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Mechanism of technological innovation and product quality management in business mode of strategic emerging industry

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Abstract. There was very important research value on mechanism research of technological innovation and product quality management in business mode of strategic emerging industry and quality control problem of various and small batch of products was adopted as the research direction; current existing advantages and disadvantages of multi quality control methods and application limitation were analyzed and improved convolutional neural network method was proposed; prior control was conducted on quality of small batch of products through prior prediction. Effective combination with grey system theory and convolutional neural network theory was achieved through the method and parallel computational capacity of the system and use ratio of available information was increased through making the best of the both worlds. System modeling efficiency and model precision were increased so as to realize control quality property of various and small batch of products beforehand through organic combination with black-box modeling and grey methods.

Key words. Emerging industry, Business mode, Technological innovation, Product quality, Convolutional neural network.

1. Introduction

Increasingly fierce globalization market competition was caused by economic rapid development and quality issue became the top drawing more and more attention of people; vitality of an enterprise was substantially represented by it and it was the fundamental starting point of sustainable development for enterprises. So, more and more attention and emphasis were drawn on quality consciousness in modern production enterprises and the important meaning of product quality was far bigger than that in the past. However, international leading level has not yet

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been reached by far for Chinese current most product quality level according to related statistical data and it is obvious that plenty of low-quality products have been produced by China when it gradually becomes "global manufacturing factory" meanwhile. Chinese rapid economic development is restricted by product quality problem to a great extent and Chinese product competitiveness is weakened and plenty of resources and energies are also wasted meanwhile. The loss due to product quality problem in China annually is as high as one hundred billion yuan and unfulfillment of quality monitoring, lack of necessary control means and low pre-control degree in product manufacturing process are the main reasons for modern manufacturing enterprises to face low quality level.

Though production capacity and technological level of modern enterprises are continually increased, there is major change of competitive market environment faced up with many enterprises; much attention is drawn on competition based on customer needs in mutual competition of enterprises. So, it is required that customer needs should be reached by modern production enterprises in aspects like product design, manufacturing process and response speed of product manufacturing, etc. There is no choice for enterprises but to adjust production mode in production process due to these competitive pressures. There are as high as about 75% products belonging to small and medium batch production type in manufacturing industry of many developed nations according to related data; the production mode of multi-varieties and small batch is selected for more and more enterprises to produce products so as to exist better and gain bigger competitive advantage in competition for modern enterprises in China; quite a ratio is occupied by product production in production mode of multi-varieties and small batch especially in manufacturing industries. So, it can be predicted that continuous forward rapid development of Chinese future manufacturing industry will be boosted by the flexible production mode of multi-varieties and small batch to be a main production mode. More and more attention is drawn on product quality control for modern production enterprises, but it is found through analysis and research of date that no satisfactory result can be gained on precision prediction of product quality pre-control technology in the production mode of multi-varieties and small batch currently; there is higher requirement of production process on quality control for products of expensive raw material and small processing quantity. There are many product types and little quantity for enterprises in the production environment of multi-varieties and small batch and the process can be ended only upon producing several pieces in special cases; in this case, the quantity of data we collect is so small that it cannot satisfy sample quantity requirement to establish traditional quality control chart commonly and sometimes it can possibly occur that production process has been finished before control chart is achieved. Generation of disqualified products cannot be effectively prevented by such quality control and plenty of resource waste is caused; it is adverse for enterprises to control production cost, so more effective quality control model needs to be proposed as the detection means to ensure product quality for enterprises. Plenty of researches have been conducted by many experts and scholars and many effective methods have been proposed to solve the problem and provide necessary technical support for quality control of products of multi-varieties and small batch in recent years.

Grey prediction model has been widely used in many fields so far as an effective prediction model in the state of poor information and the improvement method and combinational application research have been successfully implemented in many fields. Prediction model of convolutional neural network is widely used in many fields of prediction control as a kind of combinational model and one of research objects due to effectively overcoming their shortcomings through organic combination with features such as small needed samples for grey model, simple modeling and weak non-linear processing capacity, etc and features of neural network model such as large needed sample data and strong non-linear treatment capacity and self-organizing capacity, etc. Traditional prediction model of convolutional neural network is greatly improved compared with previous methods in quality control of Prediction model of multi-varieties and small batch, but there are still defects such as prediction precision failing to satisfy high requirements of current enterprises and weak adaptability, etc. So improved convolutional neural network model is proposed to conduct prediction compensation control for product production of enterprises based on deep analysis on key parameters of neural network and grey system in this thesis; beforehand control of product quality is realized through precise prediction so as to provide necessary technical and theoretical support for product quality control of multi-varieties and small batch.

2. Grey convolutional neural network

2.1. Network structure

Convolutional neural network is a neural network of multi layers and each layer is composed of multi two-dimension surfaces; each surface is composed of many neurons. There are some simple elements and complex elements in the network, respectively denoted as S-element and C-element. S-surface is composed through cluster of S-elements and S-layer is composed through cluster of S-surface; the layer is denoted as U_s. There is similar relation among C-element, C-surface and C-layer (U_s). All intermediate stage of the network is connected by S-layer and C-layer in series and there is only one layer in input stage; it is directly subject to two-dimension visual mode and extraction step of sample feature has been embedded into interconnection structure of convolutional neural network. Generally, U_s is feature extraction layer and input of each neuron is connected to local receptive field of the previous layer; the local feature is extracted and position relation between it and other features will be determined upon it; U_c is feature mapping layer and all calculation layers of the network are composed of multi feature mappings; each feature mapping is a surface and weighted value of all neurons on the surface is equal. Sigmoid function of small influence function kernel is adopted as the feature mapping structure as activation function of convolutional network to equip feature mapping with scale invariance. Besides, quantity of free network parameters is reduced and complexity of network parameter selection is also reduced because the weight value is shared by neurons on the same mapping surface. Each feature extraction layer (S-layer) of convolutional neural network is followed by a calculation layer (C-layer) to get local average and for secondary extraction and high distortion tolerance capacity of input sample is achieved through this special secondary feature extraction structure at the time of recognition.

Output connection value of neurons in the network conforms to "maximum inspection hypothesis", namely that output connection value can only b strengthened by outputting maximum neuron in a neuron set of a small area. So its output connection value will not be strengthened if there is a neuron whose output is stronger than it beside it. It is limited that only a neuron will be strengthened according to above hypothesis. Seed element of convolutional neural network is the maximum output S-element in a certain S-surface and it can not only strengthen itself, but also controls strengthening result of neighboring elements. So, the same features of almost all positions are extracted by all S-elements gradually. It needs a long time to automatically search the seed element of maximum output among all elements on a layer when a mode is trained in predominant non-supervision learning of early research of convolutional neural network; while training modes and their seed elements are all set by the teacher in current supervised learning way

2.2. Neuron model

Only input connection among S-elements is variable and input connection among other elements is fixed in convolutional neural network. Output of a S-element on the k_1th S-surface of the lth grade is indicated with $U_{s1}(k_1, n)$ and output of a C-element on the k_1th C-surface of the grade is indicated with $U_{c1}(k_1, n)$. Position of receptive field of neurons on input layer is indicated with n as a two-dimension coordinate; area of receptive field is small in the first grade and it will increase as increase of l.

$$u_{sl}(k,n) = r_l(k)\,\varphi\left[\frac{1+\sum\limits_{k_{l-1}}^{K_{l-1}}\sum\limits_{v\in A_l} a_l(v,k_{l-1},k)\,u_{cl-1}(k_{l-1},n+v)}{1+\frac{r_l(k)}{r_l(k)+1}b_1(k)\,u_{vl}(n)}-1\right]. \tag{1}$$

In Equation (1), connection coefficients of excitatory input and inhibitive input are respectively indicated with $a_1(v, k_{l-1}, k)$ and $b_1(k)$; selectivity of feature extraction is controlled by $r_1(k)$ and the bigger value indicates worse fault tolerance to noise and feature distortion; it is a constant and input of all neurons on the surface of a single inhibitor on all S-layers is controlled by it: the bigger value $r_1(k)$ of indicates bigger excitability in proportion to inhibition so as to generate a non-zero output; in another words, neurons can only be activated by quite good matching and the bigger r_1 value can generate bigger output because $r_1(k)$ needs to multiply $\phi(x)$; conversely, a small $r_1(k)$ value allows for a neuron excitation of not much matching, but only a small output can be produced; $\phi(x)$ is a non-linear function. v is a vector to indicate the relative position of neuron n in the previous layer in n respective field and the feature size to be extracted for S neuron is determined by A_1 to indicate the receptive field of n. So, all neurons in designated area are included through summing of k_{l-1}; all sub-surfaces in previous grade are included for summing of externally, so the sum term in the numerator is sometimes called excitement term; it is actually sum product and output into neurons of n is output to n_c upon multiplying their corresponding weighted value.

$$\varphi(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \tag{2}$$

Equation (2) indicates an output of a designated grade (the lth grade), a layer (S-layer), a surface (the k_lth S-surface), an element (where the vector is n). An action function of a S-element can be divided into two parts, namely excitatory action function and inhibitive action function. Excitatory action raises the membrane potential and inhibitive action has shunt effect. Excitatory action is:

$$\sum_{k_{l-1}}^{K_{l-1}} \sum_{v \in A_l} a_l(v, k_{l-1}, k)\, u_{cl-1}(k_{l-1}, n+v). \tag{3}$$

S-element is linked to all C-surfaces on C-layer of the last grade and the quantity of linked C-element is only determined by parameter reception field of the S-grade.

Another important neuron in the network is an inhibitive neuron V-element $U_{v1}(n)$ of assumed existence on S-surface to satisfy three conditions: inhibition of the ring element affects operation of the overall network; there is fixed link between C-element and V-element; output of V-element is set as the average of many C-element outputs beforehand. Inhibition of the network can be indicated by it and its input link value is received from elements similar to $U_{sl}(k_l, n)$ upon sending out a inhibitive signal to $U_{sl}(k_l, n)$ neuron and the following element is output:

$$u_{vl}(n) = \left(\sum_{k_{l-1}}^{K_{l-1}} \sum_{v \in A_l} c_l(v)\, u_{cl-1}^2(k_{l-1}, n+v) \right)^{1/2}. \tag{4}$$

Weight $c_l(v)$ is a linked weight to neurons in v in the receptive field of V-element and these values needn't to be trained, but they should decrease monotonously with increase of $|v|$. So normalized weight is:

$$c_l' = \frac{c_l}{C_r}. \tag{5}$$

Normalized constant C in the equation is offered in the following equation and $r(v)$ is the normalized distance between v and the center of receptive field:

$$C(l) = \sum_{K_{l-1}}^{K_{l-1}} \sum_{v \in A_j} a_l^{r(v)}. \tag{6}$$

Output of C neuron is offered by the following equation:

$$u_d(k_l, n) = \psi \left[\frac{1 + \sum\limits_{K_{l=1}=1}^{K_t} j_l(k_l, k_{l-1}) \sum\limits_{v \in D_t} d_l(v) u_{st}(k_l, n+v)}{1 + V_{sl}(n)} - 1 \right] . \tag{7}$$

$\psi\,(x)$ is in above equation:

$$\psi(x) = \begin{cases} \frac{x}{\beta + x}, x \geq 0 \\ 0, x < 0 \end{cases} \tag{8}$$

In the equation, β is a constant. k_l is the sub-surface quantity of S in the lth grade. D_l is the receptive field of C-element. So it is corresponding to the feature size. $d_l\,(v)$ is the weighted value of fixed excitatory linked weight and it is the monotone decreasing function of $|v|$. If the k_lth sub-surface of the S neuron receives signal from the k_{l-1}th sub-surface, then value of $j_l\,(k_l, k_{l-1})$ is one, or it is zero. Finally, output of V_s neuron on S-layer is:

$$V_{st} = \frac{1}{K_l} \sum_{K_{l-1}=1}^{K_{l-1}} \sum_{v \in V_t} dl(v) u_{sl}(k_j, n+v)\,. \tag{9}$$

Connection relation diagram of among different neurons in convolutional neural network is shown in Fig. 1 and connection relation among various different neurons can be clearly found in the figure.

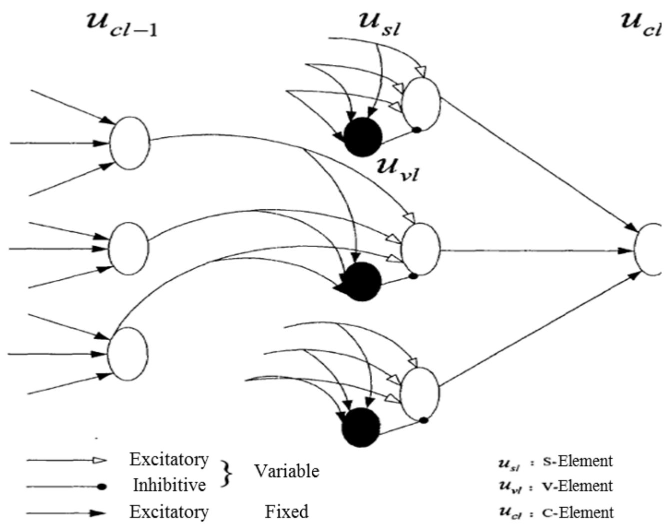


Fig. 1. Connection among different neurons in convolutional neural network

2.3. Training process of grey convolutional network

The mainstream of grey convolutional network applied to mode recognition is guided learning network and non-guided learning network is mostly applied to cluster analysis. Space distribution of samples is no longer divided according to their natural distribution tend because category of any sample is known for guided mode recognition, while a proper space division method should be found according to space distribution of samples of the same category and separation degree among samples of different categories, or a classifying boundary can be found to make samples of different categories respectively located in different areas. It needs a long and complex learning process to continually adjust the position of classifying boundary to divide sample space and divide as less and samples into different categories. Sample space can be divided into two types because human face is mainly detected in the image in the thesis: sample space and non-sample space, so learning network used in the thesis is also guided learning network. Convolutional network is essentially a mapping from input to output and it can learn the mapping relation among plenty of input and output without needing precise arithmetic expression among any input and output; the network will be equipped with mapping capacity between pairs of input and output through training convolutional network with the known mode. Mentor training is executed in convolutional network, so its sample set is composed of vector pair in form of (input vector, ideal output vector). All these vector pairs are all from actual "operation" of the system to be simulated of the network. They can be collected from actual operation systems. All weights should be initialized with some different small random numbers before the training. "Small random number" ensures that the network will not enter into saturation state due to oversize of weighted value to cause training failure; "difference" can ensure the network can normally learn. Actually the network will have no capacity to learn if the same number is used to initialize weight matrix.

Training algorithm mainly includes four steps, which are divided into two stages:

The first stage is forward communication stage:

①Take a sample (X, Y_p) from the sample set and input X into the network; pre-treat the input data with grey value:

② Calculate corresponding actual output O_p.

In this stage, the information is transmitted to the output layer through transformation from input layer step by step. This process is also executed process in the network upon the training at the time of normal operation. In this process, network execution is calculated by Equation (7):

$$O_p = F_n\left(\cdots(F_2(F_1(X_pW^{(1)})W^{(2)})\cdots)W^{(n)}\right).$$

The second stage is backward communication stage

① Calculate the difference between actual output O_p and corresponding ideal output Y_p;

② Adjust weight matrix in the method of minimized error

Work in these two stages is generally controlled by precision requirement and E_p

is calculated with Equation (10) here.

It is error measurement of the network about the pth sample. Error measurement of the network related to the overall sample set is defined as:

$$E_p = \frac{1}{2}\sum_{j=1}^{m}(y_{pj} - o_{pj})^2 \,. \tag{10}$$

As mentioned earlier, the reason why this stage is called backward communication stage is that it is corresponding to normal communication of input signal. Because only error of input layers can be obtained and errors of other layers can only be obtained through reverse deduction step by step on this error when link weight of neurons starts to be adjusted. It is sometimes called error communication stage. Firstly it is assumed that unit number of input layer, middle layer and output layer is respectively N, L and M so as to explain the training process of convolutional neural network used in this thesis more clearly. $X = (x_0, x_1, \cdots, x_N)$ is an input vector added to the network and $H = (h_0, h_1, \cdots, h_L)$ is output vector of middle layer; $Y = (y_0, y_1, \cdots, y_M)$ is actual output vector of the network and target output vector of all modes in the training group is indicated with $D = (d_0, d_1, \cdots, d_M)$; weighted value from output unit i to hidden unit j is V_{ij} and weighted value from hidden unit j to output unit k is W_{jk}. Besides, thresholds of output unit and hidden unit are respectively indicated with θ_k and ϕ_j. So output of all units in the middle layer is Equation (11):

$$h_j = f(\sum_{i=0}^{N-1} V_{ij}x_i + \phi_j) \,. \tag{11}$$

Output of all units in output layer is Equation (12):

$$y_k = f\sum_{j=0}^{L-1} W_u h_j + \theta_k \,. \tag{12}$$

S type function expression (13) is adopted for excitation function $f(\cdot)$:

$$f(x) = \frac{1}{1+e^{-kx}} \,. \tag{13}$$

Training process of the network is as follows on above conditions:

1) Select training group. 300 samples are randomly selected from sample set as the training group and input data is pre-treated with gray value.

2) Weighted values V_{ij} and W_{jk} and thresholds ϕ_j and θ_k are transformed to small random number close to zero and precision control parameter ε and learning rate α are initialized.

3) An input mode X is taken from the training group and then added it to the network and its target output vector D is offered.

4) An output vector H in the middle layer is calculated with Equation (9) and actual output vector Y of the network is calculated with Equation (10).

5) The element y_k in output vector and the element d_k in target vector are compared to calculate the term equation (14) of M output errors:

$$\delta_k = (d_k - y_k)y_k(1 - y_k)\,. \tag{14}$$

Term Equation (15) of L errors is calculated for hidden units in the middle layer:

$$\delta_j = h_j(1 - h_j)\sum_{k=0}^{M-1}\delta_k W_{jk}\,. \tag{15}$$

6) Adjustment quantity equations (16) and (17) of all weighted values are calculated respectively:

$$\Delta W_{jk}(n) = (\alpha/(1+L)) * (\Delta W_{jk}(n-1)+1) * \delta_k * h_j\,. \tag{16}$$

$$\Delta V_{ij}(n) = (\alpha/(1+N)) * (\Delta V_{ij}(n-1)+1) * \delta_k * h_j\,. \tag{17}$$

And adjustment quantity equations (18) and (19) of the threshold:

$$\Delta\theta_k(n) = (\alpha/(1+L)) * (\Delta\theta_k(n-1)+1) * \delta_k \tag{18}$$

$$\Delta\phi_j(n) = (\alpha/(1+L)) * (\Delta\phi_j(n-1)+1) * \delta_j\,. \tag{19}$$

7) Weighted value adjustment equations are (20) and (21):

$$W_{jk}(n+1) = W_{jk}(n) + \Delta W_{jk}(n)\,. \tag{20}$$

$$V_{ij}(n+1) = V_{ij}(n) + \Delta V_{ij}(n)\,. \tag{21}$$

Threshold adjustment equations are (22) and (23):

$$\theta_k(n+1) = \theta_k(n) + \Delta\theta_k(n)\,. \tag{22}$$

$$\phi_j(n+1) = \phi_j(n) + \Delta\phi_j(n)\,. \tag{23}$$

8) Whether the index satisfies precision requirement is judged when k value is set from one to M: $E \le \varepsilon$ and E is overall error function and $E = \frac{1}{2}\sum_{k=0}^{M-1}(d_k - y_k)^2$. If it is not satisfied, then it can return to (3) for continual iteration. Enter into the next step if it is satisfied.

9) Weighted value and threshold are kept in the file upon training. Then it can be considered that weighted values are stabilized and the classifier is formed. Weighted value and threshold can be exported from the file directly for training without needing initialization when the training is conducted once again.

3. Zinc-coating weight and mass model based on grey convolutional neural network algorithm

Mass of zinc coating is an important quality index in strip hot-dipping galvanizing production and gas knife is the key part to control mass of zinc layer in blowing zinc coating technology. Spray air pressure of the gas knife, the distance from gas knife nozzle to strip steel, unit operation speed and strip steel thickness are several main factors influencing mass of the zinc layer in the actual production technology. Actual production data of hot galvanizing production line of strip steel in a steel plant is the sample space in this thesis and quality prediction model of mass of zinc layer is established with grey convolutional neural network algorithm. The following evaluation indexes are adopted mainly in this thesis so as to compare the advantage of the method (grey convolutional neural network model) in this thesis, convolutional neural network model and standard BP model.

(1) Root mean square error.

(2) Coefficient R^2 of re-determination:

$$R^2 = 1 - \frac{SSR}{SSY}\,. \tag{24}$$

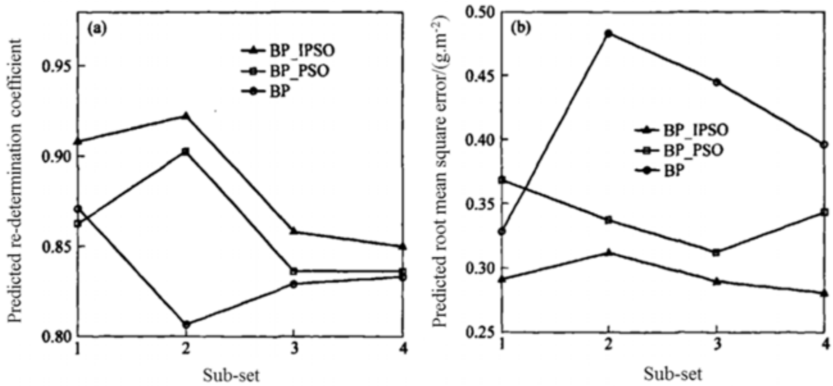
In the equation, $SSR = \sum\limits_{i=1}^{n} (y_i - \hat{y}_i)^2$ is residual sum of squares and $SSY = \sum\limits_{i=1}^{n} (y_i - \bar{y}_i)^2$ is total sum of square; $\hat{y}_i$ is the prediction value and y_i is the target value; $\bar{y}_i$ is mean of target values as prediction sample number. Percentage of soluble variation in total variation of a dependent variable is reflected by re-determination coefficient, whose value is between zero and one. The higher ratio of soluble variation to total variation of the dependent variable is indicated and regression model is more applicable if re-determination coefficient is closer to one.

(3) Relative prediction error

$$RPE = \frac{\sum\limits_{i=1}^{n} |y_i - \hat{y}_i|}{\sum\limits_{i=1}^{n} |y_i|}\,. \tag{25}$$

In the equation, RPE is relative prediction error and $\hat{y}_i$ is prediction value; y_i is target value and n is prediction sample number. Stronger prediction capacity of the model is indicated by smaller relative prediction error. Product quality model of grey convolutional neural network of network structure as 4—8—1 is established and input parameters are respectively spray air pressure P of the gas knife, distance d from gas knife nozzle to strip steel, unit operation speed □ and strip steel thickness h; output parameter is zinc layer thickness. A data set composed of 2,991 data samples is obtained in on-site actual production record. Two groups of experiment is conducted.

The first group of experiment: influence of random sample selection on prediction precision is tested. Different data starting points are selected for sampling in equal interval on condition that the quantity of regression and prediction samples is the same. The 1st, 401st, 801st and 1201st sample points of the data set are set as starting points respectively and 1200 sample points are successively selected as a data sub-set; four data sub-sets are selected. The first 1000 samples of each data sub-set are used for regression modeling and the last 200 samples are used for verification of prediction model. Prediction result is shown in Fig. 3 and relative prediction error is shown in Table 2. It can be found from Fig. 2 that prediction precision of grey convolutional neural network is better than that of convolutional neural network and BP on condition that the sample is randomly selected and it can be found from Table 2 that relative prediction error of grey convolutional neural network is better than that of convolutional neural network and BP; it is indicated that it is effective for grey convolutional neural network algorithm to increase model prediction precision.



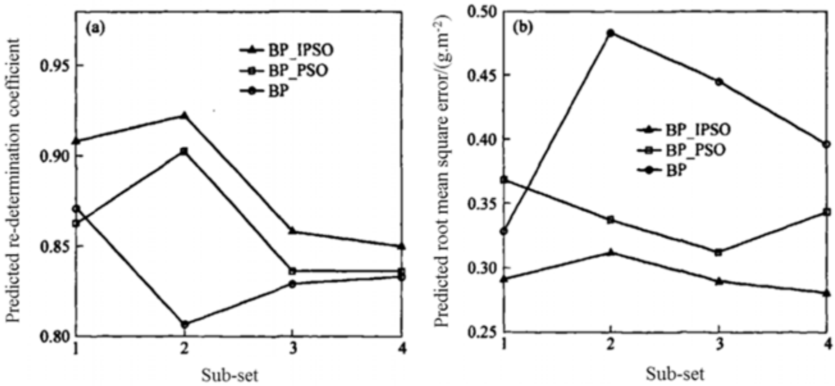
(a) Predicted re-determination coefficient (b) Root mean square error

Fig. 2. Experiment 11

Table 1. Comparison of relative prediction error in experiment 1

Method	Sub-set 1	Sub-set 2	Sub-set 3	Sub-set 4
BP	5.6	6.3	7.4	6.3
convolutional neural network	6.0	5.8	5.7	5.5
Grey convolutional neural network	4.9	4.8	4.8	5.1

The second group of experiment: influence of different regression sample number on prediction precision is tested. Different regression sample number is selected in the way of increase in the same length on condition that data starting point is the same as prediction sample number. The first sample point is set as the starting point. 1000, 1400, 1800, 2200 regression sample length is respectively selected. The subsequent 200 data sample points will be prediction sample points. Prediction result is shown in Fig. 3 and relative prediction error is shown in Table 2. It can be found from Fig. 3 that prediction precision of grey convolutional neural network is better than that of convolutional neural network and BP on condition that regression sample number is different and it can be found from Table 2 that relative prediction error of grey convolutional neural network is better than that of convolutional neural network and BP on condition that sample number is gradually increased; it is indicated that it is effective for grey convolutional neural network algorithm to increase model prediction precision, so there is important meaning for product prediction and control.



(a) Predicted re-determination coefficient (b) Root mean square error

Fig. 3. Experiment 2

Table 2. Comparison of relative prediction error in experiment 2

Method	Sub-set 1	Sub-set 2	Sub-set 3	Sub-set 4
BP	5.6	6.0	5.7	5.3
convolutional neural network	6.0	5.1	4.9	4.8
Grey convolutional neural network	4.9	4.7	5.0	4.8

4. Conclusions

A kind of optimization method of weighted value and threshold based on grey convolutional neural network and the method is verified with standard data set and actual production data of strip hot-dip galvanizing. The result indicates that better prediction precision can be obtained through grey convolutional neural network method in product quality modeling to provide beneficial try and exploration for actual industrial application.

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