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KNOWLEDGE-BASED MODELING FOR PREDICTING CANE SUGAR CRYSTALLIZATION STATE

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Abstract- This paper proposes a knowledge-based model applied to an experimental scale evaporative cane sugar crystallization process, which combines the methods of offline and online knowledge acquisition. Firstly, a data mining method based on rough set theory is utilized to extract information from the large quantity of relevant data obtained in experiment. This method products an offline predictive knowledge. Thereafter, a method for online knowledge learning and self-improvement is put forward, based on support vector machine with particle swarm optimization, to improve the predictive accuracy and generalization capacity. Furthermore, the intelligent system is tested using a self-regulating intelligent comprehensive monitoring and controlling platform that represents the cane sugar process. Results demonstrate the feasibility of the system for predicting the crystallization state in a real cane sugar process.

Index terms*:* Cane sugar crystallization state, intelligent system, knowledge acquisition, rough set, support vector machine

I. INTRODUCTION

Crystallization process is a key component in cane sugar industries, which is currently non-automated in China. Some key process parameters that influence the cane sugar crystallization are not stable and reliable for online measurement, and the dynamic crystallization state is also not able to be judged, which lead to the incorrect conduction of corresponding operations. Therefore, the operators in most cane sugar industries still mainly conduct the next action based on the size of the crystals and the concentration of mother liquor by extracting the sucrose from a sample rod manually [1-3].

The cane sugar crystallization process involves a transformation of heat and mass, which is a complex process that involves many interacting factors. So it's difficult to create a precise mathematic model for the cane sugar crystallization process.

However, the concerned experts and operators accumulate rich experience about process research from lab and large-scale industrial production practice. In some way, it is the precious experience that maintains the progress of Chinese cane sugar industry. Under this condition, we proposed a knowledge-based method to determine the cane sugar crystallization state. Firstly, an offline knowledge-obtained method for the system was developed based on rough set. And a combined support vector machine (SVM) and particle swarm optimization (PSO) was used to complete online learning and dynamic updating of the knowledge, which made the database of the system accessible to be self-improved in actual application [4]. Finally, the prediction of the cane sugar crystallization state could be completed. The realization of the prediction could make contribution to the automated technology in cane sugar industry.

II. KNOWLEDGE-BASED CONTROL

The main difficulty associated with the crystallization process control is that there is no direct method for measuring the supersaturation of solution. Usually the supersaturation is measured under a way of indirection.

One way is to develop new sensor instruments that could formulate the supersaturation according to physical quantities they could measure directly. For instance, P.F. Bordui [5] measured the electrical conductivity from an aqueous solution to obtain the supersaturation of potassium dihydrogen phosphate based on conductivity-temperature-concentration data base; ATR-FTIR, FBRM and PVM were applied by Dilum, Abhay Markande, P. Barrett and so on [6-8] to the crystallization process respectively, which could calculate out the supersaturation in crystallization process online. These kinds of instruments enable the control of modern crystallization process, but the ways of measuring the supersaturation are far from precise since the measured physical quantities are strongly influenced by the amount of impurity in the solution.

Another way is to adopt the model-based predictive approaches to the crystallization process, which has been a major advance in the field of soft sensor process measurement. The model-based approach had limitations in terms of optimization objectives and constraints, optimization variables, and methods of dealing with uncertainties. These limitations have been removed in recent more than a decade in which the Artificial Neural Networks (ANNs) have been frequently used in modeling and control of nonlinear processes. And there has been some research work published using ANNs as a crystallization model [9-11], which seems suitable for modeling purposes since they can express past and current input-output information and thus approximate nonlinear behavior of dynamic processes [12].

In this paper, an innovative knowledge-based model combined with rough set and support vector machine is proposed to predict the cane sugar crystallization state, compared with a back propagation neural network (BPNN) and a traditional SVM without optimization [13-14]. Finally, the knowledge-based model is integrated into the *eForceCon* software to form an intelligent system, which makes it feasible to dynamically update the knowledge base of the system. The modeling of the knowledge-based model for the crystallization process consists of two steps, namely, the method for obtaining offline knowledge (in section 3) and the online updating method based on SVM (in section 4).

III. METHOD FOR OBTAINING OFFLINE KNOWLEDGE

a. Evaluation of cane sugar crystallization

Those factors that influence the cane sugar crystallization state mainly include the brix and temperature of the syrup, pressure and temperature of the steam, vacuum pressure and feed flowrate. So these parameters should be controlled well to make the crystals grow up faster and reduce the reacting probability of the phenomenon of second nucleation and agglomeration.

The fraction of crystals that reach to the standard size and their uniformity at the certain moment of a batch crystallization mark the growing conditions of the cane sugar crystallization. The uniformity of the crystals is represented as the crystal size distribution (CSD). It samples the massecuite in sugar pan for calculating correlative parameters such as the number, size and mean size of the crystals. Then the growth rate of the crystals is statistically obtained and used to evaluate the current crystallization state. The crystallization state generally is divided into six classes, i.e., 5, 4, 3, 2, 1, 0, where 5 represents the best and 0 represents the worst.

b. Data mining based on rough set

The key of the intelligent system which could correctly judge the current crystallization state, is the knowledge obtained and its capability of self-improvement. With the large number of industrial data and experience knowledge accumulated, we adopt the data mining method based on rough set to obtain the offline knowledge.

b.i Basic procedure

Rough set theory is a mathematic tool to solve fuzzy and uncertain knowledge. Its main idea is that the uncorrelated or unimportant knowledge in the knowledge base could be deleted through knowledge reduction with the constant classifying ability [15-16]. The flow chart of obtaining knowledge based on rough set is showed as figure 1.

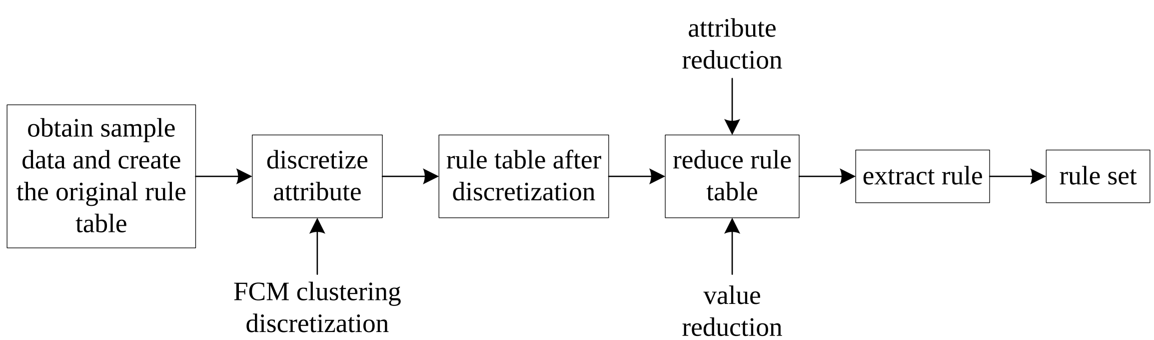

Figure 1. Basic procedure of obtaining offline knowledge

For the simplification purpose, we selected 8 samples to describe the process of offline knowledge acquisition of the cane sugar crystallization state. Actually, it came from a great number of samples.

b.ii Rough set theory

Distinguish matrix and function: The information system $S=(U,A,V,f)$, $U=\{x_1,x_2,...,x_n\}$ is a domain of discourse, and the $A=C\bigcup D$ and $C\bigcap D=\varnothing$ are the attribute set of an object where $C=\{a_i,i=1,2,...,m\}$ means the subset of condition attributes, $D=\{d_j,\ j=1,2,...,l\}$ means the subset of conclusion attribute. The $a_k(x_j)$ means the value of a sample x_j with the condition attributes a_k . $M(S)=[m_{ij}]_{n\times n}$ is defined as a $n\times n$ distinguish matrix of an information system. m_{ij} is the element of the i-th row and j-th column in the distinguish matrix, which is described as

$$m_{ij}=\begin{cases} a_k\in C, & a_k(x_i)\neq a_k(x_j)\wedge D(x_i)\neq D(x_i) \\ \varnothing, \ \ D(x_i)=D(x_j) & i,j=1,2,...,n \end{cases} \tag{1}$$

where m_{ij} represents the attribute set of the whole distinguish objects x_i and x_j under different rule conclusions. If the rule conclusions of x_i and x_j are the same, the value of m_{ij} is $\varnothing$ in the distinguish matrix. According to the definition of m_{ij}, $M(S)=[m_{ij}]_{n\times n}$ is a symmetric matrix, whose elements on the main diagonal are an empty set. So we just need to consider the upper or the lower triangular part of the matrix while calculating it.

The distinguish function could be deduced out from the distinguish matrix $M(S)$, which is described as Eq. (2).

$$f_{M(s)}(a_1,a_2,...,a_m)=\wedge\{\vee m_{ij},\ \ 1\leq j<i\leq n,\ \ m_{ij}\neq\varnothing\} \tag{2}$$

The function is a boolean function formula that includes m variables, i.e., the $a_1,a_2,...,a_m,(a_i\in C,i=1,2,...,m)$. It actually is the conjunction of the whole $(\vee m_{ij})$, and every $(\vee m_{ij})$ is the disjunction of m_{ij} [17-18].

Fuzzy c-means algorithm (FCM): The basis of rough set theory is the set theory, which demands every attribute value in a rule table to be expressed with discrete value. While analyzing continuous attribute values using rough set, they have to be discretized in order to obtain more effective information. FCM classifies data with continuous attributes by building fuzzy clustering matrix-dividing method and turns all of the continuous attribute values into a matrix to deal with. That process comes down to a nonlinear programming with a constraint, which could obtain the fuzzy dividing matrix and clustering center [19-22].

FCM is a clustering method based on objective function [23-26], which is described as

$$\begin{cases} \min J_{FCM}(U,P) = \sum_{i=1}^{c}\sum_{j=1}^{n}(\mu_{ij})^m (d_{ij})^2 \\ \quad s.t.\ \ \mu_{ik} \in [0,1], \forall i,k; \\ \quad \sum_{i=1}^{c}\mu_{ik} = 1, \forall k; \\ \quad 0 < \sum_{k=1}^{n}\mu_{ik} < n, \forall i \end{cases} \tag{3}$$

where U represents membership matrix, $d_{ik}^2 = (x_k - \upsilon_i)^T(x_k - \upsilon_i)$ represents distance. If $d_{ik} = 0$, then the k-th clustering center is selected as x_i.

So the membership function is as follows:

$$\begin{cases} \mu_{ik} = \dfrac{1}{\sum_{j=1}^{c}[\frac{d_{ik}}{d_{jk}}]^{\frac{2}{m-1}}}, d_{jk} \neq 0; \\ \mu_{ik} = 1, \quad d_{jk} = 0 \text{且} i = j; \\ \mu_{ik} = 0, \quad d_{jk} = 0 \text{且} i \neq j; \end{cases} \tag{4}$$

The clustering center is as follows:

$$\forall i, V_i^{(k+1)} = \frac{\sum_{j=1}^{n}(\mu_{ij}^{(k)})^m x_j}{\sum_{j=1}^{n}(\mu_{ij}^{(k)})^m} \tag{5}$$

The optimal membership matrix and clustering center could be obtained using Eqs. (4) and (5) with iteration [27-28].

b.iii Attribute analysis with FCM discretization method

According to the FCM discretization method, we classified the original data (knowledge the experts, operators judge out) of cane sugar crystallization state as six classes i.e., 5, 4, 3, 2, 1, 0, where 5 represents the best and 0 represents the worst. Then an original rule table was built up via the brix, syrup temperature, vacuum, liquor feed flow, steam temperature and steam pressure as condition attributes, and the crystallization state as the conclusion attributes, which is described as table 1.

Combining the knowledge that the experts judge the state of condition attribute values in cane sugar process, we discretized every condition attribute value using FCM, The clustering number of all the condition attribute values is set as 7, i.e., 6, 5, 4, 3, 2, 1, 0, where 6 represents the highest level and 0 the lowest level. The conclusion is described as table 2.

Table 1: Original data

sample *U*	**Brix /ºBx**	**Syrup temperature /℃**	**Vacuum /kPa**	**Liquor feed flow /$m^3 \cdot h^{-1}$**	**Steam temperature /℃**	**Steam pressure /MPa**	**Crystallization state class**
*x*1	82.56	62.91	82.75	0.23	107.4	0.028	3
*x*2	81.56	62.36	81.18	0.27	107.2	0.045	2
*x*3	83.36	62.85	81.69	0.17	107.5	0.026	3
*x*4	83.32	64.81	80.91	0.26	108.2	0.03	4
*x*5	82.4	61.06	82.97	0.22	106.5	0.042	3
*x*6	81.4	62.67	8139	0.19	106.5	0.027	2
*x*7	82.48	60.78	80.62	0.18	105.9	0.038	2
*x*8	83.16	64.6	81.59	0.19	107.4	0.046	3

Table 2. Results of Fuzzy C-means Discretization

Sample *U*	**Brix**	**Syrup temperature**	**Vacuum**	**Liquor feed flow**	**Steam temperature**	**Steam pressure**	**Crystallization state class**
*x*1	3	3	4	3	3	2	3
*x*2	2	3	3	4	3	4	2
*x*3	4	3	3	2	3	2	3
*x*4	4	4	2	4	4	3	4
*x*5	3	2	4	3	2	4	3
*x*6	2	3	3	2	3	2	2
*x*7	3	2	2	2	2	3	2
*x*8	4	4	3	2	3	4	4

b.iv Rule table reduction

The condition attributes in the rule table discretization need to be done with deleting the repeated sample data in the rule table to obtain reduced rule table and reduction set. In rough set theory, the knowledge reduction includes condition attribute reduction and condition attribute value reduction.

Attribute reduction: The sample set of the cane sugar crystallization state is set as $U=\{x_1,\ldots,x_8\}$. We made the a represent Brix, b the syrup temperature, c the vacuum, d the feed syrup low, e the steam temperature and f the steam pressure as condition attributes, g the crystallization state classes as the conclusion attributes, and reduced the attributes based on the basic principle of distinguish matrix reduction method. The calculating steps of the method are described as follows:

(1) Extract the kernel attributes from the distinguish matrix according to the solution of Eq. (1). The kernel attributes are described as $Core=\{c_{ij}\mid Card(c_{ij})=1, i, j=1,2,3,\cdots,n\}$, where c_{ij} represents an element of the distinguish matrix and $Card(c_{ij})=1$ represents the number of the condition attributes is 1;

(2) Find the kernel attribute group Q that excludes the kernel attributes in (1) and $c_{ij}\neq 0$ from the distinguish matrix, namely, $Q=\{c_{ij}\mid c_{ij}\cap Core=\varnothing, \text{且 } c_{ij}\neq 0, i, j=1,2,3,\cdots,n\}$;

(3) Express Q using conjunction normal form, namely, $P=\wedge(\vee c_{ij}), c_{ij}\in Q$;

(4) Turn P into disjunction normal form and simplify the disjunction normal form;

(5) If multiple equivalent results appear in the simplifying results from (4), the simplifying results need to have attribute-combining selection under an actual demand.

The distinguish matrix is as follows:

$$M(S)=\begin{bmatrix} 0 & acdf & 0 & abcdef & 0 & acd & bcdef & abcdf \\ 0 & 0 & adf & abcef & abcde & 0 & 0 & abd \\ 0 & 0 & 0 & bcdef & 0 & a & abcef & bf \\ 0 & 0 & 0 & 0 & abcdef & abcdef & abde & 0 \\ 0 & 0 & 0 & 0 & 0 & abcdef & cdf & abcde \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & abf \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & abcef \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The distinguish function obtained from the steps as mentioned above and Eq. (2) is described as follows:

$$
\begin{aligned}
f_{m(s)}(a,b,c,d) &= (a)\wedge(b\vee c\vee d\vee e\vee f)\wedge(b\vee f)\wedge(c\vee d\vee f)\\
&= (a)\wedge(b\vee f)\wedge(c\vee d\vee f)\\
&= (a\vee b)\wedge(a\vee f)\wedge(c\vee d\vee f)\\
&= (a\vee b\vee c)\wedge(a\vee b\vee d)\wedge(a\vee b\vee f)\\
&\quad \wedge(a\vee c\vee f)\wedge(a\vee d\vee f)\wedge(a\vee f)\\
&= (abc)\wedge(abd)\vee(af)
\end{aligned}
\tag{6}
$$

Therefore, it obtains three reduction results abc, abd and af from the table 2 using distinguish function. We selected abc as the attribute reduction set according to actual experience knowledge, i.e., the brix, syrup temperature and vacuum. The rule table after reduction is described as table 3.

Table 3: Rule table after reduction

U	a	b	c	g
$x1$	3	3	4	3
$x2$	2	3	3	2
$x3$	4	3	3	3
$x4$	4	4	2	4
$x5$	3	2	4	3
$x6$	2	3	3	2
$x7$	3	2	2	2
$x8$	4	4	3	4

Attribute values reduction: The attribute reduction deletes redundant information of the attributes in the rule table, but not among the samples. So the attribute values reduction is introduced to reduce the rules in the rule table 3 [29-31]. It could be started with value kernel using given information system. The rule table using heuristic attribute values reduction to table 3 is described as table 4:

Predicting rules extraction: The predicting knowledge of the crystallization state could be extracted from the table 4 that has been done with attribute and attribute value reduction, which is described as follows:

(1) IF (a=2) AND (b=3) AND (c=3) THEN (g=2);

(2) IF (a=4) AND (b=3) THEN (g=3);

(3) IF (a=3) AND (b=2) AND (c=4) THEN (g=3);

(4) IF (a=3) AND (b=2) AND (c=2) THEN (g=2);

(5) IF (a=4) AND (b=4) AND (c=3) THEN (g=4).

Table 4: Rule table after value reduction

U	*a*	*b*	*c*	*g*
*x*1	2	3	3	2
*x*2	4	3	*	3
*x*3	3	2	4	3
*x*4	3	2	2	2
*x*5	4	4	3	4

The rules mentioned above could be saved into the rule base of the system. In addition, we only selected 8 samples to describe the process of the rule acquisition, but the predicting knowledge of actual cane sugar crystallization state is extracted out from large quantity of test data.

b.v Test of predictive results

To test the accuracy between the rules extracted and the original samples of crystallization state, we used the data in table 5 as the samples. The predicting results could be obtained through rule match and compare with the conclusion attributes in table 5.

From the test results in table 5 with 200 samples, the predicting accuracy of the crystallization state was 99.0%. Therefore, we demonstrated that using brix, syrup temperature, vacuum, liquor feed flow and steam pressure have the same predicting accuracy with the original 6 factors as condition attributes and the rules extracted could be the predicting knowledge of crystallization state. Finally, the offline knowledge acquisition of the intelligent analysis system was realized after saving the rules extracted into the knowledge base of the system about crystallization state.

IV. ONLINE UPDATING METHOD BASED ON SVM

a. Online updating framework

The basic knowledge obtaining from data mining method based on rough set constitutes the initial knowledge base of the intelligent analysis system of cane sugar crystallization state, and the improvement and updating of the knowledge base have to be done through an online learning module. The essence of the dynamic updating of the knowledge base is a process of excavating the predicting rules of crystallization state, which is derived from the sample data about the crystallization state and the creating of a classifier model using classifying method. The classifier model is used to build a classifying model or function, which could map the sample data to a given classes, being applied to create predict the good or bad crystallization state [32-33]. There exist many methods to model a classifier and the classifier based on SVM classifies uncertain samples more accurate than others [34]. So we used this method to model the online learning and knowledge acquisition for the intelligent analysis system of cane sugar crystallization state. The online updating of the knowledge base of the system based on SVM is described as figure 2.

Table 5: Test results of the rules

Sample number	**A**	**b**	**c**	**d**	**d**	**f**	**g**	**Predicting results**	**Rules used**
1	3	1	3	3	5	6	3	3	1
2	6	4	1	2	5	6	1	1	2
3	2	0	3	0	3	2	3	3	3
4	3	1	1	4	4	1	2	2	4
5	1	0	5	3	4	5	5	5	5
6	4	1	4	4	1	2	4	4	6
7	4	0	3	6	2	2	3	3	22
8	4	1	4	2	3	3	4	4	7
9	3	1	1	0	3	1	2	2	4
10	3	2	2	5	3	1	3	3	14
…	…	…	…	…	…	…	…	…	…
200	2	1	5	5	3	3	4	4	148

Test results analysis				
Accurate identifying number	Inaccurate identifying number	Non-identifying number	Sample number with conflict	accuracy
198	2	0	0	99%

The components of the SVM knowledge acquisition are made up of SVM network module, data discretization module and rule extraction module and so on, where the SVM network module is the key. The learning samples through knowledge acquisition are the knowledge of the rule base of the intelligent system, namely, the actual set of experts' experience, which is used to build the network module using SVM. The dynamic updating of the cane sugar crystallization state is realized by using SVM, which is a nonlinear process from the attribute information to analyzing results that influence the crystallization state according to the experience of cane sugar experts. The knowledge acquisition process includes: submit the condition attributes and conclusion attribute values in the rule base of the intelligent system to a SVM learning network, model SVM, and save the trained model into the predicting module. When the inference engine of the intelligent system matches the online predicting rules failed, the real time condition attribute values with discretization will be made as the SVM inputs, the SVM module outputs the predicting results, the rule extraction module extracts the judging rules of the crystallization state and puts the rules into the knowledge base of the intelligent system. Finally, the dynamic updating of the crystallization state of the intelligent system is completed.

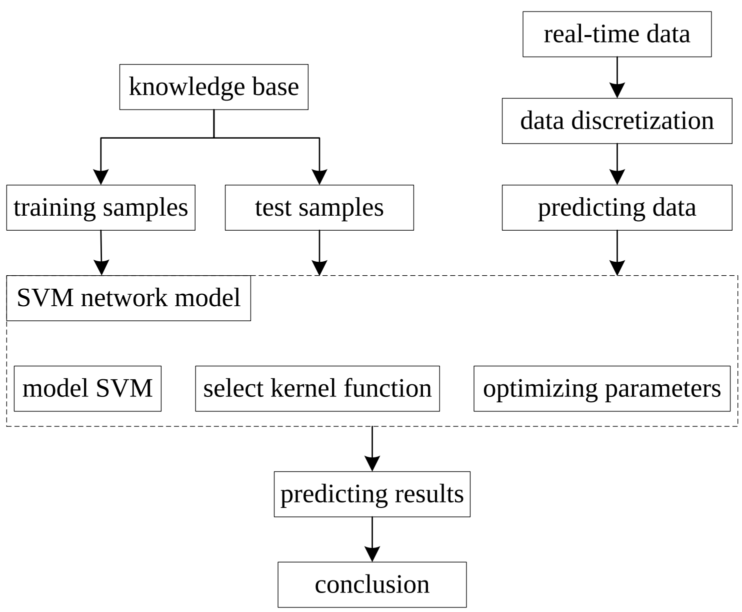

Figure 2. Online updating of the knowledge base

b. Modeling online knowledge

The training samples of the SVM module are the knowledge of the rule base of the intelligent system. Therefore, the SVM knowledge acquisition is modeled via the condition attributes of the rule base as inputs, and the conclusion attributes of the rule base as the outputs, i.e., the brix, syrup temperature, vacuum, liquor feed flow and steam pressure with FCM discretization as inputs, and the crystallization state classes as the outputs.

The sample set of the knowledge acquisition model of the predicting crystallization state of the intelligent system is $S=\{(X_i,Y)\}_{i=1}^{m}$, where m is the sample number, X_i is an auxiliary variable vector with 5 dimensions, Y is the crystallization state class(it includes six classes, namely, $Y \in \{0,1,2,3,4,5\}$,where the value is higher the crystallization state under current condition is the better). And $X_i=[x_{i1},x_{i2},x_{i3},x_{i4},x_{i5}]$, $Y=[y_1,\cdots,y_i,\cdots,y_M]^T$, where x_{i1}, x_{i2}, x_{i3}, x_{i4} and x_{i5} represent the discretized value of the Brix, syrup temperature, vacuum, feed syrup, flow steam pressure of the i-th sample, namely, the condition attribute values, y_i represents the crystallization state class corresponding to the i-th auxiliary variable vector.

The predicting of the crystallization state belongs to a classical multi-value classification problem, demanding to create 6×(6-1)/2=15 SVM binary classifiers for the predicting of the crystallization state using SVM multiple classification algorithm based on the directed acyclic graph. And those classifiers are assembled on the basis of DDAG topological structure to constitute a classifier that could classify six classes of the crystallization state. The classification model for the predicting of the crystallization state based on SVM principle is described as figure 3.

c. Optimizing parameters of the SVM based on PSO

The kernel function of the SVM model obtaining from the intelligent system is the Gaussian radial basis kernel function, which demands to determine the SVM kernel function parameter γ and the penalty factor parameter C when modeling. The purpose of optimizing parameters γ and C is to search appropriate γ and C, making the model optimally express the relationship between the auxiliary variables and the crystallization state. To improve its predicting classification accuracy, a combined PSO and k-fold cross-validation method is used to optimize the parameters of the model. In the k-fold cross-validation, the training samples are divided randomly into k subsets with equivalent number, and every subset is trained and tested as training and test set each other, to obtain the optimal kernel function and penalty factor parameters [35-36]. Otherwise, the essence of the optimization is to find the optimal parameter combination in the solution space [37]. The basic procedure of the optimization includes: express γ and C as a particle in PSO, calculate the fitness of particles using the results of the k-fold cross-validation and conduct the iteration of the algorithm, get the global optimal particle, obtain the optimal γ and C.

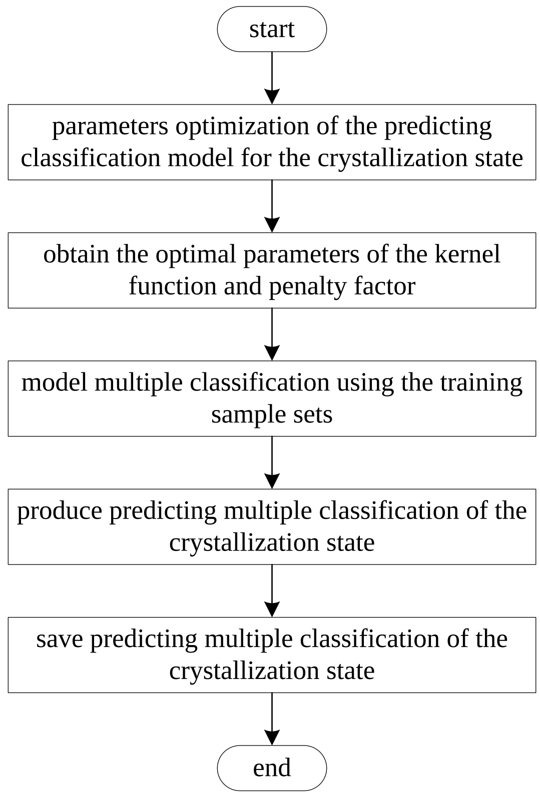

Figure 3. Classification modeling for predicting the crystallization state

In the parameter optimizing process based on PSO, the optimizing value of the objective function is the classifying accuracy of cross-validation under SVM with selected parameters. Every potential solution of γ and C makes up of a particle in the searching space, which includes a fitness determined by the classifying accuracy of cross-validation under SVM and a speed that determines the flying direction and distance. All of the particles in the solution space update their own location according to the optimal particle in the current swarm. In the every optimizing iteration of the swarm, every particle updates its own location through two extreme values [38-40]. The first is the optimal solution the swarm finds currently, which is a global extreme value,

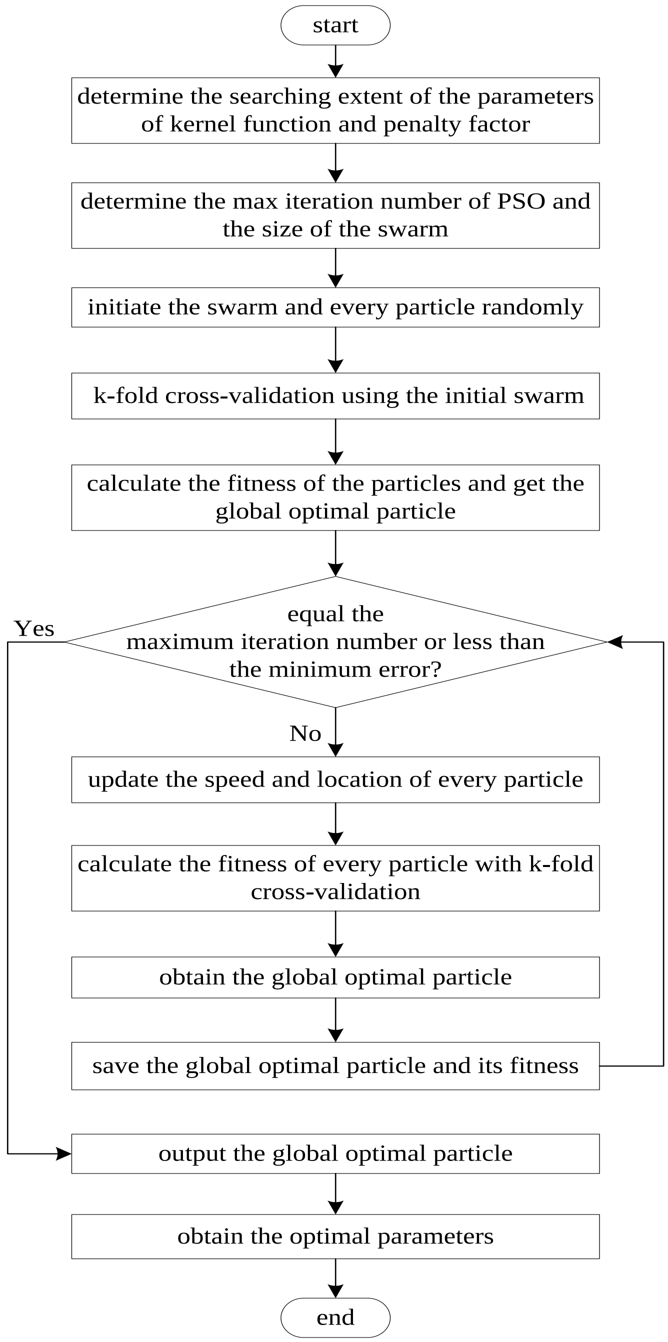

Figure 4. PSO-based parameters optimizing algorithm

described as $Nbest_i = \left(Nbest_{i1}, Nbest_{i2}, \ldots, Nbest_{in}\right)$. The second is the optimal solution the particle itself finds, which is named as individual extreme value, described as $Pb_i = \left(Pb_{i1}, Pb_{i2}, \ldots, Pb_{in}\right)$. Therefore, in the optimizing process, every particle follows the global extreme value while following the individual extreme value. The speed and location that every particle updates are described as

$$V_{in}^{k+1} = V_{in}^{k} + c_1 \bullet rand() \bullet \left(Pbest_{in}^{k} - X_{in}^{k} \right) + c_2 \bullet rand() \bullet \left(Nbest - X_{in}^{k} \right) \quad (7)$$

$$X_{in}^{k+1} = X_{in}^{k} + V_{in}^{k+1} \quad (8)$$

where X_i and V_i respectively represent the location and speed of the i-th particle in n dimensions solution space, k is the iteration number, c_1 and c_2 are accelerating constants, $rand()$ is a function produces the random values between 0 and 1. The steps of the γ and C parameters optimizing algorithm based on PSO and the k-fold cross-validation are described as figure 4.

V. MODEL TEST AND EXPERIMENTAL IDENTIFICATION

a. Model test

Table 6: Parameters setting and optimizing results of the predicting model

parameters setting	number of training samples	138
	number of test samples	20
	optimizing extent of kernel function parameter	0.01-16
	optimizing extent of penalty factor parameter	0.1-20
	fold number of cross-validation	5
	swarm size of PSO	20
	the maximum evolution algebra of PSO	200
	accuracy of parameters optimizing	10^{-4}
optimizing parameters obtained	kernel function parameter obtained	0.1
	penalty factor parameter obtained	12.4

This paper randomly selects 20 original samples as the test set, and the rest of the original samples as the training set. The parameters setting and optimizing results of the knowledge-based model are described as table 6. The predictive values of the crystallization state of the model with actual values are compared with those of the BPNN and traditional SVM without optimization in figure 5. Furthermore, their consuming time from modeling to outputting predictive crystallization state is represented in figure 6.

From the view of figure 5, the accurately predictive number of the model is more than that of the BPNN and the traditional SVM. Even though it consumes longer time than the BPNN, the difference of time between them is not obvious as described in figure 6.

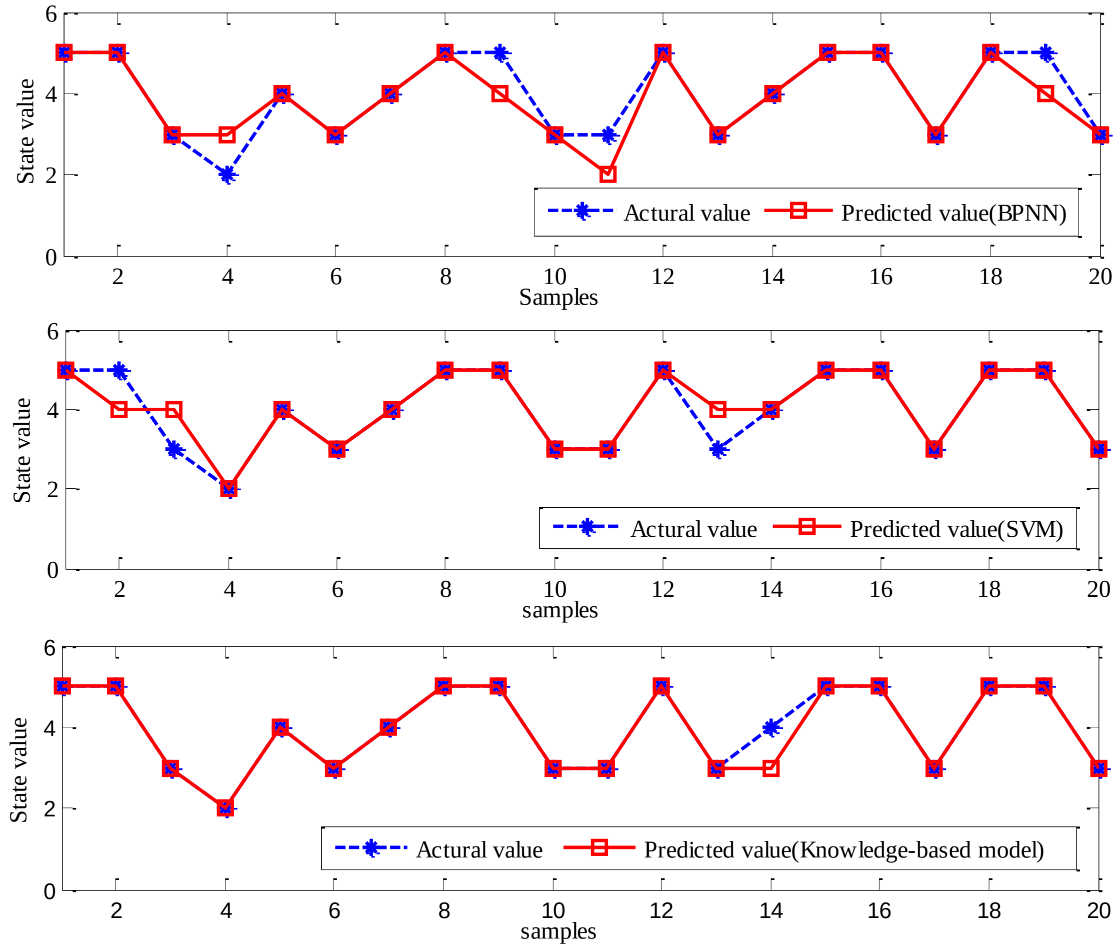

Figure 5. Test comparison of the crystallization state

b. Experimental identification

In order to test the intelligent system of cane sugar crystallization state, we made an experimental identification using a self-regulating intelligent comprehensive monitoring and controlling platform that represented the cane sugar process (Figure 7), and installed a variety of sensors on the cane sugar tank to monitor the process parameters in real time. Figure 7a shows the experimental field with hardwares to complete the cane sugar crystallization process, and figure 7b is a software interface simulating the experimental field to monitor and control the crystallization process.

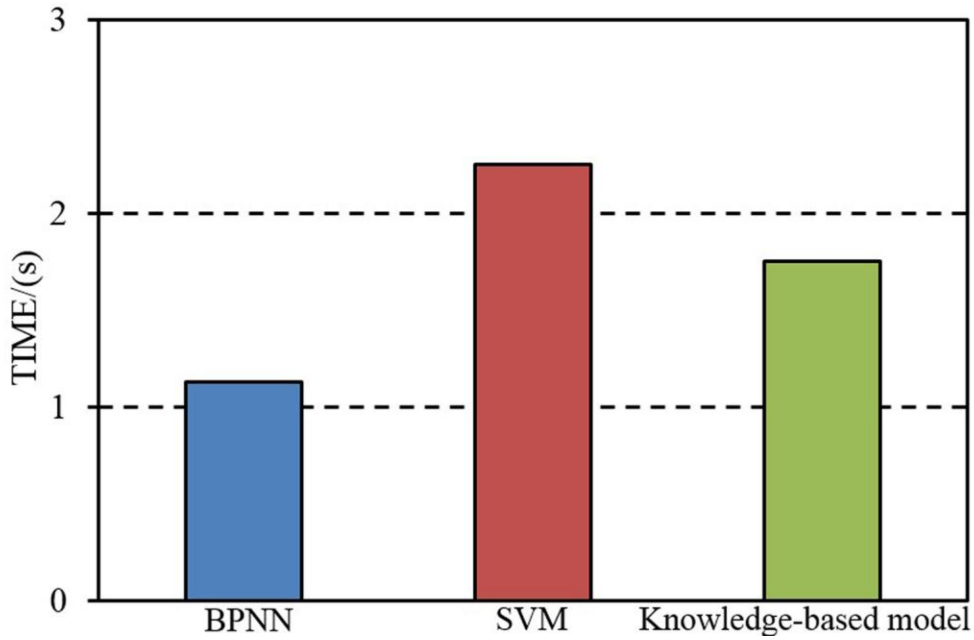

Figure 6. Time comparison

The process parameters obtained mainly include brix, syrup temperature, vacuum, steam pressure, steam temperature and liquor feed flow. Every sensor's output signal is a 4-20mA analog, and is converted to digital signal and stored in the registers of analog acquisition modules. Then the analog acquisition modules is connected to the principal computer (PC) via RS485 bus based on Modbus protocol. PC receives the collected data, processes it, and outputs the control parameters to the control modules. Eventually, the control modules output control signal to complete the action of the valves in cane sugar process.

The software of the platform includes the PC monitoring software of cane sugar process and intelligent analysis system of crystallization state, where the PC monitoring software developed by the *eForceCon* software is used as an OPC server, the intelligent analysis system as an OPC client. The system obtains parameters of the cane sugar crystallization process from the monitoring software database in real time via the OPC interface, and sends them to the dynamic database after pretreating them. The inference engine module gets the data in the dynamic database and outputs the current predicting result of the crystallization state. Finally, the online predicting process of the cane sugar crystallization state is completed when the predicting results are sent back to the monitoring software through the OPC interface.

Figure 7a. Experimental field

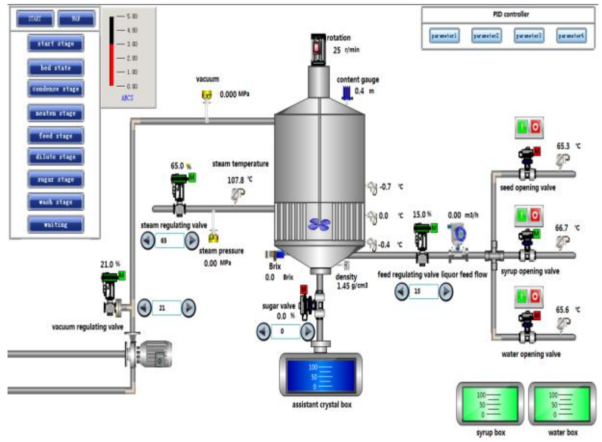

Figure 7b. Software interface

Figure 7. Comprehensive monitoring and controlling platform

The massecuite extracted from the sugar pan artificially at regular intervals during the experiment was tested and compared with the predicting results of the system. The knowledge that existed in the knowledge base of the system under the current cane sugar crystallization state was used as the predicting knowledge to test the accuracy of the system with its updating and improvement. During experiment, 150 samples were collected in one batch crystallization process and carried out through comparative analysis.

The results of the running system are described as figure 8 and figure 9. Figure 8 describes the predicting accuracy trend of the cane sugar crystallization state under the current knowledge base of the system. Figure 9 describes the increasing trends of the correct predicting number of the crystallization state and the number of rules with the increasing number of batch crystallization process.

From Figure 8, it could be concluded that predictive accuracy of the cane sugar crystallization state has been continuously improved from initial 61.33% to 96.0%, thanks to the online knowledge acquisition and the continuous updating and improvement of the knowledge base of the system. Figure. 9 demonstrates that the number of predicting accuracy of the system is increasing with the updating of the knowledge base rules, contrasting with the 150 samples collected in every test. These results indicates that the knowledge from the online knowledge acquisition modules of the system is reliable. With the online updating and improvement of the knowledge base, the system's predicting accuracy will be improved in the future. Thus, the predicting knowledge and results obtained from the online learning module of the system during the cane sugar crystallization process are consistent with the actual cane sugar crystallization state. The system has a well adaptive capacity, which could correctly reflect an actual crystallization state in cane sugar process.

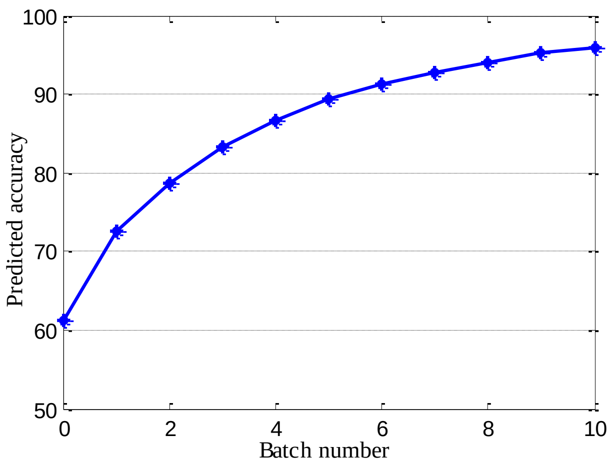

Figure 8. Predictive accuracy trend

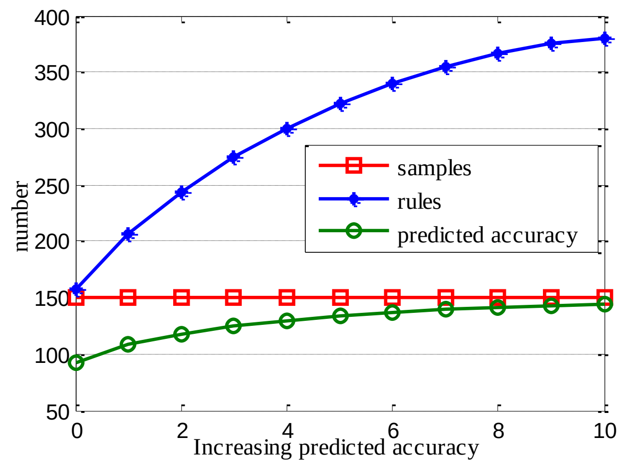

Figure 9. Increasing number trends

VI. CONCLUSIONS

In this paper, an innovative knowledge-based modelling process for predicting the cane sugar crystallization state combined with rough set and support vector machine has been presented. And the combined method is compared with a back propagation neural network (BPNN) and a traditional SVM without optimization, which indicates the better predictive results than the other two methods. In addition, the knowledge-based model is integrated into the *eForceCon* software to form an intelligent system, which makes it feasible to dynamically update the knowledge base of the system.

Furthermore, the intelligent system is tested using a self-regulating intelligent comprehensive monitoring and controlling platform that represents the cane sugar process in experiment. Then the real-time data is firstly obtained from the platform through the OPC interface and input into the inference module of the system after pretreatment. Then the system analyzes and evaluate the inferring results, and finally output the predicting results. The experimental results as showed above demonstrate that the predicting accuracy of the crystallization state of the intelligent system increases obviously with the online knowledge acquisition of the system and the continuous update and self-improvement of the knowledge base.

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