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The inventory management system for automobile spare parts in a central warehouse

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Abstract

Because of the complex structure of spare parts supply chain, the conventional approaches, which do not consider the relationships between decision factors globally, cannot achieve the optimal performance. Therefore, this paper aims to develop an enhanced fuzzy neural network (EFNN) based decision support system for managing automobile spares inventory in a central warehouse. In this system, the EFNN is utilized for forecasting the demand for spare parts.

However, without considering relevant domain knowledge, traditional neural networks are found to be suffered from the problem of low accuracy of forecasting unseen examples. Therefore, in our EFNN, the following improvement is made: First, it assigns connection weights based on the fuzzy analytic hierarchy process (AHP) method without painstakingly turning them. Second, by generating and refining activation functions according to genetic algorithm, our EFNN can provide comprehensive and accurate activation functions and fit a wider range of nonlinear models. Last, but not least, an adaptive input variable is introduced to decrease the impact of the bullwhip effect on the forecasting accuracy.

The proposed system is evaluated with the real word data and experimental results indicate that our EFNN outperforms other five models in fill rate and stock cost measures.

Keywords: Neural network; Genetic algorithm; Spare part; Inventory

1. Introduction

Spare parts inventories of a central warehouse play an important role in improving the service level and reducing the operation cost of automobile supply chains and logistic systems. In order to maximize the fill rate and assistant a maintenance staff to keep automobiles in operating condition, the central warehouse have to keep quiet large amount of safety stock. As a result, much money is tied up and the inventory cost is quickly mounted. Therefore, reducing the inventory cost while maximizing fill rate becomes a focus study topic in recent years.

So far, the literature devoting the attention to the spares inventory management is often based on the assumption that the demand changed according to a statistic process (Kennedy, Patterson, & Fredendall, 2002). As a result, the safety stock and record point are always regarded as static and constant. In fact, in automobile spare parts industries, the demand is becoming more and more variable and uncertain. Such fluctuations of demand are sometimes due to the uncertain conditions of the final customers' automobile, but quiet often the supply chain is an important source of demand uncertainty (i.e. bullwhip effect) (Lee, Padmanabhan, & Whang, 1997).

In this situation, forecasting is promising to manage automobile spares inventory in the central warehouse. Therefore, in recent years, more and more researchers focused their studies on forecasting the demand for spare parts, which was helpful to improve the service level and reduce the inventory cost. Lots of literature has discussed and analyzed the forecasting models and algorithms of spare parts. However, minor attention has been devoted

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to the cases of the automobile spare parts in central warehouses, which sever thousands of local warehouses and final maintenance stations and order from thousands of inland or oversea suppliers.

The conventional approaches to forecast the demand for spare parts include managers' judgment simply based on their knowledge and experience, analog approach (Applebaum, 1996), time series analysis and regression model.

Basically, these approaches can only provide a set of systematic steps for problem solving without consideration the relationships between the evaluate factors globally. Moreover, the final outcome may also be affected significantly by the ability and experience of analysts.

The applications of artificial neural network (ANN) in forecast domain are very promising. In recent years, there have been lots of researches on how to use ANN to help us forecast many important factors based on a set of sample data. Among many areas of applications, demand forecast has become the focused one (Charytoniuk, Box, Lee, & Chen, 2000; Gorucu, Geris, & Gumrah, 2004).

Without combining relevant domain knowledge, these techniques are found to be suffered from the problem of low accuracy of forecasting the unseen examples. Furthermore, the activation functions of these ANNs are always set to a fixed and rigid form, for example, the most popular sigmoid function. In real life, they are incompetent to describe the nonlinear models because these nonlinear models are far more complex than the simple sigmoid function.

In this study, we attempt to solve the above problems by integrating the knowledge of domain experts into enhanced fuzzy neural network (EFNN), which generates connection weights based on the fuzzy analytic hierarchy process (AHP) method without painstakingly and time-consuming turning them. Moreover, our EFNN generates and refines more comprehensive activation functions by genetic algorithm (GA), which can accurately express a wider range of nonlinear models. Finally, an adaptive input variable is introduced to decrease the impact of the bullwhip effect on the forecasting accuracy.

Based on the EFNN, the dynamic spare parts inventory management system is proposed which consists of three components: (1) hierarchical structure development of the fuzzy AHP, (2) weights determination, and (3) decision making based on the EFNN. That will be discussed in Section 3 in detail.

This paper is organized as follows: Section 2 gives an overview of related works on the spare parts inventory management and ANN for demand forecasting. Section 3 describes the structure of our inventory management system, the hierarchical structure development for the evaluation factors of spare parts, and the fuzzy AHP method to generate the weight of each evaluation factor. Section 4 offers our EFNN. In Section 5, experiments with real word data are used to demonstrate the workability of our proposed method.

2. Literal reviews

The variety of research in the management of spares inventory and demand forecasting is very broad in scope over the past decades. However, it is beyond the scope of this paper to review all these areas. We will briefly review the researches which will be most relevant for our themes.

2.1. Spare parts inventory

The literature relevant to spares inventory management mainly focused on designing and testing the models or algorithms to improve the management of existing systems.

Caglar, Li, and Simchi-Levi (2004) studied a spares inventory problem faced by a manufacturer of electronic machines with expensive parts that were located at various customer locations. Assuming that parts failed infrequently according to a Poisson process, he formulated a model to minimize the system-wide inventory cost subjected to a response time constraint at each field depot.

Schultz (2004) demonstrated how the mean and variance of machine repair or down time affected cycle times at a given workstation and downstream workstations with existing closed-form approximation methods. Then, he presented a methodology for base stock parameters selection, while considering the trade-off between reduced cycle times and inventory investment.

Cheung and Hausman (1995) investigated a multiple failures problems in a continuous, infinite horizon, order-for-order spares replenishment inventory model. And they also derived exact expressions for the distribution function and the expectation of the number of backlogged jobs.

The researches mentioned above are mainly based on the assumption that the demand for spare parts changes according to certain statistic process. Generally, it is easy to know the scope of the demand in a large scale, but it is difficult to know the exact demand at a specific time. The analysts have to always painstakingly trade-off between the inventory costs and service level. Therefore, in recent years, more and more researchers focused their studies on forecasting the demand for spare parts, which was helpful to improve the inventory performance.

Foote (1995) performed a case study at the aviation supply office regarding the implementation of a new forecasting system. His control-based forecasting system mainly focused on the philosophy, mathematical principles, and system design features. Prakash, Ganesh, and Rajendran (1994) used the AHP to evaluate the criticality of spares. Their approach was to categorize the parts using a variety of partitioning techniques that complemented the use of good forecasting procedures including ABC analysis, FSN analysis and VED analysis. Ghobbar and Friend (2003) dealt with techniques applicable to predicting spare parts demand for airline fleets. They tested 13 forecasting methods and devised a predictive error-forecasting model which compared and evaluated forecasting methods based on their factor levels.

Basically, these approaches can only provide a set of systematic steps for problem solving without consideration the relationships between the evaluate factors globally. Therefore, more and more researchers focus their studies on the demand forecast based on ANNs.

2.2. ANN in demand forecasting

Nowadays, ANN has become the most popular method applied in order to solve the demand forecasting problems. However, the conventional ANNs always suffer from the problem of low accuracy in forecasting the unseen examples. Therefore, there exist many improved ANNs, which constructed based on other artificial intelligence techniques, such as GA, fuzzy system, and expert knowledge. Kuo (2001) proposed a fuzzy neural network (FNN) with initial weights generated by GA (GFNN) for the sake of learning fuzzy IF–THEN rules for promotion obtained from marketing experts. The result from GFNN was further integrated with an ANN forecast. Model evaluation results for a convenience store company indicated that the proposed system could perform more accurately than the conventional statistical method and a single ANN. Senjyu, Mandal, Uezato, and Funabashi (2005) presented an approach for short-term load forecast problems by combining ANN and fuzzy rules. The fuzzy rules, which were constructed based on the expert knowledge, were used to correct the neural network output to obtain the next day forecasted load. The test results showed that the proposed forecasting method could provide a considerable improvement of the forecasting accuracy. Chu and Zhang (2003) compared the accuracy of various linear and nonlinear models for forecasting aggregate retail sales. They found that the nonlinear models were able to outperform their linear counterparts in out-of-sample forecasting, and prior seasonal adjustment of the data could significantly improve forecasting performance of the neural network model.

The active functions of ANNs mention above are fixed and the connection weights are turned according to painstakingly back-propagation algorithm. However, our EFNN differ these ANNs in that: connection weights are generated based on the expert knowledge and the activation functions are produced and refined by GA.

3. The proposed system

3.1. Problems definition

The first step towards the development of the proposed system is the analysis of supply chains structure of spare parts, which is rather complex. In this study, we extract the common structure of supply chains from quiet large number of spare parts logistic systems of automobile company in China, as shown as follows.

As shown in Fig. 1, the central warehouse may order from hundreds of in-company, inland, or oversea suppliers, meanwhile, serve hundreds of local warehouses. The local warehouses may serve hundreds of maintenance stations and the maintenance station serves thousands of the end-customers. Hence the central warehouse serves a multi-echelon supply chain. It can be observed that moving towards the higher level of supply chain, orders show a more variable and uncertain pattern because of the bullwhip effect. Furthermore, the lead time of the central warehouse is always very long taking into account the widely distribution of suppliers and batch ordering. For instance, the lead time of most central warehouses of automobile spare parts in China is about one month.

Important is to consider that the central warehouse has no control of the local warehouses belonging to the supply chain. Moreover, no information is available regarding the stock level at each echelon, nor the specific recording polices of customers. Therefore, the only variable the central warehouse can control to adjust its inventory performance is its own stock level. However, in order to avoid out of stock, the central warehouse has to generate the high inventory level for a long time.

In this situation, demand forecasting based on domain knowledge is a most effective step to improve the inventory performance.

3.2. The structure of spares inventory management system in the central warehouse

The proposed system, as shown in Fig. 2, consists of three components: (1) hierarchical structure development of the fuzzy AHP, (2) weights determination, and (3) deci-

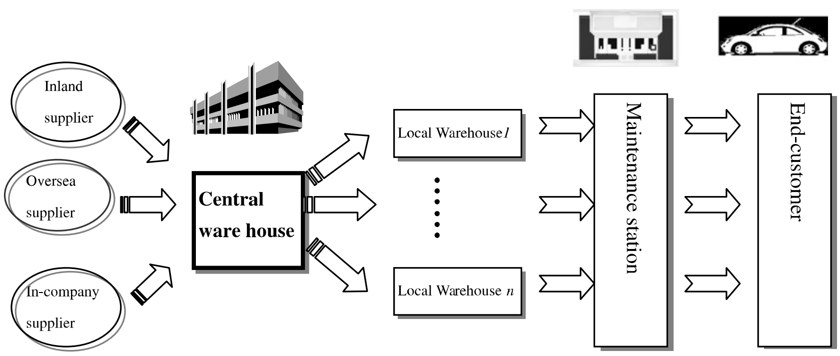

Fig. 1. The structure of spare parts supply chain.

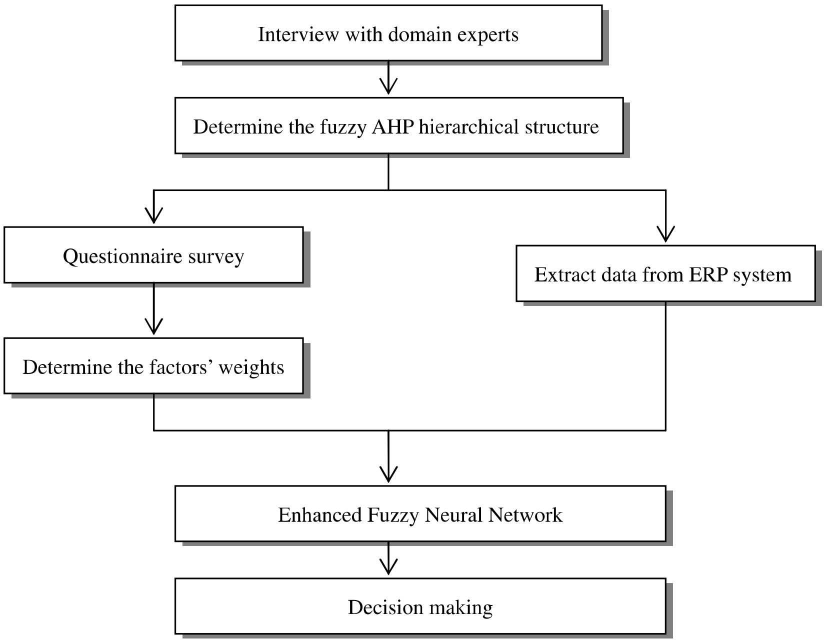

Fig. 2. The structure of spares inventory management system.

sion making based on EFNN. The evaluation factors are selected according to the knowledge of experts. The corresponding data for these evaluation factors can be extracted from the ERP system. Then, questionnaire surveys are conducted to compare relative importance of each evaluation factor to generate factors' weights. Application of EFNN, yield the decision for the safety stock and record point per period.

3.3. Hierarchical structure design for the evaluation factors

AHP is one of widely used multi-criteria decision-making methods. The main advantage of the AHP is that it can easily handle the multiple criteria and can effectively handle both qualitative and quantitative data. AHP involves the principles of decomposition, pair-wise comparisons, and priority vector generation and synthesis (Saaty, 1980).

The first step of AHP is to interview the domain experts to decompose the problem hierarchically. The structure of AHP is shown in Fig. 3. The first level demonstrates the overall objectives of the problems, that is, the demand for spare parts per period. The second level includes the criteria used for evaluating the alternatives. And the last level lists the sub-criteria (i.e. the evaluation factors).

3.4. Evaluation factors

At least 11 factors are evaluated, which are categorized into the following five dimensions:

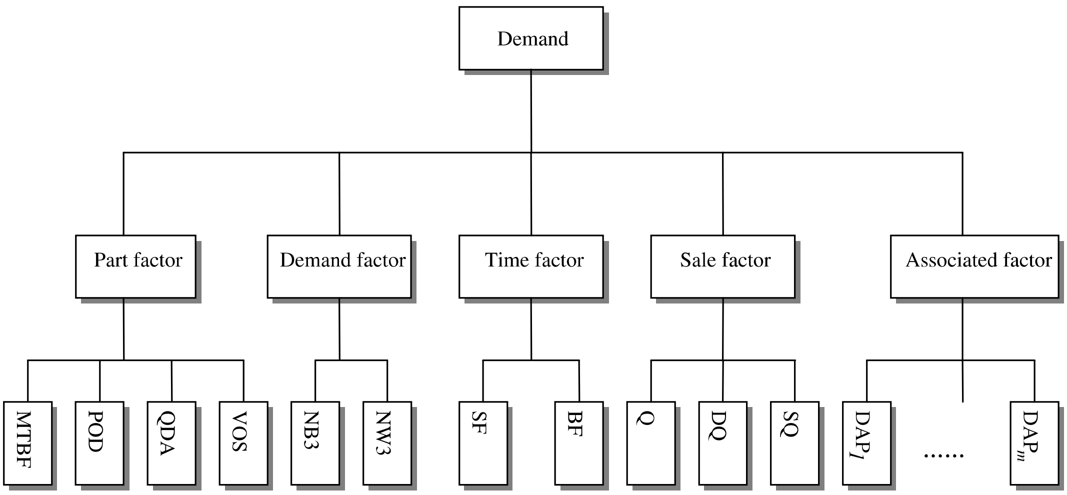

Fig. 3. The structure of AHP.

Part factors: It is found that the demand for spare parts is influenced by some features of parts, and we call these features "part factors". The part factors include the mean time between failures (MTBF), the probability of damage (POD) in general traffic accidents, the quantity assembled in one automobile (QDA), and the variety of its substitutes (VOS). MTBF and POD can be generated by reviewing some documents provided by suppliers and extracted form the historical data provided by some maintenance stations. QDA and VOS are obtained from the bill of material (BOM) offered by manufactures.

Demand factors: As to demand factors, we mainly think about the total number of automobiles sold within 20 years. And they can be further divided into two factors: the number of automobiles sold before 3 years (NB3) and those sold within 3 years (NW3). NB3 generates quiet large amounts of spare parts demand, while NA3 requires a little quantity.

Time factors: Time factors are composed of season factor (SF) and busy factor (BF). SF reflects the affection of climate indicators, such as high temperature, low temperature, humidity and the like. BF considers the busy degree of each month in a year. SF can be represented by the number of days whose temperature is beyond the usual range and the number of raining days per month. For instance, in areas k, SF can be formulated as follows:

$$\mathrm{SF}_{ij} = \sum_{k=1}^{K} (\mathrm{NB3}_k \times (H_{jk} + R_{jk})),$$

where SF_{ij} is the SF of part i in month j, $\mathrm{NB3}_k$ is the number of automobile sold 3 years ago in area k, H_{jk} is the number of days whose temperature is above 30 °C or below 0 °C in month j in area k, and R_{jk} is the number of raining days in month j in area k.

BF can be obtained by the questionnaire method. The questionnaire mainly targets on the managers of spares inventories and the working staffs in maintenance stations. However, in traditional questionnaire methods, the opinions of the domain experts are always inconsistent and sometimes contrary. In order to integrate different expert options, following steps are applied:

Step 1. Assign a weight to each expert based on their experience and knowledge on the spares inventories. We used four different degrees to evaluate each expert, namely: (1) most important, (2) very important, (3) important, and (4) a little important. These degrees ratings range in value from 4 to 1 (4 means most important and 1 means a little important).

Step 2. Send the questionnaires to the experts evaluated in step 1. In each questionnaire, five degrees are used to evaluate relative importance of each month in a year, namely: (1) absolutely important, (2) especially important, (3) important, (4) ordinary, and (5) unimportant. We also assign values to each degree, which range from 4 to 0 (i.e. 4 means absolutely important and 0 means unimportant).

Step 3. According to the options of experts, the relative importance of each month can be evaluated as follows:

$$\mathrm{BF}_i = \left[\frac{\sum_{j=1}^{J} E_j F_{ji}}{\sum_{j=1}^{J} E_j}\right],$$

where BF_i is the relative importance of month i, J is the number of forms returned, E_j is the evaluation weight of expert i, F_{ji} is the relative importance of month i provided by domain expert j.

Sale factors: During the investigation, we find that the demand can be influenced by the quantity sold in last periods. Consequently, sale factors can be acquired from historical sale data, which include the difference between the quantity sold last period and its maximum (Q), the difference between the past two periods (DQ) and the total quantity sold since the beginning of the year (SQ). All these data can be extracted from the ERP system.

Associated factors: The demand for some parts can be influenced by the sales volume of other parts belonging to the same assembly owing to the conjunction of these parts' physical structure. And we call these parts "associated parts". In this study, the associated factors comprise the demand for these associated parts ($\mathrm{DAP}_{1\sim m}$) last period.

All these factors mentioned above utilize various units of measurement; moreover, some of them are fuzzy factors. Therefore, these factors have to be transformed into the uniform format with the fuzzification operation.

In previous studies, the fuzzification interface usually defined for each parameter the possibilities of being $\{\mathrm{NL}, \mathrm{NS}, \mathrm{ZE}, \mathrm{PS}, \mathrm{PL}\}$ and relied on the triangular membership function (Li, Wu, & Pang, 2005). In this study, however, the fuzzification interface simply maps each evaluation factor to one element in the fuzzy set $\{\mathrm{NLNS}, \mathrm{ZE}, \mathrm{PS}, \mathrm{PL}\}$ and relies on the membership function shown in expression (1):

$$g(v) = \begin{cases} \mathrm{NL} & 0 \leqslant v < 0.2V, \\ \mathrm{NS} & 0.2V \leqslant v < 0.4V, \\ \mathrm{ZE} & 0.4V \leqslant v < 0.6V, \\ \mathrm{PS} & 0.6V \leqslant v < 0.8V, \\ \mathrm{PL} & 0.8V \leqslant v < 1V, \end{cases} \tag{1}$$

where V is the maximum value of v.

3.5. Weights determination

After the hierarchical structure has been established, anther questionnaire on the basis of the propose structure is formulated. The questionnaire surveys are used to compare pairs of elements of each level with respect to each element in the next higher level. We use 7-point scale, and that will be easy to answer. To avoid getting subjective results, in each questionnaire, the interviewee will be asked to select the lower value, mean value, and upper value to each question. Then fuzzy AHP methods are adopted relied on the triangular membership function. The questionnaires also target on the evaluated experts mentioned in Section 3.4. To integrate different experts' opinions, the following formulas are applied:

$$L_{ij} = \frac{\sum_{f=1}^{F} E_f l_{ijf}}{\sum_{f=1}^{F} 7E_f}, \quad M_{ij} = \frac{\sum_{f=1}^{F} E_f m_{ijf}}{\sum_{f=1}^{F} 7E_f},$$

$$U_{ij} = \frac{\sum_{f=1}^{F} E_f u_{ijf}}{\sum_{f=1}^{F} 7E_f},$$

where F is the number of forms returned, L_{ij}, M_{ij}, and U_{ij} are the lower, mean and upper width, respectively. Thus, we get the pair-wise comparison matrix which has the following format:

$$\widetilde{R} = \begin{bmatrix} (L_{11}, M_{11}, U_{11}) & (L_{12}, M_{12}, U_{12}) & \cdots & (L_{1n}, M_{1n}, U_{1n}) \\ (L_{21}, M_{21}, U_{21}) & (L_{22}, M_{22}, U_{22}) & \cdots & (L_{2n}, M_{2n}, U_{2n}) \\ (L_{n1}, M_{n1}, U_{n1}) & (L_{n2}, M_{n2}, U_{n2}) & \cdots & (L_{nn}, M_{nn}, U_{nn}) \end{bmatrix}$$

$$= \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{nn} \end{bmatrix},$$

where

$$\tilde{a}_{ij} = \begin{cases} \tilde{a}_{ij}^{-1} & \text{if } i \neq j, \\ 1 & \text{if } i = j. \end{cases}$$

Therefore,

$$\widetilde{Z}_i = (\tilde{a}_{i1} \otimes \tilde{a}_{i2} \cdots \otimes \tilde{a}_{in})^{1/n} \ \forall i,$$

$$\widetilde{W}_i = \widetilde{Z}_i \phi(\widetilde{Z}_1 \oplus \widetilde{Z}_1 \oplus \cdots \oplus \widetilde{Z}_n).$$

Given $\widetilde{W}_i = (Lw_i, Mw_i, Uw_i)$, the defuzzified value of $\widetilde{W}_i$ is determined by the*center of gravity* method: the crisp value of $\widetilde{W}_i$ is computed by finding the center of gravity under the membership function for the fuzzy variable (Klir & Yuan, 1995).

4. The EFNN

The EFNN is a five-layer hybrid neural network with the feature to self-organize its activation function based on GA in the learning process.

4.1. The structure of EFNN

The inputs and output of the EFNN, as shown in Fig. 4, represent the evaluation factors and the safety stock, respectively. The mainly layer operations of the EFNN consist of the following five components:

Layer 1 is the input layer. In this layer, all the evaluation factors are fed into EFNN.

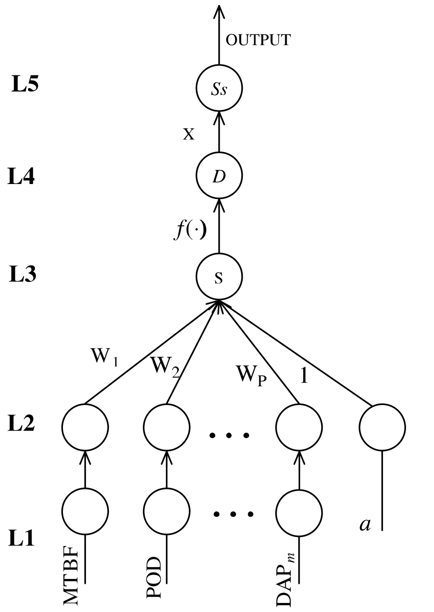

Fig. 4. The structure of EFNN.

Layer 2 is the transforming layer. In this layer, the fuzzification operation is made. Furthermore, the adaptive input variable a is also introduced to decrease the impact of the bullwhip effect on the prediction accuracy. The fuzzification operation maps each evaluation factor to the corresponding element in fuzzy set $\{\mathrm{NL}, \mathrm{NS}, \mathrm{ZE}, \mathrm{PS}, \mathrm{PL}\}$ and relies on the membership function shown in expression (1). The fuzzy set $\{\mathrm{NL}, \mathrm{NS}, \mathrm{ZE}, \mathrm{PS}, \mathrm{PL}\}$ are also transformed into a 0–4 scale (0 means NL and 4 means PL).

a can be generated from a time series with trend analysis (TA) forecast method. The time series is constructed with the parameter b_t created according to expression (2) in each period.

$$b_t = oO - \sum_i W_i d_i, \tag{2}$$

where o is a constant, the main function of o is to ensure the positive result to fit growth model of TA, O can be obtained by fuzzifying the crisp value of demand in each period according to expression (1), W_i is the weight of the evaluation factor i and d_i is the value of fuzzy variable belonging to evaluation factor i.

Layer 3 is the transfer layer. The connection weights in this layer are obtained by the fuzzy AHP method mentioned earlier in Section 3. There is only one neuron in this layer, whose value is defined in expression (3).

$$S = \sum_i W_i d_i + a. \tag{3}$$

Layer 4 is the output layer. In this layer, we will compute a crisp value for our forecast parameters: the demand for spare parts according to the activation function and the value of neuron in previous layer, that is,

$$D = f(s). \tag{4}$$

Layer 5 is output layer. It is very difficult to ensure that the forecasting result can match with the real value of demand strictly. When one is pessimistic, one anticipates the worst. Therefore, the value of demand is set to be larger than the forecasting consequence. If one is optimistic, one expects the best. Therefore, the analyst will set the value of demand less than the forecasting result. However, most decision makers are neither completely optimistic nor completely pessimistic. Consequently, a coefficient of optimism, x, is established, where, $0 < x < 3$. Then the real safety stock (Ss) can be determined by

$$\mathrm{Ss} = x \times D. \tag{5}$$

4.2. GA for generating and refining the activation function

Instead of selecting the simple sigmoid function as the activation function, we adopt the more complex function which will more fit the nonlinear models in real life based on GA method. GA originated by Holland in 1975, which has the ability of searching the optimal or near-optimal solutions in the nonlinear searching space, appears to be a feasible solution to generate and refine the activation function of our EFNN. Among all various GAs, simple GA is the simplest one without loss of the efficiency (Goldberg, 1989). We adopt a modified version of simple GA for increasing the variety in the population while enhancing the searching power. The flow chart of the modified simple GA is shown in Fig. 5.

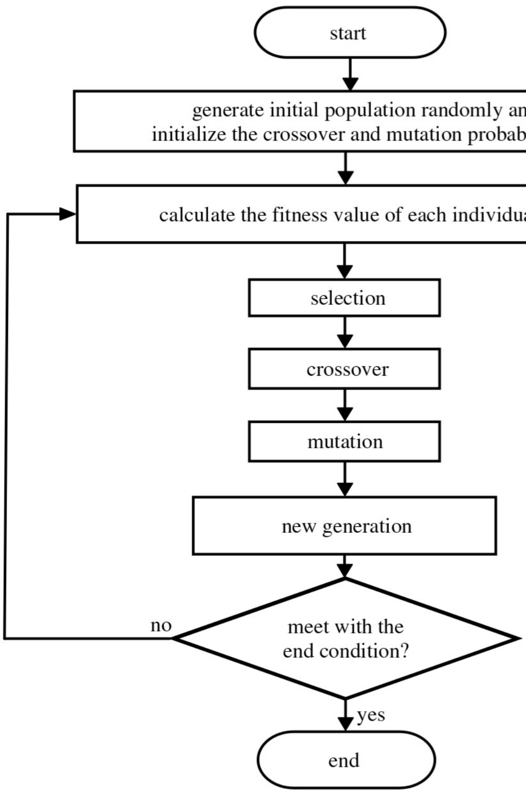

Fig. 5. The flow chart of GA.

4.2.1. Fitness function

Fitness function generates the fitness value providing a performance measure of the problem considered. Different fitness functions promote different GA's behaviors.

In this work, the fitness function represents the sum accuracy of all the test samples and can be defined as follows:

$$fit = \sum_{i=1}^{I} \frac{|Fa(t-i) - Ra(t-i)|}{Ra(t-i)},$$

where $Fa(t)$ is the forecasting result of the demand for spare parts and $Ra(t)$ is the real demand at period t, fit is fitness and I is the total time steps before period t.

4.2.2. Coding

Each activation function solution is defined by a chromosome whose coding is based on the parallel machine representation. A chromosome consists of three kinds of genes: constant gene, function gene, and symbol gene, which is represented in Fig. 6.

The operation sequence of these genes is from left to right in a chromosome. As an example, consider the following chromosome:

1	+	0.2	1	×	0.4	S	×	0.9	$sin(S)$	-	0.5	e^S	×	0.7	S^2	÷	0.9	$\sqrt{\lvert S \rvert}$

It corresponds to the activation function:

$$((1 + 0.2 \times 1) \times 0.4S \times 0.9\sin(S) - 0.5e^S) \\ \times 0.7S^2 \div (0.9\sqrt{|S|}),$$

where S can be calculated according to expression (3).

4.2.3. Initialization of chromosomes

In order to cut down the searching space of the GA and improve the searching efficiency, we initialize constant genes with the random values but ranging between 0.01 and 1. Similarly, symbol genes are generated randomly from the set $\{+, -, \times, \div\}$. Function genes are obtained randomly from the set $\{1, S, S^2, \sin(S), e^S, \sqrt{|S|}\}$ because the function composed of these genes can describe most of nonlinear models.

4.2.4. Crossover

Crossover is a genetic operator that aims to combine the better qualities among the preferred chromosomes. Instead of the single point crossover, we adopt the two point crossover to increase the candidate population variety. Moreover, the cross points are selected randomly, that also increases the candidate population variety.

4.2.5. Mutation

In order to increase the variety of population, each gene in a chromosome is a possible candidate for the mutated

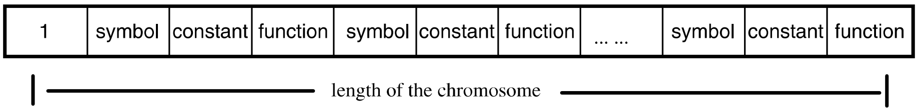

Fig. 6. The structure of chromosome.

element that may be randomly replaced by the other same kind genes according to the mutation possibility.

4.2.6. Selection

Selection operations choose the individuals in the population as parent individuals to create offspring for next generation, whose purpose is to emphasize the fitter individuals in the population. In this work, the implementation method of fitness-proportionate selection is adopted. The selection probability P_s of individual i at each generation is

$$P_s = \frac{Bfit_i}{\overline{fit}},$$

where $\overline{fit}$ is the average value of offspring's fitness in the candidate population, fit_i is the fitness of individual i in the candidate population, and B is a constant.

In order to increase the population variety, the constant B is set to 1 so that most of new offspring can be selected with the large selection possibility. Meanwhile, we also keep the best offspring found until now.

5. Experiments and discussion

5.1. Experiments design

In this section, the proposed system is evaluated with the real world data provided by shanghai Volkswagen Co. Ltd., which is one of the largest car-making bases in China with an annual production capacity of over 450,000 units.

Based on the questionnaire surveys, we acquired the weight of each evaluation factor and the relative importance of each month, as shown in Tables 1 and 2. We used two evaluation functions: the stock cost of spare parts and the times of stockout to evaluate our EFNN. Consequently, several experiments were devised to test the effectiveness of the proposed system. The main aims of these experiments were to asses the follows:

- Performance of our EFNN compares to those produced by traditional FNN with the fixed sigmoid activation function and back-propagation training algorithms.
- Performance of our EFNN compares to those obtained by conventional approaches, such as double exponential smoothing (DES) method with optimal ARIMA, trend analysis (TA) with exponential model and winters' method (WM).
- Does our EFNN always acquire the high performance for different test cases?
- Can our EFNN obtain the high performance without the support of domain knowledge, that is, can our method obtain the optimal inventory performance with the connection weights assigned randomly.

The proposed EFNN and FNN were implemented in C++ programming language on a Celeron 433 MHz machine running under windows environment. DES, TA, and WM were implemented in MINITAB software. The setting of the EFNN, FNN, and WM were:

- In EFNN, set the connection weights based on Table 2, set the crossover probability of GA to be 0.9, the mutation probability of GA to be 0.2, and the population size of GA to be 100.
- In traditional FNN, the topology structure was also based on Fig. 4, the back-propagation learning algorithm was adopted to optimize the cost function (Haykin, 1999). Set training rate to be 0.55 and the momentum term to be 1. The sigmoid function was employed for activation function, while the mean square value (MSE) was treated as the stop criteria. Among all the test cases, the MSE was set to be 0.0005.
- In WM, set seasonal length to be 2, method type to be multiplicative, the level, trend, seasonal of weights to use in smoothing to be 0.2, respectively.

Table 1
The relative importance of month from January 2004 to February 2006 (i.e. 1 means January 2004, 26 means February 2006)

Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
BF	0	2	1	1	3	1	0	1	1	2	1	1	2	0	1	1	3	1	0	1	1	2	1	1	0	2

Table 2
The weights of evaluation factors

MTBF	POD	QDA	VOS	NB3	NW3	SF	BF	Q	DQ	SQ	$DAP_{1\sim m}$
1.05	1.13	1.09	1.12	1.15	1.97	2.01	2.16	2.00	1.97	2.24	2.00

Table 3
The results of test 1

Coefficient	Cost						Out of stock times					
	ES	TA	WM	NN	EFNNR	EFNN	ES	TA	WM	NN	FNN	EFNN
1	236.43	212.49	254.07	230.62	221.83	132.03	29	28	28	27	29	26
1.2	365.782	352.66	388.83	340.86	364.09	265.43	21	19	22	18	20	12
1.4	498.37	511.37	540.18	509.01	498.62	432.34	16	13	11	11	14	3
1.6	624.64	655.16	684.72	640.91	661.58	598.37	11	10	4	5	6	2
1.8	738.15	782.28	821.88	794.62	783.67	731.62	5	6	3	3	2	0
2.0	834.47	888.10	921.01	891.37	908.14	838.56	3	3	3	2	1	0

Table 4
The results of test 2

Coefficient	Cost						Out of stock times					
	ES	TA	WM	NN	EFNNR	EFNN	ES	TA	WM	NN	FNN	EFNN
1	2561.03	2640.84	2554.63	2714.51	2578.95	2421.01	16	16	16	18	17	17
1.2	3326.107	3332.97	3257.69	3266.07	3381.20	3015.67	9	8	12	13	10	7
1.4	4293.45	4296.45	4012.44	4221.91	4036.41	3681.95	6	6	7	7	5	3
1.6	5305.97	5259.08	4727.51	5116.48	5237.40	4506.74	2	3	5	4	3	2
1.8	6289.46	6183.07	5413.59	6052.17	6182.94	5306.82	2	1	3	2	2	0
2.0	7049.21	6989.02	6048.86	6873.82	6981.33	5856.09	1	1	2	1	2	0

The test cases used in this study were as follows:

(1) A total of five samples of parts in gear-box assemblies were selected randomly from the historical data. These data were generated from January 2004 to February 2006. In each sample, the data from March 2004 to February 2005 were selected as training data and the data between March 2005 and February 2006 were used as test data.
(2) A total of nine samples for different assemblies except gear-boxes were selected randomly. Similarly, in each sample, the data from March 2004 to February 2005 were selected as training data and the next 12 data were utilized as test data.

5.2. Summary of results

We use the EFNNR to represent the EFNN with connection weights initialized randomly. Given the inventory cost of each part is \$0.5 per period, Tables 3 and 4 illustrate the average results achieved within 15 runs of the test 1 and test 2, respectively. We also provide the graphs for these summarized results, which are illustrated in Figs. 7 and 8. From these figures and tables, three prominent findings can be observed.

First, it is obvious that for each coefficient of optimism, the performance of our EFNN is better than those obtained by FNN, DES, TA, and WM whether in the same assembly test cases or different assemblies test cases.

Second, our EFNN can avoid out of stock at the price of least stock cost. For example, it can be seen from Tables 1 and 2 that our method can withhold stockout when the coefficient of optimism is no less than 1.8 in both test cases, while the corresponding stock cost is the least. The results substantially contribute to the applications of EFNN in the industry. It is apparent that the good inventory management methods should well trade-off between the fill rate and stock cost. In real life, the traditional forecast methods and FNN, which satisfy the demand for spare parts with significantly larger stock cost, will never be applied in the industry.

Last, but not least, it is evident that the performance of EFNNR is much worse than that obtained by EFNN. These outcomes show that there is a prominent effect on

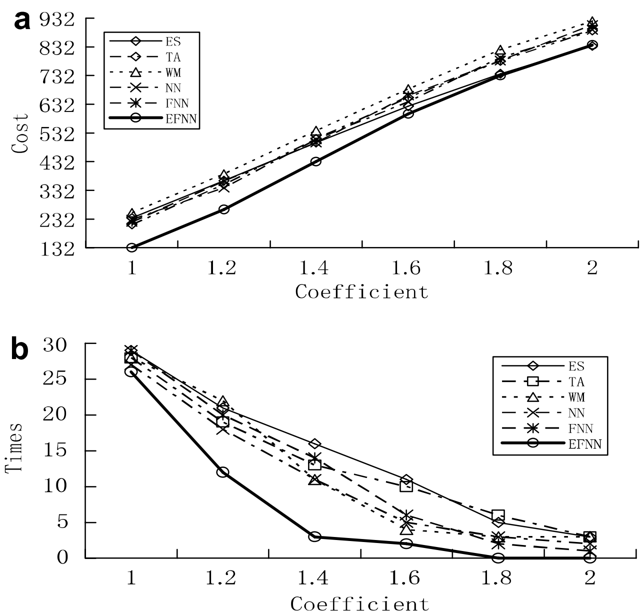

Fig. 7. The results of test 1: (a) stock cost; (b) out of stock times.

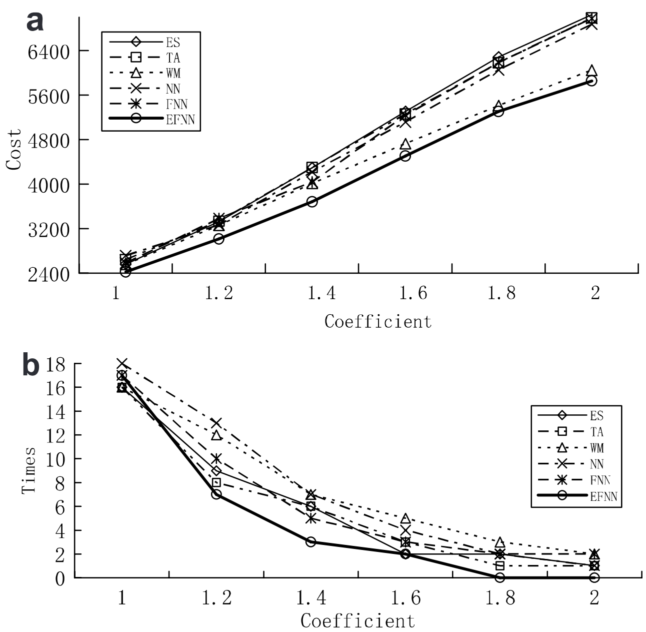

Fig. 8. The results of test 2: (a) stock cost; (b) out of stock times.

improving the performance when the connection weights generated according to the domain knowledge.

6. Conclusions and future work

This paper proposed an EFNN based system for the spare parts inventory management. The EFNN assigns connection weights based on the fuzzy AHP method without painstakingly and time-consuming turning them. Moreover, by generating and refining the activation function according to GA, our EFNN can provide comprehensive and accurate activation functions instead of traditional monotonous and approximate activation functions, therefore, it can fit a wider range of nonlinear models. Finally, the adaptive input variable is also introduced to reduce the impact of the bullwhip effect on the forecasting accuracy.

Several experiments have been made, and from the experimental results one may notices that the performance of our EFNN is much better than that of DES, TA, WM, FNN, and EFNNR. Furthermore, the EFNN can eliminate the stockout with less stock cost and is more feasible to be applied in the industry. Therefore, our EFNN also offers a new insight into the construction of better forecast systems in the future.

Our future research work will be on refining the connection weights of our EFNN because, in this study, these weights are acquired based on repeatedly interviewing domain experts, and these weights may include some subjective results although we have tried best to avoid that. We will further look into the problem of how we can achieve optimal evaluation weights by other convenient methods.

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