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Improved Inventory Management for Retail Stores based on Intelligent Demand Forecasts

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Abstract

In order to meet the increasing daily demands of customers and reduce the unnecessary cost in retail stores as far as possible, the inventory management of retail stores becoming more and more important. However, because of various characteristics of demand in retail stores, the traditional demand forecasting technologies can't work well. In this paper, we use the modified K-means clustering analysis to help determine the groups with different characteristics of demand. In addition, a demand forecasting model integrated BP neural networks and grey model is proposed to make the prediction more intelligent and general. The example illustrates that the proposed method for forecast is feasible by the comparative analysis between the predicted values and the actual values.

Keywords: *Demand forecasting, clustering analysis, retail stores, BP neural network, grey theory*

1. Introduction

With the development of the commodity economy, the retail stores provide customers with diverse types of commodities in daily life [1-3]. At the same time, the inventory management and control becoming more and more important. While the traditional inventory management technologies gradually can't satisfy the new relationship between the supply and demand [4]. Various commodities in stores make its management more difficult. In addition, it will weaken and confuse the manager of small and medium-sized stores to plan on how to place orders for the changeful demands in the future [5, 6]. And the unnecessary cost will cause with the difference between the actual demand and the order's amount increases.

So far, there are many models have been proposed for commodities demand forecast, in which neural network model is one of the most efficient one. The research on artificial neural network (ANN) has becoming increasingly important since 1980's. The BP neural network model, as one of the most important artificial neural network model, was proposed firstly [7].

In the present, the BP neural network has been used widely in engineering fields, especially in artificial intelligence, forecasting, and inventory control.

In its applications, Partovi and Anandarajan [8] presented artificial neural networks (ANNs) for ABC classification of stock keeping units (SKUs) in a pharmaceutical company. Two learning methods were utilized in the ANNs, namely back propagation (BP) and genetic algorithms (GA). Furthermore, the ANN models are compared with the multiple discriminate analysis (MDA) technique. The results showed that both ANN models had higher predictive accuracy than MDA.

Taking the BP neural network into consideration, Liu Yang *et al.*, [9] added the impact factor to modify the inventory model, which made the better prediction.

Zhao and Ji [10] proposed quantitative model to apply the flexible BP neural network to simulate the inventory system when the random (s, S) inventory algorithm failed to

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reflect the qualitative factors, causing the calculated results unable to present the real re-order point. As an important aspect of inventory management, safe inventory forecasting was able to predict the trends in the future, providing the decision making for enterprises with more evidences [11]. Moreover, accurate and in-time forecasting apparently reduced operating cost and risk of investment for enterprises. For instance, when analyzing the factors that may affect the safe inventory in retail stores, establishing the trained BP neural network was much more accurate than that of other ways [12].

Atsalakis and Valavanis [13] used a neuro-fuzzy based methodology to forecast stock market short-time trends. And the methodology presented and the reported results challenged the weak form of the EMH, since the proposed novel neuro-fuzzy system could predict with significant accuracy stock price trends using historical stock market prices.

High effective neural networks need to consider more different parameters like the training way of samples and the algorithm of artificial neural network. Bad parameters will reduce the forecasting accuracy.

When the BP neural network merged some inventory controlling technologies, it was more precise in predicting the demands by modifying the accuracy of learning and improving the speed of convergence [14, 15]. Zhang and Jia [16] found that the time-serial-based neural network model was more accurate than that in AR model while it was less accurate than that in ARI model. In fact, it was more effective when dealing with the network trapped in flaws of local minima and slow speed of convergence [17].

By the previous analysis, there were some related researches in application of inventory management and demand forecasting with BP neural network. However, most of them focused on using a primitive BP neural network to predict the demands of only one kind of commodity directly. Our purpose here tries to meet the potential requirement of the market and keep the inventory level as low as possible in the entire management of retail store at the same time. Thus, this paper proposed a novel intelligent and automatic forecasting model so as to continuously improve the quality of management of the entire retail store in the future, which is a good reference to establishing more intelligent commodities management information systems for retail stores in the future.

On the basis of related works in introduction and a new proposed commodity management model in Section 2, we proposed a modified K-means clustering analysis method to study a new intelligent model to quickly cluster the commodities with different characteristic of demand in Section 3. Taking grey theory into consideration, we use BP neural networks to establish a more reliable and intelligent forecasting model in Section 4. At last, we concluded our work in Section 5.

2. The Common Management Model for Commodities in Retail Stores

There are diverse characteristics of demands among the commodities in a retail store. For instance, some commodities with seasonal characteristic of demand sell well in certain months while the others with random characteristics have a stable level of demand throughout the year. Different levels of demand in different stages will directly affect the commodity inventories in a retail store. Wrong decisions in ordering will cause either higher or lower inventory, result in unnecessary cost. The sufficient inventory will force the manager naturally to reduce the next batch orders while too many orders will cause the additional cost in their inventory. Hence, the problems above are chiefly due to the empirical and traditional forecasting models that fail to reflect various characteristics of demand.

The key to study the problems in retail stores eventually lies in the research of commodity management in retail stores. Thus, in this section we will propose a common model in commodity management for a retail store. Suppose that there are N_g types of commodities in a retail store. It is denoted as $G=\{G_i|1\leq i\leq N_g\}$. Thus, The historical sales of the i-th commodity in the n-th month of the m-th year is a set of $\{S_{i,m,n}|1\leq i\leq N_g,0\leq m,1\leq n\leq 12\}$. If G can be divided into L levels of sales, the i-th set of commodities stands for L_i which can be defined as $\{G_{li}\}$. There is a method denoted as C to meet the mapping relationship of $G\rightarrow(L, W)$ where $W=\{W_i\}$ stands for significant level of L_i in L. The whole process of clustering and demand forecasting is shown in Figure 1.

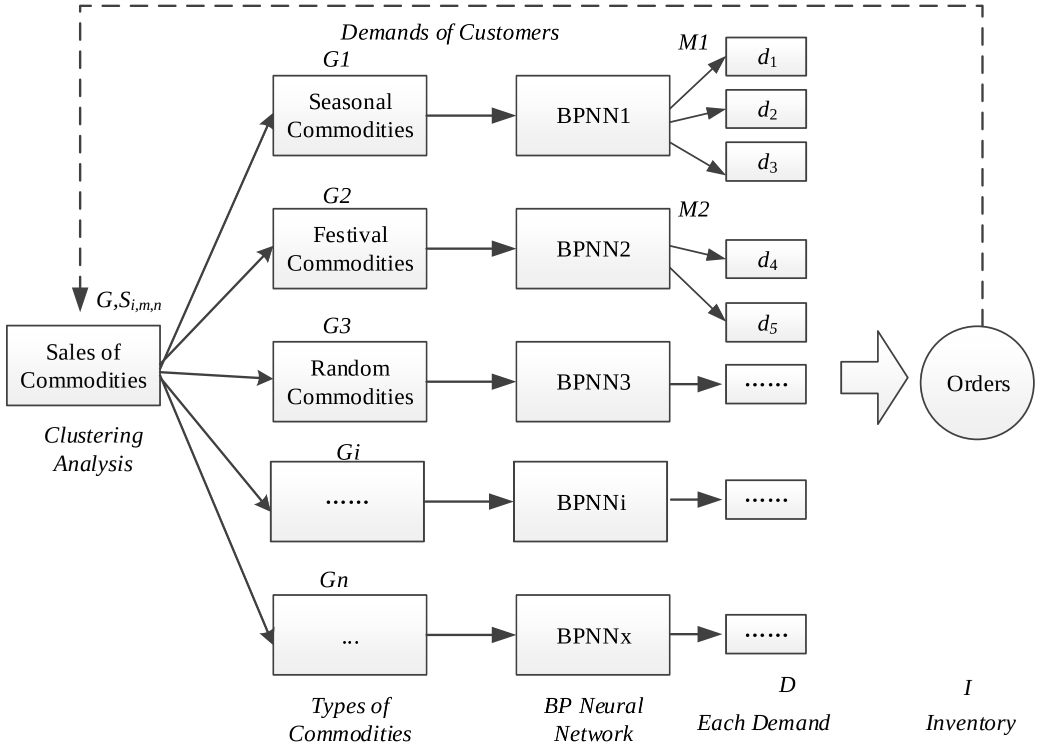

Figure 1. The Process in the Proposed Demand Forecasting

In Figure 1, suppose d is the demand for some time. C is denoted as a set of methods including the activity based ABC classification method and clustering methods, which classifies the commodities based on their different characteristics.

The commodities in the same sales level L have similar laws R, which is abstracted to the detailed demand model. Thus, there exists a relationship of mapping: $R\rightarrow M$, where M is an abstract symbol of demand forecasting model. M is a forecasting model based on historical sales data. And the demand for a type of commodities each month can be defined as $D_{i,m,n}=M(G_{i,m,n})$. Let the inventory system for each type of commodity be I_i. The model above is based on continuous changes with time changing. That is why we get predicted values, which is a basis in inventory systems to work normally.

Considering we use artificial neural network in continues inventory control in retail stores, a common intelligent inventory model in the retail store is made in Figure 1. Establishing the BP neural network needs to be based on certain amount of historical demand data. Training by BP neural network, an intelligent forecasting model with grey model in Figure 2 is created to predict the sales of commodities in the future.

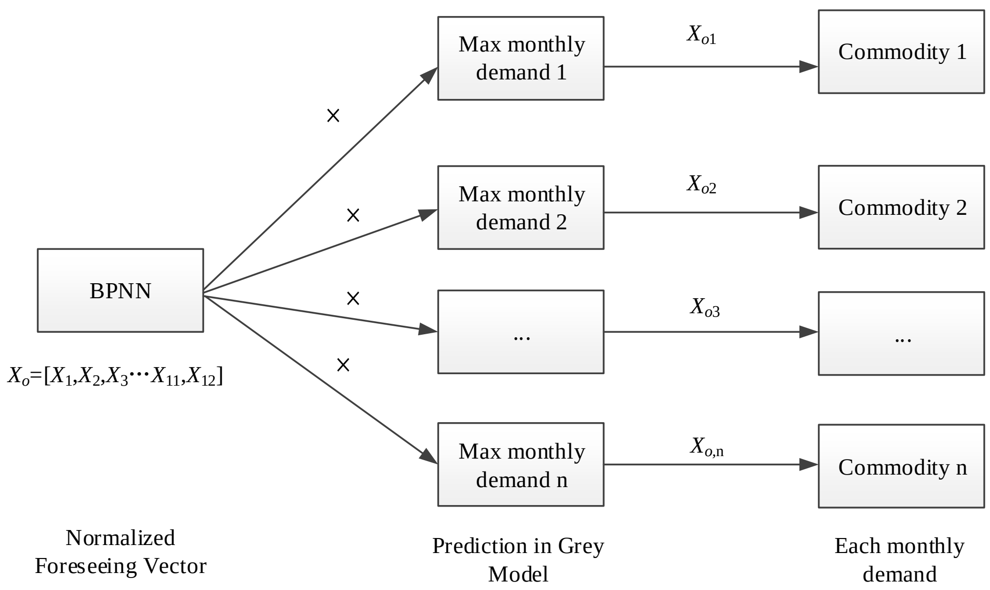

Figure 2. The Demand Forecasting for Single Commodity using Grey Model in BPNN

The determination of each order is based on the last forecasting results which have been merged into the neural network. Thus, the prediction each time will update the data of BP neural network which makes forecasting more precise, improving the whole quality of inventory in the store. After we acquire the demand next month based on the proposed model above, the next process of order management becomes more easily as in Figure 3 shown.

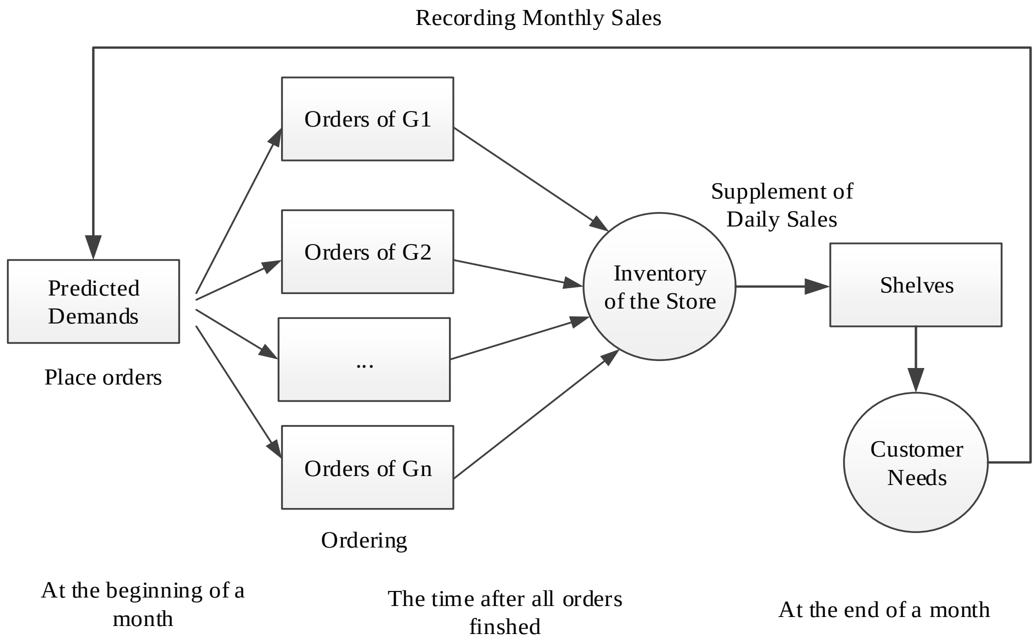

Figure 3. The Process of Ordering in Retail Stores after the Demand Prediction

In Figure 3, the manager of the store determines the orders based on the predicted demands and the current inventory level using other EOQ models. The sales staffs should check the quantity of commodities on the shelves every day to supplement the commodities that has almost sold out. Because of the wide use of management information systems nowadays, it is easy to know the monthly sales at the end of the month. So we can predict the next monthly demands for all commodities based on the new evolved intelligent forecasting model, which will be discussed as follows.

3. The Clustering Analysis of Commodities in Retail Stores

In inventory management, generally, a method called Activity Based ABC Classification is used to determine the different ways to manage the things. Using this method, we need to sort all the commodities according to the overall profit of each commodity and divide all commodities into 3 types. They are namely Type A, Type B, and Type C. The value of Type A is highest, which need to be focused cautiously by the manager. Clearly, using ABC will have many problems when applying to demand forecasting in retail stores because of the various characteristics of demand like the characteristics in festival, random, and season. How to quickly classify the commodities with different characteristics and establish the forecasting model for each type of characteristics so as to implement the same strategies of ordering for each type is very important.

Here we propose an improved K-means clustering method with a concept of weight of diversity to quickly cluster the commodities with unknown characteristics of demand. It will establish a foundation for the forecasting model later.

Based on the Clustering analysis, we can build a forecasting model and make some strategies for the commodities with the same demand characteristics so as to improve the commodity management in retail stores. In order to reduce the complication, we will choose some typical characteristics of demand to analyze in detail. As shown in Table 1, it is the raw sales data in a case of 20 commodities which we use to analyze as followed.

Table 1. The Raw Sales Data of 20 Commodities in a Year

Month	1	2	3	4	5	6	7	8	9	10	11	12
G1	134	134	135	136	133	136	137	138	139	134	132	133
G2	50	120	70	60	50	140	100	60	50	140	50	30
G3	1	2	90	120	130	90	30	20	3	1	0	1
G4	20	100	90	10	30	123	90	50	12	120	50	138
G5	10	20	190	222	500	400	345	123	123	44	44	1
G6	91	87	88	98	90	90	91	86	96	95	90	92
G7	0	0	0	0	120	344	20	0	0	0	0	0
G8	120	190	300	250	200	100	80	150	220	250	150	80
G9	46	50	45	51	46	43	47	52	44	46	50	50
G10	0	0	0	0	23	444	22	0	0	0	0	0
G11	1130	1300	1500	2110	1600	1000	800	700	1220	2344	1378	700
G12	15	40	60	30	10	12	45	70	50	30	25	3
G13	2166	2100	2337	2251	1500	2143	2317	2352	1300	1900	2400	2300
G14	0	145	120	0	0	0	0	0	0	0	0	0
G15	241	250	237	251	242	243	237	252	246	246	250	237
G16	115	140	220	130	65	112	145	170	150	130	125	63
G17	0	0	0	0	456	100	0	0	0	0	0	0
G18	0	0	0	0	0	0	0	0	0	0	30	90

G19	80	240	360	230	165	112	90	120	150	300	200	112
G20	2141	2250	2337	2251	2242	2143	2317	2352	2246	2246	2520	2237

In Table 1, apparently, we find that the monthly sales are different. As a retail store, it has a great amount of commodities. Hence, it is not realistic to establish the forecasting model for each individual commodity manually, which shows the potential value of what we try to study in this paper.

Based on data in Table 1, we implemented the standard K-means clustering analysis with a parameter 5 as the number of clustering in Origin 9.0. The monthly demand in a year is normalized by dividing the maximum monthly demand to remove their dimensionless. Finally, the results of analysis are shown in Figure 4. We found that the possible characteristic of commodities in sub graph (c) is seasonal. And sub graph (a) has the characteristic of random while sub graph (b) shows characteristic of stable demand. There are three main types of clustering in Figure 4. As we described previously, using the K-means clustering methods was much more useful and detailed than that in ABC.

However, the standard K-means clustering method uses the Euclidean distance to compare two samples mathematically. It will cause unexpected problems in practical applications. For instance, in sub graph (a), we noticed that the curve of the commodity G13 has huge variation compared with the curves of other commodities. Intuitively, G13 should be classified into sub graph (c) instead. The reason for the problem is that the K-means clustering method uses the Euclidean distance directly, not the fuzzy calculation to calculate their similarity. Hence, an improved way that modifies the function of distance calculation by importing the weight factor of variation is proposed in the followed. In other words, it rewrites the function of calculating Euclidean distance.

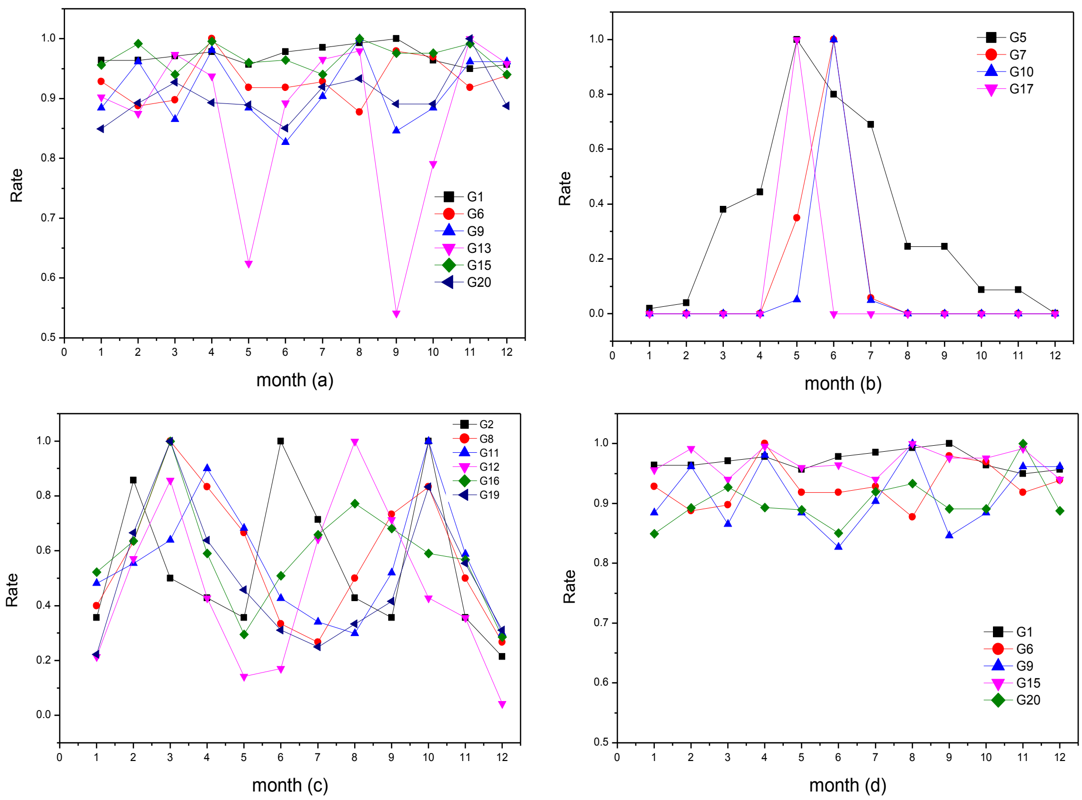

Figure 4. The Comparative Clustering Results of Commodities

Define the weight set as $W=\{w_i|0\leq i\leq n\}$ and the rate interval set R as $\{[a_i, a_{i+1})|\ 0\leq i<n\}$. And the maximum variation rate is $R_{\max}$. So we can get:

$$[a_i, a_{i+1}) = [\frac{i}{n}, \frac{i+1}{n}) \times R_{\max} \tag{1}$$

Suppose that there are two yearly demand vectors as X1 and X2, then the modified value of similarity can be calculated as:

$$r = \sqrt{\sum_{j=1}^{n_x} ((x_{1j} - x_{2j}) \times w_{ji}(x_{1j} - x_{2j}))^2} \tag{2}$$

In equation (2), $w_{ji}(x)$ can be defined as:

$$w_{ji}(x) = \begin{cases} w_i & a_i \le x \le a_{i+1} \\ 1 & otherwise \end{cases} \tag{3}$$

In (1), R_{max} is the maximum value of rate up to 1. Function $w_{ji}(x)$ denotes the relationship between the weight w_i of j-th demand vector and variation rate x. Based on (1) - (3), we used C++ to rewrite the K-means clustering method. Finally, we recalculated the clustering results using our proposed methods. And the new parameters we set up were R_{max}=1, W={1,1,1,1,2} and R={(0,0.010),(0.10,0.15),(0.15,0.20),(0.25,0.30),(0.30,1.1)}.Finally,the clustering results are shown in Table 2.

Table 2. The Clustering Results in Standard K-means Clustering and Modified K-means Clustering

ID	Standard K-means Clustering	Modified K-means Clustering
1	G1,G6,G9,G13,G15,G20	G1,G6,G9,G15,G20
2	G2,G8,G11,G12,G16,G19	G13
3	G3,G14	G2,G8,G11,G12,G16,G19
4	G4,G18	G4
5	G5,G7,G10,G17	G3,G5,G7,G10,G14,G17,G18

As in Table 2, it was found that the clustering results changed after we implemented the modified K-means clustering algorithm. Besides, in the sub graph (d) of Figure 2, we found that the commodity G13 had been removed from the clustering of commodities with characteristic of stability. We concluded that the modified K-means clustering method is much more applicable in the clustering commodities in retail stores.

4. The Demand Forecasting Model Based on BP Neural Networks

By the modified clustering analysis above, we can get a good classification of commodities. However, based on the clustering results, how to establish an intelligent forecasting model to reduce the complication of prediction for each commodity in retail stores is also the key in this paper.

As mentioned in Section 2, artificial neural network can solve more complicate problems than that in traditional methods. At the same time, the intelligent of this method makes it unnecessary for the manager to care about the details in prediction. The BP neural network in this paper is one of the most powerful artificial networks. Theoretically, if there are enough hidden layers and trained data, BP neural network can unlimitedly approach the real not-linear mapping relationship, whereas establishing the analytic equations can't work better. The BP neural network's result is calculated by finding the relationship between the input and the output by training and learning, instead of depending on prior knowledge and rules.

Here a forecasting model for the demand of a commodity is based on the BP neural network and grey theory. BP neural network is denoted as BPNN. Suppose the input vector set is X, the expected output vector is Y and the number of attributes of X is n. The samples of X and Y can separately be defined as X1, X2…, Xn and Y1, Y2, Y3,…, Yn (n equals 12 months). The number of hidden layers and the number of neurons in each layer rely on the case itself.

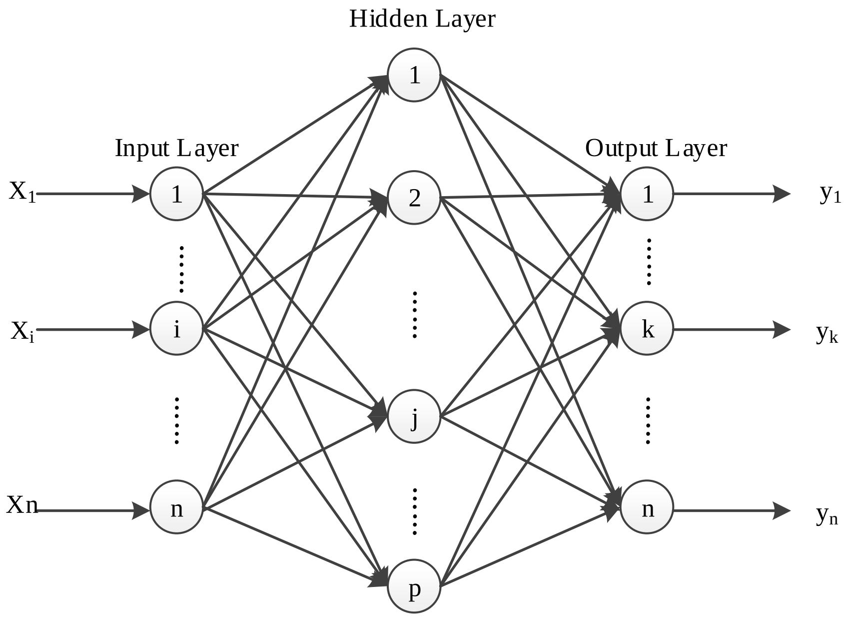

Figure 5. The BP Neural Network Diagram

The Figure 5 is a BP network with three layers which contains one input layer, one hidden layer and one output layer. Its training process consists of forward calculation and back-propagation. In this paper, a simplified engineering BP neural network can be denoted as following.

(1) Initiate W_{ij} and θ_j with random number. W_{ij} is the connection weight between the node i and j, i and j is in the different layer. θ_j is the threshold value of the node j.

(2) Read in the preprocessed training sample $\{X_{pn}\}$.

(3) Calculate the output of the nodes in each layer. The P-th sample is:

$$O_{pj} = f\sum_i (W_{ij}I_{pi} - \theta_j) \tag{4}$$

In the equation, I_{pj} is the output of the node i and the input of node i at the same time.

Calculate the error signal of nodes in each layer:

The output layer:

$$\xi_{pk} = O_{pk}(y_{pk} - O_{pk})(1 - O_{pk}) \tag{5}$$

The hidden layer:

$$O_{pi} = O_{pi}(1 - O_{pi})\sum_i \xi_{pi}W_{ij} \tag{6}$$

(4) Back-propagation

The weight correction:

$$W_{ij}(t+1) = \alpha \xi_{pi} O_{pi} + W_{ij}(t) \tag{7}$$

The threshold value correction:

$$\theta_j(t+1) = \theta_j(t) + \beta \xi_{pi} \tag{8}$$

In the above equation: α is the learning factor, β is the factor of momentum of the accelerating convergence.

(5)Calculate the error

$$E_p = (\sum_p \sum_k)(O_{pk} - Y_{pk})^2 / 2 \tag{9}$$

The equation 4-9 can be simplified as follows:

$$BNPN_0 = (X, Y, \theta, W, H) \tag{10}$$

$$X_t = BPNN_{t-1}(X_{t-1}) \tag{11}$$

In the above equations, the initiation of BP neural network depends on historical data and the threshold θ. It is trained repeatedly by X and Y based on a threshold θ. In the course of forecasting, using trained $BPNN_{t-1}(t \geq 0)$ to forecast X_t. For instance, the demand of commodities with the seasonal characteristic is mainly affected by seasonal changes. It shows the non-linear change periodically. In fact, BP neural network is able to approach the non-linear relationship by learning and training.

Here it is the data of a case in Table 3 to establish the forecasting model to predict the demand in the future.

Table 3. The Monthly Demand of a Commodity from 1997 to 2002 (×104 RMB)

	1997	1998	1999	2000	2001	2002
Jan	1.41	1.5	1.71	1.92	2.1	2.23
Feb	1.85	2.13	2.31	2.82	2.89	3.2
Mar	3.01	2.81	3.81	4.67	4.84	5.02
Apr	4.2	4.52	5.2	6.38	6.5	7.15
May	4.33	4.2	4.72	5.91	6.03	6.78
Jun	4.5	4.66	5.21	6.55	6.72	7.22
Jul	5.1	5.36	6.12	7.46	7.67	8.54
Aug	5.3	5.7	6.51	7.99	8.12	9.61
Sep	4.52	4.76	5.34	6.68	7.35	9.57
Oct	3.54	3.8	4.45	5.75	5.68	6.02
Nov	1.76	2.49	2.98	3.29	3.78	2.24
Dec	1.76	2.49	2.98	3.29	3.78	2.24

As Table 3 shown, firstly, we normalized each yearly data just like in the process of clustering. In order to train the BP neural network, we selected the data from 1997 to 1999 as input vector X and data from 2000 to 2002 as output vector Y. After we finished training BP neural network, we inputted the historical demand data in 2002 into the network. After it evolved, we can get the predicted demand in 2003 as output vector throughout the trained BP neural network.

In fact, the output of trained BP neural network is a normalized vector where all data is less than or equal to 1. Here, we use grey theory to estimate the maximum demand in the year in order to convert the normalized values to actual monthly values. For a fuzzy system, sometimes it fails to work normally. That is why we need to consider the grey theory in predicting the maximum monthly demand. In this thesis, GM(1,1) model will be used. And MATLAB is applied in solving this model.

In order to verify the predictive ability of our proposed model, we compared the trained value with the actual demand. The result is as Figure 6 shown.

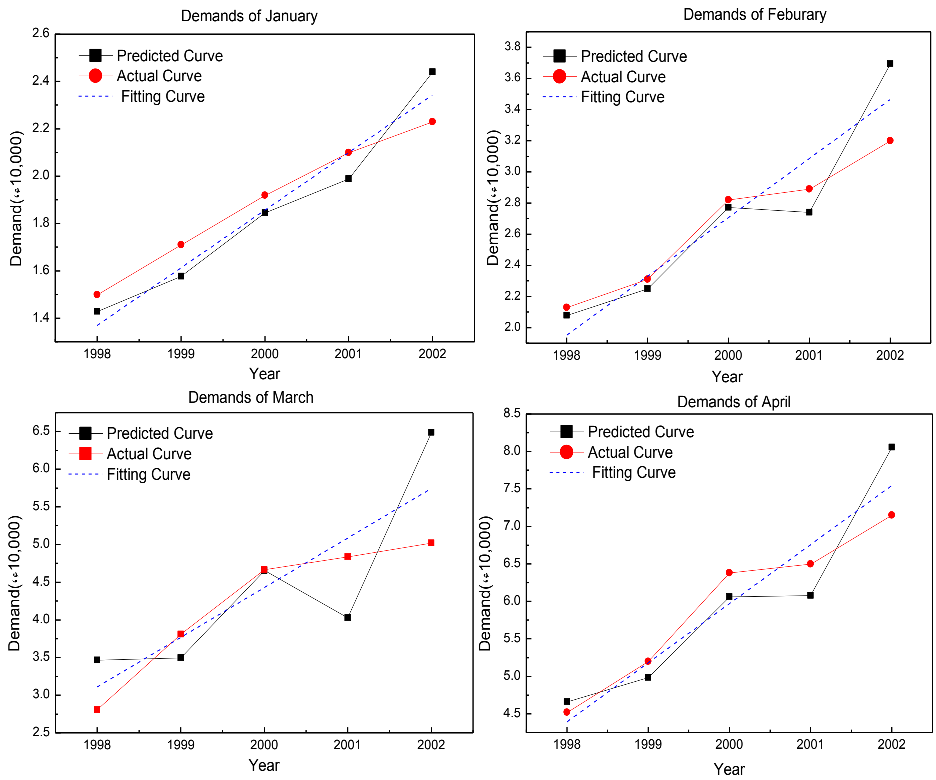

Figure 6. Comparison between the Forecasting Values and Actual Values

In Figure 6, we found that the forecasting values were rather close to the actual values and the linear fitting values. Actually as a fuzzy and intelligent forecasting model, the result we got was much more accurate relatively. The mean square error for each forecasting value is as in Table 4.

Table 4. Mean Square Errors for the Prediction each Time

MSE	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1998	0	0.041	0.316	0.016	0.015	0.004	0.001	0.013	0.415	0.015	0.511	0.011
1999	0.01	0.001	0.018	0.003	0.005	0.001	0	0.005	0.328	0.002	0.03	0.472
2000	0.02	0.025	0.171	0.275	0.2	0.317	0.294	0.294	0	0.341	0.382	0.282
2001	0.01	0.005	0.009	0.005	0.013	0	0.017	0.094	0.103	0.005	0.423	0.79
2002	0.003	0.045	0.208	0.138	0.052	0.223	0.116	0.005	1.208	0.394	1.143	1.877

In Table 4, though we found that though there were some serious errors occasionally, however, the most MSE is lower than 0.5. Thus, it was proved that BP neural network is effective and practical in forecasting to some degree.

The analysis above is about the demand forecasting for only one kind of commodities. As Figure 1 shown, we try to predict the whole demands of all commodities in retail stores at one time. Thus, it helps us to think over the combination of clustering analysis methods and multiple BP neural networks together to construct a parallel processing model. Thus, one BP neural network stands for one type of commodities with a characteristic of demand. With grey theory, it can predict the specific demand of each commodity in one type.

5. Conclusion

We firstly discussed the present problems in the demand forecasting and inventory management in retail stores. Based on the characteristics of commodities' demand in retail stores, we proposed a modified K-means clustering analysis to improve the precision of their classification. Taking the forecasting and reasoning ability of BP neural network and fuzzy prediction in grey theory into consideration, we established our intelligent demand forecasting model for retail stores. According to the comparative experiments, we proved superiority of our proposed model, which is also beneficial to the further development of the intelligent management information systems in retail stores.

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