The Application of Combination Forecasting Model in Forecasting the Total Power of Agricultural Machinery in Heilongjiang Province

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Abstract Agricultural machinery total power is an important index to reflect and evaluate the level of agricultural mechanization. Firstly, we respectively made use of exponential model, grey forecasting and BP neural network to construct models depending on historical data of agricultural machinery total power of Heilongjiang Province; secondly, we constructed the combined forecasting models that respectively based on divergence coefficient method, quadratic programming and weight distribution of Shapley value. Fitting results showed that the various combination forecasting model is superior to the single models. Finally, we applied the combination forecasting model which based on the weight distribution method of Shapley value to forecast Heilongjiang agricultural machinery total power, and it would provide some reference to the development and program for power of agriculture machinery.

Key words Total power of agricultural machinery, GM (1, 1) model, Combination forecasting model, BP neural network

1 Introduction

The total power of agricultural machinery refers to the sum of all mechanical power used for farming, forestry, animal husbandry, fishery production and transport, which is the main indicator to reflect the overall level of development of agricultural mechanization in a region[1]. The forecasting of total power of agricultural machinery is to extrapolate the future trends of power variables by establishing a stable relationship between power variables and time variables. Currently, the forecasting methods concerning total power of agricultural machinery include linear regression model, moving average, exponential smoothing, least squares method, Compartz curve, and artificial neural network forecasting model[2]. According to the actual situation of annual agricultural machinery in Heilongjiang Province, this paper performs the predictive analysis of total power of agricultural machinery in Heilongjiang Province, to provide a reference for the future development of agricultural mechanization strategy in Heilongjiang Province. Since the combination forecasting theory was first developed by Bates and Granger in the 1960s, the research and application of combination forecasting method have been developed quickly. The basic idea of combination forecasting is to use an appropriate method to integrate the calculation results of various single models so as to improve the forecasting accuracy and increase the forecasting reliability. By processing the historical data of total power of agricultural machinery and analyzing the time series graphs in Heilongjiang Province, this paper employs the exponential model[3], GM (1,1) model[4] and BP neural network model and uses coefficient of variation[5], quadratic programming[6] and Shapley value method[7 – 8] to build the combination forecasting model, respectively, in order to carry out the combination forecasting of total power of agricultural machinery in Heilongjiang Province. The precision is also compared to obtain the practical method to forecast total power of agricultural machinery.

2 Single forecasting model

2.1 Exponential curve model Table 1 shows that the historical statistical data about total power of agricultural machinery in Heilongjiang Province continue to increase over time, so the exponential curve regression analysis is used for forecasting. Using SPSS statistical software, the forecasting model is established.

$$Y(t) = 1\,201.537e^{0.07t} \quad (1)$$

Table 1 Total power of agricultural machinery in Heilongjiang Province during 1980 – 2007

Year	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989
$Y//10^4$ kW	709.30	760.4	814.1	861.6	901.7	949.5	935.2	1093.5	1105.2	1162.8
Year	1990.0	1991.0	1992.0	1993.0	1994.0	1995.0	1996.0	1997.0	1998.0	1999.0
$Y//10^4$ kW	1173.4	1179.5	1172.6	1185.3	1190.0	1226.1	1254.8	1285.4	1454.5	1559.7
Year	2000.0	2001.0	2002.0	2003.0	2004.0	2005.0	2006.0	2007.0		
$Y//10^4$ kW	1613.8	1648.3	1741.8	1807.7	1952.2	2234.0	2570.6	2785.3		

Data source: Statistical *Yearbook of Heilongjiang Province*.

where $Y(t)$ is the total power of agricultural machinery; t is the time variable, taking values of 1 – 11 for 1997 – 2007 respectively. The analysis of variance shows that the tail probability of significance test of exponential curve model is less than 0.0001, the

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coefficient of determination is $R^2 = 0.947$, and $F = 161.866 > F_{0.01}$. The model is significant, and the fitting accuracy is high. The average relative error is 4.976%, and the fitting results are shown in Table 2.

2.2 GM (1, 1) model The grey series GM (1,1) model forecasting is realistic and dynamic, and if the original series $X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(n)\}$, we select the continuous data of different length from $X^{(0)}$ series as the sub-series. For the sub-series, GM (1, 1) model is established. We determine any sub-series as follows:

$$X_i^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \cdots, X^{(0)}(m)\} \quad (2)$$

We perform the accumulated generating operation of sub-series as follows:

$$X_i^{(1)} = \{X^{(1)}(1), X^{(1)}(2), \cdots, X^{(1)}(m)\} \quad (3)$$

where $X^{(1)}(t) = \sum_{k=1}^{t} x^{(0)}(k)$, $t = 1, 2, \cdots, m$

We build the cumulative matrix B and the constant term vector Y_m:

$$B = \begin{bmatrix} -\frac{1}{2}[x^{(1)}(1) + x^{(1)}(2)] & 1 \\ -\frac{1}{2}[x^{(1)}(2) + x^{(1)}(3)] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}[x^{(1)}(m-1) + x^{(1)}(m)] & 1 \end{bmatrix} \quad (4)$$

$$Y_m = [x^{(0)}(2), x^{(0)}(3), \vdots, x^{(0)}(m)]^T \quad (5)$$

We use the least squares method to solve the grey parameters $\hat{a}$:

$$\hat{a} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T - B)^{-1} B^T Y_m \quad (6)$$

We build the GM (1, 1) model as follows:

$$x^{\hat{(0)}}(t+1) = [x^{(0)}(1) - \frac{u}{a}]e^{-at} + \frac{u}{a} \quad (7)$$

We perform the derivation and restoration of $X^{\hat{(1)}}$:

$$x^{\hat{(0)}}(t+1) = -a[x^{(0)}(1) - \frac{u}{a}]e^{-at} \quad (8)$$

Using the statistics concerning total power of agricultural machinery in Heilongjiang Province during 1997 – 2007, and the above GM (1, 1) model, we build the grey forecasting model of total power of agricultural machinery in Heilongjiang Province:

$$\hat{x}(t+1) = 16\,844.718e^{0.076\,3t} - 15\,559.318\,8 \quad (9)$$

At the same time, the posterior ratio $c = 0.3231 < 0.35$, and small error probability $p = 1.000 > 0.95$. Thus it can be found that the established GM (1, 1) model has better fitting accuracy, and the average relative error is 5.2692%, so it can be used to forecast and analyze the total power of agricultural machinery in Heilongjiang Province. The fitted value and relative error of model are shown in Table 2.

2.3 BP neural network model BP neural network is widely used in the field of forecasting, because the three-layer neural network that contains a hidden layer can approximate to any nonlinear function, so this paper uses the three-layer BP network model to predict. According to the historical data about the total power of agricultural mechanization in Heilongjiang Province during 1980 – 2007, we take the data of total power of agricultural machinery in the previous four years as input data (namely select four nodes in the input layer), and the data of total power of agricultural machinery in the fifth year as the output data, to construct the input and output samples. The network input is $[X_i, X_{i+1}, X_{i+2}, X_{i+3}]$,, and the output is X_4, $i = 1, 2, \cdots, n$. The number of nodes in the hidden layer of network is determined using the method of trial and error, and finally, the number of nodes in the hidden layer is taken 9. Then the network can quickly converge to the required accuracy. Thus, the topological structure of the selected network is 4 – 10 – 1. We take the historical data of total power of agricultural machinery in Heilongjiang Province during 1980 – 1996 for network training, and take the data during 1997 – 2007 as network calibration data. When the network transfer function is Sigmoid function, the error is $E = 0.0001$; the initial learning rate is 0.5; the momentum term is 0.85; the maximum number of training is 5000. The network accuracy meets the requirements. The fitting results of sample data are shown in Table 2. The fitted average relative error is 3.4788%.

Table 2 The forecasting results and error of models

Year	The actual value	Exponential model	GM(1,1) model	BP neural network model	Fitted relative error//%		
					Exponential model	GM(1,1) model	BP neural network model
1998	1 454.5	1 288.603	1 336.20	1 513.8	0.25	8.13	4.08
1999	1 559.7	1 381.978	1 442.20	1 588.6	4.99	7.53	1.85
2000	1 613.8	1 482.119	1 556.60	1 621.6	4.97	3.54	0.48
2001	1 648.3	1 589.516	1 680.07	1 687.1	1.50	1.93	2.35
2002	1 741.8	1 704.696	1 813.34	1 755.9	3.42	4.11	3.68
2003	1 807.7	1 828.222	1 957.19	1 849.2	4.96	8.27	2.30
2004	1 952.2	1 960.699	2 112.44	1 998.9	8.46	8.21	2.39
2005	2 234.0	2 102.775	2 280.01	2 081.5	7.71	2.06	6.83
2006	2 570.6	2 255.147	2 460.87	2 625.6	0.95	4.27	6.03
2007	2 785.3	2 418.559	2 656.08	2 819.9	5.91	4.64	4.80
Mean					4.9761	5.2692	3.4788

3 Combination forecasting model

It is assumed that we use N different forecasting models to forecast the same problem, then the combination forecasting model consisting of N different forecasting models is as follows:

$$f_i = \sum K_i f_{it} \quad (10)$$

where f_i is the forecasting value of model i; f_t is the forecasting value of model i at time t, $i = 1,2,3,\cdots,N$; k_i is the weight of model i, $i = 1, 2, 3, \cdots, N$ and $\sum_{i=1}^{N} K_i = 1$.

3.1 Determining the combination model based on dispersion coefficient method Assuming the relative forecasting errors of exponential model, GM (1, 1) model and BP neural network model are λ_1, λ_2 and λ_3, respectively, and $\lambda = \sum_{k=1}^{m} (i = 1,2,3)$, then the weight of model is $w_i = \frac{\lambda - \lambda_i}{\lambda} \cdot \frac{1}{m-1} (i = 1,2,3)$, and m is the model number. The weight of each single model is calculated as: $w(03187 \quad 0.3080 \quad 0.3733)$. According to the combination weight, combination forecasting model I is established as follows:

$$y_1 = 0.318\ 7y_1 + 0.308\ 0y_2 + 0.373\ 3y_3 \quad (11)$$

where y_t is the forecasting value of combination model I; y_1 is the forecasting value of exponential model; y_2 is the forecasting value of GM(1,1) model; y_3 is the forecasting value of BP neural network.

The fitting results of total power of agricultural machinery in Heilongjiang Province during 1998 – 2007 using this combination model are shown in Table 3.

3.2 Determining the combination model based on the quadratic programming method According to the minimum quadratic sum of error of each single forecasting model, we establish the mathematical model as follows:

$$\min w = \min \sum_{t=1}^{n} e_t^2 = \min \sum_{i=1}^{n} (y_t - f_t)^2 = \min \sum_{t=1}^{n} [y_t^2 - 2y_t \sum_{t=1}^{n} k_i f_{it} + (\sum_{i=1}^{m} k_i f_{it})^2] \quad (12)$$

where w is the quadratic sum of error; e_i is the combination forecasting error at time t; y_t is the observed value.

By substituting the forecasting value of each single forecasting model into formula (12), we can get the following combination forecasting model:

$$w = 74\ 738\ 443.77k_1 + 78\ 224\ 060.03k_2 + 78\ 847\ 542.62k_3 + 35\ 924\ 821.06k_1^2 + 39\ 001\ 296.20k_2^2 + 39\ 517\ 936.72k_3^2 + 74\ 514\ 806.12k_1k_2 + 78\ 420\ 502.02k_2k_3 + 74\ 903\ 374.9k_1k_3 \quad (13)$$

Formula (13) is consistent with the mathematical model of quadratic programming, so we can call quadprog function of MATLAB to calculate the minimum value. Enter the following command in Matlab window:

```
H = [2 × 35 924 821.06   74 514 806.12   74 903 374.9;
     74 514 806.12   2 × 39 001 296.20   78 420 502.02;
     74 903 374.9   78 420 502.02   2 × 39 517 936.72];
f =
[ -74 738 443.77; -78 224 060.03; -78 847 542.62];
Aeq = [1   1   1]
beq = [1]
lb = [zeros(3,1)]
[k] = quadprog(H,f,[ ],[ ],Aeq,beq,lb)
```

We can calculate the combination coefficient of forecasting model as: $w = (0.021\ 7 \quad 0 \quad 0.978\ 3)$. The combination forecasting model II is established as follows:

$$y_{11} = 0.021\ 7y_1 + 0.978\ 3y_3 \quad (14)$$

where y_{11} is the forecasting value of combination model II, and the fitting results of total power of agricultural machinery in Heilongjiang Province during 1998 – 2007 using this combination model are shown in Table 3.

3.3 Determining the combination model based on Shapley value method In game theory, the Shapley value is a solution concept in cooperative game theory. To each cooperative game it assigns a unique distribution (among the players) of a total surplus generated by the coalition of all players. The Shapley value is characterized by a collection of desirable properties. Assuming the average relative forecasting error of forecasting method i is E_i, there is:

$$E = \frac{1}{N} \sum_{i=1}^{N} E_i \quad (15)$$

The weight distribution formula of Shapley value method is as follows:

$$E_i' = \sum_{u_i \in u} w(|u_i|)[E(u_i) - E(u_i - \{i\})],\ w(|u_i|) = \frac{(N - |u_i|!\ (|u_i| - 1)!}{N!} \quad (16)$$

where $w(|u_i|)$ is the weighting factor, representing the marginal contribution that i should make; $u_i - \{i\}$ means the removal of model i from the combination; u stands for all sub-sets containing i; $|u_i|$ is the number of forecasting model in the combination.

By formula (16), the weight of each forecasting method in the combination forecasting is calculated as follows:

$$w_i = \frac{E - E_i'}{E(N-1)} (i = 1,2,L,N) \quad (17)$$

According to formula (15) to (17), we can calculate the combination coefficient based on Shapley value: $w = (0.3004 \quad 0.2764 \quad 0.4232)$. The combination forecasting model III is established as follows:

$$y_{III} = 0.318\ 7y_1 + 0.308\ 0y_2 + 0.373\ 3y_3 \quad (18)$$

where y_{III} is the forecasting value of combination model III.

The fitting results of total power of agricultural machinery in Heilongjiang Province during 1998 – 2007 using this combination model are shown in Table 3.

From Table 2 and Table 3, it can be found that each combination forecasting model is superior to the single forecasting model. The fitting results of combination model show that the fitting precision of the combination model based on Shapley value is greater than that of the combination model based on dispersion coefficient or quadratic programming. Therefore, this paper uses combination model III based on Shapley value to forecast the total power of agricultural machinery in Heilongjiang Province during 2008 – 2015. The forecasting results are shown in Table 4.

Table 3 The fitted values of each combination model

Year	The actual value	Combination forecasting model I	Combination forecasting model II	Combination forecasting model III	Fitted relative error//%		
					Combination forecasting model I	Combination forecasting model II	Combination forecasting model III
1998	1 454.5	1 470.70	1 514.59	1 475.65	1.11	4.13	1.45
1999	1 559.7	1 552.21	1 589.19	1 556.34	0.48	1.89	0.22
2000	1 613.8	1 621.61	1 622.96	1 622.52	0.48	0.57	0.54
2001	1 648.3	1 706.86	1 688.59	1 705.82	3.55	2.44	3.49
2002	1 741.8	1 815.99	1 806.43	1 815.30	4.26	3.71	4.22
2003	1 807.7	1 901.20	1 850.48	1 896.70	5.17	2.37	4.92
2004	1 952.2	2 030.68	1 998.68	2 027.27	4.02	2.38	3.85
2005	2 234.0	2 140.01	2 081.32	2 133.88	4.21	6.83	4.48
2006	2 570.6	2 464.14	2 713.35	2 482.86	4.14	5.55	3.41
2007	2 785.3	2 625.63	2 904.45	2 646.15	5.73	4.28	5.00
Mean					3.32	3.42	3.16

Table 4 The forecasting value of total power of agricultural machinery in Heilongjiang Province during 2008 – 2015

Year	Exponential model 0.3004	GM(1,1) model 0.2764	BP neural network model 0.4232	Forecasting value
2008	2 783.20	2 866.77	2 869.9	2 842.99
2009	2 985.01	3 094.18	3 016.4	3 028.47
2010	3 201.44	3 339.62	3 320.6	3 290.06
2011	3 433.57	3 604.54	3 464.8	3 494.04
2012	3 682.54	3 890.46	3 652.3	3 727.21
2013	3 949.55	4 199.07	3 917.2	4 004.83
2014	4 235.92	4 532.16	4 229.5	4 315.09
2015	4 543.06	4 891.68	4 459.7	4 604.14

4 Conclusions

Using exponential model, GM (1, 1) model and BP neural network model, this paper forecasts the total power of agricultural machinery in Heilongjiang Province, and the forecasting prediction of the three models is 4.9761%, 5.2692% and 3.4788%, respectively. Using dispersion coefficient, quadratic programming and Shapley value, this paper establishes the combination model for the combination forecasting of total power of agricultural machinery in Heilongjiang Province. The fitting precision of Shapley value method is 3.16%, lower than that of each single forecasting model and also lower than that of combination forecasting models based on coefficient of variation and quadratic programming (3.32% and 3.42%). Therefore, during the forecasting of agricultural mechanization, it is necessary to establish the combination forecasting model to improve forecasting precision in order to provide a reference for the development of agricultural mechanization.

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