Parameter prediction based on Improved Process neural network and ARMA error compensation in Evaporation Process

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Abstract. The traditional model of evaporation process parameters have continuity and cumulative characteristics of the prediction error larger issues, based on the basis of the process proposed an adaptive particle swarm neural network forecasting method parameters established on the autoregressive moving average (ARMA) error correction procedure compensated prediction model to predict the results of the neural network to improve prediction accuracy. Taking a alumina plant evaporation process to analyze production data validation, and compared with the traditional model, the new model prediction accuracy greatly improved, can be used to predict the dynamic process of evaporation of sodium aluminate solution components.

1. Introduction

Alumina evaporation process is a complex industrial process in which the key parameters (sodium aluminate solution concentration) with the production conditions such as the impact (pickling, washing, equipment failure) factors such as fluctuations in the use of traditional static model to predict bound resulting in loss of precision, even when serious styling model failure. Therefore, the establishment of the production process to reflect the dynamic change prediction model is imperative, especially for the dynamic characteristics of the more obvious the production process, using dynamic prediction model can effectively improve the estimation accuracy and robustness of the model [1].

At home and abroad there have been many scholars on the study of nonlinear dynamic predictive modeling, also generated a lot of dynamic prediction method. The literature [2] using historical data added to input the time variable input data to form a new vector object dynamic information integration into the data vector, using nonlinear static model characterizes the dynamic characteristics from the input variables to the output variables. The literature [3] introduced the concept of moving the window, using the finite length of the input history to form a new input vector, and as input to the neural network before, this model is similar to the nonlinear finite impulse response model, moving window length must enter enough history long to ensure that the model can fully reflect the dynamic characteristics of the object, this method will be applied to the polymerization reactor in predictive modeling and high precision estimate the concentration of the polymer. The literature [4] proposed local model network prediction model based on the use of online subtractive clustering method to update the local recursive model structure and parameters, updates the cluster centers and local model to generate new clustering and local model, nonlinear prediction model of the moving average method,

and applied to predictive modeling o-xylene fractionation column, the experiments show that the modeling method can effectively estimate of o-xylene purity. The literature [5] proposed using a feedback neural network forecasting model, and conventional networks, increasing the output feedback as an additional input, reflecting the dynamic characteristics of the object, and has been successfully used in industrial boiler emissions, erythromycin fermentation bacteria filament concentration and epoxy resin, graphite fiber composite material during the curing process viscosity and fat content. The literature [6] is based on Particle Swarm Optimization process neural network proposed a new learning algorithm. New algorithms for network input function and the connection weight function orthogonal basis function expansion; it will integrate the network structure and other parameters into a particle, then the particle swarm optimization algorithm global optimization. The new algorithm does not depend on the function gradient information, you need to manually adjust network structure. Better play to the performance of the process of neural network approach.

Based on the above basis, the paper proposes a neural network ensemble forecasting based on autoregressive moving average error compensation APSO process, and with the evaporation process for two consecutive months of production data analysis and model validation, the experimental results show that the new prediction model results, high precision, can be used exclusively for the evaporation process key parameters - sodium aluminate solution concentration line estimation.

2. APSO process neural network predictive modeling principle

2.1. Neural network forecasting process modeling principle

Process neural network in structure to the traditional artificial neural networks [7,8] is similar, except that the input process neural network connection weights and the corresponding time-varying function [9,10], the process of a neural network due to increased time aggregation operation operator, so they can fully reflect the time sequence present in time cumulative effect.

Process based on neural network prediction model of sodium aluminate solution component proposed is a three-layer process forward neural network, its topological structure is shown as in Figure 1.

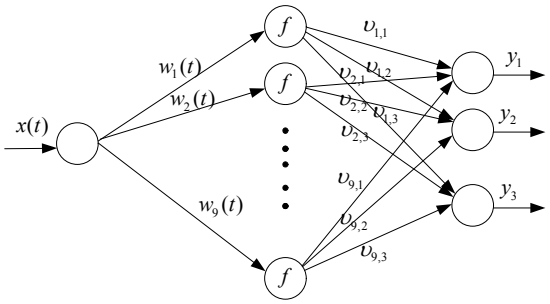

Figure 1. Process Neural Network Forecasting Model

$$y_j = \sum_{i=1}^{9} \upsilon_{i,j} f\left(\int_0^t w_i(t)x(t)dt - \phi_i\right) - \phi \tag{1}$$

among them, $x(t)$ is a function of input process neural network, $w_i(t)$ is the corresponding connection weight function, $\upsilon_{i,j}$ is the hidden layer to the output layer connection weights,[0,T] Sampling period, ϕ is threshold value, $f(\bullet)$ is transfer Function.

According to Schmidt law and Weierstrass Approximation Theorems,among D[0,T] Dimensional space can be obtained orthonormal basis $l_k(t)$,then:

$$x(t)=\sum_{k=1}^{k}a_k l_k(t)\,,\ w_i(t)=\sum_{k=1}^{k}w_{ik}l_k(t) \tag{2}$$

among them, a_k , w_{ik} are Coefficients. Depending on the nature of orthogonal functions,the formula (1) Simplification get:

$$y_j^{'}=\sum_{i=1}^{9}\upsilon_{i,j}f(\sum_{k=1}^{k}w_{ik}a_k-\phi_i)-\phi \tag{3}$$

M is group given training samples $\left(x_m(t),p_m\right)$, (m=1, 2, ..., M), p_m is the input sample, $x_m(t)$ is applied to the desired output of the network, the error function of neural network processes as follows:

$$E=\frac{1}{2}\sum_{k=1}^{M}(y_k^{'}-p_m)^2=\frac{1}{2}\sum_{k=1}^{M}(\sum_{i=1}^{9}\upsilon_{i,j}f(\sum_{k=1}^{k}w_{ik}a_k-\phi_i)-\phi-p_m)^2 \tag{4}$$

2.2. APSO process neural network parameters optimization

From the formula (4), which a_k is a known constant, as in item first coefficient kth input signal after the commencement of the basic functions, other parameters have to be adjusted: have launched a number of k, hidden layer neuron number M, hidden expansion coefficient layer connection weight function w_{ik} , hidden layer neuron threshold ϕ_i , threshold p_m and the output neuron connection weights v_{ij} . In the range of larger difference parameters, k and the value M is a positive integer, while the other parameter values are real numbers.

Based on particle swarm optimization [11,12], the characteristics of the above parameters into unified PSO models were optimized. This makes for a learning and training process of neural network target more holistic and take advantage of global search ability of particle swarm algorithm, making PNN can better play its strong approximation ability. PSO in a particle can be expressed as:

$$Q=\left\{k,M,w_{ik},\phi_i,\phi,p_m,v_{ij}\right\} \tag{5}$$

k=1, 2…K, i=1, 2…N, j=1, 2…M.

The dimensions of the particles: $d= M (NK + 2) + 3$.

Using inertia weight particle swarm particle swarm in the following adaptive strategy, such as the formula (6), so in the early evolution has a larger inertia weight, and with the increase of evolutionary generation of inertia weight decline rapidly. And inertia weight compared to linear adjustment method, this method can enhance the ability to develop local algorithms.

$$W=W_{\min}+(W_{\max}-W_{\min})\bullet e^{-(4K/G)^2} \tag{6}$$

Overall, based on particle swarm optimization of process neural network algorithm is as follows:

Step 1 of the process of neural network training performance function is set to particle swarm optimization objective function and select the orthogonal function group.

Step 2 of the process neural network parameters according to equation (5) sequence number become the dimensions of the particles in the population.

Step 3 set the particle swarm algorithm main parameters defining the search space particles, determination algorithm stops criteria.

Step 4 Run particle swarm until stopping criterion satisfied.

Step 5 If the results are not satisfied, return to Step 3.

3. Error Compensation neural network predictive model based on the process of ARMA

ARMA model [13] is based on the change of the current time series predicted that the future value of a time series model fitting sequence, in its basic for:ARMA(*p, q*), $\varphi(B)w_t = \theta(B)a_t$, a_t is a time series,

$$\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_P B^P \tag{7}$$

$$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{8}$$

The operator polynomial, $B^k w_t = w_{t-k}$ is the delay operator. p, q is value model commonly used incremental successive approximation method, And F is test criteria to determine: Let H_0: $\varphi_{2n+2} = 0$, $\theta_{2n+1} = 0$, Q_0 is model ARMA(*2n+2, 2n+1*) Residual sum of squares, Q_1 model ARMA(*2n, 2n-1*) Residual sum of squares, then

$$F = \frac{\frac{Q_1 - Q_0}{s}}{\frac{Q_0}{n-r}} \tag{9}$$

Wherein r is a function of the model parameters, S is being tested for the number of arguments, *n* is Sample length. if $F > F_a$, then H_0 invalid, Model order increases, otherwise, ARMA (2n, 2n-1) is a suitable model, where the value obtained by the pre-distribution table given confidence level.

According to the idea of the integrated model, the first use process neural network prediction model, training the model output value and the actual measured value subtraction to obtain a time sequence value on the output value of the error, and then use ARMA (p, q) model the time series modeling ARMA model error, the last two models will be integrated in parallel to get the final output of the model structure as shown in Figure 2.

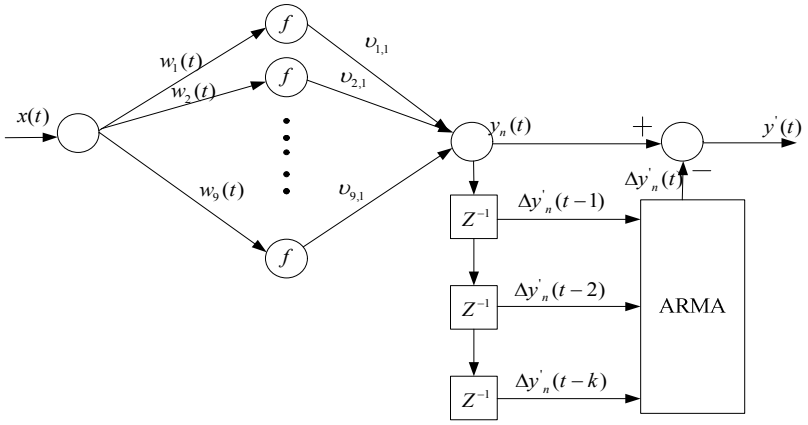

Figure 2. Forecasting Model

4. Industrial production data simulation and analysis

In order to test the validity of the model approach based on factory data sample evaporation process analysis of 300 groups as the training set, 100 set as the test set, each group join time t, constitute a function of time $x(t) = (a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, t)$ is input process neural network model,

$y(t)=(b_1,t)$ is output, $a_1,a_2,a_3,a_4,a_5,a_6,a_7,a_8,a_9$ is nine influencing factor variables after data pre-processing and gray correlation analysis, For the content of sodium aluminate solution, the model training and testing; sequence difference process neural network model training output and actual values of the constitution as an input ARMA model, the training and the error predicted output of process neural network model to compensate . Model parameters are as follows: $\alpha,\beta,\delta,\lambda\in$ [0,1], N =1000, $\varepsilon=10^{-5}$, The results as shown in Figure 3, Figure4, Figure5; error analysis as shown in Table 1.

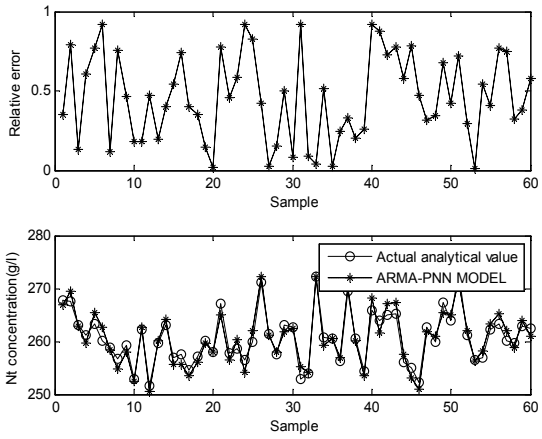

Figure 3. Simulation results

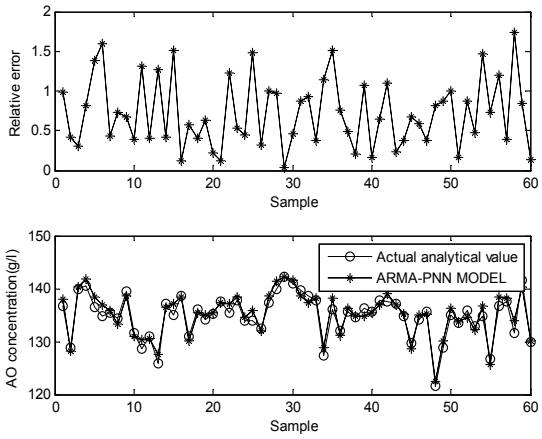

Figure 4. Simulation results

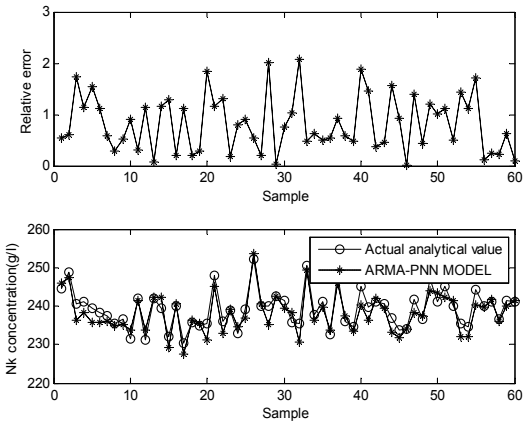

Figure 5. Simulation results

Table 1. Nk Error Analysis

	MSE	RMSE	RRMSE%
PNN-ARMA	4.271e-006	0.00206	4.5
WeightedLSSVM	1.0784e-005	0.01038	10.19
ReductionLSSVM	1.5929e-005	0.00399	6.31

As it can be seen from Figure3, Figure4, Figure5. high-precision integrated model and the proposed method is effective.

In order to further verify the performance of the proposed method, the same experimental process and optimization algorithm were compared with weighted LSSVM and reduced LSSVM respectively. The results show that weighted LSSVM can suppress the influence of noise on the regression result by adjusting the weight, and it is robust, but its prediction is the least. The RMSE of RMSE of PNN-ARMA, weighted LSSVM and reduced LSSVM are 4.5, 10.19 and 6.31, respectively. It is obvious that the proposed model is stable and can be used for the prediction of sodium aluminate solution parameters.

5. Conclusion

Drift prediction accuracy for the decline in the concentration of sodium aluminate solution evaporation process static model with working conditions, we propose a mathematical model to predict PNN and ARMA based on the analysis results on-site verification of production data show that the proposed method can more good learning ability and generalization ability, stable performance, high prediction accuracy, strong adaptability, can be used for online operation optimization of the evaporation process.

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