

Research on Energy Consumption Prediction of Combined Models in Discrete Manufacturing Enterprises

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Abstract. In discrete manufacturing enterprises, accurate prediction of energy consumption provides an important data basis for the strategic development and strategy formulation of enterprise managers. This paper uses the GM(1, 1) model and System Dynamics model to predict and analyze the energy consumption of a shipbuilding enterprise respectively. Secondly, the Shapley value method is used to determine the weight of each prediction model in the combined model, and to construct the energy consumption combination prediction model of a shipbuilding enterprise. The prediction results show that the prediction accuracy of the combined model is higher than that of the single prediction model, which provides a new prediction method for a shipbuilding enterprise and has reference value for other discrete manufacturing enterprises.

1. Introduction

Energy is the source of power for shipbuilding enterprises. The characteristics of energy consumption in shipbuilding enterprises are large and variety. Energy costs account for a significant proportion of the operating costs of manufacturing enterprises. In particular, the profits of manufacturing companies have been declining in recent years, and the operating costs have been continuously improved. The short-term indispensability of energy costs and the short-term capital liquidity are increasingly prominent. The scientific energy demand prediction and analysis can provide a basis for the strategic development and strategy formulation of enterprise managers. Therefore, accurate prediction of the trend changes of energy demand in manufacturing enterprises seems very necessary.

The essence of combined prediction is to combine the advantages of different models, learn from each other's strengths, and improve the accuracy and the reliability of prediction results. The difficulty and focus of combined prediction is to determine the weight of the predictive model. Reasonable weight can improve the accuracy and reliability of the prediction result. Based on the qualitative analysis of energy consumption of shipbuilding enterprises, this paper selects the GM(1, 1) [1, 2] and System Dynamics model [3], and applies Shapley value method to determine the weight of each prediction model [4], so as to establish a combined prediction model to predict energy consumption of a discrete manufacturing enterprise [5]. The data used in this paper is the energy consumption data of a shipbuilding enterprise from 2006 to 2015. The modeling data interval is selected from 2006 to 2013, and the verification data interval is selected from 2014-2015.



2. Prediction model

2.1. GM (1, 1) gray model

2.1.1. *Outline.* The gray model is a model that uses discrete random numbers to generate random differential equations that are significantly weakened and more regular, and is used to study and describe the process of change [6].

2.1.2. *Establish model.* Given the original data column $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$ to accumulate the original data column, that is, to establish an accumulation generation sequence

$$x^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)).$$

Among:

$$x^{(1)}(i) = \left\{ \sum_{j=1}^i x^{(0)}(j) \mid i = 1, 2, \dots, n \right\}$$

The gray derivative of $x^{(1)}$ is:

$$x^{(0)}(i) = x^{(1)}(i) - x^{(1)}(i - 1)$$

The neighboring generation sequence $z^{(1)}(i)$ of $x^{(1)}(i)$ is:

$$z^{(1)}(i) = \alpha x^{(1)}(i) + (1 - \alpha)x^{(1)}(i - 1)$$

The GM (1, 1) model is established as follows:

$$x^{(0)}(i) + az^{(1)}(i) = b \tag{1}$$

Among, $x^{(0)}(i)$ is the gray derivative, \mathbf{a} is the development coefficient, $z^{(1)}(i)$ is the whitening background value, and \mathbf{b} is the gray action amount.

Substituting the timetable $i=2, 3 \dots N$ into (1), introducing the matrix vector

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

Then, the GM (1, 1) model can be represented as $Y=Bu$.

Using the regression analysis method, the values of \mathbf{a} and \mathbf{b} are obtained, and the corresponding whitening model is obtained.

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b \tag{2}$$

The predicted value is obtained.

$$\hat{x}^{(1)}(i + 1) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-ai} + \frac{b}{a}, \quad i = 1, 2, \dots, n - 1$$

Restore value

$$\hat{x}^{(0)}(i + 1) = \hat{x}^{(1)}(i + 1) - \hat{x}^{(1)}(i), \quad i = 1, 2, \dots, n - 1$$

Using the GM (1, 1) model, using the energy consumption statistics of a shipbuilding enterprise, the prediction model of the energy demand of the manufacturing industry is established as

$$\hat{x}^{(1)}(i+1) = 297.6344e^{0.1465i} - 256.8344, \quad i = 1, 2, \dots, n-1 \quad (3)$$

Then, the residual test is performed on the model, and $C=0.1172$, $P=1$. It is known that the prediction accuracy of model is very good.

2.1.3. Prediction result. For the prediction of the total energy consumption of a shipbuilding enterprise from 2006 to 2015, analyze its prediction results and errors, as shown in Table 1.

Table 1. Prediction results and errors of each model

Years	Actual value	GM (1, 1)model		System Dynamics model		Combined Prediction model	
		fitted value	error	fitted value	error	fitted value	error
2006	49.17	49.9678	-0.7978	48.4555	0.7145	48.7201	0.4499
2007	52.7	54.3795	-1.6795	51.5183	1.1817	52.0188	0.6812
2008	57.92	62.9608	-5.0408	56.2653	1.6547	57.4366	0.4834
2009	66.03	72.8962	-6.8662	65.3698	0.6602	66.6864	-0.6564
2010	83.52	84.3995	-0.8795	80.0457	3.4743	80.8073	2.7127
2011	103.71	97.718	5.992	107.5404	-3.8304	105.8221	-2.1121
2012	115.97	113.1383	2.8317	118.1404	-2.1704	117.2654	-1.2954
2013	134.94	130.992	3.948	135.1775	-0.2375	134.4453	0.4947
2014	157.51	159.663	-2.153	152.0357	5.4743	153.37	4.1400
2015	166.68	175.5959	-8.9159	166.1598	0.5202	167.8105	-1.1305
average value			3.9104		1.9918		1.4156

2.2. System Dynamics Model

2.2.1. Outline. System dynamics is to fully understand the feedback and dynamics in the system, and gradually establish the structural model of system dynamics according to certain rules. In fact, it is a feedback process based on information, researching the relationship between complex problems of the system, qualitative and quantifying the relationship between internal variables or subsystems from the perspective of the system, and establishing a causal relationship diagram. System dynamics is more about the purpose of modeling, considering the problem from the whole, considering the impact of various factors, therefore, the variable parameters of the problem and data requirements are less. System dynamics is applied in many fields in prediction, and its accuracy is very high. In terms of energy consumption prediction of discrete manufacturing enterprises, system dynamics has great advantages, which not only solves the factor issues that it was difficult to quantify in energy consumption statistics in the past. Such as labor, weather, economy, etc [7]. Moreover, the connection between it and the whole system is established. In energy consumption prediction and statistics, it is no longer just an insignificant factor, but one of the factors that must be considered.

2.2.2. Establish model. According to the actual research, in discrete manufacturing enterprise, energy consumption is related to factors such as energy consumption structure, energy recovery, energy loss during product production and transportation, and energy performance. Through the interconnection and mutual restraint of various factors, a complex system of energy consumption is formed. Based on the feedback of dynamic variables, a causal relationship diagram is established as shown in Figure 1. In the figure, "+" means positive causality and "-" means negative causality.

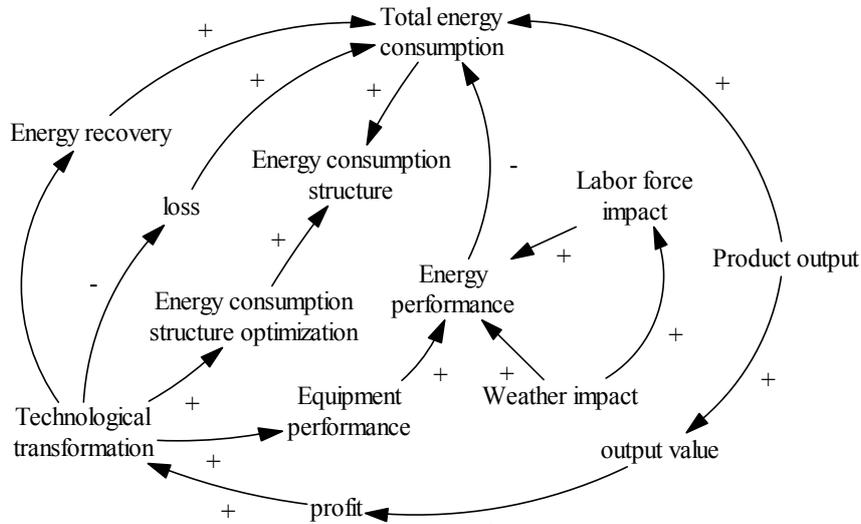


Figure 1. Energy consumption causality diagram

The energy consumption system can be regarded as composed of subsystems such as energy, product output, and output value. The operation of each subsystem is related to its internal structure and to external interconnection. The energy consumption dynamic analysis model established with Figure 1 is shown in Figure 2.

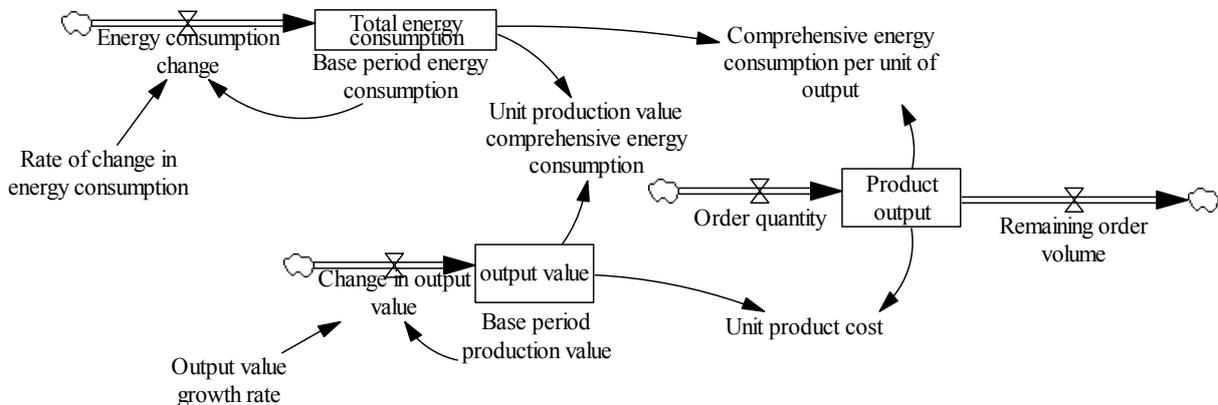


Figure 2. Energy consumption dynamic analysis model diagram

2.2.3. Prediction result. Taking the 2005 energy consumption data as the initial value of the simulation, the data related to the energy consumption, product output and output value of a shipbuilding enterprise are simulated as the initial state variables of the system, and the simulation results of 2006-2015 are compared with the actual data. The results are as follows Table 1.

3. Combined prediction model

3.1. Establish combined prediction model

For the same prediction problem, using N different prediction models to predict separately, then the comprehensive prediction model consisting of N prediction models is:

$$y(t) = \sum_{k=1}^n \partial(k)y(kt), k = 1, 2, \dots, n \tag{4}$$

Among, $y(t)$ is the predicted value of the combined prediction model at time t , $y(kt)$ is the predicted value of the k th model at time t , $\vartheta(k)$ is the weight of the k th model, and $\sum_{k=1}^n \vartheta(k) = 1$.

3.2. *Optimal weight calculation method*

In this paper, the Shapley value method is used to assign the weights of N models [8]. The Shapley value method uses the characteristics of total error redistribution to redistribute the weights of each prediction model according to the contribution error of each model.

Assuming that there are N prediction methods, $G = \{1, 2, \dots, N\}$. For any subset \mathbf{a} and \mathbf{b} of G (representing any combination of N methods), $P(\mathbf{a})$ and $P(\mathbf{b})$ represent the errors predicted by each. Defined as:

(1) For any subset \mathbf{a} and \mathbf{b} of G , $P(\mathbf{a}) + P(\mathbf{b}) \geq P(\mathbf{a} \cup \mathbf{b})$.

(2) The total error P generated by N prediction models is fully assigned to the N prediction models.

As

$$P = \sum_{i \in N} P'_i$$

Where P'_i is the error assigned to the model, as Shapley value.

Let the average value of the absolute value of the prediction error of the i -th prediction model be P_i , $P'_i \leq P_i$, and

$$P = \frac{1}{N} \sum_{i=1}^N P_i \tag{5}$$

Then the weight distribution formula is

$$P'_i = \sum_{a_i \in \mathbf{a}} w(|a_i|) [P(\mathbf{a}_i) - P(\mathbf{a}_i - \{i\})] \tag{6}$$

Among, $w(|a_i|)$ is the weighting factor, indicating the marginal contribution that the i -th prediction model should assume in the combined predict, $w(|a_i|) = \frac{(N-|a_i|)! (|a_i|-1)!}{N!}$; $\mathbf{a}_i - \{i\}$ is removes the i -th prediction model from the combined prediction; \mathbf{a} is all subsets containing the i -th prediction model; $|a_i|$ is the number of prediction models in the combined predict.

The formula for calculating the weight of each prediction model w_i from equation (6) is

$$w_i = \frac{P - P'_i}{P(N-1)} \quad (i = 1, 2, \dots, N) \tag{7}$$

3.3. *Combined prediction model*

It can be seen from Table 1 that the average values of the absolute values of the prediction errors of GM(1,1) and System Dynamics model are 3.9104 and 1.9918, respectively, and the total error with $P=2.9511$ of the combined prediction is obtained by equation (5).

In the combined prediction model, the elements participating in the total error allocation are $G = \{1, 2\}$, and the combined errors of the three subsets are $P(\{1\})$, $P(\{2\})$, $P(\{1, 2\})$, which is 3.9104, 1.9918, 2.9511.

Therefore, according to formula (6), $P'_1 = 2.4349$

Similarly, $P'_2 = 0.5162$, and $P'_1 + P'_2 = 2.9511$, the error of the allocation is the accuracy of each prediction model in the combined prediction model, and according to formula (7), the prediction model can be calculated in the combined model. The weight distribution ratios in the group are $w_1 = 0.17$ and $w_2 = 0.83$.

Then the combined prediction model is:

$$y(t) = 0.17y(1t) + 0.83y(2t), t = 1, 2, \dots, n \tag{8}$$

Where $y(1t)$ is the prediction result of GM (1, 1) model at time t , and $y(2t)$ is the prediction result of System Dynamics model at time t .

The combined model is used to predict the data of a shipbuilding enterprise from 2006 to 2015. The calculation results are shown in Table 1. From the calculation results, the absolute value of the combined prediction error is 1.4156, which is lower than single prediction errors of the GM (1, 1) and System Dynamics model, the combined model's prediction accuracy is higher than the single prediction model.

4. Conclusion

Taking the energy consumption data of a shipbuilding enterprise from 2006 to 2015 as the data source, the GM (1, 1) model and the system dynamics model are used to predict the energy consumption. From Table 1, the accuracy of the System Dynamics prediction model is higher than that. GM (1, 1) prediction model. At the same time, based on the Shapley value method, the energy consumption total combined prediction model is constructed. The predict accuracy of the combined prediction model is higher than that of single forecasting model, which improves the prediction accuracy of total energy consumption of a shipbuilding enterprise, and has reference value to other discrete manufacturing enterprises.

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