The Application of Neural Network Soft Sensor Technology to an Advanced Control System of Distillation Operation

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***Abstract*-For successful monitoring and controlling chemical process, an accurate on-line measurement of important quality variables is essential. However, these variables usually are difficult to measure on-line due to the limitations such as the time delay, high cost and reliability, so they cannot be directly close-loop controlled. In view of the problem above existing in an industry distillation column, a new design methodology is proposed in this paper. At first, an adaptive soft sensor instrument based on neural network technology was constructed as an alternative for the physical sensors. Then, the soft-instrument is correctly applied to an advanced control system and run successfully on DCS equipments. The data measured on-line show the control system has realized well the quality close-loop control.**

***Keywords*-Industrial distillation operation; neural network; soft sensor; advanced control.**

I. Introduction

In the actual industry circumstances, for insuring the equipment to run safely and efficiently, the important process variables that related closely with system stabilizations and product qualities have to be real-time controlled. However these variables can hardly be measured on-line by physical sensors for the technological or economical problem [1]. For the sake of the control problem, the following methods were usually adopted past: The first method is a quality open-loop control. In which the excessive purification is usually adopted to achieve the quality target; the second method is the indirect quality close-loop control, such as sensitive plate temperature control and temperature error control [2]. But sometimes this method cannot also control well product quality; the third method is on-line process-gas chromatography. However, due to its limitations such as cost, reliability and the time delay, it cannot satisfy the on-line control require of quality. Aiming at the problem above, if the soft sensor technology is adopted, the product quality will be able to be measured on-line.

At the same time, as a result of the broad application of distributed control systems (for short, DCS) in the many petrochemical corporations, the calculation ability of the system was enhanced, which are propitious to design some new system constructions and control arithmetic. Therefore, the applied condition of the soft sensor technology is provided.

In this paper, a soft sensor model based on neural network is built to realize well on-line estimation of the product quality about an industrial distillation operation. And on the base of the former control system of the butadiene distillation equipments, an advanced control scheme is designed correctly through using the soft sensor inferential technique. After running practically on the DCS equipments, the scheme has realized direct closed-loop control of product quality. Consequently the control problems existing in the industrial distillation column have been nicely resolved.

II. Technology Backgrounds

The main subject of this article is focused on the distillation workshop of butadiene-producing equipments, column DA107. The Column contains 85 trays; the C4 raw material is fed to the 30th tray. The products are out from the top of column, and the high-boiling-point impurities (cis-butene-2, butadiene-1,2, ethyl acetylene and C5) are expelled from the column bottom, as shown in the Fig 1. in the former control system, the open-loop control and given-value control systems are basically adopted, and there is no quality close-loop control. Moreover, the most important operation variable influencing product quality, circulatory flux (F-139), is also monitored by the given-value control system, whose initial value is given by hand according to the butadiene-1,3(for short, BD-1,3) content in

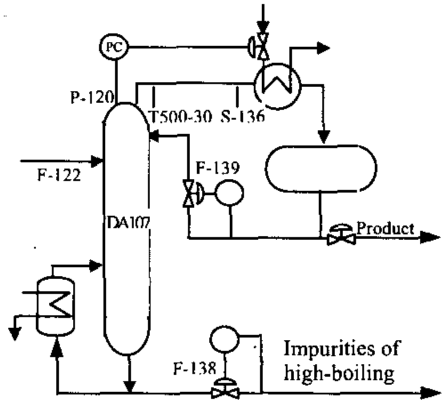

Fig.1 flow and control chart of column DA107

products. Therefore, in the past distillation operation, the method of excessive purification is usually adopted to attain the excellent control target, as the results of not only increasing energy loss but also decreasing the product yield.

The both product control targets of column DA107 are BD-1,3 $\geq$ 0.993kg/kg and ethyl acetylene (for short, EA) $\leq$ 50 mg/ kg. The product components are gained through manual assays (every 4 hours), and it exists 1~2 h delay-time. Therefore the assaying data cannot be used to optimizing control on-line.

The soft-sensor model of the BD-1,3 and EA content in the product is built through applying neural network (NN) technology in the paper. According to technical analysis and theoretical model's simulation, the following variables are selected as assistant variables of the NN model: the feeding (F-122), the bottom byproduct flux (F-138), the circulatory flux (F-139), the top temperature (T500-30) and the top pressure (P-120); the estimated variables are the BD-1,3 and EA contents in the product.

III. The Soft Sensor Instrument of Quality

The key for soft sensor technology is building a reliable industrial model. The empirical methods of artificial neural network (ANN)[3][4] and multivariate regression are often adopted in the process of building soft-sensor model. In view of the multivariate linear regression model only show a linear relation among many variables, i.e. the product process is linearized, moreover its precision is lower than the ANN model's precision. So, in the paper a three-layer Back Propagation Neural Network (BP NN) technology is adopted to build a soft-sensor model of BD-1,3 and EA content in the product.

A.. NN training sample set gaining

For the NN models applied on-line to industry process, it need choose correctly network training data, as well as need design some network frames and learning arithmetic with quick learning-speed and strong robustness, so that the model has better smoothness and extrapolation ability [5].

When applying NN technology to build industrial process model, the common method is to collect the training sample directly from the industrial worksite. However, in view of the importance of column DA107 in whole butadiene distillation workshop, it is impossible to gain the all-training samples through experimental test. Moreover, the changes of spot operating-data are also very small. Therefore, this paper applies the theoretical math model to simulate real producing process of column DA107 by orthogonal design method, and gains 50 groups of simulated data [6]. These simulated data and 450 groups of on-the-spot operated data constitute the training sample set of the soft-sensor mode, which enriched orthogonality and completeness of sample space. At the same time, the 500 group data are classified as the two parts: 300 group data are defined as the reference set, and 200 group data is used as validation set. The training sample set may be defined as follows:

$$\mathbf{X}_i = [x_1{}^i, x_2{}^i, x_3{}^i, x_4{}^i, x_5{}^i] \quad (1)$$

$$\mathbf{Y}_i = [y_1{}^i, y_2{}^i] \qquad i = 1,2,\cdots,500 \quad (2)$$

Where:

$x_1^{(i)} \sim x_5^{(i)}$: The operation data of F-122, F-139, F-138, T500-30,P-120;

$y_1{}^i, y_2{}^i$: The analysis value of BD-1,3 and EA content

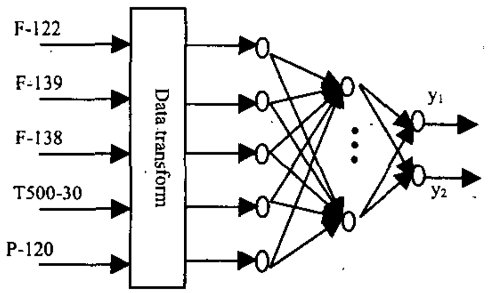

Fig.2 frame of NN model about DA107column

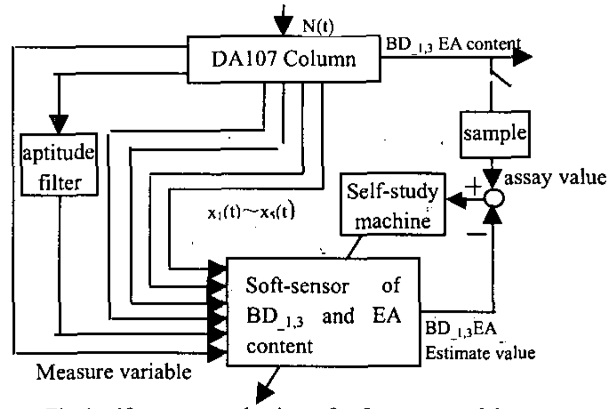

Fig.4 self-correct mechanism of soft-sensor model

B. The BP NN soft sensor model.

Considering the training sample data are small, a BP nerve network with 5 × 7 × 2 construction is applied to build the soft sensor model directly by the reference set, as shown in the Fig.2. Whose input variables include F-122, F-139, F-138, T500-30 and P-120, and output variables (y_1, y_2) are the BD-1,3 and EA contents in the product. The hidden layer uses the sigmoid functions; the output layer used the pure linear functions. After initialized rightly, the network was trained 12000 times, its err-goal≤0.0002. The simulation and cross-validation effects of the model are shown in Fig.3. In the training plot, the front 250 groups data is the operation data that is arranged by the sample time, the other 50 groups data is simulated data that can compensate effectively the shortcoming that the change of on-the-spot data was too small.

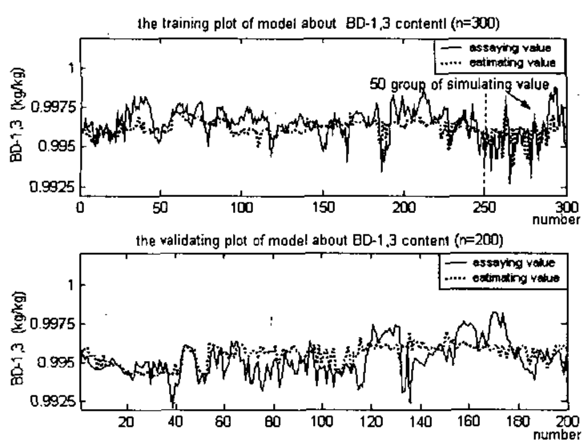

Fig.3 BP training effect of BP model about BD-1,3 content

D. On-line correction of the soft sensor model

Due to the change of the operation condition and the material quality, the soft sensor model gained above merely can be applied in a certain operation range, it need be corrected periodically to fit the work condition change. Because of no on-line chromatogram instruments, the assaying data in the labouratory were used to correct the BP NN model, as shown in the Fig 4. The correcting work may classify into two parts. One is long-time correction, that is, after the distillation process running for a period of time, reconstruct a new model to substitute the former model; the other is short-time correction that is carried out on-line according to the error between the assaying value of S136 and mode's calculating -value. In the practical operation, for the sample time is a stochastic in a period of fixed time, and it exists delay-time (τ) in course of sample and assay; therefore, the output value (y_1) of model is corrected every 4 hours by the error between the assaying-value of BD-1,3 content and the calculating average of the soft instrument in the sampling time. Correction formula is as follows:

$$\Delta y(t) = \alpha[\bar{y}_{1.cal}(t-\tau) - y_{1.ass}(t-\tau)] \tag{3}$$

Where:

$\Delta y(t)$: The corrected value of the BD-1,3 content at t;

α : The corrected coefficient, here is 0.5;

τ : The assay delay-time;

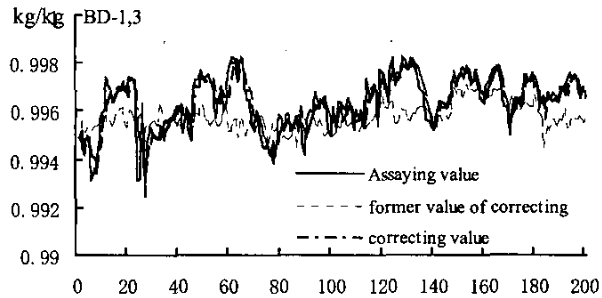

Fig.5 on-line correcting effect chart of soft model

$y_{1.ass}(t-\tau)]$: The assaying value of BD-1,3 content ;

$\bar{y}_{1.cal}(t-\tau)$: The average calculated-value of BD-1, 3 content at sample-time;

The running result on the DCS equipments is shown in fig.5. The better estimation precision was gained through on-line correction, and the calculating values of the model can keep in step with the change of product quality closely.

IV. THE ADVANCED CONTROL SYSTEM PROJECT AND ACTUAL APPLICATION

In terms of technical analyzing above, the most important operation variable influencing the product quality is the circulatory flux (F-139), therefore the follows design an inferential control scheme based on the soft sensor model, and have realized close-loop control of quality on DCS equipments. The control scheme is shown in Fig. 6.The

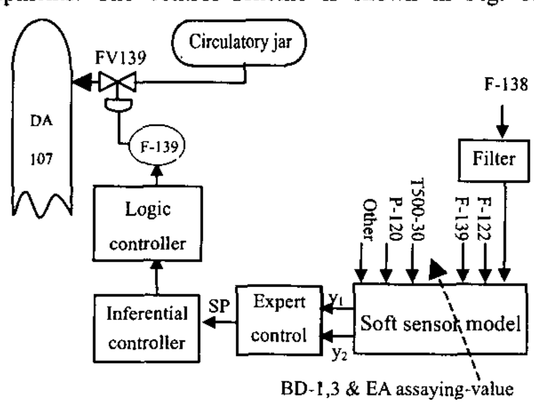

Fig.6 inferential control scheme chart of circulatory flux

scheme includes a soft-senor model,, an expert control module, an inferential controller and a logic control module.

The soft sensor model used in the scheme is the soft instrument realized above on DCS equipments. In the scheme, firstly the input of soft-instrument (F-138) is filtered. In the practical operation, the bottom byproduct flux (F-138) often has the bigger fluctuation, which will arouse the output of model fluctuating in big range. In view of the bigger fluctuation of F-138 influencing the product quality behind a larger -time, here a filter module is designed specially with software, that is, when the fluctuation of F-138 exceeds an ideal range, the fluctuation quantity will be divided into several steps and added step by step to the input of model (F-138) at the former moment.

On account of the both control target (BD-1,3 $\geqslant$ 0.993kg/kg &EA$\leqslant$50mg/kg), moreover, soft sensor model have two output (y_1,y_2). However, the inferential controller has only one input. Therefore, in the inferential scheme an expert control module was designed additionally. Its control rules were composed of actual operation experience and the theoretical simulation. The main expert rules are as follows:

IF $y_1 \geqslant 0.995$kg/kg and $y_2 \leqslant 50$mg/kg THEN SP=y_1-0.995;

IF $y_1 \geqslant 0.995$kg/kg and $y_2 \geqslant 50$mg/kg THEN SP=y_2-50;

IF $y_1 \leqslant 0.995$kg/kg THEN SP=y_1-0.995;

Where:

y_1,y_2: the output value of soft sensor model;

SP: the input of the inferential controller.

Considering the control precision is ± 0.002, the control goal is set as 0.995kg/kg in order to avoid the unqualified product. In view of probability and facility of the project realization, the traditional PID arithmetic is applied for the inferential controller.

The logic control module is a soft selector that set a max-limit and min-limit value for the circulatory flux (F-139) of Column DA107. According to the original design target of the column (4.0$\times$the feeding$\leqslant$the circulatory flux$\leqslant$5.0$\times$ the feeding), here the relation between input and output of the module is:

$$y_{out} = \begin{cases} L_{\max}(.) & y_{in} \geq L_{\max}(.) \\ y_{in} & L_{\min}(.) \leq y_{in} \leq L_{\max}(.) \\ L_{\min}(.) & y_{in} \leq L_{\min}(.) \end{cases}$$

Where:

y_{out}: the output of selector;

y_{in}: the output of inferential controller;

$L_{\max}(.)$:the max-circulatory flux=5.0×(F-122) ;

$L_{\min}(.)$: the min-circulatory flux=4.0×(F-122);

Finally the inferential control scheme is run on the DCS equipments, which can run smoothly for a long time on the industry field so as to arrive at the quality goal, and realized close-loop control of quality. The practical control effect is shown in Fig. 7. It is shown in the figure that BD-1, 3 content changes smoothly (0.993~0.996) and meets justly the control request, consequently reaches the borderline control purpose of the product quality.

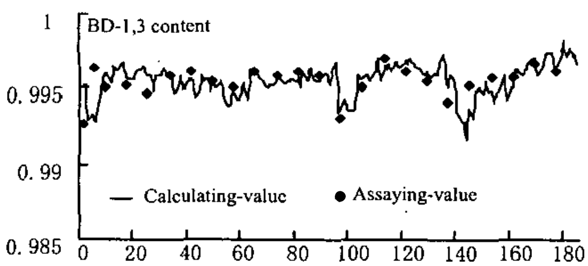

Fig.7 the system's control effect chart (a)

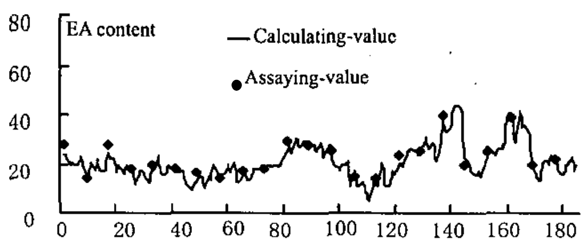

Fig.7 the system's control effect chart (b)

V. CONCLUSTIONS

This paper puts forward an inferential control scheme based on the NN soft sensor model, and according to the practical requirement, logic control and expert control is added to the scheme, which strengthened the engineering practicability of inferential control. As a result that the close-loop control of quality substituted the form open-loop control, and canceled the operation method of excessive purification, not only the quality of the product can be guaranteed effectively but also the energy consume was decreased greatly. Therefore, the corporation gained economic benefit.

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