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FUZZY SOFT SENSORS FOR CHEMICAL AND OIL REFINING PROCESSES

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Abstract: The paper offers an approach to soft sensors design for chemical and oil refining processes. The approach proposed is based on virtual models and associative search techniques. Takagi-Sugeno fuzzy model is applied in combination with production knowledgebase to compensate for the lack of lab data.

Keywords: Process identification, knowledgebase, virtual models, associative search models, soft sensors.

1. INTRODUCTION

Soft sensors (Albertos and Goodwin, 2002) are becoming increasingly popular in oil refining, chemical, petrochemical, and other process industries where product qualities cannot be measured directly. A soft sensor (SS) is a mathematical relationship between a certain product quality measured periodically by plant laboratory or by stream analyzer and one or more process variables, such as temperatures, pressures, flow rates, etc., measured directly at the process.

Plant laboratories and analytical services are typically not able to provide the operations with timely and consistent information on product qualities, because sampling, sample transportation, and analysis are usually long-term and laborious, and can be hardly executed more than once or twice per shift. This often results in either off-spec product manufacture or large giveaways and, hence, lost benefits in either case.

Automatic stream analyzers were believed to overcome the challenge, but their high ownership costs hamper their extensive dissemination. At the same time, SS demonstrate comparable accuracy in many applications, higher reliability, and by orders of magnitude lower costs, thus providing an attractive alternative to stream analyzers. At present, SS are being developed using ANN techniques, hybrid neuron technologies (genetic algorithms), adaptive algorithms used for real-time model adjustment, and other techniques.

The paper discusses an approach to SS development based on fuzzy virtual models (Chadeev, 2004) and adaptive associative search algorithms (Bakhtadze *et al*., 2007). These algorithms ensure quick adjustment to specific process even in case of significant nonlinearities. Moreover, the fuzzification of certain model parameters using process operator's expertise enables the compensation for the lack of lab data necessary for building a valid process model.

The developed SS software interacts both with process and workshop databases and with LIMS. The software is compatible with DCS from various vendors such as ABB, Foxboro, Honeywell, Yokogava, etc., with SACADA, such as GE Fanuc, AdAstra, Wonderware, etc., with realtime databases such as OSISoft PI System, and other industrial information systems.

2. NONLINEAR PREDICTION ALGORITHM BASED ON VIRTUAL MODELS DEVELOPMENT

An identification algorithm for complex nonlinear dynamic objects such as continuous and batch processes was presented in (Chadeev, 2004). The identification algorithm with continuous real-time self-tuning is based on *virtual models* design. The algorithm enables product quality adjustment in advising mode by statistical treatment of process and lab data.

At every time step, a new virtual model is created. To build a model for a specific time step, a temporary "ad hoc" database of historic and current process data is generated. After calculating the output forecast based on object's current state, the database is deleted without saving.

The linear dynamical prediction model looks as follows:

$$y_t = a_0 + \sum_{i=1}^{r} a_i y_{t-i} + \sum_{j=1}^{s}\sum_{p=1}^{P} b_{jk} x_{t-j,p}\,, \qquad (1)$$

where y_t is the object's output forecast at the t-th step, x_t is the input vector, r is the output memory depth, s is the input memory depth, P is the input vector length.

The original dynamic algorithm consists in the design of an approximating hypersurface of input vector space and the related one-dimensional outputs at every time step (see Figure 1). To build a virtual model for a specific time step, the points close in a manner to the current input vector are selected. The output value at the next step is further calculated using least squares method (LSM).

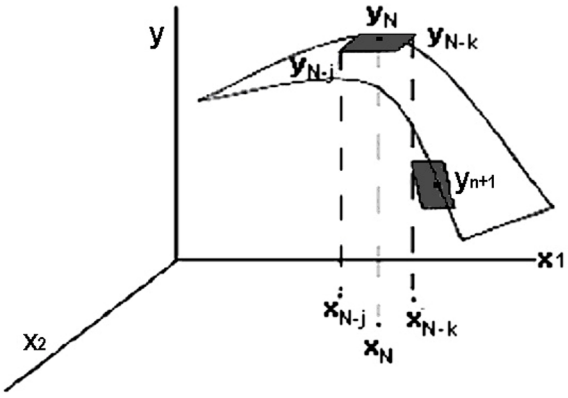

Fig. 1. Approximating hypersurface design

3. ASSOCIATIVE SEARCH TECHNIQUE FOR VIRTUAL MODELS DESIGN

High-speed approximating hypersurface design algorithms enabling the usage of fuzzy models for various process applications were offered in (Bakhtadze *et al*., 2007).

The following quantity

$$d_{t,t-j} = \sum_{p=1}^{P} \left| x_{tp} - x_{t-j,p} \right|,\ j = 1,\ldots, s\,, \qquad (2)$$

was introduced as distance (metric in $\Re^P$) between points of P-dimensional input space, where, generally, $s < t$, and x_{tp} are the components of the input vector at the current time step t.

Assume that for the current input vector $\boldsymbol{x}_t$:

$$\sum_{p=1}^{P} \left| x_{tp} \right| = d_t\,. \qquad (3)$$

To build an approximating hypersurface for $\boldsymbol{x}_t$, we select such vectors $\boldsymbol{x}_{t-j}$, $j = 1,\ldots,s$ from the input data archive that for a given D_t the following condition will hold:

$$d_{t,t-j} \le d_t + \sum_{p=1}^{P} \left| x_{t-j,p} \right| \le d_t + D_t,\ j = 1,\ldots, s\,. \qquad (4)$$

The preliminary value of D_j is determined on the basis of process knowledge, e.g., product quality specifications. If the selected domain does not contain enough inputs for applying LSM, i.e., the corresponding SLAE has no solution, then the chosen points selection criterion can be slackened by increasing the threshold D_t.

To increase the speed of the virtual models-based algorithm, an approach is applied based on employing a model of process operator's associative thinking for predicting.

For modeling the *associative search* (Bakhtadze *et al*., 2007) procedure imitating intuitive prediction of process status by operator, we assume that the sets of process variable values, which are the components of an input vector, as well as the system outputs at previous time steps altogether create *a set of symptoms, making an image of the plant's output at the next step.*

The associative search process consists in the recovery of all symptoms describing the specific object based on its images. Denote the image initiating the associative search by P and the corresponding resulting image of the associative search by R. A pair of images (P,R) will be further called *association* A or $A(P,R)$. The set of all associations on the set of images forms the *memory* of the *knowledgebase* of the intelligent system.

At the system learning phase, an archive of images is created. In our case, a set of n input vectors selected form the process history according to the algorithm described in Section 1 will be considered as an image.

At the prediction stage, the input vector x_t will be considered as an initial image P^a of the associative search, while approximating hypersurface formed by the input vectors from the process history built with the help of the algorithm from Section 1 will be the final image R^a of the associative search. This means that to build a virtual model, one should select the existing hypersurfaces stored in the archive at the learning phase rather than individual vectors close to x_t. The selected hypersurface is an image of the current input vector which is used for output

prediction. The algorithm implements the process of image R^a recovery based on P^a, i.e., the associative search process, and can be described by a predicate $\Xi = \{\Xi_i(P_i^a, R_i^a, T^a)\}$, where $P_i^a \subseteq P$, $R_i^a \subseteq R$, and T^a is the duration of the associative search.

For the algorithm described in Section 2, this predicate is a function asserting the truth or the falsity of input vector's membership of the specific domain in the inputs space. Therefore, the associative search process is reduced to the selection of a certain set of input vectors satisfying the condition (4) from the process archive. If the process history contains no image satisfying (4), then either the threshold D_t should be increased, or for a certain image of our input vector, some symptom should be replaced with a more relevant one. Formally, this means that the "worst" (i.e., located farther away from the current input then the rest ones w.r.t. the chosen criterion) vector from the process history will be deleted and replaced with a more relevant one, and so on.

4. FUZZY VIRTUAL MODELS

Assume that one or more variables in (1) are fuzzy. In real life this may mean the following. Product qualities are measured by the laboratory as seldom as once or several times per shift. In model (1), the values of process variables at any time steps can be used, while the results of lab analyses can be specified as a range of values of some product quality. Such ranges reflect process knowledge by some experts.

Generally, (1) can be represented as a fuzzy Takagi–Sugeno (TS) model (Takagi and Sugeno, 1985). The fuzzy TS model consists of a set of production rules with linear finite difference equations in the right-hand member (for simplicity, a single input case, i.e., P=1, is considered):

If $y(t-1)$ is Y_1^θ,…, $y(t-r)$ is Y_r^θ,
$x(t)$ is X_0^θ,…, $x(t-s)$ is X_r^θ,

then $y^\theta(t) = a_0^\theta + \sum_{k=1}^{r} a_k^\theta y(t-k) + \sum_{l=0}^{s} b_l^\theta x(t-l)$,

$\theta = 1,...,n$, (5)

where

$\boldsymbol{a}^\theta = (a_0^\theta, a_1^\theta, ..., a_r^\theta)$, $\boldsymbol{b}^\theta = (b_0^\theta, b_1^\theta, ..., b_s^\theta)$ are adjustable parameter vectors; $\boldsymbol{y}(t-r) = (1, y(t-1),\ldots, y(t-r))$ is state vector; $\boldsymbol{x}(t-s) = (x(t), x(t-1),\ldots, x(t-s))$ is an input sequence; $Y_1^\theta,...,Y_r^\theta$, $X_0^\theta,...,X_r^\theta$ are fuzzy sets.

By redenoting input variables: $(u_0(t), u_1(t), \ldots, u_m(t)) = (1, y(t-1), \ldots, y(t-r), x(t),\ldots, x(t-s))$, finite difference equation's coefficients: $(c_0^\theta, c_1^\theta, ..., c_m^\theta) = (a_0^\theta, a_1^\theta, ..., a_r^\theta, b_1^\theta, ..., b_s^\theta)$, and membership functions:

$\left(U_1^\theta(u_1(t)),...,U_m^\theta(u_m(t))\right) =$
$= \left(Y_1^\theta(y(t-1)),...,Y_r^\theta(y(t-r)), X_0^\theta(x(t)),...,X_s^\theta(x(t-s))\right)$,

where $m=r+s+1$,

one can obtain the analytic form of the fuzzy model (4), intended for calculating the output $\hat{y}(t)$:

$$\hat{y}(t) = \boldsymbol{c}^T \tilde{\boldsymbol{u}}(t), \quad (6)$$

where $\boldsymbol{c} = (c_0^1,...,c_0^n,...,c_m^1,...,c_m^n)^T$ is the vector of the adjustable parameters;

$\tilde{\boldsymbol{u}}^T(t) = (u_0(t)\beta^1(t),...u_0(t)\beta^\theta(t),...u_m(t)\beta^1(t),...u_m(t)\beta^n(t))$ is the extended input vector;

$$\beta^\theta(t) = \frac{U_1^\theta(u_1(t)) \otimes ... \otimes U_m^\theta(u_m(t))}{\sum_{\theta=1}^{N}\left(U_1^\theta(u_1(t)) \otimes ... \otimes U_m^\theta(u_m(t))\right)}$$

is a fuzzy function, where $\otimes$ denotes the minimization operation or fuzzy product.

If for t = 0, the vector $\boldsymbol{c}(0)$ = 0, the correcting $nm \times nm$ matrix $Q(0)$ (m is the number input vectors, n is the number of production rules), and the values of $u(t)$, t = 1 ,…, N are specified, the parameter vector $\boldsymbol{c}(t)$ is calculated using the known multi-step LSM (Buckley, 1993):

$$\boldsymbol{c}(t) = \boldsymbol{c}(t-1) + Q(t)\tilde{\boldsymbol{u}}(t)[y(t) - \boldsymbol{c}^T(t-1)\tilde{\boldsymbol{u}}(t)] \quad (7)$$

$$Q(t) = Q(t-1) - \frac{Q(t-1)\tilde{\boldsymbol{u}}(t)\tilde{\boldsymbol{u}}^T(t)Q(t-1)}{1 + \tilde{\boldsymbol{u}}^T(t)Q(t-1)\tilde{\boldsymbol{u}}(t)},$$

$$Q(0) = \gamma I,\ \gamma >> 1, \quad (8)$$

where I is the unit matrix.

The above equations show that even in case of one-dimensional input and few production rules, a lot of observations are needed to apply LSM that makes the fuzzy model too unwieldy. Therefore, only a part of the whole set of rules ($r < n$) should be chosen according to a certain criterion.

The application of the associative search techniques where one or more model parameters are fuzzy, is reduced to such determination of the predicate $\Xi = \{\Xi_i(P_i^a, R_i^a, T^a)\}$, that the number of production rules in the TS model is significantly reduced according to some criterion.

For example, the following matrix:

$$\begin{matrix} \beta_1^{\Theta_t} & ... & \beta_P^{\Theta_t} \\ ... & ... & ... \\ \beta_1^{\Theta_{t-s}} & ... & \beta_P^{\Theta_{t-s}} \end{matrix}$$

can be defined for P-dimensional input vectors at time steps t–j, j = 1,…,s. If the rows of this matrix are ranged, say, w.r.t. $\sum_{p=1}^{P}\left|\beta_p^{\Theta_i}\right|$ decrease and a certain number of rows, are selected, then such selection combined with the condition (4) will determine the predicate Ξ and, respectively, the criterion for selecting the images (sets of input vector) from the history.

5. PREDICTING THE QUALITIES OF DELAYED COKING UNIT'S DISTILLATES

Quality control of delayed coker distillates for their subsequent utilization as hydrotreater's feedstock is a challenge. The reason is that coker's fractionator was originally designed for some average feed rate and quality, while in real life both change several times per day sufficiently for making a serious disturbance for downstream process equipment.

The traditional control strategy for a fractionator under disturbances is temperature profile stabilization closer to the steady-state values established at design phase for average feed rate and quality, and their further slight adjustment subject to lab data. The product samples are analyzed by refinery lab 3–6 times per day. This makes the control strategy ineffective because the object's state cannot be identified unambiguously from such scanty samples.

SS-based virtual models were built for this plant using both process history and lab data. Those models enabled on-line calculation of desirable product qualities with sufficient accuracy. This resulted in process unit's throughput increase combined with more consistent product quality.

The SS-based quality analyzers were built for coker naphtha IBP, 50%, 90% distillation points, and EP and coker gas oil IBP, 50%, and 90% distillation points. Based on these, a predictive model structure for distillation points of key product streams was obtained as well as the forecast accuracy estimate.

The forecast was calculated using a mathematical model whose inputs were process variable measured on-line. The forecast accuracy depends on right selection of informative variables, memory depth, and the amount of available plant data.

Typically, the precise forecast is impossible for such complex objects as fractionator because the existing measurements do not observe all factors affecting the product qualities. For example, there were no tools at the process unit to measure feedstock makeup changes. In such case, the informative variables had to be selected from the vast amount of data. This was done using process history. At design operation of the model-based predictor, its adaptation to plant dynamics and input properties changes is executed automatically with the changes of the nonlinear model's structure, while its dynamic depth remains the same.

Figure 2 shows an example of a predictive model for naphtha 50% distillation point (ASTM D86). The model was built for the delayed coking unit of LUKOIL-Perm refinery, Russia. The model prediction accuracy is 95%.

The SS-based control system can calculate control actions with adaptive models adjustment.

After site acceptance tests in advising mode are complete, the recommended control action can be further used in the closed loop, i.e., in the automatic control system with an identifier (Figure 3).

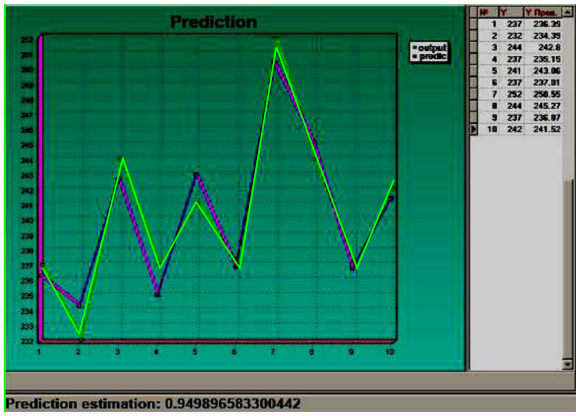

Fig. 2. Naphtha 50% distillation point model

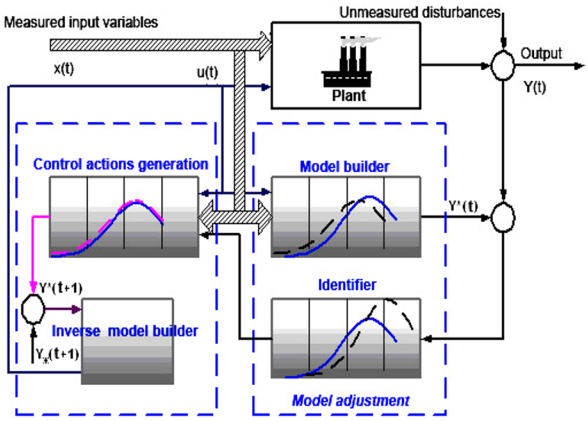

Fig. 3. Adaptive control system with identifier

6. CONCLUSIONS

To develop decision making support for process operator, soft sensors are offered underlain by a novel approach to identification. The approach presumes forecast generation on every time step based on *virtual models* rather than the time approximation of the process. To simplify the identification algorithm, an *associative search* procedure is offered based on process knowledge employment for generating the images of the variables under investigation. The application of this approach is especially effective whilst compensating for insufficient lab data for model development. In such case, fuzzy specification of certain process variables using process knowledgebase is practiced.

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