as to avoid the shortage caused by an increase in supply or demand.

If it is subject to the normal distribution during the lead time, with a mean value of μ and standard deviation of σ, the lead time is p, and the demand of each period is independent from each other; D is the demand of lead time, and the standard deviation is σ_D. According to the nature of normal distribution, then:

$$D = \mu p \quad (33)$$

$$\sigma_D = \sqrt{p\sigma^2} \quad (34)$$

The safety factor is k, and then the expression of safety inventory Iss is:

$$Iss = k \cdot \sigma_D = k \cdot \sqrt{p\sigma^2} = k \cdot \sqrt{p} \cdot \sigma \quad (35)$$

Therefore, the expression of reorder point s is:

$$s = \mu p + Iss \quad (36)$$

- Determination of maximum S

Maximum S is the order level S. Since the strategic materials belong to the material with high value, their inventory level S should be reduced as much as possible. That is, the consumption within the lead time can be satisfied on the basis of reorder point s. The expression of S is:

$$S = s + \mu p \quad (37)$$

- Order quantity Q

The order quantity at time t is set to Q_t and according to the operation process of *(s, S)* strategy, the expression is:

$$Q_t = S - I_t \quad (38)$$

The (*s, S*) strategy also needs to consider the constraints of the minimum order unit when ordering. Therefore, it can be further written as follows:

$$Q_t = nQ_0 \quad (39)$$

$$n = roundup\left(\frac{S - I_t}{Q_0}\right) \quad (40)$$

Leveraged materials – (T, s, S) strategy model

Leveraged materials have a high value, strong universality, and low influence from suppliers. Some materials should be selected to set the inventory and reduce the times of purchase. Therefore, the (*T, s, s*) strategy model is more appropriate. (*T, s, S*) strategy is a comprehensive strategy that combines (s, S) strategy with (*T, S*) strategy, which can provide greater flexibility than the fixed-cycle, unified ordering strategy (*T, s*). Where *T* represents the basic order interval time, *s* and *S* respectively represent the order point and maximum inventory of materials. According to this strategy, materials are inspected periodically, and each material adopts an independent and periodic (*s, S*) strategy. Inventory is checked at intervals of *T*. If the inventory level of material *i* is below or equal to its order point, it will be replenished to the maximum inventory *S*. Therefore, four parameters need to be determined, namely *T*, *s*, *S* and *Q*.

- Order cycle T

Similar to (*T, S*) strategy model, the order cycle T of (*T, s, S*) strategy is a fixed value. Generally speaking, order cycle *T* needs to be determined according to the consumption of materials.

- Order point s

Different from the continuous inventory, the corresponding period of time to determine the demand to be met by the inventory at the ordering point is not only the lead time of order, but also an inventory cycle. Replenishment may be not replenished at the time of inventory when taking periodic inventory. If there is no replenishment, the opportunity for replenishment is at the next time of inventory. It can be seen that the service level to meet the material demand is within the time range $(T + p)$ when periodic inventory is adopted. Safety inventory and order point are determined on the basis of total demand in time $(T+p)$, and the value is $s=\mu(T+p)+Iss$. Where $\mu(T+p)$ is the expected value of the total quantity demanded in time $(T+p)$; Iss is the safety inventory. For the given service level requirement α, the corresponding safety factor k can be obtained by referring to the standard normal distribution table. In addition to meeting the demand in lead time, the order point of each cycle also meet the demand within the inventory period, thus:

$$s=\mu(T+p)+k\sigma(T+p) \tag{41}$$

where $k\sigma(T+p)$ is the safety inventory, and $\sigma(T+p)$ is the standard deviation.

- Maximum inventory S

The determination method of maximum inventory S is the same as in (s, S) strategy, so the value of maximum S should be as small as possible, that is, the consumption in advance period can be satisfied on the basis of the order point S, which is the mean value of p in advance period, and the expression of S is:

$$S=s+\mu(T+p) \tag{42}$$

- Order quantity Q

Let the order quantity at time t is Q_t, and the expression for Q_t is:

$$Q_t=S-I_t \tag{43}$$

The constraint of the minimum order unit should also be considered when ordering. Therefore, it can be further written as:

$$Q_t=nQ_0 \tag{44}$$

$$n=roundup\left(\frac{S-I_t}{Q_0}\right) \tag{45}$$

4. Results and discussion: Inventory model application model application

In this paper, a chemical Enterprise A was selected as the research sample to apply the multi-attribute material classification model and the inventory control strategy matching model. The inventory of enterprise A mainly includes the following 60 types of materials, as shown in Table 2.

Table 2 Main material categories of Enterprise A

No.	Name	No.	Name	No.	Name
1	Metallurgical materials and cast iron pipes	21	Labour protection articles	41	Welding materials
2	Petroleum special pipes	22	Oil special equipment	42	Fasteners
3	Common steel	23	Special equipment for refining and chemical industry	43	Bearing
4	Wire and metal ropes	24	Construction machinery and equipment	44	Valves
5	Nonferrous metals and processed materials	25	Lifting and conveying equipment	45	Fire equipment
6	Building hardware	26	General machinery and equipment	46	Other mechanical equipment
7	Petroleum and products	27	Metalworking machinery and equipment	47	Special tools for petroleum
8	Coal	28	Power equipment	48	Petroleum drilling equipment accessories
9	Non-metallic building materials	29	Transportation equipment	49	Accessories for refining and chemical equipment
10	Cement and products	30	Textile equipment	50	Textile equipment and accessories
11	Wood and products	31	Electrical and electrical equipment	51	Industrial and mining accessories
12	Petroleum special chemical products	32	Electrical materials	52	Pipe fittings
13	Catalyst and additive	33	Electrical components	53	Sealing elements
14	Rubber and products	34	Daily-use electric appliances	54	Internal combustion engine parts
15	Plastic and products	35	Communication equipment	55	Heavy-duty auto parts
16	Paint and pigments	36	Electronic industrial products	56	General auto parts
17	General chemical products	37	Petroleum special instruments	57	Fittings for waterway railway equipment
18	Glass instrument	38	Universal instruments	58	Other mechanical parts
19	Pyrotechnic products	39	Small machinery	59	Packing materials
20	Textile products	40	Tools and measuring tools	60	Miscellaneous products

4.1 Application of multi-attribute material classification model

Based on the evaluation index system of material attributes, this paper adopted 12 attribute indicators (Table 1) to classify 60 kinds of material attributes of Enterprise A. Firstly, the evaluation index of material attributes was reduced by the grey rough set algorithm, and then, based on the reduction results, the PNN discrimination model was used to realize the effective classification of 60 types of materials.

- *Application of material attribute reduction algorithm based on grey rough sets*

Before the material classification of Enterprise A, attribute reduction was needed to remove duplicate and redundant indicators. This process adopted the grey rough set algorithm, which can effectively support the whole process from data pre-processing to attribute reduction analysis. Among these 12 attribute indicators, C_2, C_6, C_7 and C_8 were clear number information, and C_1, C_3, C_4, C_5, C_9, C_{10}, C_{11} and C_{12} were linguistic item information. Due to the large variety of materials, partial material sample data with multiple information forms are listed, as shown in Table 3.

In order to solve the problem of indicator reduction, the calculation process using the algorithm given above is briefly explained below.

Firstly, material classification indicator data with multiple information forms will be standardized according to Eq, 1 to Eq. 6 as shown in Table 4.

Table 3 Partial material sample data with multiple information forms

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Metallurgical materials and cast iron pipes	B	20	M	W_e	M	109	8	7	B	B	B	EW
Petroleum special pipes	EW	7	P	B	B	260	12	10	B	EW	B	EW
Common steel	We	26	B	M	P	100	5	3	M	B	We	We
Wire and metal ropes	B	18	EW	P	P	80	3	2	P	We	We	M

Table 4 Standardization of sample data of some materials with various forms of information

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
Metallurgical materials and cast iron pipes	0.84	0.60	0.52	0.68	0.52	0.79	0.88	0.88	0.84	0.84	0.84	0.95
Petroleum special pipes	0.95	0.08	0.34	0.84	0.84	0.39	0.82	0.81	0.84	0.95	0.84	0.95
Common steel	0.68	0.84	0.84	0.52	0.34	0.73	0.93	0.96	0.52	0.84	0.68	0.68
Wire and metal ropes	0.84	0.52	0.95	0.34	0.34	0.93	0.96	0.98	0.34	0.68	0.68	0.52

Secondly, the grey correlation degree of attribute set among materials was calculated according to Eq. 7 and Eq. 8. Then, according to Eq. 9 to Eq. 16, considering the losses faced by Enterprise A in material classification and assuming loss functions, then:
$\delta_{aA} = 0.26$, $\delta_{mA} = 0.64$, $\delta_{uA} = 0.72$, $\delta_{aD} = 0.79$, $\delta_{mD} = 0.67$, $\delta_{uD} = 0.09$. The optimal critical value can be obtained as follows:

$$\alpha = \frac{(\delta_{aD} - \delta_{mD})}{(\delta_{aD} - \delta_{mD}) + (\delta_{uA} - \delta_{mA})} = 0.600$$

$$\beta = \frac{(\delta_{mD} - \delta_{uD})}{(\delta_{mD} - \delta_{uD}) + (\delta_{uA} - \delta_{aA})} = 0.558$$

According to the optimal critical value, the set of all the materials with a high correlation degree, medium correlation degree, and low correlation degree can be determined, as shown in Table 5.

Table 5 The correlation degree division of materials

U	$AF_A^{(\alpha,\beta)}(n)$	$MB_A^{(\alpha,\beta)}(n)$	$DN_A^{(\alpha,\beta)}(n)$
1	{1,2,5,7-8,12,37,47}	{3-4,6,9-11,13-36,38-46,59-60}	{48-58}
2	{1,2,5,8,12,24,31,37}	{3-4,6-7,9-11,13-23,25-30,32-36,38-48,52,56,58-60}	{49-51,53-55,57}
3	{3-4,6,9-11,13-21,32-36,38,40-45}	{1-2,5,7-8,12,37,47-60}	{22-31,39,46}
4	{4,11-19,35-44,48-52,60}	{1-3,5-10,20-23,31-34,45-47,53-59}	{24-30}

According to the division of material correlation degree shown in Table 5, the correlation degree of materials can be determined thus: {1-2,5,7-9,22-30,46}, {3-4,6,10-20,32-39,42-45,47-49,58-60}, {21,31,40-41,50-57}; that is:

$$X = U/C_A = \left\{ \begin{array}{l} \{1-2,5,7-9,22-30,46\}; \\ \{3-4,6,10-20,32-39,42-45,47-49,58-60\}; \\ \{21,31,40-41,50-57\} \end{array} \right\}$$

Finally, index reduction is carried out according to the classification of correlation degree. Conditional attribute indexes are found and deleted. By calculation, reduction is as follows:

$X_1 = U/(C - C_1)$; $X_2 = U/(C - C_2)$; $X_3 = U/(C - C_3)$; $X_4 = U/(C - C_4)$; $X_5 = U/(C - C_5)$; $X_6 = U/(C - C_6)$; $X_7 = U/(C - C_7)$; $X_8 = U/(C - C_8)$; $X_9 = U/(C - C_9)$; $X_{10} = U/(C - C_{10})$; $X_{11} = U/(C - C_{11})$; $X_{12} = U/(C - C_{12})$.

Reduction results of

$U/(C - C_2)$, $U/(C - C_2 - C_4)$, $U/(C - C_2 - C_4 - C_6)$,
$U/(C - C_2 - C_4 - C_6 - C_8)$, $U/(C - C_2 - C_4 - C_6 - C_8 - C_9)$,
$U/(C - C_2 - C_4 - C_6 - C_8 - C_9 - C_{10})$, and $U/(C - C_2 - C_4 - C_6 - C_8 - C_9 - C_{10} - C_{12})$

are equal, and it is found that the reduction does not influence the classification results. Therefore, the minimum set of attributes can be obtained as $\{C_1, C_3, C_5, C_7, C_{11}\}$; that is, the original 12 indicators can be reduced to 5.

- *Application of PNN material classification discriminate model*

Based on the material attribute reduction, the materials of Enterprise A are classified into four grades from material value, importance, complexity, and risk by experts' evaluation, according to the five attributes of material attributes reduction (each attribute of each classification is scored with a score of 0−10 points). The classification result is verified by PNN. The four grades of materials after material classification are: I (strategic material), II (bottleneck material), III (general material) and IV (leveraged material).

As can be seen from the material attribute reduction results, there are five main attributes that influence the material classification of Enterprise A, namely the influence of supplier interruption, substitutability, product complexity, proportion in total procurement expenditure, and the influence of materials on product quality. Therefore, the input layer of PNN has five nodes corresponding to these five characteristic parameters. In this paper, cross-validation is applied to cross-train and tests the 60 sample data in Table 2. The number of radial basis neurons is determined by the number of the training samples and the number of the neurons in the second layer of PNN is equal to the number of the classification patterns, which are I (strategic material), II (bottleneck material), III (general material), and IV (leveraged material). Therefore, the number of the neurons in the second layer of PNN is four. The transfer function of the second neuron layer is a competitive transfer function, which selects the results with the largest distance weight values as the network's output; that is, the most possible classification pattern results, corresponding to the input vectors, are taken as the output.

In this paper, Matlab is used to write the simulation program, and network training adopts the method of cross-validation [30].

Step 1: Randomly select a number of sample data (32 groups) from each category of expert evaluation for PNN training and the remaining 28 groups for testing. The training results and prediction effect of PNN are shown in Fig. 3 and Fig. 4.

Step 2: Test data in Step 1 (28 groups) are used for training, while the 32 groups training data in Step 1 are used for testing. The training results and prediction effect of PNN are shown in Fig. 5 and Fig. 6.

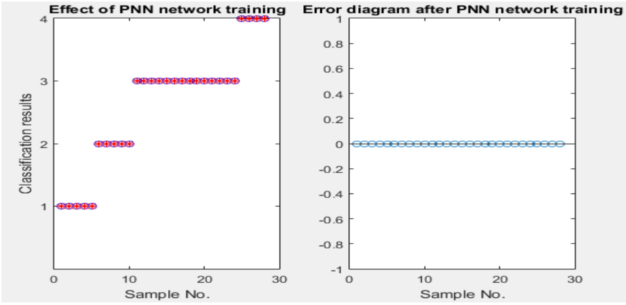

Fig. 3 Effect and error diagram of PNN network training 1

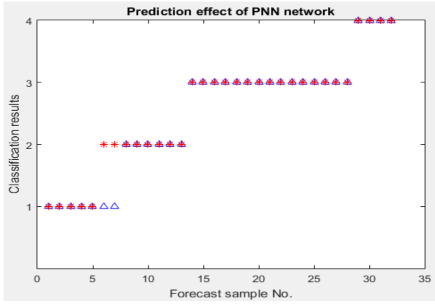

Fig. 4 Prediction effect of PNN network 1

Fig. 5 Effect and error diagram of PNN network training 2

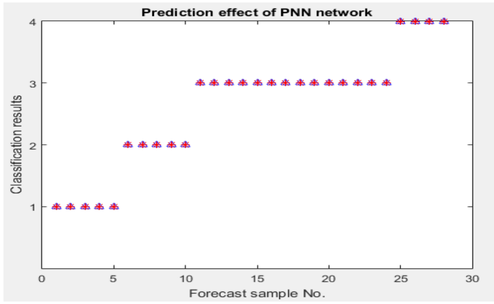

Fig. 6 Prediction effect of PNN network 2

This is equivalent to testing all the data in this way. The probability of each category is obtained by cross-validation. Finally, the classifications are given. Combining the results of the two rounds of training tests, the total accuracy of 98.3 % is obtained by calculation. From the classification results, the established PNN has the ability of accurate classification recognition.

4.2 Application of inventory control strategy matching model based on material classification

- *Application of (T, S) strategy model*

According to the inventory control strategy matching model, it can be seen that (T, S) strategy is suitable for the inventory control of strategic materials. This paper takes material 26 (general machinery and equipment) as an example to apply the (T, S) strategy model. According to the personnel experience of inventory management of material 26, the inspection cycle is generally set for 12 weeks, thus $T = 12$; the lead time of order is four weeks (i.e., $p = 4$); the service level is 95 %, and the minimum number of packages is four. According to the table of customer service level and safety factor (Table 6), the safety factor $k = 1.65$, and according to the normal distribution test results of enterprise demand prediction, $\mu = 41$ and $\sigma = 22$. Thus, there are:

Maximum inventory $S = Iss + \mu(T + p) = 1.65 \times 4 \times 22 + 41 \times 12 = 801.2$

Check that the inventory level at the beginning of the month is 779, and order quantity is $Q = roundup\ [(801.2 - 779)/4] \times 4 = 24$.

Table 6 Common customer service level and safety factor table

Service level (%)	100	99	98	97	96	95	90	85	80
Safety factor	3.09	2.33	2.05	1.88	1.75	1.65	1.28	1.04	0.84

- *Application of (Q, R) strategy model*

From the matching model of inventory control strategy, it can be seen that (Q, R) strategy is suitable for the inventory control of bottleneck materials. This paper takes material 48 (petroleum drilling equipment accessories) as an example to apply (Q, R) strategy model. According to the inventory information of material 48, its purchase price is $p = 79.19$ yuan/piece, the cost of a single order is $C_i = 24885$ yuan/time, the single shortage cost is $C_{i\eta} = 420$ yuan/piece, and the unit storage cost is $S_i = 2.5$ yuan/piece/week. According to the fitting result of material 48 demand data in time t ($t = 36$), the demand distribution of material 48 in unit time is $D_i \sim N(185, 8)$. Therefore, demand distribution in time t is $D_{it} \sim N(6660, 36^2 \times 8)$; that is: $\mu_{D_{it}} = 6660$, $\sigma_{D_{it}} = 72\sqrt{2}$; lead time $p = 8$, and the demand distribution within the lead time p is:

$D_{ip} \sim N(1480, 8^2 \times 8)$, that is $\mu_{D_{ip}} = 1480$, $\sigma_{D_{ip}} = 16\sqrt{2}$; the service level is 95 %, and the shortage rate $\eta = 0.05$, and set $H(R_i) = \int_{R_i}^{+\infty} (D_{ip} - R_i) \cdot h \cdot (D_{ip}) \cdot d(D_{ip})$. Eq. 32 is rewritten thus:

$$\begin{cases} H(R_i) = \frac{\eta \times C_{i\eta} \times \mu_{D_{it}} - S_i \cdot t \cdot Q_i}{\eta \times C_{i\eta} \times \mu_{D_{it}}} \\ Q_i^2 = \frac{2\mu_{D_{it}} \left\{ C_i + \eta \times C_{i\eta} \left[\sigma_{D_{ip}}{}^2 \times h(R_i) - \left(R_i - \mu_{D_{ip}}\right) \times (1 - H(R_i)) \right] \right\}}{S_i t} \end{cases} \tag{46}$$

$$\begin{cases} H(R_i) = \frac{0.05 \times 420 \times 6660 - 2.5 \times 36 \times Q_i}{0.05 \times 420 \times 6660} = 1 - \frac{90 Q_i}{139860} \\ Q_i^2 = \frac{2 \times 6660 \left\{ 24885 + 0.05 \times 420 \left[512 \times h(R_i) - (R_i - 1480) \times \frac{90 Q_i}{139860} \right] \right\}}{2.5 \times 36} \end{cases} \tag{47}$$

Take $Q_i = \sqrt{\frac{2\mu_{D_{it}} \cdot C_i}{S_i t}} = \sqrt{\frac{2 \times 6660 \times 24885}{2.5 \times 36}} = 1919.11$ and substitute $Q_i = Q_1$ in Eq. 1 for Eq.47 to obtain R_1; then $R_i = R_1$ in Eq. 2 is substituted with Eq. 47 to obtain Q_2; substitute $Q_i = Q_2$ in Eq. 1 for Eq. 47 to obtain R_2; then $R_i = R_2$ in Eq. 2 is substituted with Eq. 47 to obtain Q_3; iterate over and over again until the convergence state of $Q_{k+1} = Q_k$ is reached. At this point, Q_k and R_k are solved. The final solution is:

$$\begin{cases} Q_k = 2064 \\ R_k = 1848 \end{cases}$$

- *Application of (s, S) strategy model*

From the matching model of inventory control strategy, it can be seen that (*s, S*) strategy is suitable for inventory control of general materials. This paper takes material 59 (packaging materials) as an example to apply (*s, S*) strategy model. According to the personnel experience of inventory managers, the lead time of material 59 is two weeks, the service level is 90 %, and the safety factor is 1.28, which is obtained by Table 6. The mean demand in lead time is $\mu = 7198$ and the standard deviation is σ =3288. Therefore,

Order point $s = \mu \times p + k \cdot \sqrt{p} \cdot \sigma = 7198 \times 2 + 1.28 \times \sqrt{2} \times 3288 = 20348$ pieces;

Maximum inventory level $S = s + \mu p = 20348 + 7198 \times 2 = 34744$ pieces;

Material 59 is inspected once a week. If the inventory level is 18,000 on Monday, which is less than 20,348 at the ordering point, the order should be issued. If the minimum number of packaging units for the material is 1,000, then:

Order quantity $Q = roundup\ [(34744 - 18000)/1000] \times 1000 = 17000$ pieces.

- *Application of (T, s, S) strategy model*

According to the matching model of inventory control strategy, it can be seen that (*T, s, S*) strategy is suitable for inventory control of leveraged materials. This paper takes Material 2 (petroleum special pipe) as an example to apply (*T, s, S*) strategy model. According to the personnel experience of inventory management of Material 2, the inspection cycle is generally set for eight weeks; thus, T = 8, the lead time is two weeks, that is p = 2; the service level is 95 %, and the minimum packing number is 2 tons. From the common customer service level and safety factor table (Table 6), the safety factor k = 1.65. According to the normal distribution results of enterprise demand prediction, μ = 18, σ = 7. Therefore,

Order point $s = \mu(T + p) + k\sigma(T + p) = 18 \times 10 + 1.65 \times 7 \times 10 = 295.5$ tons;

Maximum inventory level $S = s + \mu(T + p) = 295.5 + 18 \times 10 = 475.5$ tons.

If the inventory level after inspection is 280 tons, less than the order point 295.5 tons, and the minimum package quantity is 2 tons, then:

Order quantity $Q = roundup[(475.5 - 280)/2] \times 2 = 196$ tons.

5. Conclusion

Inventory control is an important issue in supply chain management. There are many attributes of inventory materials in enterprises, and the degree of influence of different materials on enterprises is also different. Faced with the new production and delivery, the manner of scientifically classifying the materials of the enterprises and making scientific inventory control strategy are of great practical significance for effectively reducing the operating costs of enterprises, improving the ability of material support, and further promoting the development, transformation and upgrading of the enterprises.

In this paper, the classification and inventory control strategies of multi-attribute materials were systematically studied. Firstly, the evaluation index system of material attributes was constructed from three aspects: procurement risk, proportion of the value and strategic importance. Then, the grey rough set algorithm was used to reduce the attribute of the material attribute index to achieve the aim of removing repetitive and redundant attributes. On this basis, the discriminate model of material classification was constructed based on the PNN approach. It is simple and practical; it has a fast training speed and a good output effect on network simulation, which can solve the material classification problem well. Then, based on the classification results, different inventory control strategy models for strategic materials, bottleneck materials, general materials and leveraged materials were proposed. That is to say, an inventory control strategy matching model based on material classification was built to provide a powerful basis for enterprises to formulate targeted inventory control strategies. Finally, taking a chemical enterprise (i.e., Enterprise A) as an example, using the classification approach, inventory control strategy and the corresponding model proposed in this paper, the material classification scheme of Enterprise A was obtained, and the order schemes under different inventory control strategies were obtained by calculation. The results strongly illustrate the feasibility and validity of the model and the method built in this paper.

The limitation of this paper is that only static inventory control strategy is considered. However, the improvement of other inventory control strategies, such as the dynamic inventory control strategy and the static-dynamic inventory control strategy need to be further studied.

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