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Grey forecast model for torpedo development cost based on neural network

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Cumulative curve of development cost for torpedo shows similar to shape S. Then grey Verhulst model of development cost for torpedo can be established by collecting the development cost historical data for several years. The fitted values and the predictive value can be gotten. To take full advantage of information contains in the historical data, a mapping between historical data and the predictive value using BP neural networks can be found through BP Neural Networks. Example shows that this method has good prediction accuracy.

[**Keywords:** Development cost; BP neural networks; Grey Verhulst model; Torpedo]

Introduction

The LCC of torpedo means all expenses paid in the life cycle, including demonstration cost, development cost, production cost, operation and maintenance cost. The development cost is an important part of LCC. It only accounts for 18% of total cost, but determines 95% of the total cost. Substantial increase in consumption funds with the progress of life cycle, however, the impact capacity of LCC is getting less and less. This shows that studying development cost has great significance[1] for reducing LCC.

Many methods is used in modeling the development cost of products. Reference 2 presented an evolutionary learning process, called DEP(MGA), using a modified genetic algorithm(MGA) to design the dilation-erosion perception(DEP) model of development cost. Reference 3 proposed a non-parametric approach that integrates a neural network method with cluster analysis to estimate development cost. Reference 4 used wavelet neural networks to set up development cost model. Reference 5 newly introduced the Cost Correction Factor(CCF) and Low Cost Small Satellite (LCSS) adjustment factor as additional parameters for development cost estimation. Reference 6 developed the Lagrange relaxation decomposition(LRD) method with heuristics to solve the development cost problems. Reference 7 proposed a rule-based approach for estimating software development in the requirements analysis phase cost. Reference 8 proposed a method combined knowledge mining by rough set and neural network. Reference 9 researched development cost estimation for airborne fire control radar based on effectiveness indexes. Reference 10 predicted missile development cost based on neural network. The author of this paper proposed grey Verhulst model of development cost in Reference 11.

Grey model has several advantages, such as relevant factors for forecast isn't need take into account, the randomness of time series is reduced, and wealthy information from small sample sequences can be gotten. But it has several drawbacks too, such as prediction accuracy is low, and error accuracy can not be controlled. Because of powerful processing capabilities of nonlinear problems, neural network has a strong advantage in data fitting and function approximation. But it needs a large amount of computation, and needs a large number of sample data in training. In this paper, full advantage of the complementarities of the two theories[12&14] is taken, information of development cost data is mined as much as possible.

Materials and Methods

Grey Verhulst prediction model[15]

The raw data series is as follows:

$$X^{(0)}=\left(x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\right) \quad (1)$$

Accumulative generation operation series (named 1-AGO series) can be gotten:

$$X^{(1)}=\left(x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\right) \quad (2)$$

where, $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i),\quad (k=1,2,\cdots,n)$;

From the 1-AGO series $X^{(1)}$, the MEAN series is:

$$Z^{(1)}=\left(z^{(1)}(1),z^{(1)}(2),\cdots,z^{(1)}(n)\right) \quad (3)$$

where, $z^{(1)}(k)=0.5\left(x^{(1)}(k)+x^{(1)}(k-1)\right),(k=1,2,\cdots,n)$

Then, $X^{(0)}+aZ^{(1)}=b\left(Z^{(1)}\right)^2$ is the grey Verhulst model.

In this formula, a,b are model parameters. $-a$ is called developing coefficient, the value reflects the growth rate of series $X^{(0)}$. b is called grey input. LSE parameters vector of grey differential equation is met:

$$\hat{a}=\begin{pmatrix}a & b\end{pmatrix}^T=\left(B^TB\right)^{-1}B^TY \quad (4)$$

$$B=\begin{bmatrix}-z^{(1)}(2) & \left(z^{(1)}(2)\right)^2\\ -z^{(1)}(3) & \left(z^{(1)}(3)\right)^2\\ \vdots & \vdots\\ -z^{(1)}(n) & \left(z^{(1)}(n)\right)^2\end{bmatrix},\quad Y=\begin{bmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(n)\end{bmatrix}$$

The time response series of grey Verhulst model is:

$$\hat{x}^{(1)}(k+1)=\frac{ax^{(1)}(0)}{bx^{(1)}(0)+\left(a-bx^{(1)}(0)\right)e^{ak}} \quad (5)$$

where, $\hat{x}^{(1)}(0)=x^{(0)}(1)$.

Inverse accumulated generating operation series (named 1-IAGO series) of $x^{(1)}(i)$ can be gotten:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k),\quad (k=1,2,\cdots)$$

Then grey Verhulst model series is:

$$\hat{X}^{(0)}=\left(\hat{x}^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\ \right) \quad (6)$$

And the predictive value of point $n+1$ is $\hat{x}^{(0)}(n+1)$.

Grey Verhulst prediction model Accuracy Test

Usually, posterior difference method is used in grey model accuracy testing[15]. Accuracy is determined by the mean square error ratio (MSE ratio) and small error probability together. The basic method is as follows:

$x^{(0)}$ is raw data series, $\hat{x}^{(0)}$ is model series, $\varepsilon^{(0)}$ is residual error series,

$$\varepsilon^{(0)}(k)=\hat{x}^{(0)}(k)-x^{(0)}(k) \quad (7)$$

The MSE of the raw data series is S_1^2, and the MSE of the residual error series is S_2^2, then

$$S_1^2=\frac{1}{n\text{-}1}\sum_{k=1}^{n}\left(x^{(0)}(k)-\bar{x}\right)^2,\ S_2^2=\frac{1}{n\text{-}1}\sum_{k=1}^{n}\left(\varepsilon^{(0)}(k)-\bar{\varepsilon}\right)^2$$

where, $\bar{x}=\frac{1}{n}\sum_{k=1}^{n}x^{(0)}(k)$, $\bar{\varepsilon}=\frac{1}{n}\sum_{k=1}^{n}\varepsilon^{(0)}(k)$

The mean square error ratio is defined as

$$C=\frac{S_2}{S_1} \quad (8)$$

Small error probability is defined as

$$p=P\left\{\left|\varepsilon^{(0)}(k)-\bar{\varepsilon}\right|<0.6745S_1\right\}=\frac{\sum g}{n} \quad (9)$$

where, $\sum g$ is the total number of $\left|\varepsilon^{(0)}(k)-\bar{\varepsilon}\right|<0.6745S_1$.

Index C is the smaller, the batter. Small C means S_1 is big and S_2 is small. Big S_1 indicates that the MSE of $x^{(0)}$ is big, namely, the swing rang of $x^{(0)}$ is big, and the rule of $x^{(0)}$ is not obvious. Small S_2 indicates that the MSE of $x^{(0)}$ is small, namely, the swing rang of $x^{(0)}$ is small, and discrete degree of $x^{(0)}$ is small. Small C indicates that although the rule of $x^{(0)}$ is not obvious, the differences of fitted values and fact values are not discrete. Index p is the bigger, the batter. Big p means more point which difference of residual error and the average residual error less than $0.6745S_1$. The grade of predictive precision for grey model is shown in table 1[16].

BP Neural Networks

Neural network[17,18,19&20] has the ability of self learning, self adapting and nonlinear processing. It obscures the knowledge getting from self learning into the network structure. Its way dealing with complex nonlinear system has the essential differences from traditional methods and has its own predominance. As a typical learning algorithm of artificial neural networks, BP neural network is multi-layer network using nonlinear differentiable function with weight training. It contains the essential part of the neural networks. Its structure is simple and fictile.

Table 1 Grade of predictive precision for grey model

Grade of predictive precision	p	C
1 grade (good)	$p \geq 0.95$	$C \leq 0.35$
2 grade (qualification)	$0.95 > p \geq 0.80$	$0.35 < C \leq 0.5$
3 grade (grudging qualification)	$0.80 > p \geq 0.70$	$0.5 < C \leq 0.65$
4 grade (disqualification)	$p < 0.70$	$C > 0.65$

Results and Discussion

Grey Forecast Model for Torpedo Development Cost Based on Neural Network

From study, it is found that if the develop course follows a normal procedure (that is, blue print demonstration, elementary design, detailed, trial-manufacture, experiment, validate, finalize the design.), the development course according to the plan on the whole, and there is no big gusty alteration, the development cost for torpedo needs few at the beginning, and as the time goes by, it grows and reach a pinnacle, then drops. The cumulative development cost curve of torpedo shows a growth trend, increased slowly at the beginning, and then grows rapidly. Finally, it tends to a limit slowly. So the development cost of torpedo present a growth situation similar to the growth of plant: rise slowly at the beginning, then increase rapidly, go to limit at last. The figure is similar to shape S. As shown in fig. 1.

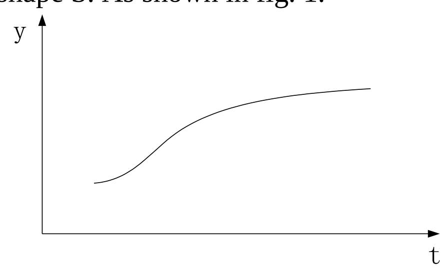

Fig. 1—The curve of cumulative development cost for torpedo

Grey Verhulst model is fit for characterization the trend of saturated S shape, so it is selected to set up the model of development cost for torpedo.

Although grey Verhulst model has the superiority of less information and simple, BP neural network has the characteristic of effective simulation. To take full advantage of the information contained in the original data, combination model of grey Verhulst neural network is established. The method is as follows:

First, grey Verhulst model according to original data series (1) is established, and the model series (6) ($\hat{X}^{(0)}$) and residual error series (7) ($\varepsilon^{(0)}(k)$)can be gotten.

Residuals may be positive or negative, therefore, all the residuals are made positive first: plus the absolute value of the minimum negative and plus 1 for each data. Use $e^{(0)}(k), k=1,2,\cdots,n$ to distinguish.

$$e^{(0)}(k)=\varepsilon^{(0)}(k)+\left|\min\left(\varepsilon^{(0)}(k)\right)\right|+1,\ \ k=1,2,\cdots,n \quad (10)$$

Regrouping series (1) and (10), s consecutive years of practical value is input, and the modified residual of grey model of next year is output, then all data can be divided into t groups($s+t-1=n$).

Matrix can be accessed:

$$\begin{pmatrix} x^{(0)}(1) & x^{(0)}(2) & \cdots & x^{(0)}(s) & e^{(0)}(s+1) \\ x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(s+1) & e^{(0)}(s+2) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x^{(0)}(t-1) & x^{(0)}(t) & \cdots & x^{(0)}(n-1) & e^{(0)}(n) \\ x^{(0)}(t) & x^{(0)}(t+1) & \cdots & x^{(0)}(n) & \overline{e}^{(0)}(n+1) \end{pmatrix} \quad (11)$$

where, $\overline{e}^{(0)}(n+1)$ is unknown.

Neural network model is established using the matrix mentioned above. The input layer is s, namely the s row of the matrix. And output layer is 1, namely the $(s+1)$ th row of the matrix. For network training, frontal $t-1$ line of data is used, and a series of weights and threshold corresponding to each node can be gotten.

To avoid falling into local optimal solution, LM algorithm is used training BP network in this paper. The network consists of input layer, hidden layer and output layer. The tangent Sigmoid function is used as activation function between input layer and hidden layer, and linear function is used between hidden layer and output layer. The range of Sigmoid function is [0, 1]. At the same time, the Sigmoid function varies very slowly, which is not good for the draw of character. In this paper, the input sample is normalized to [0.1, 0.9] for improving the speed of network convergence.

Suppose $X^{(0)}=\left\{x^{(0)}(k)\right\}$ is the raw series, and n is the sample capacity, the normalize method is as follows:

$$x^{*}(k)=\frac{x^{(0)}(k)-\overline{x}}{S},\quad (k=1,2,\mathrm{L}\ ,n;) \qquad (12)$$

where, $x^*(k)$ is the normalized data (define $X^* = \{x^*(k)\}$). $\bar{x} = \frac{1}{n}\sum_{k=1}^{n} x^{(0)}(k)$; $S = \sqrt{\frac{\sum_{k=1}^{n}\left(x^{(0)}(k)-\bar{x}\right)^2}{n-1}}$.

With this normalization, the mean value of the variable is 0, and the MSE of the variable is 1, and the influence of dimension is eliminated. But X^* is not in the range of [0.1, 0.9] definitely. The following transform can reach this aim:

$$x^{\#}(k) = 0.1 + \frac{0.8\left[x^*(k) - \min\limits_{1\le k\le n}\left\{x^*(k)\right\}\right]}{\max\limits_{1\le k\le n}\left\{x^*(k)\right\} - \min\limits_{1\le i\le n}\left\{x^*(k)\right\}} \quad (13)$$

After completing the training, k line of matrix (9) is used to predict, then predictive value of residual $\bar{e}^{(0)}(n+1)$ at time n+1 can be gotten.

$\bar{e}^{(0)}(n+1)$ can be converted into $\bar{\varepsilon}^{(0)}(n+1)$;

$$\bar{\varepsilon}^{(0)}(n+1) = e^{(0)}(n+1) - \left|\min\left(\varepsilon^{(0)}(i)\right)\right| - 1 \ ,$$

$$i = 1, 2, \cdots, n \quad (14)$$

Predictive value of residual $\bar{\varepsilon}^{(0)}(n+1)$ is compensated in the predictive value of grey Verhulst model. Ultimately, the combination prediction is $\bar{\hat{x}}^{(0)}(n+1) = \hat{x}^{(0)}(n+1) + \bar{\varepsilon}^{(0)}(n+1)$.

Example

The development costs of a torpedo year after year are shown as table 2.

It's assumed that the development costs of 10th year is unknown. In order to predict the development costs of 10th year, a model using the data of former 9 years is established, and it's compared with the actual costs.

$$X^{(0)} = \left(55, 58, 90, 152, 215, 263, 245, 202, 138, 108\right) \quad (15)$$

a and b can be gotten from equation (4):

$a = -0.63727$, $b = -0.00039$

From equation (5), the time response function can be gotten:

$$\hat{x}^{(1)}(k+1) = \frac{35.0498}{0.0215 + 0.6158e^{-0.6373k}}$$

From the time response function, the fitted value series of grey Verhulst model is:

$$\hat{X}^{(1)} = (55, 101, 181, 311.6, 503.7, 747.3, 1004, 1226.8, 1389.8, 1494.9)$$

$$\hat{X}^{(0)} = (55, 46.0, 80, 130.6, 192.1, 243.6, 256.7, 222.8, 163.1, 105.1)$$

(16)

$\hat{X}^{(0)}(11)$ can be predicted. The predicted value of $\hat{X}^{(0)}(11)$ is 1557.2, then the predicted value of $\hat{X}^{(0)}(11)$ is 62.2.

From equation (7), grey Verhulst residual series can be gotten:

$$\varepsilon^{(0)} = (0, -12.01, -9.96, -21.43, -19.43, 11.69, 20.80, 25.08, -2.92)$$

Substituted into the accuracy formula (8) and (9), it can be gotten that the accuracy of model is 1.

In order to obtain more accurate model, BP neural network is used to improve model.

According to function (10), $\varepsilon^{(0)}$ can be converted to positive series $e^{(0)}$:

$$e^{(0)} = \left(23.91, 11.9, 13.95, 2.48, 1, 4.48, 35.59, 44.71, 48.99, 20.98\right)$$

(17)

According to matrix (11), data (15) and (17) is grouped. s is 4, then it can be divided into 7 line of data(t is 7).

The matrix can be gotten:

$$\begin{pmatrix} 55 & 101 & 181 & 311.6 & 1 \\ 101 & 181 & 311.6 & 503.7 & 4.48 \\ 181 & 311.6 & 503.7 & 747.3 & 35.59 \\ 311.6 & 503.7 & 747.3 & 1004 & 44.71 \\ 503.7 & 747.3 & 1004 & 1226.8 & 48.99 \\ 747.3 & 1004 & 1226.8 & 1389.8 & 20.98 \\ 1004 & 1226.8 & 1389.8 & 1494.9 & \bar{e}^{(0)}(11) \end{pmatrix}$$

The BP network can be structured by MATLAB control box. After multiple test, BP neural network of 4×3×1 is used, tangent Sigmoid function between input layer and hidden layer is selected, and linear function between hidden layer and output layer is selected. 6 line of data is used as a sample for training network, the maximum learning times is set 1 000, learning rate is set 0.01, the error sum of squares as learning objectives is set 0.0001, input values are normalized to [0.1, 0.9](equation (13)), the initial value of network connection weights is set a stochastic value in [-1, 1].

Table 2. Development Cost Unit:10 000 RMB￥, (first fiscal year)

Year	1	2	3	4	5	6	7	8	9	10	10
Development Cost	55	58	90	152	215	263	245	202	138	108	73

Table 3. Comparison Table of 11th Actual and its Predicted Value

Year	Actual value	Grey Verhulst Model		Combination Model	
		Predicted Value	Relative Error(％)	Predicted Value	Relative Error(％)
11	73	62.2	14.79	65.75	9.93

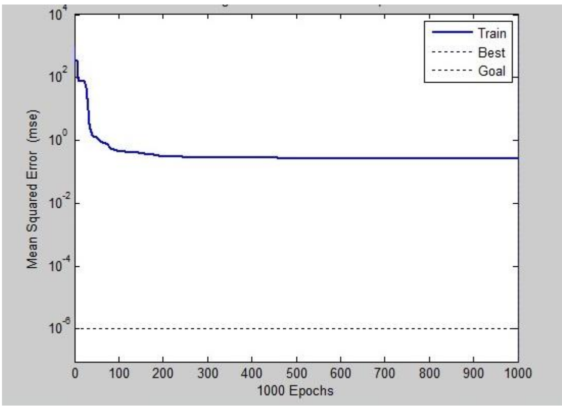

Fig. 2—The effect of training

The effect of training is show as fig.2. Network converges in 1000 Epochs or so when simulated by Matlab, and the expected error can be met. Through section 7 sets of data, the residual of 11th year $e^{(0)}(11)$ is 20.36, and the actual residual of 11th year $\varepsilon^{(0)}(11)$ is -3.55 through equation (14). Then the combined predictive value of 11th year is 65.75 according to equation (7).

From table 3, it can be drawn that the accuracy of grey Verhulst neural network model is better than grey Verhulst model. Re-modeling by all raw data of table 1, then the predicted value of 12th year is 56.76.

Conclusion

Torpedo development cycle is not too long, which determines that the sample of annual development cost is less. Grey theory suitable for prediction of small sample, but its accuracy is lower. In the paper, the complementarily of the two theories is taken full advantage of, and information value of data is mined as much as possible. Grey Verhulst neural network successfully predicted the development cost for torpedo. Example shows that the model has higher accuracy.

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