Acta Technica 62 (2017), No. 5B, 129–138

The naphtha dry point of atmospheric tower modeling and predictive control

Xiu Yang[2]

Abstract. The quality of naphtha which is the product of atmospheric tower has a significant influence on the processing of subsequent product. The characteristics of the product quality parameters are difficult to be measured and controlled directly. So the soft sensor modeling of naphtha dry point based on PSO-SVM is developed by analyzing the operational characteristic, and the output of the model is corrected by using the time-varying characteristics of ARMA which is used to estimate prediction error. On the basis of this model, in order to control the controlled variable in time, the optimization feature of PSO is used to optimize the rolling process. The simulation results show that this method solves the problem that model predictive control is difficult to establish an accurate nonlinear model, reduces the complexity of solving objective function when rolling optimization, and has good prediction effect and tracking characteristics.

Key words. Naphtha dry point, SVM, PSO, Predictive control.

1. Introduction

Oil is an important source of energy for economic life line of the country and social stability. The quality parameters of petroleum products are different from the parameters such as temperature and flow, and can not be measured directly by sensors. Usually, we need to collect samples first, and then do off-line analysis. The result of analysis is lagged behind in time, so we can't control and adjust product quality in time. In order to solve the problem of quality index detection, through the analysis of technological principle, establishing the soft sensor model of auxiliary variables and controlled variables is a hotspot of research and application at current.

There are many methods for soft sensing modeling, such as mechanism modeling, regression modeling and so on. The atmospheric pressure tower is characterized by many side lines and complex structures, and the composition of the crude oil which used for evaporation is diversified. Therefore, the establishment of the soft sensor

[1]Acknowledgement - This work supported by the Natural General Fund of Anhui Sanlian University: The predictive control of Quality parameters of atmospheric pressure tower (Grant No. KJYB2017010).

[2]Workshop 1 - Anhui Sanlian University, Hefei 230000, Anhui, China; e-mail: 114910935@qq.com

model is mostly used in recent years. The support vector machine (SVM) which is based on the statistics has good results in solving this problem. It is suitable for small samples and high dimensional nonlinear systems. For example, in document [1], the author obtained real-time detection information of naphtha dry point value by using SVM method. The results showed that it could meet the process requirements. However, there was no clear selection method for the parameters affecting the model.

There was little literature on the control of quality indicators. The traditional control method was indirect index control, such as Controlled the temperature of sensitive plate or controlled[2−4]by difference in temperature and double difference in temperature .However, it is not a simple linear relationship between the temperature and the quality parameters. The error of the results was very large and the better control effect cannot be reached. BP networks and fuzzy neural networks as the inference control strategy were proposed in literature [5], but there were still shortcomings in the model.

The naphtha dry point value of the atmospheric is used as the control target in this paper. The soft measurement model of support vector machine is established and the parameters of the model are selected by particle swarm optimization (PSO).On this basis, the prediction error is estimated and the output of the model is corrected by the time series characteristics of the auto regressive moving average (ARMA) model. The corrected soft measurement model is used as the prediction model of predictive control, and the process of rolling optimization control variables is realized by using PSO.

2. Soft Sensor Modeling of Naphtha Dry Point of Atmospheric Tower

2.1. Process Flow and Selection of Auxiliary Variables for Atmospheric Tower

The choice of auxiliary variables is an important step before the establishment of the soft measurement model[6]. In this paper, the naphtha dry point value of atmospheric in a factory is taken as the test target. The simple flowchart of the device is shown in Figure2.The atmospheric tower has 60 layers of trays, 2 middle sections, and three side lines. The top product of the tower is passed through the heat exchanger and the condenser enters the reflux tank, and a part of the tower is refused as the top of the tower, part of the top product is the naphtha.

The main factors affecting the quality parameters of naphtha are temperature, pressure, flow and other parameters of the atmospheric pressure tower. The selection of auxiliary variables should be considered from three aspects: quantity, type and detection position[7].According to the above process analysis and the experience of the field staff, the following 7 variables are selected as the input auxiliary variables of the soft measurement model: (1)The temperature of the top of the tower x_1;(2)The pressure of the top of the tower x_2; (3)The temperature of feed position x_3; (4)The recirculation temperature of the top of the tower x_4; (5)The reflux ratio of the top of the tower x_5(The ratio of reflux L and the flow naphtha flow D,R=L/D.) ; (6)The flow of naphtha x_6.

2.2. Soft Sensor Modeling

The support vector machine algorithm is proposed by Vapnik based on statistics, it follow the structural criterion strictly in statistics. It is suitable for small sample information processing and has good generalization ability.

A nonlinear mapping method is applied to SVM theory. It maps the input samples to the high dimensional feature space, and then constructs the optimal objective function in the feature space. According to the analysis of the regression model, we can find that there are three main variables that affect the accuracy and generalization ability of the model: Penalty parameter$C$, radial basis function parameter$g$, non sensitive loss parameterε. The previous results shows that the change of ε had little effect on the change trend of $C$and$g$.So determine the value of ε firstly, and then find the optimal selection of the penalty parameter C and radial basis function parameters$g$. The parameter of traditional SVM is determined by repeated calculation or grid searching. These methods lack of theoretical basis with large calculation. In this paper, the PSO algorithm is used to find the optimal value of $C$and $g$in order to achieve a better prediction accuracy[8].

2.3. Correction of Soft Measurement Based on ARMA Model

The sample data used in soft sensing modeling is generally collected when the system runs smoothly.However, in the actual industrial production process, there will be a downward trend in the performance of the soft sensor model, which is not able to meet the accuracy of process control, due to the uncertain factors such as the change of external environment[9].Aiming at the deviation which caused by the long running, set up effective correction module of soft measurement can widen the range of application conditions of the model and increase the anti-interference ability of the model.

The traditional deviation correction only uses the off-line test value and the model output historical data. Set t as a sampling time ,and use the offset of time $t$correction the forecast output of time$t+1$. The prediction error model is established by ARMA model is proposed by this paper. The estimation of the prediction error is realized by using the influence of the value of the previous several moments on the current time. The outputs of the model are corrected by the predictive output at the same time. It can instead of the method of correct by the previous moment error.

The mathematical description of the ARMA model is as follows:

Supposing that$X\left(t\right)$represents time series, x_tThe formula of $x_t$is expressed as follows:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} - \theta_1 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \tag{1}$$

In the formula, $p$and$q$represent the order of the ARMA model respectively. $x_t$stationary time series. Then the error model is identified, and the prediction error is obtained.

$$\hat{e}\left(t+1\right)=f\left(e\left(t\right)\right) \tag{2}$$

Set the $y(t)$ as the offline analysis value, and $\hat{y}\left(t\right)$is the prediction output of the model.The predicted output of the model is as follows at the next moment:

$$y\left(t+1\right)=\hat{y}(t+1)+\hat{e}(t+1) \tag{3}$$

3. Predictive Control of the Naphtha Dry Point of Atmospheric Tower

Predictive control is a control algorithm based on prediction model, feedback correction and rolling optimization.The classical predictive control models mostly use the impulse response or the step response model,but the phenomenon of model mismatch is easy to be caused by the strong nonlinear controlled system.Intelligent model predictive control, which does not require in-depth study of the controlled object, is a hot topic in recent years[10].The SVM soft sensing model improved by PSO is chosen as the predictive control model in this paper.Feedback correction is the process of predicting and correcting the deviation of the model, in this paper, the error correction based on the ARMA model is used as feedback correction.The rolling optimization of the controlled quantity can be used to optimize the objective function by nonlinear optimization.The PSO algorithm is characterized by its simple implementation, fast convergence speed and a wide range of constraints, which have been widely used in the predictive control algorithm[11,12].The system block diagram is shown in Figure 1.

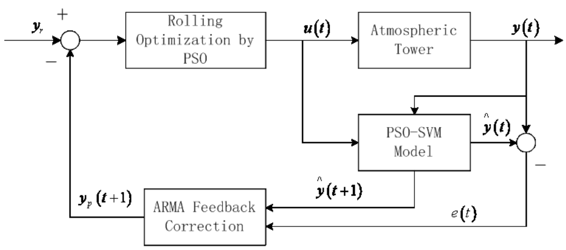

Fig. 1. The block diagram of naphtha predictive control

The steps of the predictive control algorithm are as follows:

(1)The auxiliary variables and sampling samples are determined.The samples are divided into two parts: training set and test set, and the PSO-SVM model is established by training samples.

(2)The error between the output of the model and the off-line test value of the same time is calculated.The stability of the prediction error is tested.The order of the ARMA model is determined and the model is modeled.In this paper, Eviwes6.0 is used to determine the stability of the prediction error data by unit root test.The model is determined by correlation and partial correlation analysis through Eviwes6.0.

(3)It is assumed that at time t, $u\,(t)$ is the controlled variable, the off-line test value is $y\,(t)$, and the predictive output obtained by the PSO-SVM prediction model is $\hat{y}\,(t)$.The prediction error $e^{'}\,(t)$is obtained by substituting the calculated model error $e\,(t)$ into the ARMA model.The prediction output is obtained by substituting the controlled variable $u\,(t+1)$which need to be optimized for the PSO-SVM prediction model:

$$y_p(t+1) = y(t+1) + e^{'}\,(t) \tag{4}$$

(4)Setting the reference trajectory of the control system:

$$y_r(t+1) = \alpha^i y_p(t) + (1-\alpha^i) y_{sp} \tag{5}$$

In the formula, αrepresents the diffusion coefficient, y_{sp}represents the value of tracking.$u\,(t+1)$represents the position vector of the particle group, and the objective function is:

$$\begin{aligned} J = q[y_r\,(t+1) - y_p\,(t+1)]^2 \\ + \lambda[u\,(t+1) - u\,(t)]^2 \end{aligned} \tag{6}$$

Min s.t.

$$u_{\min} \leq u\,(k) \leq u_{\max} \tag{7}$$

q and λ represent weighting coefficients, calculate the fitness of each particle, compare and update the best and global optimality of particles, and then update the location and speed of particles.The optimal control variable$u\,(t+1)$ is output when particle swarm conditions are satisfied.

(5)Take the $u\,(t+1)$ into the model for control.Set$t = t+1$,turn to step (3) until the end of the control.

4. Simulation of the Example

This paper selects the background of the atmospheric tower in a factory.200 groups of naphtha dry point values were recorded by off-line analyzer and 200 groups of auxiliary variables were collected on the DCS system.In order to represent the same importance of each variable in modeling, all variables are normalized.The first 150 groups of data were used as training samples, and the latter 50 groups were tested.The PSO algorithm is used to optimize the penalty parameterε and radial basis function $g$of SVM.The change of the fitness function value in the optimization processis shown in Figure 2.The number of population is 20, and the number of iterations is 200.The result of optimization is $c = 49.17$,$g = 0.01$.

The contrast curve between the prediction output of the naphtha dry point value and the original data based on the PSO-SVM soft sensing mode shows in Figure3 .The mean square error of the prediction value of the training sample and the original data MSE=0.0038, Square correlation coefficient SCC=0.95.The mean square error of the test sample and the original dataMSE=0.076, Square correlation coefficient SCC=0.92, It can be concluded that the model can satisfy the detection precision

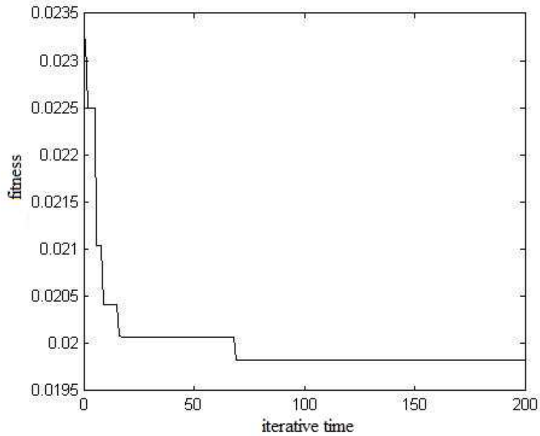

Fig. 2. The curves of fitness function on the processing of the PSO optimization

and the generalization ability is good.

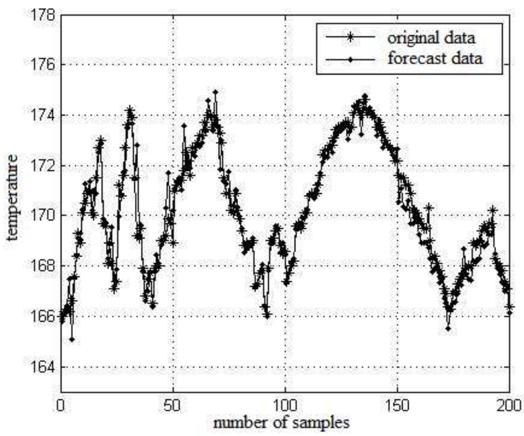

Fig. 3. The comparison of original data and forecast data

After the prediction error is obtained, the Eviwes6.0 is applied to the unit root test of the prediction error data, as shown in Figure 4.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.748095	0.0057
Test critical values:	1% level	-3.546099	
	5% level	-2.911730	
	10% level	-2.593551	

Fig. 4. Unit root test (ADF)

As shown in the picture, the value of P is 0.0057, and ADF=-3.748095, less than any critical value, the prediction error is a stationary sequence, and the ARMA model can be established directly.Then the model was determined by autocorrelation and partial correlation analysis, and p=2, q=1 was analyzed.

Figure 5 is the error contrast curve of the 50 sets of test data.Figure 6 is the contrast curve of the original data, the predicted data and the corrected forecast data.It can be seen from the graph that the output error of the model corrected by the ARMA model is obviously reduced and the fitting degree is better.

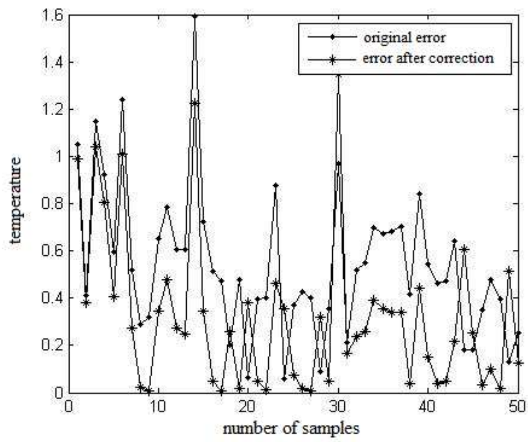

Fig. 5. The contrast curve of the error after correction and the original error

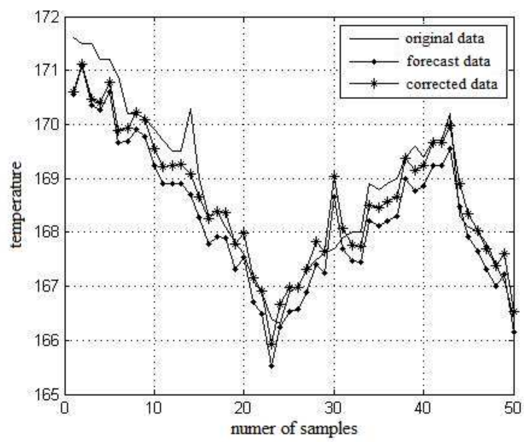

Fig. 6. The comparison of original data?pforecast data and the forecast data after correction

According to the operating conditions of the atmospheric tower in the factory??the adjustment of the naphtha dry point value mainly depends on the control of the reflux and extraction of naphtha products indirectly.

In this paper, the reflux ratio is set as the controlled variable to control the dry point value of the naphtha.The soft coefficient of the nreference trajectoryα=0.3,the weighting coefficient of the performance index function$q$ = 1, λ=0.5, the sampling period is 20S, Figure 7 is the tracking effect of the set point.

The optimization time of particle swarm optimization for each control variable is about 0.8s. It can meet the requirement of real-time optimization of the dry point value of naphtha.

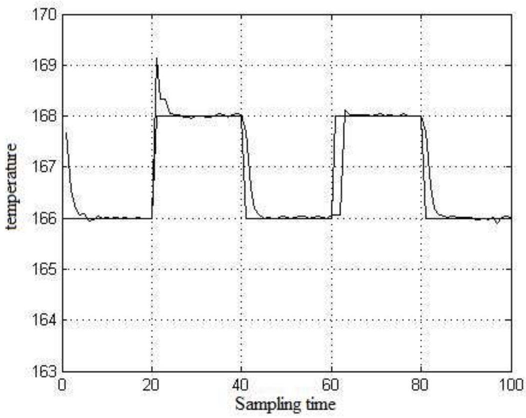

Fig. 7. The tracking effect of the set point

5. Conclusion

In view of the high nonlinearity and strong coupling of the atmospheric pressure tower, the PSO-SVM soft sensing model was designed as the prediction mode, and the ARMA model of the prediction error was used as the deviation correction. And then the predictive control system based on PSO algorithm for rolling optimization was established. The simulation results show that the system can effectively predict and control the dry point value of the naphtha, and has good real-time performance and tracking performance.

References

[1] Q. C. Wang, L. Ang, L. Ang: *Dry Point Soft Sensing Application to Naphtha Based on SVM Regression.* Mechanical Engineer *07* (2008) 19–22.

[2] T. Mejdell, S. Skogestad: *Estimation of Distillation Composition from Multiple Temperature Measurement Using Partial Least Squares Regression.* Ind. Eng. Chem. Res *30* (1991), No. 12, 384–390.

[3] D. Cooper, D. Dougherty: *Enhancing process control education with the Control Station training simulator.* Computer Applications in Engineering Education *7* (2015), No. 4, 203–212.

[4] J. A. Mandler, M. Morari, J. H. Seinfeld: *Control System Design for a Fixed-bed Methanation Reactor*. Chemical Engineering Science *41* (1986), No. 6, 1577–1597.

[5] S. Bhartiya,J. R. Whiteley: *Development of inferential measurements using neural networks.* ISA Transactions *40* (2001), No. 4, 307–323.

[6] J. S. Shu: *Soft Sensing Technology and Its Application.* Process Automation Instrumentation *01* (2008) 1–7.

[7] J Wang, Y Yang, G Ma: *Research on Method of Soft Measurement Secondary Variables Selection.* Electric Power Science and Engineering *27* (2011), No. 7, 37–40.

[8] X. Yang, W. Yang.: *The Method of Soft Sensor Modeling for Fly Ash Carbon Content Based on ARMA Deviation Prediction.* International Conference on Advances in Materials, Machinery, and Electronics *2* (2017) 060025.

[9] F. Xu, Y. Wang, X. Luo: *An Adaptive Soft Sensor Based on Nonlinear Differential-Algebraic Observer for Chemical Processes.* IEEE Sensors Journal *15* (2015), No. 6, 3249–3257.

[10] J. D. Chen, F. Pan: *Online support vector machine and genetic algorithm based predictive control.* Systems Engineering and Electronics *35*, (2013), No. 6, 1275–1280.

[11] M. C. Zou, W. Long: *LSSVM predictive control for HVAC system with PSO algorithm.* Journal of Central South University (Science and Technology) *43* (2012), No. 7, 2642–2647.

[12] B. Luo, Z. J. Shao, X. Z. Hua, J. Zhao, L. F. Zhou: *PSO Based Model Predictive Control and its Hardware Implementation.* Control Engineering of China *20* (2013), No. 2, 227–230.

Received November 16, 2017