Hybrid Dynamic Continuous Strip Thickness Prediction of Hot Rolling

Lijie Sun, Cheng Shao and Li Zhang

Abstract—**Short-term forecasting in strip thickness of hot rolling is critical to rolling technology, so that dynamic control can be accomplished to increase production and improve product quality. Predicting strip thickness behavior has been always a challenging task due to its complex and non-linear nature. Autoregressive integrated moving average(ARIMA) model has been verified with a better short-term forecasting performance, for the problem of low multi-step prediction accuracy, the rolling strategy is proposed to update model parameters, which develops rolling ARIMA(RARIMA) model. In addition to improve the overall forecasting accuracy of strip thickness, hybrid forecasting of time series data is considered. Hybrid forecasting typically consists of an ARIMA prediction model for the linear component of time series and a nonlinear prediction model for the nonlinear component. In this paper, back propagation neural network(BPNN) is further introduce-d to forecast the residual of RARIMA model, and rolling ARIMABPNN(RARIMABPNN) continuous forecasting model will be developed, in which rolling forecasting mechanism is used. To the effectiveness of the comprehensive evaluation method, a stability evaluation index is presented, in addition, the proposed method is examined on the two groups of strip thickness data from 620mm strip finishing mill group of hot rolling and the results are compared with some of the basic forecast methods. The results show that the proposed hybrid method could provide a considerable improvement for the forecasting accuracy and stability.**

Index Terms—**ARIMA; BPNN; hybrid prediction; rolling updating**

I. INTRODUCTION

NOT only strip thickness accuracy of hot rolling affects usability and operation process, but also strip thickness deviation impacts on saving metal effect[1], while it is the most difficult to control in the process of production. Short-term forecasting of strip thickness is critical to rolling technology so that dynamic control can be accomplished to increase production and improve product quality. However, it presents non-stationary random characteristics of strip thickness samples in short-term forecasting and modeling to predict is more difficult.

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Predicting strip thickness behavior has been always a challenging task due to its complex and non-linear nature. There are, essentially, two ways can be used to accomplish the strip thickness prediction[2]. The first, known as prediction by fundamentals, consists of identifying the main factors affecting the strip thickness, analyzing how rolling variables interact with each other, and finally, building a causal model, such as regression model. An alternative way of predicting process parameters of hot rolling is to use time series model, in which future strip thickness behavior is inferred from its own historical data. It is difficult to build mathematical model because the process of hot rolling mill is a non-linear system, in which lots of processing parameters such as rolling force, roll speed, frictional force, temperature, roll-gap etc. have been interacted. Thus a number of data-driven models have been successfully applied to short-term prediction behavior. These models can be divided into two categories:

(1)Classical statistical models such as MA(Moving Average), AR(Auto-Regressive), ARMA(Auto-Regressive Moving Average), and ARIMA(Auto-regressive Integrated Moving Average)[3]. Another typical model is Grey model [4]. These models are typically linear, only taking historical values of the predicted variable as input data, hence computationally less expensive;

(2)Non-conventional machine learning models based on time series such as ANNs(Artificial Neural Networks)[5], SVM(Support Vector Machines)[6], and Fuzzy Logic[7]. The machine learning also are called black-box or data -driven models, and they are non-parametric modeling methods that only use historical data to learn the stochastic dependency between past and future.

Strip thickness prediction aims at high accuracy and reliability. Unlike one-step prediction, multi-step prediction is more difficult[8], since it have to deal with various additional complications, like accumulation of the error, accuracy reduction problem, and increasing uncertainty[9]. It has been verified that no single method or model works well in all situations. In general, it is more effective to combine individual models for making forecasts[10]. Then, two new forecasting methodologies are emerging, namely combined forecasting and hybrid forecasting[11].

Combined forecasting model tackles the task in two steps, with the first step being to make forecasts using multiple plausible model, and the second step being to combine these forecasts using weighting algorithms. The key of this prediction strategy is to seek effective weights in order to improve the prediction performance. For example, strip flatness and gauge complex control based on combined GA-BP algorithm with multi-encoding was proposed in literature[12]. In addition, DS(Dempster-Shafer) evidence theory fusion algorithm is typically applied in the combined forecasting models[13].

Hybrid model merges two time domain models. The first model is used to identify the time series dynamics and the remaining model is used to approximate the residuals[14]. On the other hand, other hybrid models are made of a preprocessing block, which decomposes the time series into several sub-series using WT(wavelet transform)[15-16] or EMD(empirical mode decomposition) technique[17]. After that, conventional or machine learning based models are used to forecast the sub-series. By merging the obtained sub-series forecasting results, the forecast of original time series is achieved.

It is necessary to save the data trend, namely, higher prediction accuracy is important in the multi-step prediction. Many studies have shown that ARIMA is an effective forecasting method with high forecasting accuracy in 1-step ahead prediction as demonstrated [18], but the information is progressively lost in the iterative multi-step forecast[19], and prediction accuracy gradually declines. For this problem, current solutions rely heavily on the compensation function in residual model, that is, introducing other algorithm to improve the prediction accuracy of ARIMA model, which increases the computational complexity significantly. As is known to all, the prediction principle of ARIMA is that the model equation is obtained by fitting and the future point is computed according to the correlation coefficients. Considering real-time volatility of strip thickness, in order to track the changes, there is the evidence to assume that real-time updating ARIMA model equation coefficients in the process of prediction can improve its prediction accuracy. In addition, the studies also have shown that the error of the traditional prediction method(also called residual) should be given enough attention. It has verified that the compensation effects of prediction deviation can improve the accuracy of prediction for original predicted results[20]. So it is an efficient way to improve the prediction accuracy that introducing the prediction deviation estimation to form a new prediction method in the traditional way[21]. At present, many scholars at home and abroad have tried to form hybrid ARIMA time series forecasting model to solve low prediction accuracy problem in many research fields[22-23]. Based on this experience, it will be tried to combine rolling ARIMA with error compensation attempt to obtain better prediction results in this paper. Nonlinear forecasting performance of BP neural network has been widely used and recognized[24-25], and previous research more confined to the static forecast. At present, it is verified that the rolling mechanism can increase the prediction accuracy and robustness[26-27], so this mechanism is also used in error compensation from BP neural network.

On theoretical basis of rolling ARIMA model and BP neural network, a new hybrid dynamic continuous forecasting model will be proposed for strip thickness of hot rolling. In this paper, it is the main goal to build a kind of forecasting method, which can obtain multi-step prediction with high performance and provide enough time to predict the strip thickness values in advance so that time delay problem can be avoided in dynamic control of strip thickness. Firstly, experimental data is collected from sampling device to ibaAnalyzer software in the computer, in which ibaAnalyzer is used preliminary analysis of strip thickness in order to determine effective strip thickness data. The performance in this paper is compared with other models using three indexes, in which the first two are widely used to evaluate prediction accuracy of model, the third evaluation index is put forward to access the stability of the model. Second, it is verified that ARIMA model is suitable for forecasting strip thickness of hot rolling in this paper, and rolling updating strategy is proposed to fit ARIMA model coefficients in real time in order to keep trend information of strip thickness, which is formed a new ARIMA model denoted as RARIMA model. It is helpful in improving the forecasting performance without increasing computational complexity. It is known to all that ARIMA is a kind of linear method, and it is an efficient way to improve the prediction accuracy that introducing the prediction deviation estimation to form a new hybrid prediction method in the traditional way. BP neural network is adopted as nonlinear forecasting model, and it is necessary to build BP neural network with rolling forecasting performance. A kind of dynamic rolling strategy is presented, which is to set output node as 1 and realize multi-step prediction through rolling forecast mechanism according to rolling dynamic prediction idea so that it avoids renewing the net. Thus it is saving time and space complexity. Finally, a hybrid forecasting model denoted as RARIMABPNN is built, which consists of RARIMA prediction model for the linear component and rolling BP neural network prediction model for the nonlinear component. Through comparing the forecasting results of multiple prediction methods, it is verified that hybrid forecasting strategy proposed in this paper is beneficial to overall forecasting efficiency for strip thickness of hot rolling in aspects of prediction accuracy and stability.

II. PRELIMINARIES

A. Experimental data acquisition

Object of this study was strip finishing mill group of hot rolling from a certain steel mill, which consists of nine racks with the width of 620mm rolling surface and 1.3 mm strip target thickness. Experimental data is collected from the sampling device to ibaAnalyzer software in the computer, in which ibaAnalyzer soft is used as preliminary analysis, then programming for processing the data is undertaken on Matlab R2010a flat. Two different batches of exit strip thickness are selected on September 20 in 2012, and the part of the signals from the ninth roll are shown in Fig.1 and Fig.2, in which ordinate units are mm . The sample data plays an important role in the prediction process of strip thickness, and the selected data must cover entire data space and representative. Therefore, the data sample number is sufficient to reflect the mill state in the case of the interval is 0.2s. The first set of rolling exit data is from 01:33:00 to 01:33:40 in Fig.1, and the second set of rolling exit data is from 02:45:00 to 02:45:40 in Fig.2, in which sampling time is 40s. Two groups of exit thickness data under the ninth rack are extracted, and each group of data contains 200 data samples, in which 150 as the training samples for fitting prediction model, and 50 as testing data. Two groups of strip thickness data are shown in Fig.3 and Fig.4, respectively.

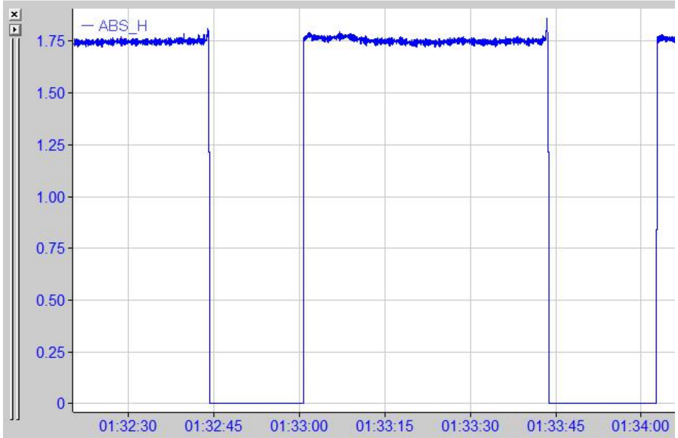

Fig.1. Original signal from the first batch of plate

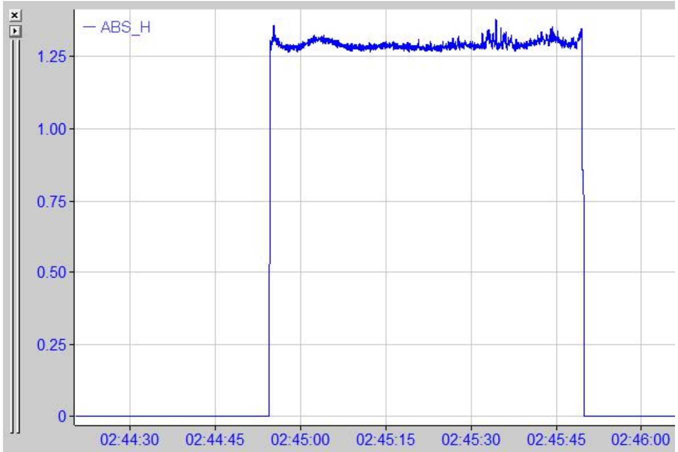

Fig.2. Original signal from the second batch of plate

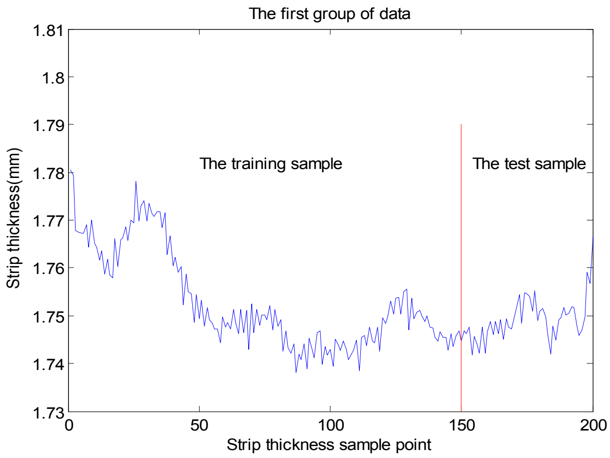

Fig.3. The first group of data

Fig.4. The second group of data

B. Dynamic rolling forecasting mechanism

In general, forecasting strategies are divided into two kinds, namely, dynamic and static prediction. Dynamic prediction undertakes multi-step prediction in the selected certain estimated interval, while in the static prediction, only rolling 1-step ahead prediction is implemented, in which real values instead of the predicted values are added to the estimate interval in each step prediction. In the prediction process, static prediction is chosen within the sample or model fitting estimate, and dynamic prediction must be used outside the sample. It is obvious that the static prediction can not grasp nonlinear fluctuation characteristics of strip thickness, so in this paper, dynamic strategy is applied in multi-step prediction of strip thickness.

To fairly compare the performances under different forecasting models, five different forecasting horizons are applied, including 1, 3, 5, 7 and 9-step ahead, respectively. In the case of 1-step ahead, the M observations are used to predict the 1-step ahead value. For the forecasting horizons more than 1 step, rolling forecasting mechanism is used. For instance, 3-step ahead forecasting is performed based the available M-2 observations and the predicted values of the two data points which are closest to the prediction point but currently unavailable from observation. In fact, the second closest point is predicted first and the first closest point is predicted based on M-1 observations and the predicted value of the second closest point. Similarly, 5, 7 and 9-step ahead forecasts make use of the closest 4, 6, and 8 predicted data points, respectively.

C. Evaluation indicators

The goal of this paper is to obtain higher multi-step prediction accuracy and stability for strip thickness of hot rolling. The performance of the proposed forecasting model is compared with other models using three indexes, in which the first two are widely used to evaluate prediction accuracy of model[28], the third evaluation index is put forward to access the model stability.

The first index is the root mean square error(RMSE), which compares the predicted time-series data with the real time-series data. The RMSE is defined as,

$$RMSE = \sqrt{\sum_{t=1}^{N} \frac{(f_t - o_t)^2}{N}} \tag{1}$$

Where f_t denotes the predicted value for strip thickness at moment, and o_t refers to the real value of strip thickness at moment. The second index is the mean absolute error (MAE), which is defined as,

$$MAE = \sum_{t=1}^{N} \frac{|f_t - o_t|}{N} \tag{2}$$

The third index is the error variance(EV). For the variance represents the degree of data off center and may measure the fluctuation magnitude of a batch of data. Under the condition of the same sample size, the greater the variance, the more unstable the data is. EV is defined as,

$$EV = \frac{1}{N} \sum_{t=1}^{N} \left((f_t - o_t) - \overline{f_t - o_t} \right)^2 \tag{3}$$

Where $\overline{f_t - o_t}$ is the average error of strip thickness prediction.

III. ARIMA AND RARIMA

A. ARIMA forecasting model

ARIMA is a popular statistical model for time series analysis and forecasting applications[29-31], which is expressed in the formula (4),

$$\varphi(B)\nabla^d X_t = \theta(B)u_t \tag{4}$$

Where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$, $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_p B^q$, and $\nabla = 1 - B$. In the formula, $\{X_t\}(t = 1,2,3,\cdots)$ is the strip thickness time series; $\{\alpha_t\}$ is normal white noise with 0 mean value and σ_a^2 variance; $\varphi_i(i = 1,2,\cdots p)$ and $\theta_j(j = 1,2,\cdots q)$ is being estimated coefficient; B represents backward difference operator.

B. Setting the orders

In the process of building ARIMA model, it is important to determine the orders of p, d, and q, Setting the orders includes three major steps: model identification, parameter estimation and diagnostic checking. In model identification process, one or more model candidates could be found suitable for the time series. In such case, autocorrelation function(ACF) and partial autocorrelation function(PACF) can be applied to make the first guess about the order. Then typical Akaike's information criterion(AIC) is adopted to determine the model orders[32]. AIC criterion function is shown in formula (5). The model under minimum AIC value is optimal. Once the model is identified, the parameters need to be estimated, and the selected parameters should generate the lowest residual in principle. The common method of testing the residual randomness is Ljung-Box Statistics, and the proposed model is suitable for fitting the historical data when the residuals are uncorrelated.

$$AIC(S) = \ln \hat{\sigma}^2 + \frac{2S}{N} \tag{5}$$

Where S is the total number of unknown parameters in the model, $\hat{\sigma}^2$ is the estimation of variance in some way, and N is the sample size.

For the first group of data, strip thickness time series is denoted as $\{X_t\}$, in which the first 150 data points as $\{X_{1t}\}$ are used to model for ARIMA. The original time series is non-stationary shown in Fig.5, then it is necessary to undertake first order difference processing and obtain the series $\{X_{2t}\}$. It is obvious that ACF and PACF are both trailing, so the series $\{X_{2t}\}$ belongs to $ARIMA(p,d,q)$, in which $d=1$. In order to reduce computational complexity produced by the evaluation parameters, high order AR model fitting is adopted in this paper. Set p among 1-10, when AIC= -11.9166, the model is optimal, that is ARIMA (9, 1,0), which is used to fit $\{X_{1t}\}$. The fitting equation is obtained and shown in formula (6) :

$$\begin{aligned}\varphi(B) = 1 - 0.232B - 0.8333B^2 + 0.2259B^3 + 0.1628B^4 - 0.4156B^5 \\ - 0.05584B^6 + 0.3897B^7 + 0.2403B^8 - 0.09652B^9\end{aligned} \tag{6}$$

For dynamic rolling forecasting mechanism, L-step prediction of the model $X_t = \varphi_1 X_{t-1} + \varphi_1 X_{t-2} + \cdots + \varphi_9 X_{t-9} + u_t$ is calculated by the formula (7):

$$\hat{Z}n(L) = \varphi_1 \hat{Z}n(L-1) + \varphi_2 \hat{Z}n(L-2) + \cdots + \varphi_p \hat{Z}n(L-p) \tag{7}$$

Where $\hat{Z}n(-j) = X_{n-j}$ $(j \geq 0)$. For the first group data, the fitting equation of first order difference sequence $\{X_{2t}\}$ is shown in formula (8):

$$\begin{aligned}\hat{Z}n(L) = 0.232\hat{Z}n(L-1) + 0.8333\hat{Z}n(L-2) - 0.2259\hat{Z}n(L-3) \\ - 0.1628\hat{Z}n(L-4) + 0.4156\hat{Z}n(L-5) + 0.05584\hat{Z}n(L-6) \\ - 0.3897\hat{Z}n(L-7) - 0.2403\hat{Z}n(L-8) + 0.09652\hat{Z}n(L-9)\end{aligned} \tag{8}$$

The predicted values of final strip thickness are obtained by inverse difference for the predicted results of $\{X_{2t}\}$. 1-step prediction results are shown in Fig.6 for the first group of strip thickness data. Table I records the forecasting performance from 1-step to 10-step prediction for the first group of strip thickness data under ARIMA (9, 1,0) model.

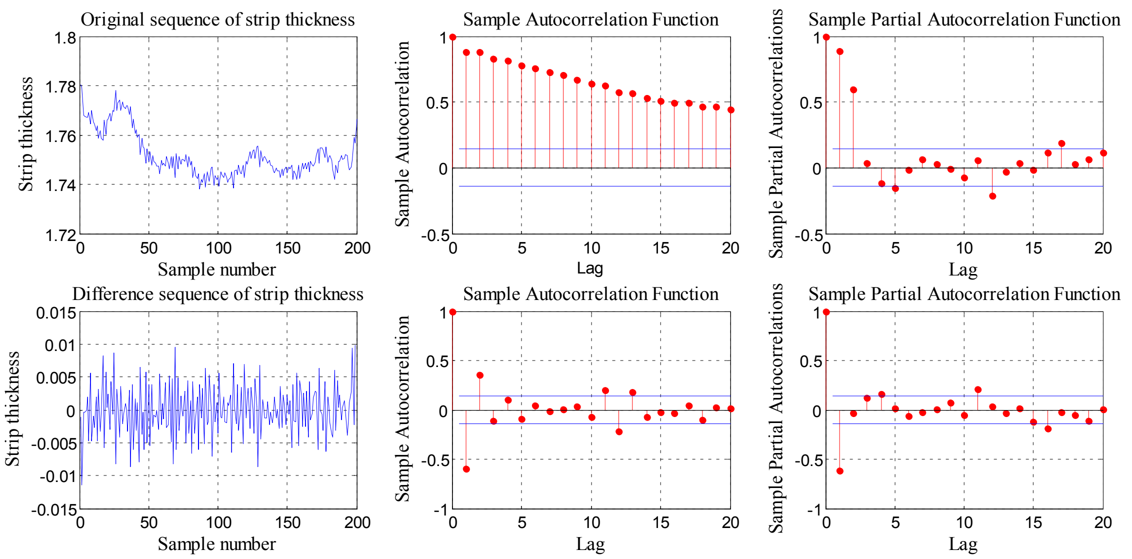

Fig.5. ARIMA model determination for the first group of data

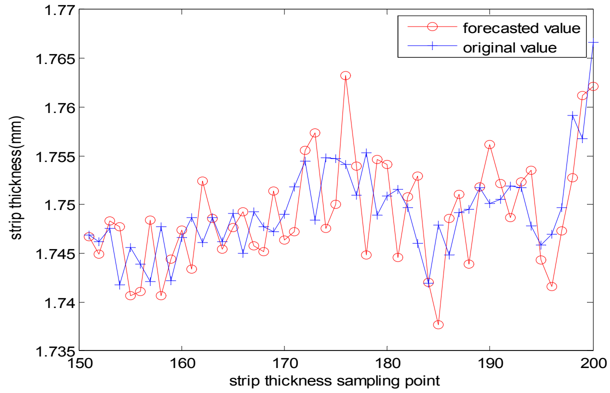

Fig. 6. 1-step prediction results for the first group of data

TABLE I

THE FORECASTING PERFORMANCE OF 10-STEP AHEAD FOR THE FIRST GROUP OF DATA

ARIMA	RMSE	MAE	EV
1	0.0048	0.0040	2.3362e-5
2	0.0051	0.0043	2.6353e-5
3	0.0056	0.0045	3.0918e-5
4	0.0069	0.0055	4.6535e-5
5	0.0065	0.0045	4.1958e-5
6	0.0061	0.0048	3.7106e-5
7	0.0089	0.0070	7.5933e-5
8	0.0107	0.0080	1.1410e-4
9	0.0088	0.0071	3.1865e-5
10	0.0070	0.0074	4.6337e-5

It can be seen from Fig.4 that ARIMA has a good performance for 1-step prediction of strip thickness, but with the increase of step length, the forecasting accuracy drops and predicted results become unstable. Why can appear such result? Looking bake the process of building ARIMA model, for L-step ahead prediction, the observed thickness values for the calculation in next cycle was introduced when and only when completing iteration calculation of L time, which leads that intermediate process of L-step forecasting must be used the predicted value of previous moment. While the model equation coefficients were not estimated again using the predicted value of strip thickness, and the more iteration number is, the more the model equation coefficients are not suitable for new sequence characteristics, so the accuracy becomes lower. In practical engineering, the less step ahead thickness prediction can not provide enough time for rolling equipment parameters to timely adjust to achieve accurate control of strip thickness, so it is necessary to increase forecasting step length and maintain or improve the stability of the ARIMA model prediction accuracy and prediction results.

C. *RARIMA forecasting model*

In view of ARIMA model problem, namely significant reduction in the multi-step prediction accuracy, this paper puts forward rolling update parameter thought: in the process of multi-step ahead prediction calculation, forecasting value at t moment is got through iteration, which is taken advantage of re-estimating the model parameters in order to get new model equation, including the predicted information, then undertake the prediction at $t+1$ moment. After completing L-step in advance, introduce measured values to correction model parameters and undertake next cycle of multi-step prediction calculation. Namely, for L-step prediction, it involves $M-(L-1)$ practical values and $L-1$ predicted values. Use the predicted values to update model coefficients, then forecast next step prediction.

RARIMA forecasting method needs two major steps to implement strip thickness prediction, including model fitting and extrapolation prediction. Prediction process of RARIMA model is shown in Fig.7. 10-step ahead forecasting results of ARIMA and RARIMA are contrasted in Fig.8 and Fig9. It is obvious that RARIMA model has a better improvement for 10-step ahead prediction of ARIMA model, which verifies the effectiveness of rolling updating idea.

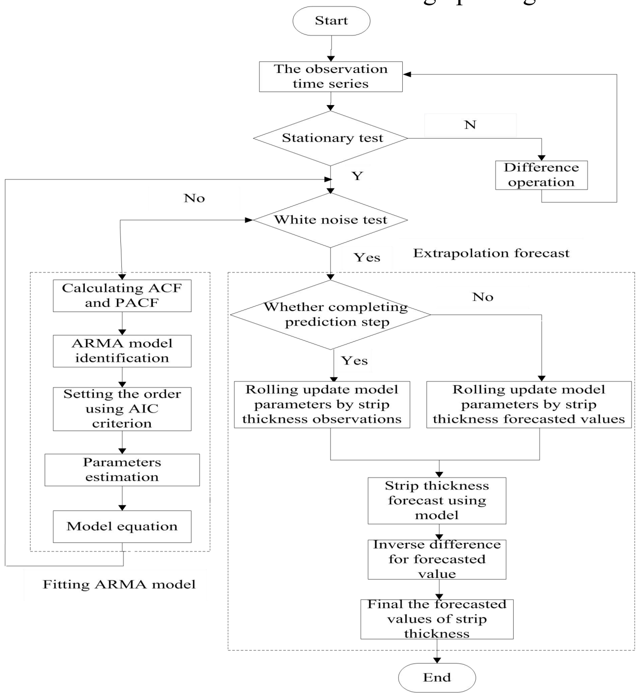

Fig.7. Flowchart of RARIMA modeling for strip thickness prediction

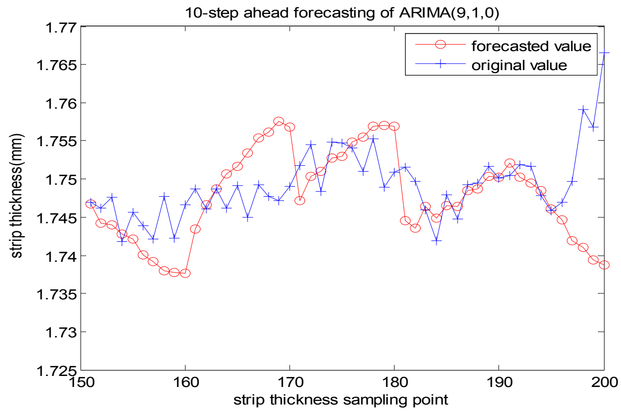

Fig.8. 10-step ahead prediction of ARIMA

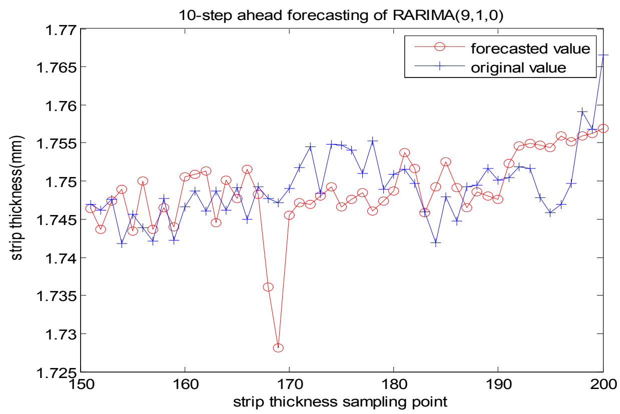

Fig.9. 10-step ahead prediction of RARIMA

IV. RARIMABPNN HYBRID DYNAMIC PREDICTION

A. RBPNN forecasting method

As is known to all that BP neural network(BPNN) is a nonlinear model[33]. It is one of the most popular neural network models in business applications, especially for time series prediction. BPNN is used as the selected nonlinear models to combine with the linear ones fitted by ARIMA model. The key motivation for doing so is due to the truth that BPNN do not make any assumption about the data[34]. Instead, they try to learn the functional form of true model from the data itself. For BPNN, it typically employs three or more layers of processing elements: an input layer, an output layer, and at least one hidden layer.

In order to achieve hybrid dynamic multi-step prediction of strip thickness, it is necessary to build BP neural network with rolling forecast performance. In general, there are two schemes to achieve this goal: the one is to set output layer node equal to forecasting step length. Due to simple thought, the present studies mostly adopt this way of network build[35-37]. While this strategy need renew net and train at every time of changing forecasting length, both time and space complexity significantly increases; another strategy is to set output node as 1. According to rolling dynamic prediction idea, rolling forecast mechanism[38-39] avoids renewing the net. It has been proved in theory that without limiting the number of hidden layer nodes, three layers (only one hidden layer) of the BP network can achieve arbitrary nonlinear mapping, in addition, residual of the model is small data, therefore, as a kind of error compensation model, it is not necessary to build complex network structure and spend a lot of time and space. As demonstrated in literature [40] that the parameter p of ARIMA model is consistence to the number of input layer nodes in BPNN. Therefore, set input layer node number as 9, and implicit layer node number according to the empirical formula $n_1 = \sqrt{n+m} + a$, in which m refers to output node number, n is input node number, and a is constant that is an integer from 1 to 10. The experiment verifies that implicit layer node number is 10 under optimal performance. Output node number is 1. This paper adopts the second strategy to achieve hybrid dynamic multi-step prediction of strip thickness. The residual of RARIMA(9,1,0) model for the first group of strip thickness is denoted as $R_t,\ t = 1,2,\cdots,200$. RBP neural network is built as three layer net structure (9,10,1), in which learning factor is 0.28 and excitation function is S logarithmic function. For instance the first group of data, rolling multi-step prediction strategy of RBP neural network is shown in Fig.10.

B. RARIMABPNN strip thickness forecast

Specifically, RARIMABPNN prediction method includes the following six steps:

(1)Fit ARIMA model using historical strip thickness data to get the coefficients of the model equation;

(2)Compare to the original strip thickness with the observed value and obtaining the residual of ARIMA model, build and train rolling BP neural network.

(3)Determine whether reaching the prediction step length, if less than the prediction step length, using the predicted values to update ARIMA model equation coefficients, otherwise, update the ARIMA model coefficients with the observed strip thickness values;

(4)Use RARIMA model to get linear part prediction of strip thickness;

(5)Apply the trained RBPNN to obtain the residual prediction, and among them, L is lagging step length;

(6)Summing $\hat{y}_t$ and $\hat{R}_t$, and the final strip thickness values are obtained, denoted as f_t, in which $f_t = \hat{y}_t + \hat{R}_t$.

C. Experiment and result analysis

Experiment 1

In order to estimate the contribution of modeling strip thickness of hot rolling using RARIMABPNN model, the latter is compared to the models of basic ARIMA, RARIMA and RBPNN using two groups of hot rolling time series and three estimation indexes. Table Ⅱ shows the forecasting performance in advance 1, 3, 5, 7 and 9 steps for the first group of strip thickness.

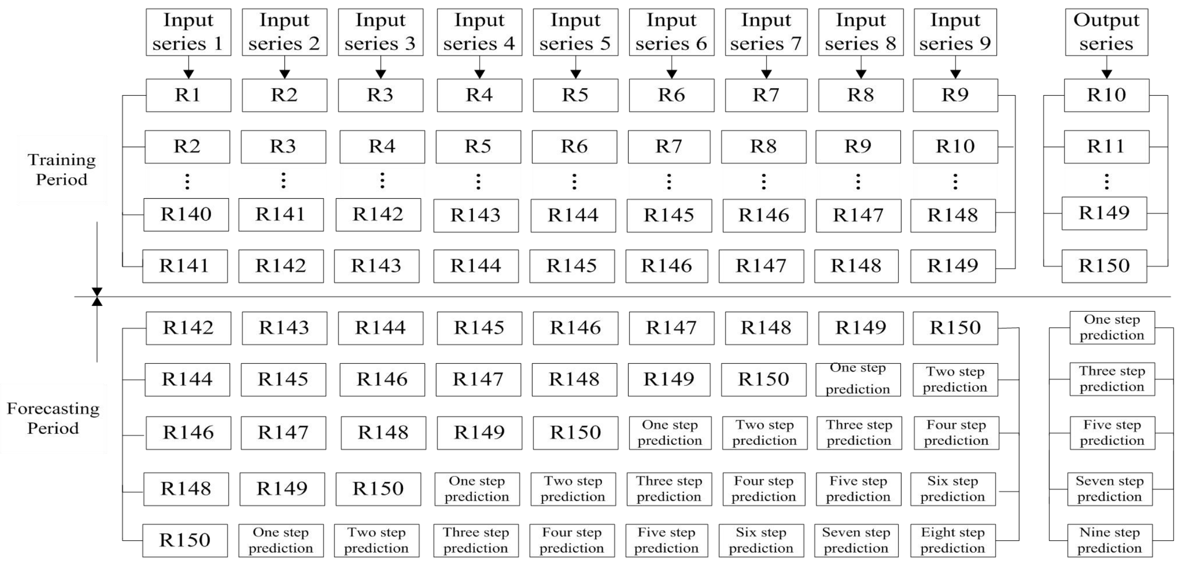

Fig.10. Rolling multi-step prediction strategy of RBPNN

TABLE II
MULTI-STEP FORECASTING PERFORMANCE FOR THE FIRST GROUP OF DATA

Evaluation indicators	Step length	ARIMA	RARIMA	RBPNN	RARIMA-BPNN
RMSE	1	0.0048	0.0045	0.0061	0.0054
	3	0.0056	0.0050	0.0061	0.0053
	5	0.0065	0.0051	0.0060	0.0058
	7	0.0089	0.0046	0.0065	0.0052
	9	0.0088	0.0055	0.0061	0.0059
MAE	1	0.0040	0.0036	0.0048	0.0044
	3	0.0045	0.0036	0.0048	0.0043
	5	0.0045	0.0051	0.0048	0.0045
	7	0.0070	0.0046	0.0052	0.0041
	9	0.0071	0.0055	0.0061	0.0050
EV	1	2.3362 e-5	1.9957 e-5	1.8205 e-5	2.8872 e-5
	3	3.0918 e-5	2.4519 e-5	1.9051 e-5	2.6360 e-5
	5	4.1958 e-5	4.7270 e-5	1.9607 e-5	2.7845 e-5
	7	7.5933 e-5	3.1391 e-5	2.2346 e-5	3.3324 e-5
	9	3.1865 e-5	3.7912 e-5	1.9385 e-5	2.0492 e-5

It can also be observed that depending on forecasting horizon, hybrid method outperforms the other single model approaches, namely, ARIMA, RARIMA, RBPNN. Rolling updating strategy has obvious improving effect on basic ARIMA; RBPNN has a great advantage in aspect of forecasting stability, and the advantage of RARIMABPNN model is obvious with forecasting step length increasing.

Experiment 2

The second group of strip thickness data applies the same process to model with the first group of data. The model of optimal performance is ARIMA(5,1,0), and fitting equation is shown in formula (9):

$$\hat{Z}_n(L) = -0.4079\hat{Z}_n(L-1) - 0.1566\hat{Z}_n(L-2) + 0.1236\hat{Z}_n(L-3) + 0.3241\hat{Z}_n(L-4) + 0.1874\hat{Z}_n(L-5) \quad (9)$$

In the same way, RBPNN is used to forecast the residual from the second group of strip thickness, the best network structure is three layer structure (5,10,1). Table III shows the forecasting results 1, 3, 5, 7 and 9 steps in advance for the second group of strip thickness.

TABLE III
MULTI-STEP FORECASTING PERFORMANCE FOR THE FIRST GROUP OF DATA

Evaluation indicators	Step length	ARIMA	RARIMA	RBPNN	RARIMA-BPNN
RMSE	1	0.0076	0.0076	0.0073	0.0127
	3	0.0091	0.0087	0.0084	0.0085
	5	0.0096	0.0091	0.0087	0.0082
	7	0.0108	0.0101	0.0092	0.0079
	9	0.0149	0.0135	0.0128	0.0078
MAE	1	0.0058	0.0057	0.0055	0.0106
	3	0.0068	0.0065	0.0062	0.0063
	5	0.0076	0.0070	0.0067	0.0058
	7	0.0085	0.0076	0.0068	0.0059
	9	0.0121	0.0113	0.0105	0.0058
EV	1	5.7560 e-5	5.8076 e-5	5.3282 e-5	1.6139 e-4
	3	8.2041 e-5	7.4910 e-5	7.1198 e-5	7.2145 e-5
	5	8.2111 e-5	7.7460 e-5	6.9592 e-5	6.6678 e-5
	7	1.1593 e-4	1.0222 e-4	8.4258 e-5	6.2485 e-5
	9	2.1847 e-5	1.8181 e-5	1.6167 e-4	6.0508 e-5

RBPNN still has good prediction stability for the second group of strip thickness data, but the model prediction accuracy is relatively lower. The second group of data further verifies that the rolling updating strategy has obvious improvement in prediction performance for basic ARIMA model.

ARIMA is an effective forecasting method with high forecasting accuracy in 1-step ahead prediction, but the information is progressively lost in iterative multi-step forecast. The advantages of the rolling updating strategy proposed in this paper increases less computational complexity and space complexity. Also, being a linear model, data dynamics trend is preserved and prediction accuracy and stability are high. RBPNN has a great advantage in both forecasting accuracy and stability, which further illustrates that dynamic rolling forecast mechanism in multi-step prediction plays an important role, and the advantages of RARIMABPNN model are obvious with forecasting step length increasing. In addition, higher prediction accuracy can be got only using one dimensional time series, which reduced the demand for training data with higher timeliness of prediction algorithm.

V. THE SELECTION OF FORECASTING STEP LENGTH

In the engineering, strip thickness control system is constructed by process computer, AGC controller, hydraulic screwdown, finishing mill and thickness gauge controller as shown in Fig.11.

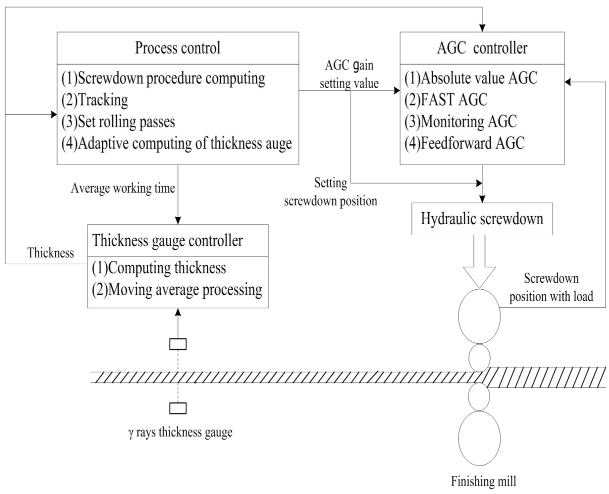

Fig.11. Strip thickness control system structure

The monitor AGC is a gauge control method which is in common used in strip rolling processing; exit strip thickness is measured by gauge meter, and then thickness feedback control will be carried out by adjusting roll gap[41]. As gauge meter is installed at 2-5 m behind mill stand usually, a delay time τ exists in thickness measurement, so monitor AGC system is a pure time delay system. The time-delay of control object will reduce system stability and deteriorate transition characteristic. Strip thickness prediction control is to add a prediction model in the feedback loop, which uses m consecutive sampling data before the current time k to obtain the predicted value at the moment $k+m$ through certain prediction algorithm, in which the prediction error $e_p = r(k) - y(k+m)$ replaces current measurement error

$e(k)=r(k)-y(k)$, among them, $r(k)$ is the desired thickness sequence[42]. This kind of control structure is shown in Fig.12.

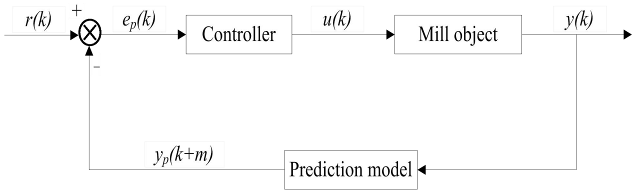

Fig.12. Strip thickness control structure based on prediction

Step length of strip thickness prediction is closely related to time-delay of strip thickness system. Minimum prediction step is usually 1, however, when time-delay of the system is τ as known, minimum prediction step should be τ / T , where, T is the sampling time. In theory, the time-delay is $\tau=\frac{l}{v}$, where, l is the distance between the thickness gauge and test points, and v is rolling speed, but the speed is a transformation, which is gradually from zero to maximum rolling speed, therefore the measured lag time is usually greater than the minimum delay time $\tau=\frac{l}{v_{\max}}$. The maximum prediction step length is usually closer to the general system rising time, and it is necessary to make rolling optimization meaningful, which should include the controlled object's dynamic section.

VI. CONCLUSION

Short-term forecasting of strip thickness is critical to rolling technology so that dynamic control can be accomp-lished to increase production and improve product quality. Strip thickness prediction behavior of hot roll possess dynamic and highly nonlinear characteristics, and "once and for all" data-driven prediction method in the past is interval or static prediction essentially, in order to timely control strip thickness of hot rolling, saving data trend is necessary, namely, implement multi-step prediction with higher prediction accuracy and stability. According to current research situation, this paper presents a hybrid RARIMA-BPNN prediction method.

In order to verify the effectiveness of RARIMABPNN, the predicted results are undertaken with two data sets from 620mm strip finishing mill group of hot rolling with nine racks and the comparative studies of multiple prediction methods are presented.

In comparison to the previous works above, our research has some advantages:

(1)The performance of the proposed method is compared with other models under three indexes, in which the first two are widely used to evaluate prediction accuracy of model, the third evaluation index is put forward to access the stability of the model called the error variance and denoted as EV, and it has been proved that EV can reveal the stability degree under different forecasting steps and methods.

(2) It can be seen from Fig.4 and Table Ⅰ, ARIMA method is an effective forecasting method with high forecasting accuracy in 1-step ahead prediction, but the information is progressively lost in the iterative multi-step forecast.

(3)ARIMA model is used to fit historical data model equation, and rolling updating equation parameters strategy is applied in the future prediction aiming at retaining more strip thickness trend information, which develops rolling ARIMA model. Through experimental analysis from Table Ⅱ and Table Ⅲ, it can be seen that RARIMA has an average of 1% improvement than ARIMA model in aspect of the forecasting accuracy under the same good stability. Rolling updating strategy proposed in this paper increases less computational complexity and space complexity. Also, being a linear model, data dynamics trend is preserved and the prediction accuracy and stability are high.

(4)From the fifth column in Table Ⅱ and Table Ⅲ, it can be seen that RBPNN has good advantage in both forecasting accuracy and stability, which further illustrates that dynamic rolling forecasting mechanism in multi-step prediction plays an important role.

(5)ARIMABPNN model takes advantages of RARIMA with good linear performance and RBPNN with high nonlinear performance, and the sum of the predicted results from two part is regarded as final predicted results of strip thickness. Through two groups of experiments, it is concluded that the advantages of RARIMABPNN model is obvious with forecasting step length increasing. In addition, higher prediction accuracy can be got only using one dimensional time series, which reduced the demand for training data with higher timeliness of prediction algorithm.

(6)This program also provides a new idea to control delay problem in other areas.

(7)Generally, the greater the system lag, the greater the prediction step length. With prediction step length increasing, the prediction accuracy will decrease, which is caused by unknown factors, so dynamic updating strategy has a demonstrable effect for multi-step prediction performance.

To sum up, the research has obtained certain achievement in strip thickness prediction of hot rolling. Our future work will be to use the proposed model as internal model of the model predictive controller aiming at controlling strip thickness of hot rolling with high accuracy.

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