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Soft Measurement System for Monitoring Syrup Supersaturation During a Sugar Crystallization Process Based on a Least Squares Support Vector Machine

Yanmei MENG, Haifeng PANG, Guancheng LU, Chunwa QIN, Haiping He

College of Mechanical Engineering, Guangxi University,
Nanning, 530004, Guangxi, China
Tel.: +8613207713906, fax: +8607713273600
[1] E-mail: panghaifenggx@163.com

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Abstract: It is difficult to monitor syrup supersaturation during the sugar crystallization process so we developed an online soft measurement system for syrup supersaturation analysis based on a least squares support vector machine (LSSVM). The application of a sparseness method reduced the support vector levels of the model, so the learning and modeling speed of the algorithm increased. A combined genetic algorithm (GA) and k-fold cross-validation method was used to optimize the parameters of the soft measurement algorithm, and to obtain the optimal parameters of the kernel function and the optimal penalty factor. Ultimately, this online soft measurement system was tested using a self-regulating comprehensive experimental platform that represented the sugar crystallization process, which showed that the soft measurement values were close to the actual values where the mean squared error was 0.001. Thus, we demonstrated that our system could measure the syrup supersaturation level based on the auxiliary variables. *Copyright © 2013 IFSA.*

Keywords: Syrup supersaturation, Soft measurement, Least squares support vector machine, Sparseness method, Genetic algorithm, K-fold cross-validation.

1. Introduction

Cane sugar crystallization is a key component of the sugar industry, which is currently non automated in China. The sugar crystallization process involves a heat and mass transformation, which is a complex process with many interacting factors. Syrup supersaturation is the main process parameter considered during sugar crystallization. The monitoring of supersaturation is related directly to the efficiency and the quality of sugar production. At present, massecuite formation readily fouls the surface of the measurement sensor, which makes it difficult to measure the syrup supersaturation level accurately in the long-term using an online instrument 0. Thus, many researchers have attempted to develop syrup supersaturation monitoring techniques. For example, Liu 0 developed a syrup supersaturation model using the least squares method where the syrup supersaturation was the primary variable while the temperature and Brix were the secondary variables. Yan 0 aimed to overcome the difficulties of detecting syrup supersaturation during the process by developing a data acquisition and analysis system based on data fusion technology,

using a back-propagation (BP) neural network as the data fusion algorithm. Fan et al. 0 used the temperature, pressure, and valve opening as the inputs and syrup supersaturation as the output to build a dynamic response model of the sugar crystallization process based on an improved BP neural network. However, there are no reports of the successful application of these methods during practical production in China. The least squares support vector machine (LSSVM) uses the structural risk minimization principle to find the global optimal solution and to solve the problems generated by small sample sizes, nonlinearity, and high-dimensionality because of its excellent generalization capacity.

In the present study, we used six auxiliary variables as the inputs, i.e., the vacuum, syrup temperature, steam pressure, steam temperature, feed syrup temperature, and feed syrup flow, and the syrup supersaturation as the output. We employed a LSSVM to construct a soft measurement algorithm, which was used to model syrup supersaturation, thereby facilitating the soft measurement of syrup supersaturation during the sugar crystallization process.

2. Construction of the Soft Measurement Algorithm for Syrup Supersaturation Based on LSSVM

2.1. The Syrup Supersaturation Soft Measurement Algorithm

We set the sugar syrup supersaturation soft measurement sample as $S=\{(\mathbf{x}_i,y_i)\}_{i=1}^{m}$, where m is the number of samples; the soft measurement auxiliary variables vector, $\mathbf{x}_i=[x_{i1},x_{i2},x_{i3},x_{i4},x_{i5},x_{i6}]$, $x_{i1}\in R$, $x_{i2}\in R$, $x_{i3}\in R$, $x_{i4}\in R$, $x_{i5}\in R$, $x_{i6}\in R$, x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5}, x_{i6}, respectively, represents the vacuum, syrup temperature, steam pressure, steam temperature, feed syrup temperature, and feed syrup flow of sample i; and y_i represents the sugar supersaturation sample value that corresponds to the auxiliary variable i. According to the principle of the LSSVM, let the functional relation of syrup supersaturation and the soft measurement auxiliary variables be:

$$y(\mathbf{x}_i)=\mathbf{w}^T\cdot\phi(\mathbf{x}_i)+b, b\in R, \tag{1}$$

where $\mathbf{w}$ is the weighting vector and b is the offset term.

The sugar crystallization process is nonlinear so the syrup supersaturation and soft measurement auxiliary variables have a nonlinear relationship. $\phi(\mathbf{x}_i)$ is a nonlinear mapping of (1), which maps the sugar supersaturation and nonlinear input space of the soft measurements into high-dimensional space. Therefore, the nonlinear input space is transformed into a linear high-dimensional space.

The syrup supersaturation and soft measurement algorithm based on LSSVM can be expressed as a constrained optimization problem that involves solving the equation, which is described as follows [5-11].

The optimization objective function is as follows:

$$F(\mathbf{w},e)=\frac{1}{2}\mathbf{w}^T\mathbf{w}+\frac{1}{2}C\sum_{i=2}^{m}e_i^2 \tag{2}$$

The constraint condition of the optimization problem is as follows:

$$y_i=\mathbf{w}^T\cdot\phi(\mathbf{x}_i)+b+e_i, i=1,\cdots,m, \tag{3}$$

where e_i is the empirical error variable and C is the error penalty factor, which also indicates the degree of the empirical error. After constructing the Lagrangian function according to formulae (2) and (3), we obtain the following:

$$\begin{aligned}L(\mathbf{w},b,e,\alpha)&=F(\mathbf{w},e)-\sum_{i=1}^{m}\alpha_i\{\mathbf{w}^T\phi(\mathbf{x}_i)+b+e_i-y_i\}\\&=\frac{1}{2}\mathbf{w}^T\mathbf{w}+\frac{1}{2}C\sum_{i=1}^{m}e_i^2-\sum_{i=1}^{m}\alpha_i\{\mathbf{w}^T\phi(\mathbf{x}_i)+b+e_i-y_i\},\end{aligned} \tag{4}$$

where α_i is the Lagrange multiplier. We take the partial derivatives of $L(w,b,e,\alpha)$ on w,b,e,α, respectively, and make them all equal to zero, so we obtain the optimal solution conditions (5).

$$\begin{cases}\dfrac{\partial L}{\partial \mathbf{w}}=0\rightarrow \mathbf{w}=\sum_{i=1}^{m}\alpha_i\phi(\mathbf{x}_i)\\ \dfrac{\partial L}{\partial b}=0\rightarrow \sum_{i=1}^{m}\alpha_i=0\\ \dfrac{\partial L}{\partial e_i}=0\rightarrow \alpha_i=Ce_i\\ \dfrac{\partial L}{\partial \alpha_i}=0\rightarrow \mathbf{w}^T\phi(\mathbf{x}_i)+b+e_i-y_i=0\end{cases}, i=1,\cdots,m \tag{5}$$

According to Mercer theory, the vector inner product of a high-dimensional can be replaced with the kernel function when the Mercer conditions are met [12, 13]. Therefore, the solution to the syrup supersaturation process soft measurement algorithm does not need to be concerned with the specific form of the nonlinear mapping $\phi(\mathbf{x}_i)$ and it simply needs to apply the kernel function value of the auxiliary variable vector in the original input space.

We set the kernel function equal to $K(\mathbf{x}_i, \mathbf{x}_j)$ so $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)\phi(\mathbf{x}_j)$.

We use the Gaussian radial basis function $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \mid \mathbf{x}_i - \mathbf{x}_j \mid^2)$ as the kernel function of the syrup supersaturation soft measurement algorithm, where γ is the kernel function parameter. By solving each equation simultaneously in the associated vertical (5), we obtain the solution to the optimization problem (6).

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(\mathbf{x}_i,\mathbf{x}_j)+\frac{1}{C} & \cdots & K(\mathbf{x}_i,\mathbf{x}_m) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(\mathbf{x}_m,\mathbf{x}_j) & \cdots & K(\mathbf{x}_m,\mathbf{x}_m)+\frac{1}{C} \end{bmatrix} \times \begin{bmatrix} b \\ \alpha_i \\ \vdots \\ \alpha_m \end{bmatrix} = \begin{bmatrix} 0 \\ y_i \\ \vdots \\ y_m \end{bmatrix}, i, j = 1. \quad (6)$$

Formula (6) is a linear equation, which can be solved as the numerical solution of a linear equation. The Lagrange multiplier vector α and offset term b can be obtained by solving linear equation (6). Finally, we associate formula (1) and $\mathbf{w} = \sum_{i=1}^{m} \alpha_i \phi(\mathbf{x}_i)$ with formula (5) so the functional relationship between the soft measurement auxiliary variables and the nuclear syrup supersaturation can be determined:

$$\hat{y} = \sum_{i=1}^{n} \alpha_i K(\mathbf{x}, \mathbf{x}_i) + b = \sum_{i=1}^{n} \alpha_i \exp(-\gamma \left| \mathbf{x} - \mathbf{x}_i \right|^2) + b, \quad (7)$$

where n is the number of support vectors, x is the vector of the syrup supersaturation auxiliary variable that needs to be soft measured, x_i is the support vector i, and $\hat{y}$ is the soft measurement value of the syrup supersaturation that corresponds to x.

2.2. The Syrup Supersaturation Sparseness Algorithm

The syrup supersaturation soft measurement model is not offline and static, but instead it is an online model with dynamic learning and updating. The syrup supersaturation soft measurement algorithm has to complete the learning and updating function before the next auxiliary variable data arrives, which will affect the subsequent measurement. Therefore, it is very important to improve the processing speed for the online soft measurements of syrup supersaturation.

Compared with standard support vector machine (SVM), the LSSVM lacks a requirement for sparseness so the number of training support vectors is the same as the number of training samples [14, 15]. This deficiency of the LSSVM means that the number of calculations (7) increases with the number of training samples. An increase in the number of training samples leads to a larger coefficient matrix of linear equations (6), which means that many more linear equations need to be calculated. The coefficient matrix of the linear equations (6) is as follows.

$$CoefficientMatrix = \begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & K(\mathbf{x}_i,\mathbf{x}_j)+\frac{1}{C} & \cdots & K(\mathbf{x}_i,\mathbf{x}_m) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & K(\mathbf{x}_i,\mathbf{x}_m) & \cdots & K(\mathbf{x}_i,\mathbf{x}_j)+\frac{1}{C} \end{bmatrix} \quad (8)$$

Formula (8) shows that greater numbers of training samples will increase the dimensions of the coefficient matrix, thereby generating a large coefficient matrix. Therefore, a moderate reduction in the number of training samples can improve the calculation speed of the syrup supersaturation soft measurement algorithm. To address this problem, we propose a LSSVM sparseness method based on an analysis of the modeling principles of LSSVM and Gan et al. 0, thereby producing an algorithm that reduces the training sample set by developing a soft measurement sparseness algorithm. The application of the sparseness algorithm can reduce the sample number used by the syrup supersaturation soft measurement algorithm, which improves the learning and modeling speed of the soft measurement algorithm, and reduces the support vectors used in the soft measurement model.

From formula (5) $\mathbf{w} = \sum_{i=1}^{m} \alpha_i \phi(\mathbf{x}_i)$, we know that the weight vector $\mathbf{w}$ is a linear combination of the high-dimensional feature space vector $\phi(\mathbf{x}_i)$. According to the definition of the maximal linearly independent vectors group, the original vector group can be represented by its maximal linearly independent group, which means that the maximal linearly independent group is equivalent to the original vector group. Therefore, the weight vector $\mathbf{w}$ can only be represented by the maximal independent group of the high-dimensional feature space vector group so the linear correlation vector in the high-dimensional feature space can be removed to reduce the number of training samples and the number of support vectors.

The soft measurement sparseness algorithm we propose solves the maximal linear independent group in the high-dimensional feature space vectors set, $\{\phi(\mathbf{x}_i)\}_{i=1}^{m}$, and removes the linearly correlated samples from the high-dimensional feature space to reduce the number of training samples and support vectors used by the soft measurement algorithm, while retaining only their corresponding original input space samples as training samples. Thus, the goal of sparseness is achieved.

The norm of the vector $\varphi(\mathbf{x}_i)$ is $\mid \varphi(\mathbf{x}_i) \mid = \sqrt{\varphi(\mathbf{x}_i)\varphi(\mathbf{x}_i)}$ and based on the kernel

function we know that $|\varphi(\mathbf{x}_i)|=\sqrt{\exp(-\gamma|\mathbf{x}_i-\mathbf{x}_i|^2)}\neq 0$, so $\varphi(\mathbf{x}_i)$ is not a zero vector. If the high-dimensional feature space vectors need to be represented using other vectors, they should satisfy the follow conditions.

$$\phi(\mathbf{x}_k)=\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j),\eta_j\neq 0 \tag{9}$$

$$\phi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)=0,\eta_j\neq 0 \tag{10}$$

It is difficult to determine η_j directly, so we set $t=\varphi(\mathbf{x}_i)-\sum_{j=1,j\neq i}^{m}\eta_j\varphi(\mathbf{x}_j)$ to construct the following function based on solving the extrema for the following quadratic function.

$$F(t)=t^2-\left[\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)\right]^T\cdot\left[\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)\right],\quad \eta_j\neq 0 \tag{11}$$

The derivative of function t relative to $F(t)$ is as follows:

$$\frac{dF(t)}{dt}=2t=2\times\left[\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)\right],\eta_j\neq 0 \tag{12}$$

because the derivative of the function $F(t)$ at the extreme points has to be 0. Thus, the extrema of $F(t)$ can be obtained using the following formula.

$$\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)=0,\eta_j\neq 0 \tag{13}$$

We know from the derivation above that if the high-dimensional feature space vectors $\varphi(\mathbf{x}_k)$ need to be represented using other vectors, they should satisfy the follow condition.

$$\left[\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)\right]^T\left[\varphi(\mathbf{x}_k)-\sum_{j=1,j\neq k}^{m}\eta_j\varphi(\mathbf{x}_j)\right]=0,\eta_j\neq 0 \tag{14}$$

Therefore, we can conclude that the minimum value of the discriminator formula (11) is either 0 or not when determining whether the high-dimensional feature space can be represented using other vectors. We use Q to represent the linearly independent group that corresponds to the original input vector set of the high-dimensional feature space vector, P to represent the linearly related vector to the original input vector set, and A to represent all of the original input vector set. $Q\bigcup P=A$, $A-\mathbf{x}_k$ represents a vector where vector $\mathbf{x}_k$ has been eliminated from the full set A. We construct the following function based on the above derivation.

$$\begin{aligned}f(\mathbf{x}_k,\mathbf{x}_i,\eta)&=\left[\varphi(\mathbf{x}_k)-\sum_{\varphi(x_j)\in Q}\eta_j\varphi(\mathbf{x}_j)\right]^T\left[\varphi(\mathbf{x}_k)-\sum_{\varphi(x_j)\in Q}\eta_j\varphi(\mathbf{x}_j)\right]\\&=\varphi(\mathbf{x}_k)\varphi(\mathbf{x}_k)-2\varphi(\mathbf{x}_k)\sum_{\varphi(x_j)\in Q}\eta_j\varphi(\mathbf{x}_j)+\\&\quad\sum_{x_i\in Q}\sum_{x_j\in Q}\eta_i\eta_j\varphi(\mathbf{x}_i)\varphi(\mathbf{x}_j),\eta_i\neq 0,\eta_j\neq 0\\&=k_{kk}-2\eta^T\mathbf{k}_{kq}+\eta^T\mathbf{K}\eta\end{aligned} \tag{15}$$

where q is the number of the vectors in set Q and $1\le q\le m$; $\mathbf{x}_k$ is the vector used to determine whether it has a linear correlation with linear vectors in set Q; $\mathbf{x}_j$ is the vector in set Q; $k_{kk}=K(\mathbf{x}_k,\mathbf{x}_k)$; η is a coefficient vector, $\eta=[\eta_1,\cdots,\eta_i,\cdots\eta_q]$, $1\le i\le q$; $\mathbf{k}_{kq}$ is a column vector, $\mathbf{k}_{kq}=[K(x_k,x_1),\cdots,K(x_k,x_i),\cdots K(x_k,x_q)]^T$, $1\le i\le q$; and $\mathbf{K}$ is a $q\times q$ dimensional matrix, which is represented as follows.

$$\mathbf{K}=\begin{bmatrix}K(\mathbf{x}_1,\mathbf{x}_1) & \cdots & K(\mathbf{x}_1,\mathbf{x}_i) & \cdots & K(\mathbf{x}_1,\mathbf{x}_q)\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ K(\mathbf{x}_i,\mathbf{x}_1) & \cdots & K(\mathbf{x}_i,\mathbf{x}_i) & \cdots & K(\mathbf{x}_i,\mathbf{x}_q)\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ K(\mathbf{x}_q,\mathbf{x}_1) & \cdots & K(\mathbf{x}_q,\mathbf{x}_i) & \cdots & K(\mathbf{x}_q,\mathbf{x}_q)\end{bmatrix},1\le i\le q \tag{16}$$

We can obtain $K(\mathbf{x}_i,\mathbf{x}_j)=\exp(-\gamma|\mathbf{x}_i-\mathbf{x}_j|^2)$ using the soft measurement algorithm nuclear function discussed above, where γ is the parameter of the soft measurement algorithm kernel function so matrix $\mathbf{K}$ is a symmetric positive definite matrix and it has an inverse matrix. Thus, we denote the inverse matrix of $\mathbf{K}$ as $\mathbf{K}^{-1}$. If the minimum value of function $f(\mathbf{x}_k)$ is 0, the vector in the k-th sample's vector set in the high-dimensional feature space is linearly related to Q, whereas otherwise it is not linearly related to Q.

The algorithm used to find the maximal linearly independent group of the high-dimensional feature space vector set is described as follows 0:

1) Initialize set $Q=\{\mathbf{x}_1\}$, $P=\varnothing$, $A=A-\mathbf{x}_1$;

2) Remove a vector $\mathbf{x}_k$ from A, $A=A-\mathbf{x}_k$ and substitute $\mathbf{x}_k$ and the vectors in set Q into function (15). To determine whether the minimum value of function (15) is 0, a value of 0 indicates that $\mathbf{x}_k$ is linearly correlated with the vectors in set Q in the high-dimensional feature space, which adds $\mathbf{x}_k$ to set P, otherwise it is added to set Q;

3) Repeat operation (2) until $A=\varnothing$.

We know from the Lagrange for extreme conditions that when function (15) has a minimal value, its partial derivative for η is 0, so we can determine the coefficient vector η using function (15) at its minimum point. Thus, the minimum value of function (15) with $\mathbf{x}_k$ and the elements of set Q is obtained. The algorithm used to obtain the minimal value of function (15) is as follows.

$$\frac{\partial f}{\partial \eta} = 2\mathbf{K}_0 - 2\mathbf{K}\eta = 0 \tag{17}$$

$$\eta = \mathbf{K}^{-1}\mathbf{k}_{kq} \tag{18}$$

Therefore, when function (15) obtains the minimal value, we substitute the vector η, $\mathbf{x}_k$ and the vectors in set Q with its minimal value.

If we consider the maximal independent group of the high-dimensional feature space vector, it can only satisfy the following formula when all of $\eta_1,\cdots,\eta_j,\cdots\eta_q$ are equal to 0.

$$\phi(\mathbf{x}_k) - \sum_{j=1, j\neq k}^{q} \eta_j \varphi(\mathbf{x}_j) = 0 \tag{19}$$

Therefore, the maximal independent set of the high-dimensional feature space vector constitutes the base vector set of the original input space samples in the high-dimensional feature space. Thus, we use the original input space sample set that corresponds to the base vector to build a sample dictionary and save it to replace the training samples set in the soft measurement algorithm, thereby reducing the number of training samples and support vectors, which increases the online modeling and soft computing speed of the syrup supersaturation soft measurement algorithm. The method used for sample dictionary updating is to substitute the newly obtained sample and the sample dictionary into function (15), before calculating the minimal value, and if the minimal value is 0, the newly acquired samples, which are linearly related to the samples set in the dictionary, need to be removed immediately, otherwise add the samples to the dictionary sample set and use the earliest time sample from the sample dictionary.

2.3. Parameter Optimization Method for the Soft Measurement Algorithm

The syrup supersaturation soft measurement algorithm parameters are the LSSVM kernel function parameter γ and the penalty factor parameter C. The basic aim of parameter optimization for the soft measurement algorithm is to find suitable kernel function parameters and penalty factor parameters, which ensure that the relationship between the auxiliary variables and syrup supersaturation is reflected as well as possible by the syrup supersaturation soft measurement model. Genetic algorithm (GA) and k-fold cross-validation are combined to optimize the parameters of the syrup supersaturation soft measurement algorithm, thereby obtaining the optimal kernel function parameters and the penalty factor parameters. Basically, this involves searching for the best combination of parameters from a continuous range of data, which is a continuous parameter optimization process that involves the individual encoding GA, local search for parameter optimization, parametric search precision, and optimization efficiency. Gray code is based on absolute encoding using the characteristics of the reflection cycle and it is single-step self-complementary [17-18]. The Hamming distance is 1, which is different from Gray code encoding where any adjacent number has only one binary bit and the conversion efficiency is very good when the mutual conversion between them only needs to change a binary bit. This makes Gray code more suitable for implementing parameter optimization, which involves local search, efficiency optimization, and improving the search accuracy. It also facilitates the implementation of individual crossover and mutation by the GA. Therefore, we encode the GA using Gray code.

The soft measurement parameter optimization process integrates the kernel parameters and penalty factor parameter into the GA and encodes them with Gray code. Next, we verify the individual fitness results using the k-fold cross-validation method and iterate the GA. Finally, it decodes the global optimal individual fitness results to obtain the optimal kernel function parameters and the penalty factor parameters.

The parameter optimization process for the soft measurement method based on the GA and the k-fold cross-validation method is shown in Fig. 1.

2.4. Construction of the Syrup Supersaturation Soft Measurement Model

We use the auxiliary variable information in the training set and the sugar over-saturation as the input and output, respectively, to build the syrup supersaturation model with the soft measurement algorithm. The soft measurement model is constructed based on online auxiliary variable measurements. Fig. 2 shows the syrup supersaturation soft measurement dynamic online modeling process and the online soft measurements.

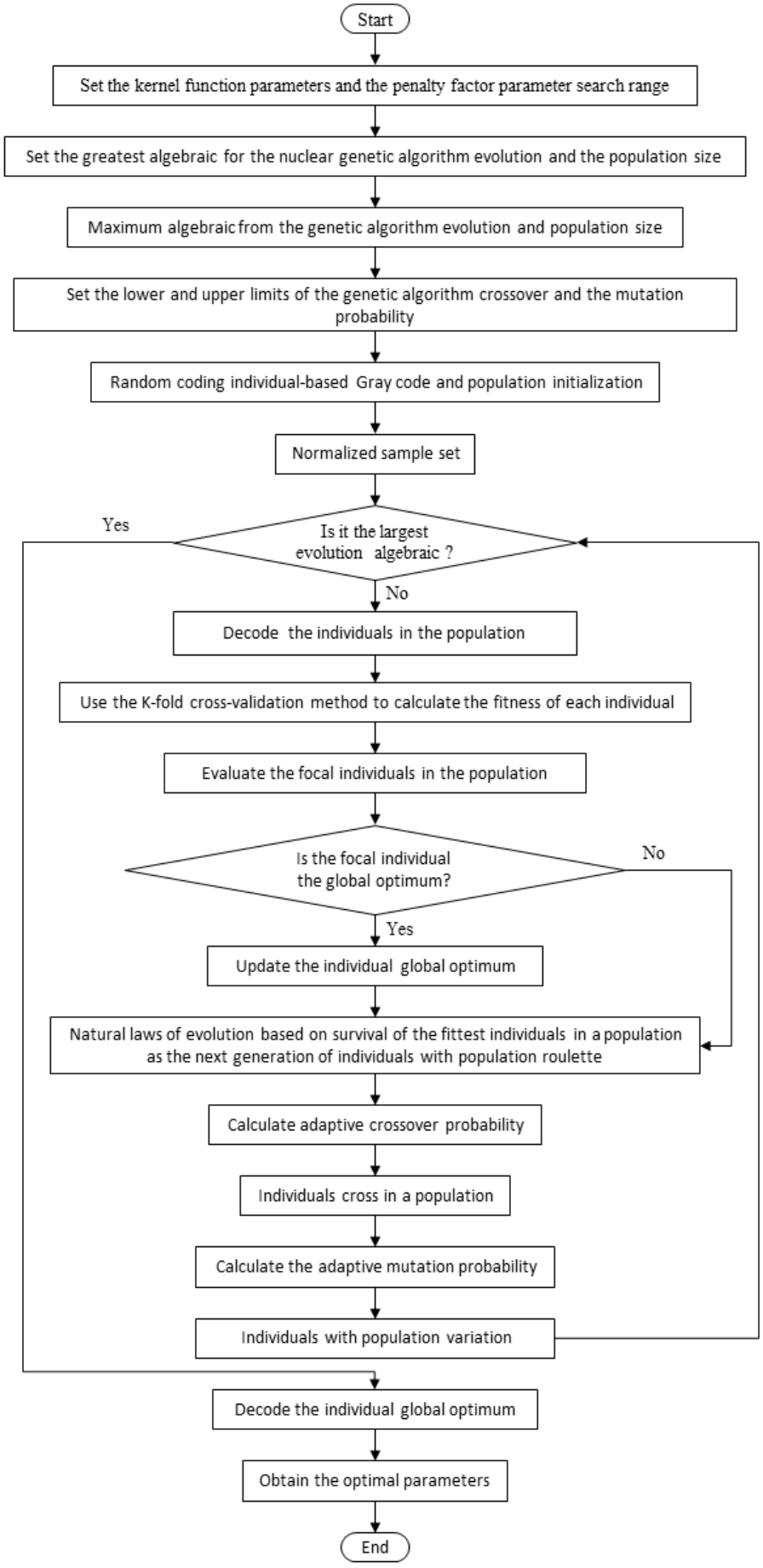

Fig. 1. Parameter optimization for the cane sugar supersaturation soft measurement algorithm.

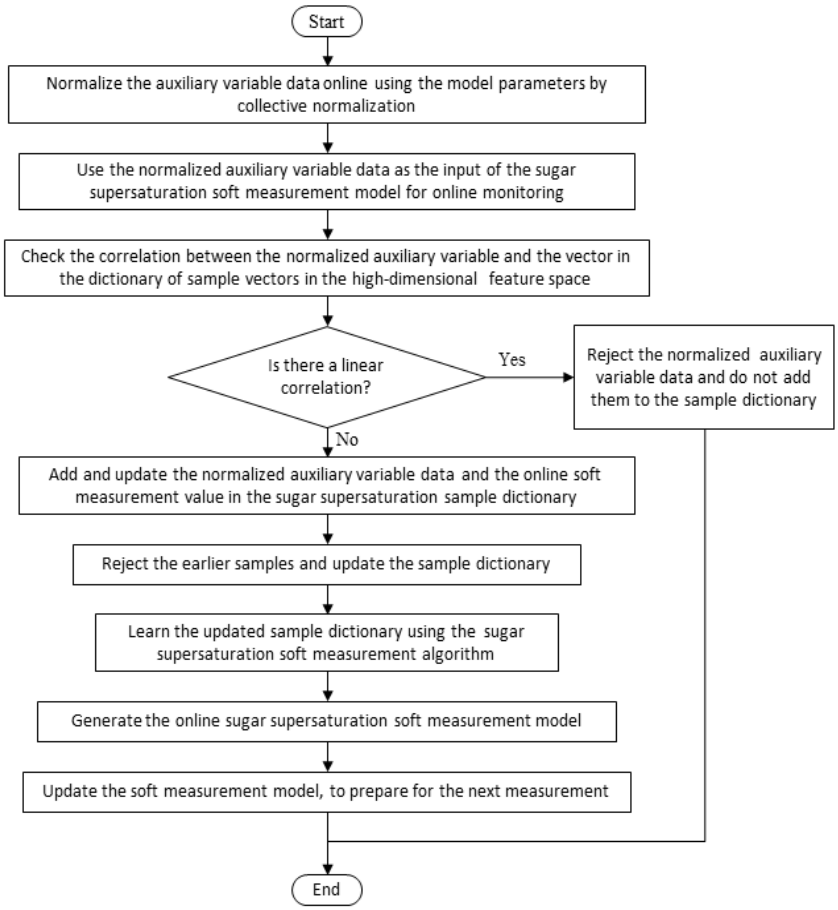

Fig. 2. The process used for online modeling and online soft measurement.

3. Analysis of the Soft Measurement System

3.1. Hardware Components of the Comprehensive Experimental Platform

To verify the effectiveness and feasibility of the soft measurement system, we built a novel, comprehensive experimental platform for monitoring the cane sugar crystallization process automatically. The input and output interfaces of the experimental platform were open and each part of the hardware system was modular and reconfigurable. The platform was capable of simulating the actual sugar crystallization process and monitoring the main parameters in real-time. The software component, which was modular and extensible, used different algorithms and compared all of the different types of control strategies to facilitate the automatic adjustment of the material flow velocity, syrup temperature, steam pressure, and other control parameters during the crystallization process.

As shown in Fig. 3, we combined the principles of the automatic detection system to develop a vacuum pan with various types of sensors for the sugar crystallization process system. This pan was designed to acquire the process parameters, such as the vacuum, syrup temperature, steam pressure, steam temperature, feed syrup temperature, and feed syrup flow of the sugar crystallization process. The analog signal outputs of various types of sensors were converted into a digital signal data by the acquisition module and connected to the monitoring host computer via an RS485 bus.

Fig. 3. The self-regulating comprehensive experimental platform used to replicate the sugar crystallization process.

3.2. Software Components of the Comprehensive Experimental Platform

The monitoring host computer mainly comprised the configuration software and the supersaturation soft measurement module. SCADA software communicated with the acquisition devices via an IO device configuration. The critical data were captured from the sugar crystallization experimental platform and saved in a real-time database, which was displayed on the SCADA software system monitoring screen. The soft measurement module used the real-time data, which were derived from the SCADA software system and used by the OPC interface as the input for the soft measurement module, before sending the results back to the monitoring screen of the SCADA software for display and storage after the online soft measurements. The relevant parameters of the sugar crystallization process were then adjusted based on supersaturation feedback to control the sugar crystallization process automatically. The structures of the software components are shown in Fig. 4.

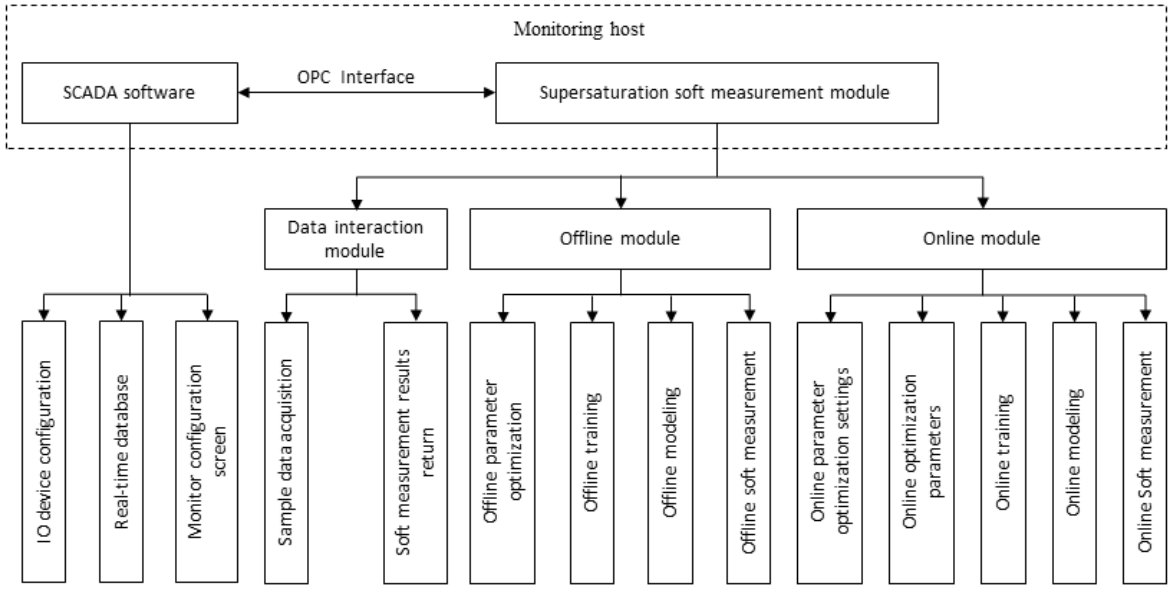

Fig. 4. Components of the software framework.

3.3. Soft Measurement System Tests and Experimental Analysis

The real-time database of SCADA software system is an open data platform and its OPC interface is both convenient and efficient. The PC program could read and write data to the SCADA software database via the OPC interface 0.

The soft measurement model was tested and verified by comparing the effects of the six auxiliary variables on the crystallization process with the empirical syrup supersaturation data. We ordered 210 samples randomly and used the first 130 samples as the training set and the other 80 samples as the test set. We set the target error value of the convergence criteria to 0.0001. The actual and predicted syrup supersaturation values of different methods are compared in Fig. 5. It is obvious that the proposed GA-LSSVM method excels BP, SVM, and LSSVM approaches, the presented GA-LSSVM method outperforms the other methods with the minimal prediction errors. The mean squared error of the syrup supersaturation prediction results using GA-LSSVM method was 0.001. Therefore, performing soft measurements based on a GA-LSSVM is feasible and this method is capable of providing accurate and reliable results.

4. Conclusion

The syrup supersaturation is critical during the sugar crystallization process but it is difficult to be measured online directly and in a stable manner. Thus, we developed a soft measurement algorithm and used it to model syrup supersaturation during the sugar crystallization process, which was based on a LSSVM, GA, and k-fold cross-validation. The algorithm fed the dynamic online sample data back to the model to optimize the modeling of the online dynamic parameters, thereby facilitating more accurate predictions of syrup supersaturation to improve the generalizability of the model. The interaction between the soft measurement model of syrup supersaturation and the SCADA software was achieved via OPC interfaces supported by the

SCADA software, thereby allowing online syrup supersaturation monitoring during the sugar crystallization process. Our soft measurement system was tested using a self-regulating comprehensive experimental platform that represented the sugar crystallization process and the soft measurement values were very close to the empirical values. The mean squared error was 0.001, which indicated that the results were favorable.

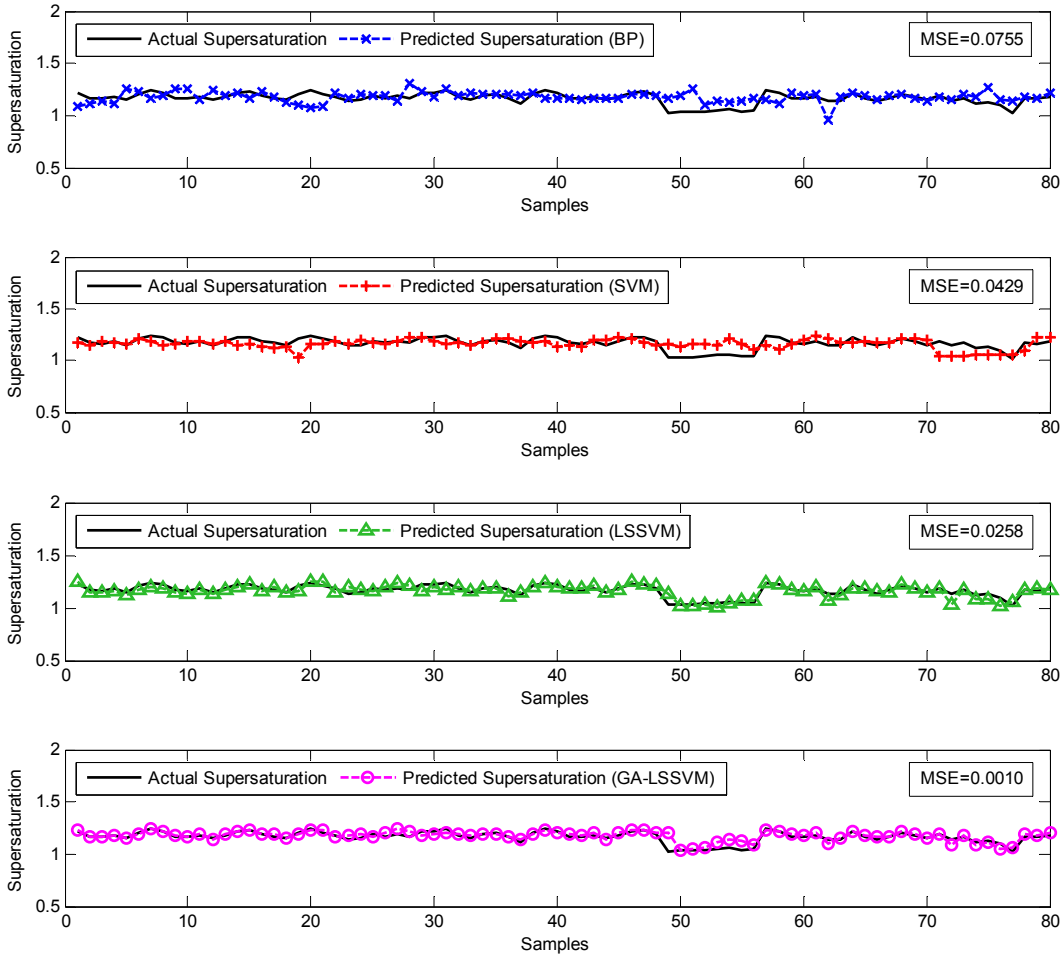

Fig. 5. The syrup supersaturation prediction results of BP, SVM, LSSVM, and GA-LSSVM methods in the soft measurement system.

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