THE ADVANCED PROCESS CONTROL SYSTEM FOR AN INDUSTRIAL DISTILLATION COLUMN[1]

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Abstract: The control problem of an industrial distillation column is studied. Just the top control loop is discussed in this paper. By means of data collected from the distributed control system (DCS), two soft sensors are first developed. Based on this work, an inferential control project was proposed, and an optimization framework added on it, to improve control performance further. This advanced process control system has been used successfully in practice and produced a satisfying result. *Copyright © 2005 IFAC*

Keywords: Process Control, Industrial Control, Distillation Column, Soft Sensing, Regression Analysis, Model-based Control

1. INTRODUCTION

The study background of this paper is an industrial butadiene plant in Yangzi Branch of SINOPEC. The distillation section addressed here includes two columns. The process flow is shown in Fig. 1.
Prior to the improvements described here, this process had several problems. The operating load had increased far beyond the design capacity, and its existing control system was not capable of adequately controlling it. This resulted in the yield per unit of C_4 being low, the energy cost being large and in the process not running smoothly. The fundamental improvement made was that the former normal analog control instrumentation was changed to a distributed control system (DCS). This made possible a more sophisticated control method. Only the control changes to column DA107 are discussed in this paper. The advanced process control system designed for column DA107 is composed of two loops respectively located at the column bottom and column top. The study about the bottom loop has been previously published (Zhang et al., 2002). Analysis and changes to the top loop are the subject of this article.

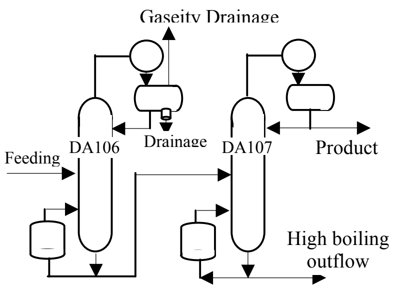

Fig 1 the flow sheet of distillation section

2. ANALYSIS OF THE CONTROL PROBLEM

2.1 Survey of DA107 process flow and former control project

There are 85 tower trays in this distillation column. The feeding comes into from the 30th tray, which is composed of butadiene-1.3 (the wanted product) and impurity including butadiene-1,2, maleic, ethylic acetylene and C_5. The column DA107 is a product column, and its control performance directly affects the quality and yield of product. The product quality indexes of the column are: the composition of butadiene-1.3 should be more than 99.3% (weight ratio, the same followed), the ethylic acetylene should be less than 50ppm. The control target of this column is that the product indexes must be satisfied, and the composition of butadiene of the high-boiled drainage in the column bottom should be limited less than 5%, for higher yield. The former process controls are shown in Fig. 2.
It can be seen clearly from Fig. 2 that the control project is

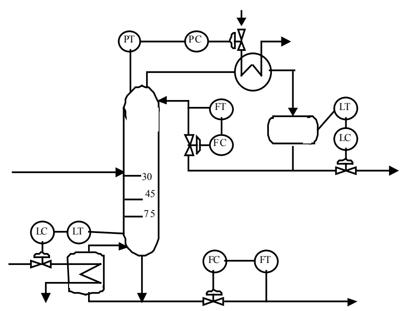

Fig. 2 The control schematic of the column DA107

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entirely composed of simple PID loops, and has not any closed loop control for product quality.

2.2 The basic analysis of the control problem

Being without closed loop control of product quality, compounded by operation at far over designed capacity had caused a large degradation in control quality. Lacking on-line sensing instrumentation, the operators were forced to rely on an off-line lab analysis performed once every 8 hours. This resulted in the operators used of a fixed over-reflux set point to attempt to maintain product quality. The fixed over-reflux set point control method cannot adapt to variable operating condition; the phenomenon of the operating state being erratic therefore cannot be avoided. Furthermore, the over-reflux operation method requires more heat from the reboiler and cooling water from the condensator. This not only consumes much more energy, raising producing costs, but also causes a shortage of cooling water for the entire plant, especially in the summer. As far as this distillation column as concerned, the shortage of cooling water makes the pressure of tower top go beyond the high limit in summer. In order to guarantee the product quality under the high tower pressure, the operators have had no choice but to increase the content of light component in bottom. The content of butadiene1,3 in the high-boiled drainage of the tower bottom is commonly above 15%. This greatly exceeds the 5% limit set and thus substantially reduces yield from that expected.
Based on this analysis, the conclusion may be drawn that on-line sensing of the distillate quality in the top end of tower DA107 could provide timely knowledge of the production state. With on-line sensing, the operators will be able to know the performance of product quality promptly. Closed loop control can also becomes possible, by means of advanced control strategies based on on-line sensing of product quality.
Yangzi Branch realized the importance of product component on-line sensing and a substantial investment was made in on-line industrial gas chromatographic instrument for sensing the composition in the tower top product. For several reasons, this set instrumentation has not proven to be either completely reliable or sufficiently accurate. It has proven to be unsuitable for using in closed loop control directly and barely serves as an operating reference by operators.
As a result, the “soft sensing” technique was next considered as a viable method. A soft sensor can be used not only as operating guidance, but also in closed-loop control of some components of the column in some future process control improvement (Sungyong Park and Han, 2000).
In recent years, reports about soft sensing technique applied in components estimation have been frequently published (Yu et al., 2000). Many commercial software packages of soft sensing have been developed by some companies over the world, and have been used in practical process. However, the initial high cost of these S/W packages has limited their application.
After some discussion, our client requested a complete solution for control of the distillation towers instead of just procurement of soft sensors. Thus, our activity shifted to developing a soft sensor system for measuring and as a basis of controlling the composition of the tower products.

3. SOFT SENSING MODELS

The core of a soft sensor is soft sensing model. There are mainly two modeling methods, mechanism modeling and empirical modeling. But in the actual industrial application, the empirical method constructing the control model is consistently chosen (A. A. Linningger et al, 2000). We developed soft sensing models with the empirical modeling technique based on field data collected from DCS.
To solve the control problem, the components that need to be estimate on-line are Butadiene-1,3 and alkyne (mostly ethylic acetylene, marked with EA). So there are two soft sensing models needing to be built. Certainly, one multiple output model to evaluate the two component can also be used to reach same target, but it is more convenient for actual engineering application to separate them.

3.1 The choosing of primary and secondary variables and the processing of data

It is easy to confirm primary variables of this study, which are the two components of the top product. They are identified as S136-BD and S136-EA respectively. The real values of the primary variables are the sampling analysis values taken every 8 hours. The secondary variables can be chosen from all available on-line measurements from the industrial DCS.
All the measurements related to column DA107 include: 4 temperature values (the temperatures of the tower trays of the stripping section, TW11, TW22, the temperature of the tower top T500-30 and the temperature of the tower bottom T300-6), two flow values (the outflow from tower bottom F138 and the reflux F139), and two pressure values (the pressure of tower top P118 and the pressure of tower bottom P119). Besides, the feeding flow of DA106, F122, is available, though there is no feeding of DA107.
After being processed with empirical filtration and stepwise regression to those candidate secondary variables, finally F122, F139, F138, TW11, TW12, T500-30, T300-6, and P120 are chosen as the secondary variables.
Because empirical models are based on the data, their success depends totally on the quality of the field data collected. Some data preprocessing techniques are frequently used, for example, noise reduction, data transformation, and filtering. This paper will just focus on building of the soft sensors and designing of control system, so data processing will not be discussed here.

3.2 The building and validation of the soft sensing models

The most commonly used approaches in soft sensing modeling are statistics and artificial neural network (Yu et al., 2000). Limited by the programming function of the DCS, we choose a regression analysis to build the models.

All the data from the DCS (430 sets) are divided into two sets: 380 data sets as the modeling set for building the models, 70 data sets as the validation set for examining the models. By using multiple linear regression approach, two models of the following form have been built up:

$$y(t) = a_0 + \sum_{i=1}^{8} a_i \times x_i \qquad (1)$$

In the formula(1):

$y(t)$: It shows the estimated values of S136-BD and S136-EA by the models;

x_i: $i = 1, 2,\ldots,8$, the values of 8 secondary variables declared above;

a_i: $i = 0, 1,\ldots,8$, coefficients obtained from regression, and will not been given in detail in the article.

The validation result of the soft sensing model of S136-BD is shown in Fig. 3. The effect of S136-EA's is similarly to S136-BD, and is omitted.

It can be seen from Fig. 3 that both evaluation accuracy and the extrapolate capability of the two models are not completely satisfactory.

In the controlled process with the component as the output, some nonlinearity exists. Hence, to the models built above which don't have satisfying linear regression effect, its nonlinearity should be considered. In this paper, a simplified nonlinear relationship is defined as follows:

$$y = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{j=1}^{m}\sum_{k=1}^{m} b_h x_j x_k \qquad (2)$$

Where: m: counts of the secondary variables;

b_h: $h = 1, 2,\ldots, m^2$, regression coefficients of nonlinearity items.

Other symbols are defined as in Formula 1.

Illustrated in Formula 2, this kind of nonlinear regression relationship is merely accounted for by adding some quadratics items of secondary variables to the base of multiple linear regression. Using all of these quadratics items and the original secondary variables as regression variables, multiple linear regression is used to model once again, and nonlinear regression models then are obtained.

Moreover, it can be noticed that those soft sensing models are all steady-state models. Industry production processes cannot always be in a steady state. Therefore, the dynamic characteristic of the process should be considered, and dynamic models could simulate actual process better.

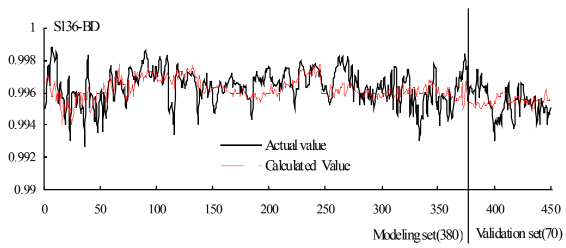

Fig 3 The effect of the multiple linear regression model of S136-BD

It is difficult to build an adequate dynamic model of the process in the rigorous sense. In order to build a dynamic model, the input/output data of the process must first be collected. The basic condition of collecting data is that the sampling theorem should be satisfied. However, for building models of chemical industry processes, this sampling theorem can rarely be observed. Generally, the product quality (for instance the components of distillation column) can only be obtained by means of lab analysis methods, and the interval between samplings in this case is several hours. Hence, it is impossible for those data to meet the sampling theorem. It has been suggested that most methods of building dynamic models are no longer applicable in this kind of situation (Wang and Shao, 1997).

In this paper, a particular dynamic compensation method is proposed. By following this course, not only is the effect of dynamic characteristic taken into account in the regression models, but also the difficulty of establishing a dynamic model is avoided. The regression model that has dynamic compensation is defined as follows:

$$y(t) = a_0 + \sum_{i=1}^{m} a_i x_i(t) + \sum_{j=1}^{m}\sum_{k=1}^{p} c_q x_j(t-kl) \qquad (3)$$

Where:

l: step length of the dynamic compensation;

p: the limiting order of the dynamic compensation;

c_q: $q = 1, 2,\ldots, m\times p$, regression coefficients of dynamic items.

The other symbols are as in Formula 1.

Therein, the step length and limiting order of the dynamic compensating should be decided on the basis of the actual situation. In this paper, set l as 5 minutes, p as 2.

Of course, it might cause problems to directly use Formula 2 and 3, for regression variables might expand greatly. In this paper, stepwise regression, principal component analysis and partial least squares regression are used to certify the independence of regression variables.

By this means, two satisfying, nonlinear regression models with dynamic compensation are obtained. The regression variable set is made up with:

{F122, F139, F138, T500-30, T300-6, Tw11, Tw12, P120, $(x_4)^2$, $x_4\times x_8$, $x_4(t-l)$, $x_4(t-2l)$, $x_8(t-l)$, $x_8(t-2l)$}

Where, x_4 expresses the temperature of the tower top (T500-30), x_8 expresses the pressure of the tower top (P120). The regression coefficients are omitted in this paper.

It can be seen from the collection of regression variables that those two regression models result from combining Formula 1(multiple linear regression), Formula 2 (nonlinear regression), and Formula 3

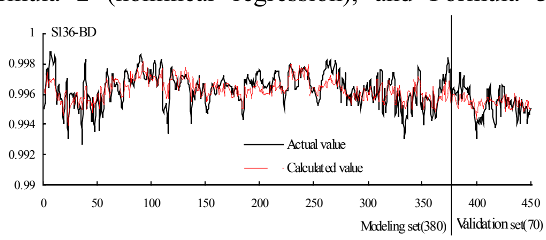

Fig. 4 The effect of the nonlinear regression model of S136-BD with dynamic compensation

(regression with dynamic compensation).
The effect of the nonlinear regression model of S136-BD with dynamic compensation is given in Fig. 4. Compared with Fig 3, it can be clearly seen that the models built by this hybrid regression method are much better at predicting actual performance than the one depicted by Fig 3, regardless of the effects of regressing accuracy or extrapolating accuracy. The effect of S136-EA is similar, and omitted.

3.3 Revision of the soft sensing models

Because of the fact that the production process is often affected by many factors, such as time-variability, nonlinearity, imperfection of process information and so on, the models built only based on field data can never be perfect. So, the soft sensing models must be revised for practical use. In this paper, the job of revision is divided into two parts. One is executed off-line over an extended period, and another is performed on-line in a short period. For the first, the process is run for a period of time and the models are rebuilt based on the new collection of data. The second is executed on-line automatically and periodically. Only the latter is discussed in this paper.
The short-term revision functions in two ways, which are based on the gas chromatographic instrumentation or lab analysis respectively. Having mentioned that the industrial chromatographic instrumentation was not found to be reliable, however, the fact cannot be excluded that in some times, or in certain situations, industrial chromatography does have some value as a reference. On the basis of operating experience, some operators could be sure whether the industrial chromatographic instrumentation can be relied on or not. Under this situation, those values taken from industrial chromatographic instrumentation should be used as much as possible to revise the soft sensor models. For the delay of industrial chromatographic instrument response (which is about 15 minutes) is obviously shorter than that of the lab analysis (It is about 90 minutes. Moreover, the sampling period for lab analysis is as long as 8 hours).
The basic idea of revision by analysis values of sampling is like this: when the analysis values are sent to the operation room from the lab every 8 hours, the operators should input them into DCS as soon as possible, and then, the revising program of the DCS takes these analysis value as the standardized signal to revise the parameters of the soft sensors.
The revising algorithm is as following:

$$y_{out}(t) = y_{cal}(t) + \alpha[\bar{y}_{cal}(t-\delta) - y_{any}(t-\delta)] \qquad (4)$$

Where:

$y_{out}(t)$: Output value of soft sensor at time t having been revised;
$y_{cal}(t)$: Output value of soft sensor at time t having not yet been revised;
α: Revision coefficient being suitably chosen;
δ: Delay of analysis value;
$y_{any}(t\text{-}\delta)$: Analysis values of primary variable at sampling time of $t\text{-}\delta$;
$\overline{y_{cal}}(t\text{-}\delta)$: The average value of soft sensors' output during a period of time of the sampling time.

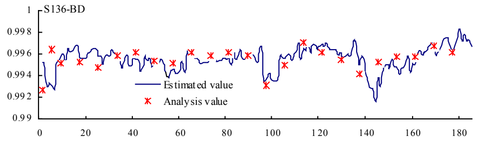

Fig. 5a The application effect of soft sensor S136-BD running at DCS

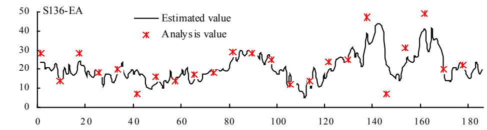

Fig. 5b The application effect of soft sensor S136-EA running at DCS

Similarly, the industrial chromatographic instrument also introduces delay, and the revision should be executed in same way when the measured values of the chromatographic instrument are taken as standardized data.

3.4 Actual application of the soft sensing models

After realized by programming in the DCS, the two models have been put into practical running. Based on the field data collected from the DCS, Fig. 5a and Fig. 5b respectively reflect the actual effect of models S136-BD and S136-EA. It is obvious that the soft sensing models can function quite well to sense product quality of the distillation column.

4. THE ADVANCED CONTROL PROJECT AND ITS APPLICATION

The most successful advanced control strategies applied in industrial distillation columns are model predictive controls (Foss and Cong, 1999), inferential controls (Luo et al., 1995) and some orthers.
When a model predictive control strategy is used, on-line identification of the model is necessary. This process of identification not only takes a long period of time, but also excites the process to fluctuate because of application of step or pulse input signals, which is often unacceptable by industry. The idea of inferential control has existed for a long time, and there are numerous successful industrial applications (Parrish and Brosilow, 1985).
We choose inference control strategy based on soft sensing to constitute the advanced control system of this distillation system.
As for the column DA107, two inference control loops are designed. One is designed to control the compositions of butadiene (BD) and ethylic acetylene (EA) located on the top of the tower, and the other is to control the discharge composition of butadiene at the bottom. The whole basic control project is illustrated as the following Fig. 6.

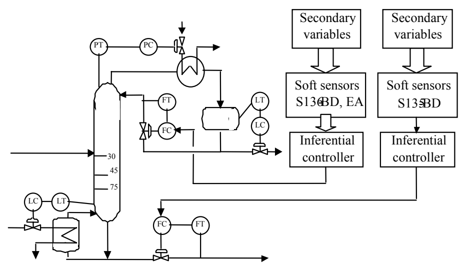

Fig. 6 The advanced control system of column DA107

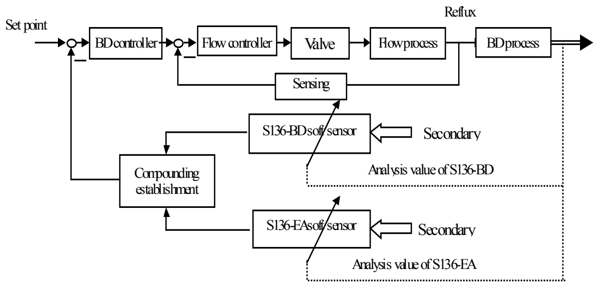

Fig. 7 The block diagram of inferential control project on DA107's top

Generally speaking, the control system is prone to arouse a coupling influence between the two quality control loops when product quality control strategy is used both on top and bottom of a distillation column (Jiang and Yu, 1988). But as to this tower, the coupling between the two loops of quality control is not very serious. It can be simply analyzed as followings: First, as seen in Fig. 6, the manipulated variable of the control loop at the top is reflux flow, so it is an energy-balanced control and the manipulated variable at the bottom of the tower is discharging flow so as to constitute a material-balanced control. This design idea can alleviate the coupling action (Shinsky, 1984). Second, paying attention to tuning of the PID parameters of the two controllers can also ease any remaining coupling influence. If the parameters of two controllers are so tuned that the adjusting periods of two controllers are very different, the coupling can be weakened still more. So, decoupling control does not need to be designed.

Since the study about the control loop at the bottom of DA107 has been previously published, just the control at the top of DA107 is discussed in this paper.

4.1 Basic control project

As shown in Fig. 7, the top control loop is a special inference control project based on the soft sensors, which has two controlled variables and only one manipulated variable.

In this project, the output of the flow process is reflux, and the output of the BD process are the contents of butadiene-1,3 and ethylic acetylene in the distillate. The two soft sensors illustrated in Figure 7 are the very soft sensing models of S136-BD and S136-EA, which have been introduced in the last section.

With the multi-output, single-input controlled process, in which there are two main control targets: that content of butadiene-1,3 in the product of tower top should be higher than 99.3%, and EA be lower than 50ppm. There is only one manipulated variable: the reflux flow. An integrating function has been designed to complete the design. It has been illustrated in Fig. 7.

4.2 The design and realization of the integrating function

The basic design idea for the integrating function is to incorporate the benefits of the operators' experience. Through extensive conversations with the operators, the operating experience can be summarized as follows:

(1) There is a kind of relationship between S136-BD and S136-EA, , which is not clearly understood: when the control quality is high, S136-BD is certainly higher than 0.993 and in the same time S136-EA lower than 50. IF the control quality is poor, either S136-BD is lower than 0.993 or S136-EA higher than 50. But this does not mean that the higher S136-BD corresponds with the lower S136-EA, vice versa.

(2) If S136-BD is close or lower than 0.993, the controller should function with the performance S136-BD.

(3) If S136-EA is close or higher than 50, the controller should run according to the performance S136-EA.

(4) Commonly, S136-EA is much less than 50, s so control target is commonly based solely on the performance of S136-BD.

Therefore, generally, only the criterion of butadiene-1,3 needs to be considered, unless EA is beyond its criterion. The main idea is to design this integrating function so that the share of EA beyond the EA max is converted into the amount of butadiene-1,3 under the controller performance. Based on this idea the function of the compounding establishment is defined as follows:

$$y = \begin{cases} y_{DB} & if\ EA < EA_{\max} \\ y_{BD} - k(y_{EA} - EA_{\max}) & if\ \ EA \geq EA_{\max} \\ BD_{\min} - k(y_{EA} - EA_{\max}) & if\ \ BD \geq BD_{\min}\ and\ y_{EA} \geq EA_{\max} \end{cases} \tag{5}$$

In the formula, BD, EA, is the soft sensing values of S136-BD and S136-EA respectively.

y: the output value of the compounding establishment;

y_{BD}, y_{EA}: the output value of the soft sensors respectively;

BD_{min}: the safe min limitation of BD, defined as a constant (a little bigger than 0.993);

EA_{max} the safe max limitation of EA, a constant (a little smaller than 50ppm);

k the converting constant.

The function of converting constant k is to convert the amount of EA beyond the safety max limitation into the reducing amount of BD from the safe min limitation of BD.

It is relatively easy to implement the integrating function on the DCS. It should, however, be noticed that a discontinuity could occur when the third in the formula's 5 switches with the other two formulas. Thus, a slope module needs be set to perform the transition process smoothly. This module can be easily added with the configuration software of the DCS.

4.3 The actual application of the control system

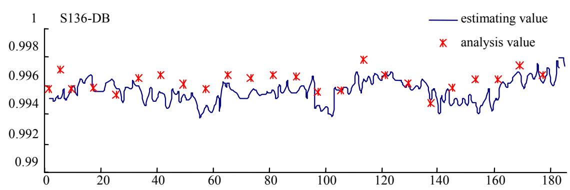

Fig. 8 The actual effect of the advanced control loop of DA107

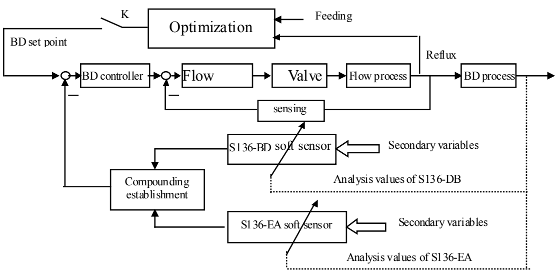

Fig 9 The control project of components of DA107 with the function of optimization of set point

After implementation and formal delivery, the control system has been used for regular production. The actual result is depicted in Fig. 8.

It is obvious in the figure that this control system can satisfy the requirement of quality. But an over-purified phenomenon still exists. Commonly, S136 is well over 0.995. The main reason is that the operator habitually puts the set point of controller S136-BD much higher than the required value.

To solve this problem, an optimization module was designed, with the function of optimizing and adjusting the set point of the BD controller.

4.4 The optimization and adjustment of the set point of product quality

The final control system formed by adding the framework of optimization to the system shown in Fig. 7 is figured out in Fig. 9.

Based on operational experience that in the normal working condition, when the ratio of the reflux flow F139 and the feeding flow F122 is about 4.5, the control quality of the whole column is much better, and the composition of both top and bottom can meet the control indexes in the same time. Utilizing this operation idea and the methods of reference literature (Luo et al., 2002), the calculated relationship of the optimization is defined as:

$$sp = sp_0 + \Delta sp \qquad (6)$$

Where, sp expresses the output value of optimization framework (namely, the set point of BD controller), sp_0 expresses the set point in the last step, its increment (Δsp) is confirmed by the following formula:

$$\Delta sp = \begin{cases} sp_{\max} & if \quad sp \geq sp_{\max} \\ a \times \mathrm{sign}(r - r^*) \left| \dfrac{r - r^*}{b} \right|^n & if \quad sp_{\min} \leq sp \leq sp_{\max} \\ sp_{\min} & if \quad sp \leq sp_{\min} \end{cases} \qquad (7)$$

In the formula, $sp_{\max}$ and $sp_{\min}$ are the max limitation and the min limitation of the set point respectively, chosen with experience. The r is real measured value of the ratio of F139 and F122, and r^* is the ratio expected, set to 4.5. The a and b are adjustable parameters. The adjustable exponent n ($n >= 1$), decides the shape of optimization curve.

The cycle of optimization adjustment is decided by time switch k, commonly, which needs to be set much longer than the work cycles of both two controllers.

This control project represents much better control quality than that shown in Fig. 7. Limited by the length, the record curve of actual field data is omitted from the paper.

5. CONCLUSION

The control system proposed in this paper has been running successfully and smoothly for more than a year. In addition to the product index being guaranteed, the energy consumption has decreased markedly, and product waste from the tower bottom is also reduced. The plant benefits not only from earning's increase but also from the production situation's improvement, since the problems of shortage of cooling water becomes lighter and the hot solvent heating reboilers of all distillation columns can be balanced better. This control system works so well that the company has requested that the same work be done for its second butadiene plant. We have signed a contract with the company, including optimizing control of two butadiene distillation columns, load control system and fault diagnosis system of whole butadiene plant.

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