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Product form feature evolution forecasting based on IGMBPM model

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ABSTRACT

In view of the problem of generational product consistent form feature is difficult to be predicted quantitatively, this paper presents a novel approach based on grey theory, Back propagation neural network (BP NN) and Markov chain, which is hereafter called the improved Grey-BP model with Markov chain (IGMBPM model). In the process of forecasting, due that the raw sequence consisted of product form feature points' positions has the characteristics of poor sample, irregular and high volatility, firstly the traditional grey model is improved to be more suitable for the oscillating raw data, and the improved grey model is combined with BP NN for the purpose of enhancing the mutual influence between anterior and posterior data in sequence, in addition Markov chain is used to amend the final prediction results. The radiator grill profile of a certain type of automobile are taken as an example, the results of the IGMBPM model are compared with other models, the former shows better performance, which verifies the effectiveness of the proposed method. Study results can be helpful to both designers and stakeholders working in mature or developing manufacturers.

1. Introduction

Products' appearance or styling plays a key role in their brands' recognition [8]. When new generational products entering the market, the consistent form feature can help manufactures to keep and reinforce the brand identity and styling impression. Therefore a lot of manufacturers, especially relatively mature manufacturers, paid more attention to keep the consistent form feature and brand identity. Examples of such consistent form feature include the "waisted" bottle shape adopted by Coca Cola or the "kidney-grille" seen on every BMW car [13], as shown in Fig. 1. These features have been shown to come under particular scrutiny in the styling process and are becoming increasingly important aspects of the core brand values [9].

Meanwhile, some new developing product manufacturers need to use the form feature evolution trend of mature manufacturers for reference, due to their short brand history and not clear identity elements. However designers create new form mainly relying on personal experience or intuition and designers has little support about previous or future form feature with respect to brand consistency and recognition in existing product form design practices. Therefore, form feature evolution of generational products has been regards as one of the most challenging problems in product design field,

which will be helpful in providing recommendations for industry and guidelines for mature or developing manufacturers.

Form feature evolution prediction methods currently exist can be classified into two main categories, including qualitative and quantitative methods. Qualitative forecasting methods include trending forecasting based on product image [2], building mapping model based on shape grammar and users' expectation [15]. Meanwhile, quantitative forecasting methods include genetic algorithm [6], neural networks [10], and so on. Compared with qualitative forecasting methods, quantitative forecasting methods can provide more explicit information to designers or stakeholders. While the above quantitative methods are limited by human subjective perception, human evaluation is used in process of evolutionary algorithm frequently. This study aims to propose a novel approach for predicting product form feature evolution quantitatively based on data-driven rather than priori knowledge.

Most mature product manufacturers have theirs unique brand elements, which mainly reflects in product feature lines consisted of feature points. The decomposition of feature line and points are a common approach to help designers to understand product form, which is based on shape grammar in architecture, engineering and

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Figure 1. The "kidney-grille" of BMW car.

design field [16]. Karjalainen [9] explored the aesthetic properties of vehicles and their branding through feature line decomposition. Ranscombe et al. [14] proposed a series of form feature decomposition methods. Chen [1] constructed a vehicle image assessment through feature line decomposition to the side view of automobile. Chiu et al. [3] performed Support Vector Regression (SVR) to incorporate the psychological response of customers into the design of form feature of green cars.

In the research, generational product feature points' positions are chosen as the objects of study. According the feature points' positions of previous generational products belong to the same brand or type in product family, the future generational feature points' positions are forecasted through data analysis. However the samples size of feature points' positions is too small for traditional quantitative forecasting methods, such as time series analysis [17] or linear regression analysis [7], which require a large number of variables. The majority of evolutional generations of products are less than 30. Take automobile industry as example, Audi A4 has experienced merely eight changes from 1972 to 2008 and Toyota Camry has experienced eight changes too between 1980 and 2012. Hence, the forecasting of product feature points' positions is a typical small sample data prediction problem.

The grey system uses four datasets to build the grey forecasting model put forward by Deng [4], which frequently used to solve small sample data prediction. Beside the characteristics of poor sample, the data series of product feature points' positions are irregular, chaos and high volatility generally, consequently it is difficult to establish an ideal prediction model system by single method. In recent years, there is a trend to combine the grey system and other method, such as the hybrid grey model, Grey-Fuzzy [23], Grey-Markov [24], Grey-neural network [18], etc. Among these hybrid methods, Grey-neural network is a powerful approach. For small sample oscillating sequence, the advantage of grey model prediction is efficient to short-term prediction, and that the disadvantage is poor fitting ability to great changed data, the merit of artificial neural network is strong nonlinear mapping ability, while the limitation is long training time and easy to premature convergence. The combination of them could integrate their advantage and overcome their disadvantage.

Many researchers made efforts to study the integration of grey model and neural network and the relevant work can be found in many literature. Ma and Zhu utilized the NN-GM(1,1) model to predict the important samples of coal mine safety accidents successfully [11]. Yang applied an intelligent forecasting system based on a feedforward neural network aided grey model to the experimental results of a robot, results proved the proposed method had high accuracy for both trajectory prediction and target tracking [22]. Min solved the long-term prediction problem based on grey neural network model [12]. Han et al. established the real-time model predictive control based on the NN-GM(1,1) model for nonlinear systems with prospective accuracy [5]. Wang combined the residual modified GM(1,1) model with the improved neural network in order to forecast postgraduates' employment confidence index [19].

However, the forecast accuracy of Grey-neural network model with large random fluctuations is lower. In order to enhance the forecast performance, Markov chain model is integrated into Grey-neural network model to extract the random fluctuation of results and solve the influence of them on forecast accuracy [24].

The remainder of this paper is organized as follows. In Section 2, the basic concepts of the GM(1,1), BP NN and Markov chain method are described. Section 3 proves the advantage of the IGMBPM model put forward in this paper over the EMD-ARIMA method proposed in Ref. [20]. In Section 4, the prediction concerning product feature points' position of vehicle form will be conducted, including data acquisition, data simulation and prediction results. Comparison among different models is carried out in detail to reveal that the IGMBPM model is outperformed high than others. Finally, the paper concludes with some comments in Section 5.

2. Theory and method

2.1. The outline of method

In the study, a novel forecasting model named the IGMBPM model is presented. Firstly, the traditional GM(1,1) is improved aimed to obtain better oscillating data prediction effect. Then the improved GM(1,1) (IGM) model and Back Propagation neural network (BP NN) are combined to establish the IGMBP model. In this model, the prediction results of IGM model are input variables of BP NN, the measured values are output variables. The residue of the IGMBP model still limit the oscillating data forecast performance to a certain degree. Therefore, Markov chain is applied to amend results.

Finally, the IGMBPM model is set up and used to product feature points' position forecasting. The flowchart is shown in Fig. 2.
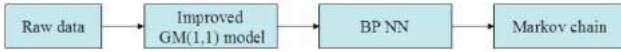

Figure 2. The forecast method based on GM (1, 1) model, BP NN and Markov chain.

2.2. The improved GM(1,1) to small sample oscillating sequences

GM(1,1) model is especially useful since it can be employed when data are scarce, as it only needs four training data values to determine the parameters of the model for forecasting with a reasonable degree of accuracy. Nevertheless the general GM(1,1) is suitable for monotonous sequence rather than oscillating data series. In the improved GM(1,1) model, raw oscillating sequence is transformed to monotone sequence, the former is replaced by the latter. After the operation of GM(1,1), monotone fitting values is recovered to oscillating fitting results.

The following is about the definition of monotonous sequence:

Definition 1: Assume that the original sequence with n samples is:

$$x = \{x(1), \ x(2), \ \cdots, \ x(n)\} \qquad (1)$$

(1) $\forall k = 2, 3, \cdots, n, \ x(k) - x(k-1) > 0, \ x$ is monotone increasing sequence;
(2) $\forall k = 2, 3, \cdots, n, \ x(k) - x(k-1) < 0, \ x$ is monotone decreasing sequence;
(3) $\exists k, \ k' \in \{2, 3, \cdots, n\}, \ x(k) - x(k-1) > 0, \ x(k') - x(k'-1) < 0, \ x$ is oscillating sequence.

The procedures of the improved GM(1,1) are expressed as:

Step 1: Establish new sequence which replaces the previous ones:

$$x' = \{x(1)', \ x(2)', \ \cdots, \ x(n)'\} \qquad (2)$$

When $n = 1, \ 2, u(n) = 0, x(n)' = x(n)$;

When $n = 3, 4, \cdots, \ x(n)' = x(n) + \sum_{j=3}^{n} u(n), \ j = 3, 4, \cdots n$. When $x(1) > x(2)$, if $x(n-1) \geq x(n)$, $u(n) = 0$, whereas, $u(n) = -2[x(n) - x(n-1)]$; when $x(1) < x(2)$, if $x(n-1) \leq x(n)$, $u(n) = 0$, whereas, $u(n) = 2[x(n) - x(n-1)]$.

Step 2: New monotonous sequence is $x'^{(0)} = \{x'^{(0)}(1)$, $x'^{(0)}(2), \ \cdots, \ x'^{(0)}(n)\}$, Where the superscript (0) of $x'^{(0)}$ represents the original series. Establishing the one-time AGO sequence:

$$x'^{(1)} = \{x'^{(1)}(1), \ x'^{(1)}(2), \ \cdots, \ x'^{(1)}(n)\} \qquad (3)$$

$$x'^{(1)}(n) = \sum_{i=1}^{n} x'^{(0)}(i) \qquad (4)$$

Establishing the grey differential equation:

$$\frac{dx'^{(1)}}{dt} + ax'^{(1)} = b \qquad (5)$$

Where a is the developing coefficient and b is the grey input. This is a one-order one-variable differential equation model.

Solving this equation and getting the parameter approximation,

$$\hat{x}'^{(1)}(j+1) = \left(x'^{(0)}(1) - \frac{b}{a}\right)e^{-aj} + \frac{b}{a}, \ j = 1, 2, 3, \cdots \qquad (6)$$

The operation of IAGO for the first-order series is defined as follows:

$$\hat{x}'^{(0)}(j+1) = \hat{x}'^{(1)}(j+1) - \hat{x}'^{(1)}(j) \qquad (7)$$

Step 3: Take out non-zero values from the sequence $u(n)$ and build the sequence $v^{(0)}(n)$, $u(n) = \{u(3), u, (4) \cdots, u(n)\}$. If the number of non-zero values of $v^{(0)}(n)$ is more than equal to 4, repeat the operation of *step 2*, obtain fitted value sequence $\hat{v}^{(0)}(n)$. Then establish new sequence $\hat{u}(n) = \{\hat{u}(3), \hat{u}(4), \cdots, \hat{u}(n)\}$, where non-zero value of $u(n)$ is replaced by the corresponding value in $\hat{v}^{(0)}(n)$, zero value remains unchanged. If the number of non-zero values of $v^{(0)}(n)$ is less than 4, then $\hat{u}(n) = u(n).\hat{u}(n) = u(n)$

Step 4: Data recovery.

When $j = 1, \ 2, \hat{x}^{(0)}(j) = \hat{x}'^{(0)}(j)$;

When $j = 3, 4, \cdots, n, \hat{x}^{(0)}(j) = \hat{x}'^{(0)}(j) + \sum_{k=3}^{j} u'(k)$, if $x(1) > x(2), \ u'(k) = \hat{u}(k)$; if $x(1) < x(2), \ u'(k) = -\hat{u}(k)$.

2.3. The combination of the improved GM(1,1) and BP NN

BP NN is one of the most widely used artificial intelligence-based approaches, which has unique approximation ability and simple structure. It has been extensively applied in parameter optimization [21], small sample data forecasting in industrial engineering and yielded good prediction performance in most cases.

BP NN learning process works in small iterative steps, and the network produces some output based on the current state of its synaptic weights. This output is compared to the known-good output, and a mean-squared error signal is calculated, the error value is then propagated backwards through the network, and small changes are made to de weights in each layer, the weight changes are calculated to reduce the error signal for the case in question. The whole process is repeated for each of the example cases, then back to the first case again, and so on.

However, the general BP NN may not perform so well in prediction of a series data, because it takes no account of the influence of the anterior data during the prediction. That means the way of BP learning is principally based on pattern collation to map the relationship between input and output without taking account into the influence of the previous outputs. The improved Grey-BP NN (IGMBP) model has the capability of storing previous information for future prediction to overcome this drawback in the general BP NN.

The IGMBP model consists of three layers: the input layer, hidden layer and output layer. $\hat{x}^{(0)} = \{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n)\}$ is the input vector, and the output is the measured value $x = \{x(1), x(2), \cdots, x(n)\}$. Take the top 75 percent of $\hat{x}^{(0)}$ as training set, the rest as test set. The node number of output layer is 1, that of hidden layer is 3, forecasting sequence is r, $r = \{r(1), r(2), \cdots, r(n)\}$ the structure is shown in Fig. 3.
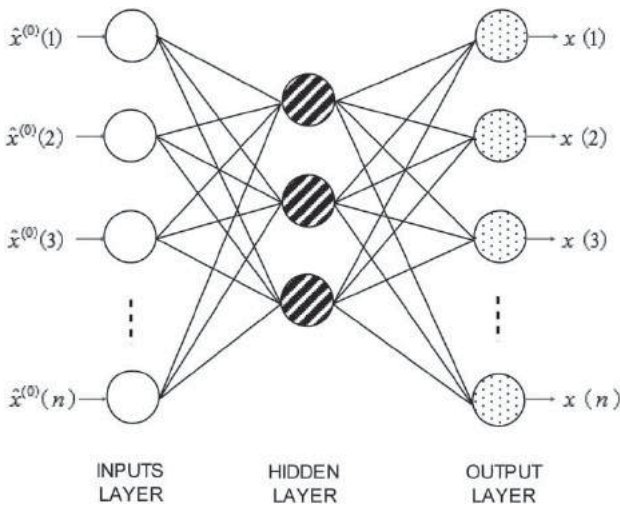

Figure 3. The structure of IGMBP model.

2.4. Markov chain is used to amend results

There are a lot of stochastic phenomena in the forecasting process. The existence of these stochastic phenomena reduces the predictive effect. Markov chain can be used to explain the stochastic phenomenon, which is applied to reduce the random factor effects and greatly improve the prediction accuracy.

When the system state is at the moment of t, the system state at the moment $t + 1$ is only related to the state at the moment of t, and has nothing to do with the previous state of t. The method is available to changing rule of system state from the known data. It adjusts predicted value by means of calculating the probabilities of state transition. Consequently, on the basis of studying the changing rule of the known data, we could adopt the way to adjust the prediction results aiming at increasing the prediction credibility.

Suppose that the original series data and predict results respectively are:

$$x = \{x(1), x(2), \cdots, x(n)\} \tag{8}$$
$$r = \{r(1), r(2), \cdots, r(n)\} \tag{9}$$

The modified approach of predict value is as follows.

Step 1. Choose former k group data and calculate the relative error of predict results:

$$e_k = (x(k) - r(k))/x(k), \quad k < n \tag{10}$$

Step 2. The division of state.

Divide the ratio e_k into h kinds of state according to its range, the interval range of each state is $R_1 [R_{1-}, R_{1+}]$, $R_2 [R_{2-}, R_{2+}], \cdots, R_h [R_{h-}, R_{h+}]$. Obtain the mean value of e_k is $\bar{Z}$, and make normalization processing on it. Supposed that the golden ratio is $\Omega = 0.618$, break point λ is estimated as:

$$\lambda_i = \Omega^s \bar{Z}, \quad |s| < h, \quad h = 1, 2, \cdots \tag{11}$$

In this study, take s is 1 and -1, and get three states $[0, a_1]$, $[a_1, a_2]$, $[a_2, 1]$. $R_{1-} = e_{\min}$, $R_{1+} = R_{2-} = e_{\min} + a_1(e_{\max} - e_{\min})$, $R_{2+} = R_{3-} = e_{\min} + a_2(e_{\max} - e_{\min})$, $R_{3+} = e_{\max}$. Where $e_{\min}$ and $e_{\max}$ is maximums and minimums among e_k respectively.

Step 3. Confirm the state grade of each pair of data according to the division of state.

Step 4. Construct the state transfer matrix P_{t+1}.

$$P_{t+1} = P_0[\mathbf{P}^{(1)}]^{t+1} \tag{12}$$

P_{t+1} is the probability distribution at the moment $t + 1$. P_0 is the unconditional probability distribution at the initial moment $\mathbf{P}^{(1)}$, that is one-step transition probability matrix and is expressed as:

$$\mathbf{P}^{(1)} = \begin{bmatrix} p^{11} & p^{12} & \cdots & p^{1m} \\ p^{21} & p^{22} & \cdots & p^{2m} \\ \vdots & \vdots & & \vdots \\ p^{1m} & p^{2m} & \cdots & p^{mm} \end{bmatrix} \tag{13}$$

Table 1. Actual values and simulated results of the IGBPMM model.

Date	Jan. 21	Jan. 22	Jan. 23	Jan. 24	Jan. 25	Jan. 26	Jan. 27	Jan. 28
Actual value	139618.5	142804.2	130070.9	157811.5	260115.4	351227.5	302161.2	373370.5
IGMBPM	129857.7	131646.6	142651.3	157057.7	257848.9	295835.1	312032.5	379440.7

Where, $P^{ij} = M^{ij}/M^i$ is the probability of state i transferred to state j through one steps, M^{ij} is the times of state i.

Step 5. According to the Eqn. (13) to get the probability of state after k steps, calculate the final prediction value $\breve{r}$ is:

$$\breve{r}(k+1) = r(k+1) * \left(1 + \frac{R_- + R_+}{2}\right) \qquad (14)$$

Where R_- and R_+ are respectively the upper and lower bounds of selected state.

2.5. Model verification

Average relative percentage error (*ARPE*) compares the measured and forecasted values to evaluate the precision. *ARPE* is defined as:

$$ARPE = \frac{1}{n-1}\sum_{i=2}^{n}\left|\frac{x_i - \hat{x}_i}{x_i}\right| \times 100\%, \; i = 2,\,3,\,\cdots,\,n \tag{15}$$

Where x_i is the measured value, $\hat{x}_i$ is the forecasted value, n is the generation number of product form changing and upgrading.

3. Verification of the IGMBPM method

In this section, the advantage of the IGMBPM method is demonstrated by an example of forecasting demand of commodities after natural disasters in Ref. [20]. Based on the cabbage daily trading volume data from January 21, 2008 to January 28, 2008 in the literature, the accuracy of the IGMBPM model and that of EMD-ARIMA method mentioned in Ref. [20] are compared, in order to demonstrate the improvement of the IGMBPM model. The simulated results of the IGMBPM model are shown in Table 1.

According to the results, the ARPE of the EMD-ARIMA method is 9.1%, that of IGMBPM model is 5.8%, the latter show a higher accuracy than the former. As shown in the two simulated curves in Fig. 4, the IGMBPM model surpasses the EMD-ARIMA method in better simulation results.

IGMBPM model is effective with the advantage of high precision and less samples required, which makes full use of the similarities and complementarities between
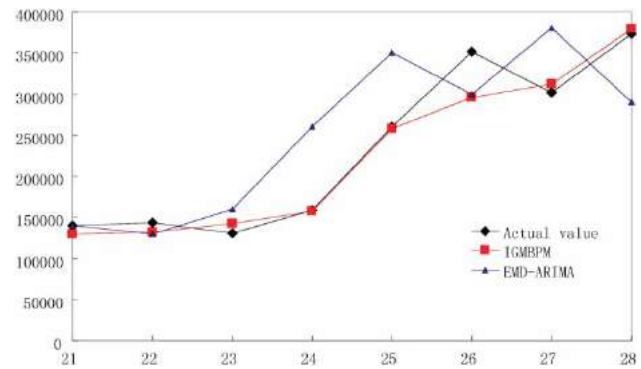
Figure 4. Curve of actual values and simulated values using two models.

grey model and artificial neural network to settle the disadvantage of applying grey model and neural network separately.

4. Results and discussion

The purpose of this study is to research the evolution of product form feature using the improved forecasting model, which has a consistent brand identity. A series of radiator grill profiles belong to a certain vehicle type are taken as example, which styling has experienced eight generations changes since 1982.

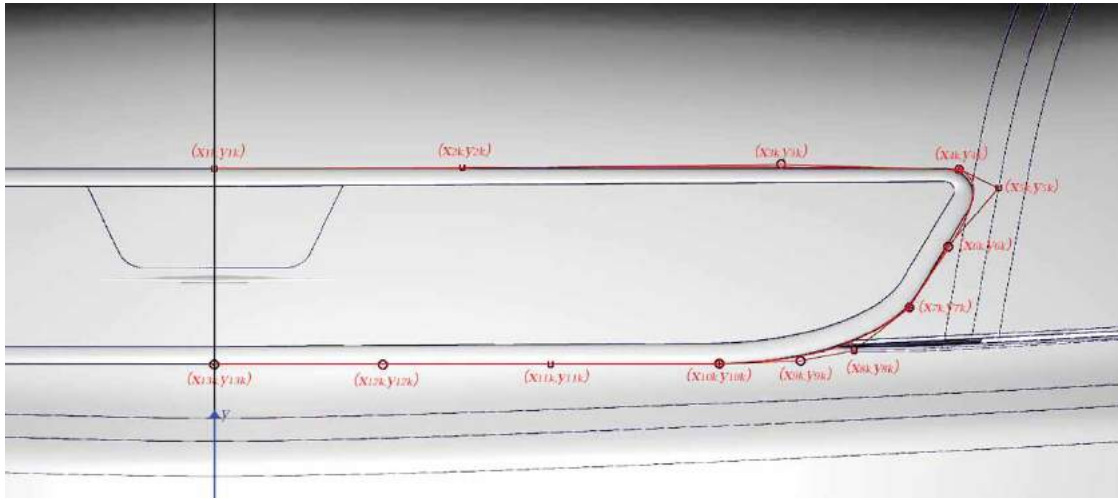**Figure 5.** The radiator grill profiles of vehicle bodies.

Figure 6. The coordinates of form feature points.

Table 2. The original sequences of vehicle form feature points' positions.

	Coordinate axis X		Coordinate axis Y
X_1	{0, 0, $\cdots$, 0, 0}	Y_1	{221.77, 174.77, $\cdots$, 257.25, 258.72}
X_2	{68.14, 60.51, $\cdots$, 54.77, 55.51}	Y_2	{221.77, 174.79, $\cdots$, 257.08, 258.73}
X_3	{136.03, 121.03, $\cdots$, 109.55, 110.56}	Y_3	{222.09, 174.74, $\cdots$, 256.42, 259.21}
$\vdots$	$\vdots$	$\vdots$	$\vdots$
X_{11}	{141.03, 115.39, $\cdots$, 50.40, 67.21}	Y_{11}	{154.65, 153.08, $\cdots$, 178.11, 187.95}
X_{12}	{70.15, 57.69, $\cdots$, 25.21, 35.43}	Y_{12}	{151.90, 153.21, $\cdots$, 177.84, 187.46}
X_{13}	{0, 0, $\cdots$, 0, 0}	Y_{13}	{150.07 153.34, $\cdots$, 177.18, 186.75}

4.1. Data acquisition

Scale all vehicle models according to the same front tread and extract half of the radiator grill profile of vehicle body (the red line in Fig. 5.), which is described in form of Bezier curve in Alias AutoStudio software, obtain thirteen feature points and respective coordinates.

The ground is axis X and front view axis is axis Y, the intersection of them is the coordinate zero point. The two-dimensional coordinates of each point are expressed as $(x_{i,j}, y_{i,j})$, as shown in Fig. 6. Hence the original sequence of generational vehicle form feature points' position is:

$$X_i = \{x_{i,1}, x_{i,2}, \cdots, x_{m,k}\}, \ Y_i = \{y_{i,1}, y_{i,2}, \cdots, y_{m,k}\} \tag{16}$$

Where $i = 1, 2, 3, \cdots, m, j = 1, 2, 3, \cdots, k, m$ is the number of feature points, k is the number of vehicle evolutional generations. The data sequences are shown in Table 2. (Complete data are shown in Table 5.)

4.2. Simulation modeling

Take X_2 as example randomly, $X_2 = \{68.14, 60.51, 46.85, 48.21, 44.07, 59.20, 54.77, 55.51\}$, which means the X position changes of this feature point from the first to the eighth generation.

Based on the IGM model in Section 2.1, X'_2 and u are obtained:

$X'_2 = \{68.14, 60.51, 46.85, 45.48, 41.34, 26.21, 21.78, 21.05\}$;

$u_{x_2} = \{0, 0, 0, 2.72, 0, 30.27, 0, 1.47\}$.

X_2 is replaced by x'_2, a and b are solved and Eqn. (6) can be solved as:

$a = 0.1784, \ b = 78.0179,$

$$\hat{X}'^{(1)}_{2,n+1} = 437.415 - 369.273e^{0.1784n},$$
$$n = 1, 2, 3, \cdots \tag{17}$$

After the IAGO to $\hat{X}'^{(1)}_2$, $\hat{X}'^{(0)}_2$ is obtained:

$$\hat{X}'^{(0)}_2 = \{68.14, 60.32, 50.47, 42.23, 35.33, 29.56, 24.73, 20.69\}$$

Since the number of non-zero values is less than 4, $\hat{u}_{x_2} = u_{x_2}$. Thus, the model result of IGM model is:

$$\hat{X}^{(0)}_2 = \{68.14, 60.32, 50.47, 44.95, 38.05, 62.55, 57.72, 55.15, 51.77\}.$$

In BP NN, the inputs are $\hat{X}^{(0)}_2$, the outputs are X_2, the values from $\hat{x}^{(0)}_{2,1}$ to $\hat{x}^{(0)}_{2,6}$ are training set, the values from

$\hat{x}_{2,7}^{(0)}$ to $\hat{x}_{2,8}^{(0)}$ are test set. The simulation results of IGMBP model is:

$$R_{x_2} = \{68.13,\ 58.16,\ 49.09,\ 48.36,\ 42.75,\ 59.48,$$
$$56.30,\ 53.00,\ 49.61\}.$$

The relative error of simulation results is defined as r_{x_2} and calculated based on R_{x_2} and X_2. Divide former seven group data of r_{x_2} into three kinds of state according to its range based on Eq. (11), the data number of R_{x_2} in each state is 2, 3, 2 respectively.

$r_{x_2,1} \in [-0.048,\ -0.0196], r_{x_2,2} \in [-0.0196,\ 0.0262],$
$r_{x_2,3} \in [0.0262,\ 0.0389].$

One-step transition probability matrix is:

$$P^{(1)} = \begin{bmatrix} 0 & 1/2 & 1/2 \\ 1/3 & 0 & 1/3 \\ 1/2 & 1/2 & 0 \end{bmatrix} \tag{18}$$

According to Eqn. (12), the state transition probability of the eighth group data in R_{x_2} is $r_{x_2,2}$. The actual value of $x_{2,8}$ is 55.51, the simulation results of $x_{2,8}$ in IGM model is 53.00, the amended results of IGMBPM is 54.72. As a result, the relative error is reduced from 4.52% to 1.42% after the operation of Markov chain, the proposed method is effective.

4.3. Results analysis

A variety of models are used to forecast X_2, including the general GM(1,1) model, the general BP NN, the IGM model, the IGMBP model and the IGMBPM model. The results of simulation are shown in Table 3, it can be seen that the results by the IGMBPM model are better than the other models. The IGMBPM model improves the general GM(1,1) model by 7.43%, the general BP NN by 8.84%, the IGM model by 3.36%, the IGMBP model by 0.44% at the *ARPE* statistic.

As shown in Fig. 7 which is scatter plot of each model. The fitting curve of the general GM(1,1) is monotonous decreasing, general BP NN performs well merely at local
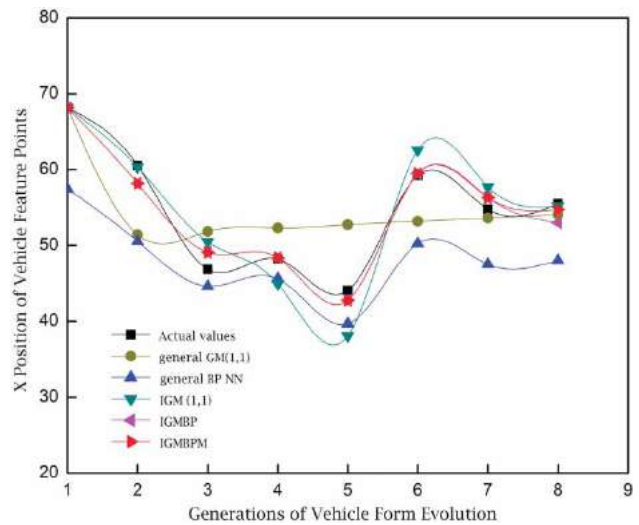

Figure 7. Scatter plot of models.

fitting, the IGM model greatly improves the fitting effect, the results of the IGMBP model are very close to the actual value, the model accuracy is improved by the IGMBPM model further. Experimental results showed that IGMBPM model has highly fitting and predicting precision advantages over the other models.

4.4. Forecasting results and implication

Table 4 shows the forecasting results of thirteen feature points' coordinates of the ninth generation.

Table 4. The forecasting result of thirteen feature points' coordinates.

$x_{1,9}$	$x_{2,9}$	$x_{3,9}$	$x_{4,9}$	$x_{5,9}$	$x_{6,9}$	$x_{7,9}$
0	51.23	100.96	143.1284	144.51	140.54	135.33
$x_{8,9}$	$x_{9,9}$	$x_{10,9}$	$x_{11,9}$	$x_{12,9}$	$x_{13,9}$	
132.01	117.21	102.38	99.24	63.96	0	
$y_{1,9}$	$y_{2,9}$	$y_{3,9}$	$y_{4,9}$	$y_{5,9}$	$y_{6,9}$	$y_{7,9}$
257.78	257.26	256.56	255.44	242.59	229.55	225.34
$y_{8,9}$	$y_{9,9}$	$x_{10,9}$	$y_{11,9}$	$y_{12,9}$	$y_{13,9}$	
222.62	218.37	215.5.2	215.64	211.71	211.91	
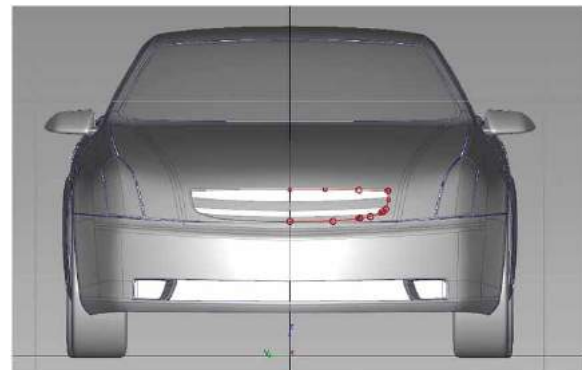
Figure 8. The forecasting radiator grill profile.

Table 3. Original data and simulated results.

	Simulated results				
Actual value	General GM(1,1)	General BP NN	IGM	IGMBP	IGMBPM
68.14	68.14	57.44	68.14	68.13	68.13
60.51	51.40	50.52	60.32	58.16	58.16
46.85	51.84	44.63	50.47	49.09	49.09
48.21	52.28	45.61	44.95	48.36	48.36
44.07	52.72	39.67	38.05	42.75	42.75
59.20	53.17	50.22	62.55	59.48	59.48
54.77	53.62	47.52	57.72	56.30	56.30
55.51	54.08	48.02	55.15	53.00	54.72
ARPE%	9.81	11.22	5.74	2.82	2.38

Table 5. The complete original sequences of vehicle form feature points' positions.

Coordinate axis X		Coordinate axis Y	
X_1	{0, 0, 0, 0, 0, 0, 0, 0}	Y_1	{221.77, 174.77, 182.89, 192.63, 233.09, 261.49, 257.25, 258.72}
X_2	{68.14, 60.51, 46.85, 48.21, 44.07, 59.20, 54.77, 55.51}	Y_2	{221.77, 174.79, 182.89, 192.84, 234.18, 261.49, 257.08, 258.73}
X_3	{136.03, 121.03, 93.69, 96.42, 88.26, 118.40, 109.55, 110.56}	Y_3	{222.09, 174.74, 182.89, 192.65, 233.33, 261.24, 256.42, 259.21}
X_4	{203.43, 181.54, 140.54, 144.62, 132.70, 177.29, 164.32, 164.21}	Y_4	{227.74, 173.74, 182.89, 192.26, 230.74, 260.75, 255.08, 260.16}
X_5	{205.58, 178.72, 140.03, 138.97, 130.12, 174.21, 157.93, 161.01}	Y_5	{201.31, 166.98, 173.79, 182.56, 215.74, 255.65, 238.75, 236.49}
X_6	{207.74, 175.90, 139.52, 133.16, 123.06, 170.48, 151.54, 149.99}	Y_6	{179.87, 160.21, 164.70, 173.16, 202.58, 250.20, 222.42, 217.24}
X_7	{209.89, 173.02, 139.02, 127.20, 113.10, 166.18, 144.27, 130.58}	Y_7	{158.44, 153.05, 155.60, 164.47, 190.06, 244.91, 205.21, 202.89}
X_8	{209.89, 173.02, 138.95, 124.36, 109.42, 161.76, 122.84, 121.41}	Y_8	{158.44, 153.05, 154.38, 160.33, 185.45, 239.49, 195.76, 196.12}
X_9	{209.89, 173.02, 137.95, 119.76, 104.10, 155.38, 98.48, 110.57}	Y_9	{158.44, 153.05, 153.42, 157.73, 182.45, 236.02, 186.62, 191.98}
X_{10}	{209.89, 173.02, 136.73, 114.75, 98.25, 148.43, 75.58, 99.22}	Y_{10}	{158.44, 153.05, 153.40, 157.44, 181.79, 235.27, 178.64, 190.93}
X_{11}	{141.03, 115.39, 91.15, 76.51, 66.10, 98.83, 50.40, 67.21}	Y_{11}	{154.65, 153.08, 152.77, 155.22, 177.67, 229.91, 178.11, 187.95}
X_{12}	{70.15, 57.69, 45.57, 38.27, 33.10, 49.25, 25.21, 35.43}	Y_{12}	{151.90, 153.21, 153.06, 153.86, 175.30, 227.61, 177.84, 187.46}
X_{13}	{0, 0, 0, 0, 0, 0, 0, 0}	Y_{13}	{150.07 153.34, 153.06, 152.70, 174.15, 227.13, 177.18, 186.75}

Input the forecasting results of thirteen feature points' coordinates of the ninth generation back to Alias AutoStudio software, obtain the ninth generation radiator grill profile of vehicle body. As shown in Fig. 8.

5. Conclusion

In this study, we proposed a data-driven method using small-sample forecasting model to research the product form, which could help the reserve of form feature for relative mature manufacturer and the reference of form feature for developing manufacturer.

The products feature points' positions are forecasted quantitatively, which is a highly effective way to study the product form evolution. Because of the fluctuation and irregular of product form evolution, it may have a poor prediction performance of applying the general single model. A hybrid forecasting method is applied which is an integration of the improved GM(1,1) (IGM), BP neural network and Markov Chain. Due to characteristics of IGM and BP NN can successfully catch the intrinsic characteristics of the original data which is nonlinearity and oscillating. The accuracy of hybrid forecasting method is greatly enhanced on the average relative percentage error statistic.

We chose the radiator grill profile as the object of the form feature line which is two-dimension line, however, there are many other key styling brand elements which play a important role in brand consistency, such as headlamp, intake grill, and so on, which could be researched based on three-dimension coordinate. Therefore, in the future study, the forecasting model is to involve more complicated form feature research.

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