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DESIGN AND IMPLEMENTATION OF INTELLIGENT INTEGRATED MEASURING AND CONTROLLING SYSTEM FOR SUGAR CANE CRYSTALLIZATION PROCESS

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Abstract- The deficiency in existing sugar cane crystallization automatic control system is difficult to measure some key parameters on line, such as mother liquor supersaturation, mother liquor purity, crystal content and crystal size distribution. Controlling brix with PID can only reflect the massecuite concentration of sugar cane crystallization process, but it is hard to guarantee the crystal quality. During crystallization process, change of mother liquor purity will affect the crystallization rate and supersaturation. The less mother liquor purity in the final stage is, the better absorption of crystals have. Crystal size distribution, including mean area (MA) and coefficient of variation (CV), influences the quantity and quality of crystals. In order to produce sucrose which has uniform size and small coefficient of variation, it's necessary to study the law of crystal size for sugar cane crystallization. According to the difficulties in measuring some key parameters, an intelligent integrated measuring and controlling system is researched by this paper. The overall structure of this system is designed at first, and also the monitoring system of host computer is developed. Combining with data-driven modeling and hybrid modeling method, the intelligent soft-sensor component for sugar cane crystallization process is implemented. This system realizes automatic monitoring of sugar cane crystallization process, which includes on-line measurement of mother liquor supersaturation, mother liquor purity, crystal content and crystal size distribution (CSD). Experimental results show that this designed intelligent integrated measuring and controlling system for sugar cane crystallization process has not only achieved great on-line prediction for immeasurable parameters, but also has good openness and scalability, which can provide complete parameter detection for the implementation of sugar cane crystallization automatic control system.

Index terms: Sugar cane crystallization, soft sensor, crystal size distribution, hybrid modeling, on-line prediction.

I. INTRODUCTION

Current automatic control system for sugar cane crystallization mainly obtains process parameters through sensors, and completes effective control in process object [1-2]. Danish DDS Company developed an automatic control system named DDS-DS independently, which can obtain good result on saving steam and crystallization time [3]. However, this system didn't consider the effect of crystal content, which would easily lead to pseudo crystal phenomena and result in poor quality of the massecuite. NAHMAT automatic control system, developed by Siemens, integrated PLC control system and PC industrial control software, which was the most reliable control system for sugar cane crystallization and widely used in many countries [4-5]. The key of above systems is using brix sensor (refraction brix sensor or microwave brix sensor) to measure brix during crystallization process, and achieving automatic control by combining traditional PID method. Brix control can only reflect the massecuite concentration of crystallization process, but cannot reflect other key parameters, such as mother liquor supersaturation and CSD. So the above automatic control system can only accomplish liquid-to-solid transition process, which is unable to guarantee the quality of massecuite. Generally speaking, under the situation of stable material and crystallization environment, the above control systems just can satisfy the production need basically, and the quality of massecuite is worse than artificial operation. If the material and crystallization environment is not stable, then the effect of automatic control system would reduce greatly.

In actual sugar cane crystallization, due to inconsistent size of different crystals, the quantity and quality of sugar product reduces after filtering. Therefore, it has an important significance for sugar cane crystallization to research the crystal size, and find out crystal size distribution (CSD) controlling method. CSD is mainly characterized by two parameters, which are mean area (MA) and coefficient of variation (CV). CV is generally used to characterize crystal growth dispersity. The bigger CV is, the wider range CSD is. And the wider range of CSD represents the more serious crystal dispersity.

Soft sensor has become an important research area to predict immeasurable variables [6]. Nowadays, soft sensor with good stability and reliability, has been widely used in petrochemical and food engineering [7]. Taking measurable parameters as input and immeasurable parameters as output, the basic idea of soft sensor is building mathematical relationship between input and output, and using input variables to estimate output variables [8]. Soft sensor combines computer and industrial process knowledge, using software instead of hardware and featuring low cost and easy promotion [9]. There are mainly three kinds of modeling methods in soft sensor, including simplified mechanism modeling, data-driven modeling and hybrid modeling [10]. Among them, the hybrid modeling method drew great attention in the field of immeasurable parameters. P. Georgieva and S. Feyo de Azevedo modeled and optimized the intermittent and continuous crystallization process based on Neural Networks, which obtained the best status and reduced the cost of crystallization process [11]. What's more, they also applied their hybrid model to intermittent sugar cane crystallization process, which achieved the purpose of approximate crystal kinetic parameters measurement. Compared with traditional model, experimental results showed that the hybrid model was much better than mechanism model and data-driven model [12]. LA. Suarez and P. Georgieva also developed a more effective calculation framework, which included recursive Neural Networks, feedforward Neural Networks, reservoir computing network and MPC. Results showed that this method can be effective to establish non-linear system only if the input and output data were obtained [13]. A. Andrasik and A. Meszaros adopted hybrid Neural Networks as an indirect adaptive control strategy, and established a continuous reactor model by combing with Lyapunov stability algorithm [14]. M. Von Stosch and R. Oliveira established a new dynamic modeling method by combining hybrid modeling and discrete time series. Experimental results showed that this new method can not only build discrete dynamics model, but also have better superiority than traditional hybrid modeling method [15]. However, because of the complexity of sugar cane crystallization, there is no corresponding automatic control system which can applies soft sensor technology to detect key parameters.

In this paper, an intelligent integrated measuring and control system is researched, which is aimed to solve the problem of estimating immeasurable key parameters, such as mother liquor supersaruration and purity, crystal content and CSD. Combining with data-driven modeling and hybrid modeling method, the intelligent soft-sensor component for sugar cane crystallization process is implemented. In the meanwhile, the crystallization kinetics is studied to predict crystal content and CSD. Experimental results show that this designed intelligent integrated measuring and controlling system for sugar cane crystallization process has not only achieved great on-line prediction for immeasurable parameters, but also has good openness and scalability, which can provide complete parameter detection for the implementation of sugar cane crystallization automatic control system.

II. OVERALL SCHEME DESIGN

The intelligent integrated measuring and controlling system, which is a comprehensive system of mechanical, electrical and intelligent detection technology, mainly includes hardware architecture and software architecture.

a. Design of hardware architecture

The hardware of intelligent integrated measuring and controlling system is divided into three parts, which are the field level, control level and operation level. Hardware architecture is as shown as Figure 1.

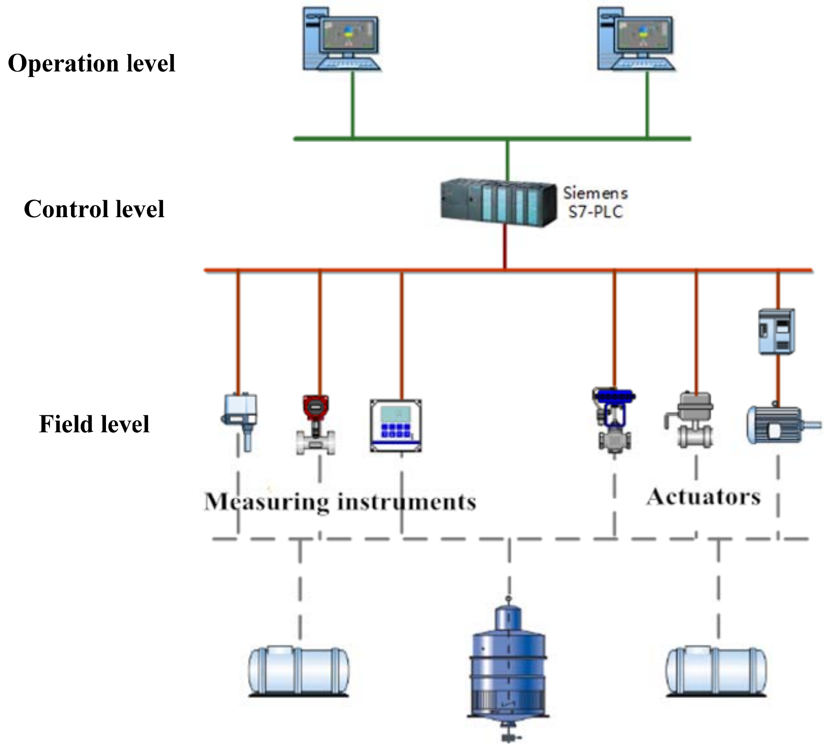


Figure 1. The hardware architecture of intelligent integrated measuring and controlling system for sugar cane crystallization process

Field level mainly includes measuring instruments and actuators [16]. Measuring instruments are used to detect parameters for sugar cane crystallization on line. Actuators are used to adjust and control the rate of material feeding, steam and vacuum. Control level is the PLC control system, which is mainly using Siemens S7 series programmable logic controller and related expansion module. The PLC control system is used to collect and process data from measuring instruments, and is also responsible to control the actuators [17]. Through the use of modular design, the PLC control system has a powerful ability to expand, communicate and calculate [18-20].

Operation level is the PC monitoring platform, which is used to monitor and operate automatic process for sugar cane crystallization. By using visual dynamic monitoring picture, curve, report form and alarm to display the operation process and control operation, this designed system has a very friendly human-computer interface.

b. Design of software architecture

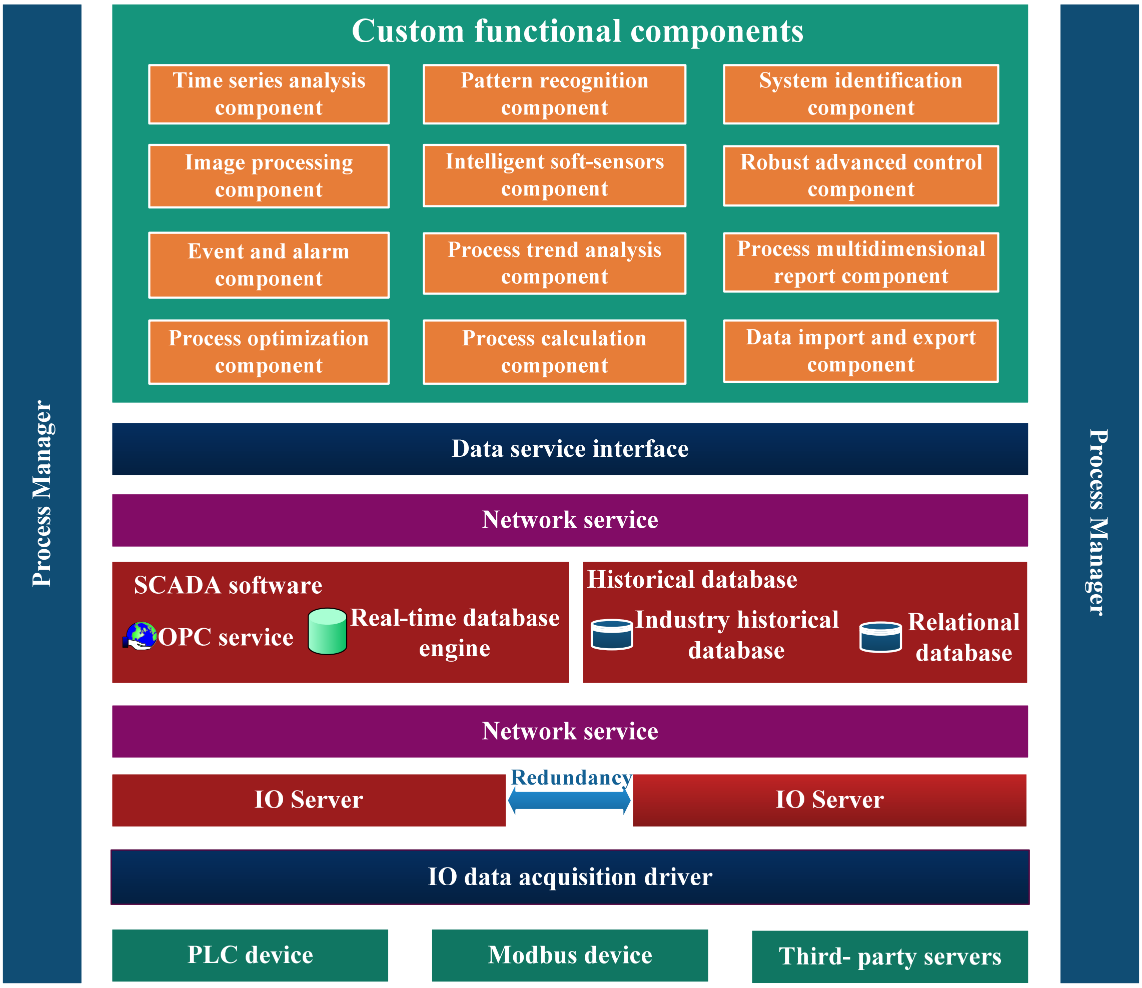


Figure 2. The software architecture of intelligent integrated measuring and control system for sugar cane crystallization process

The software of intelligent integrated measuring and controlling system for sugar cane crystallization is a highly integrated and open architecture, which is shown as Figure 2. By using modular and hierarchical design concept, this designed system includes process manager, IO Server, data management unit, data monitoring unit, data service interface and custom functional components. Custom functional components include image processing component, intelligent soft-sensors component, process advanced control component, process calculation component, event and alarm component, process trend analysis component, multidimensional report analysis component and data import and export component.

Process manager is responsible to manage all the process of designed system [21]. IO Server integrated a variety of drivers for industrial equipment, which can communicate with most industrial equipment, such as Modbus protocol equipment and PLC equipment. Data management unit is used for storing, managing and scheduling large amount of data. As the key part of designed system, data monitoring unit is used for managing and scheduling process operation for sugar cane crystallization, including system configuration, task management and operation configuration, which are displayed by dynamic monitoring picture, curve, report and alarm. Data service interface, which is the communication between data management unit and data monitoring unit, can support remote/local access and satisfy data service demand of industrial field. Common data service interface includes OPC interface, dynamic link library (DLL), DDE interface and API interface. Image processing component is responsible to collect and analyze real-time massecuite images. Through the analysis of image processing component, particle information including number, size and area, can be extracted. Intelligent soft sensor component realizes on-line predicting of key parameters for sugar cane crystallization, which combines mechanism modeling and data driven modeling method. Process advanced control component realizes multi-variable predictive control and non-linear predictive control by combining advanced control theory and predictive control theory. Process calculation component is responsible to calculate the ratio of various materials according to the process requirement. Event and alarm component is responsible to obtain real-time alarm information and historical alarm information. Process trend analysis component is responsible to analyze the trend of process data. Multidimensional report analysis component can generate different kinds of report, such as daily, weekly, and monthly report.

III. DESIGN OF KEY PARTS

a. PC monitoring system

a.i Design of multi-task process manager

Multi-task process manager is designed based on Windows platform. If any component of this designed system terminates abnormally, multi-task process manager can restart this component again, which makes up for the shortcomings of instability in Windows platform and is suitable for sugar cane crystallization [22].

As is shown in Figure 3, multi-task process manager mainly includes three parts, which are configuration management module, process operation module and process monitoring module.

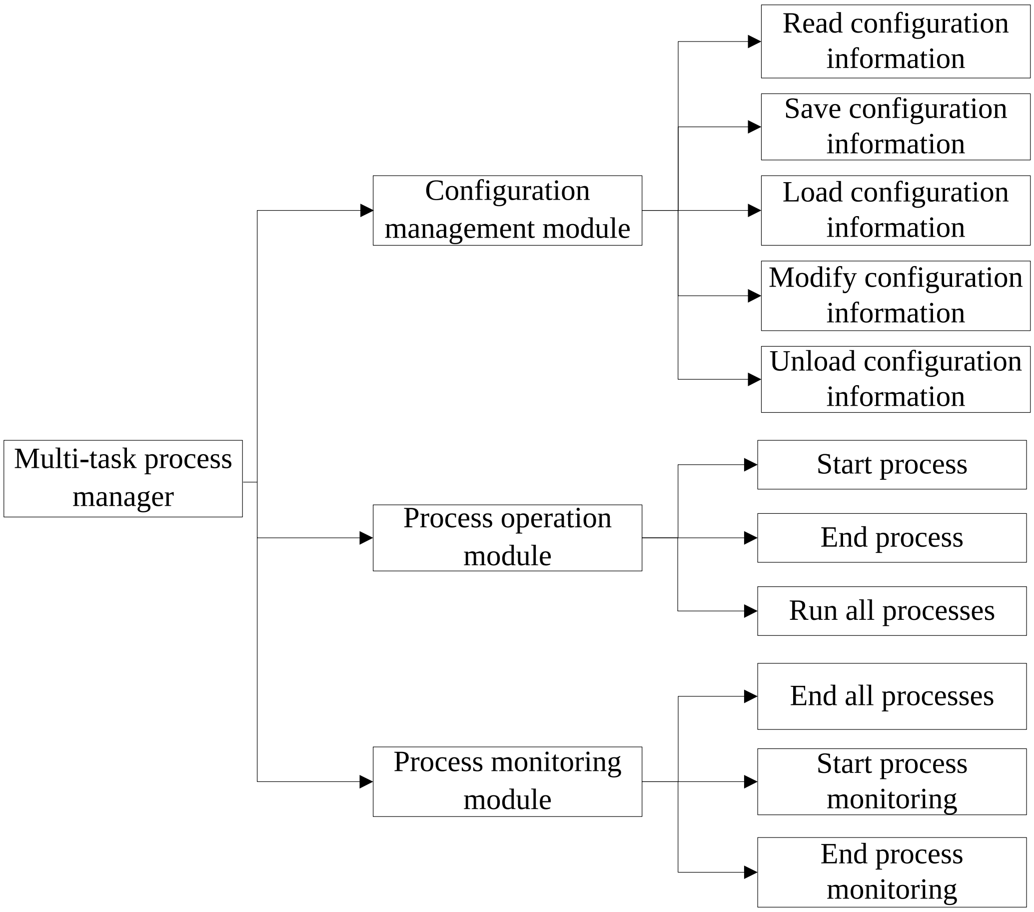


Figure 3. Architecture of the multi-task process manager for sugar cane crystallization process

a.ii Process monitoring picture configuration

The main interface is shown as Figure 4, which is used to monitor the whole process of sugar cane crystallization and display process parameters. Users can not only set target value, upper and lower limit of the alarm, process configuration, but also view the operation state. This monitoring picture can realize manual/automatic switching, and accomplish automatic monitoring of sugar cane crystallization.

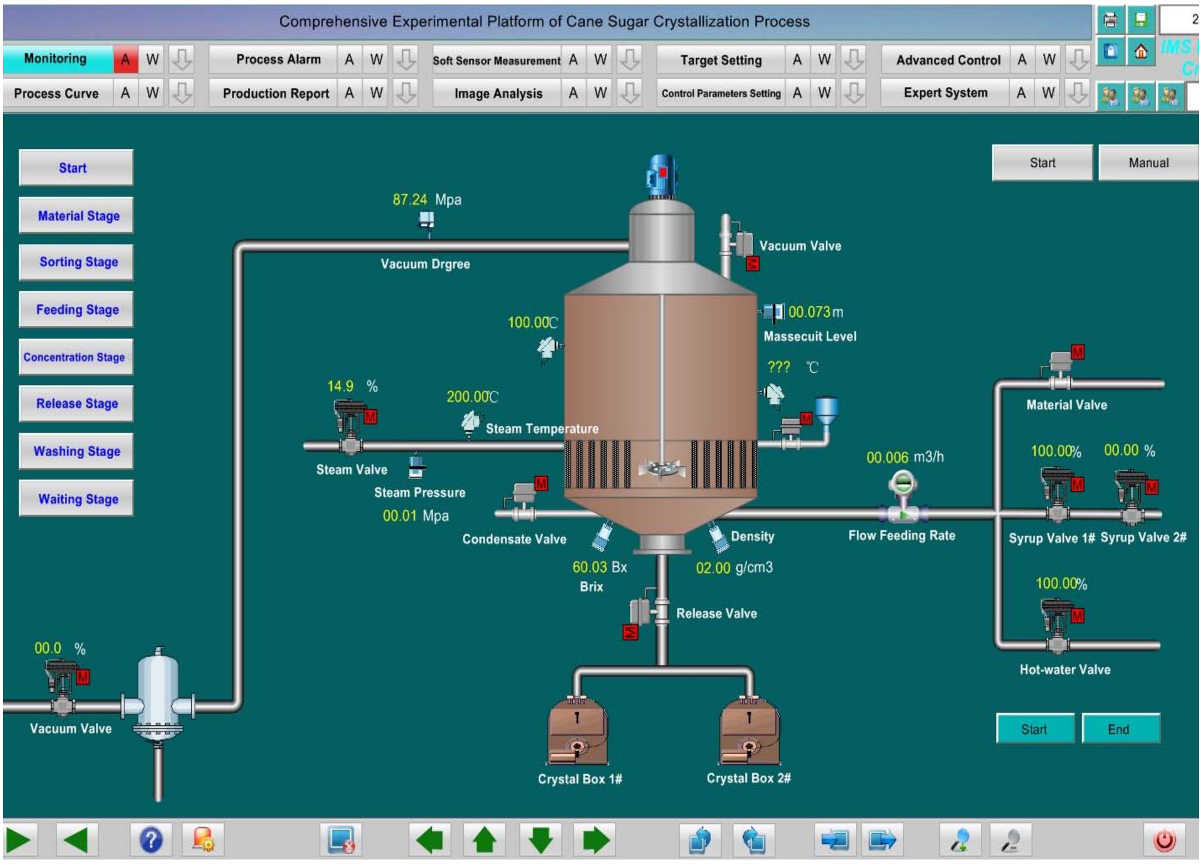


Figure 4. Main interface of process monitoring system

b. Intelligent soft-sensors component

b.i Overall structure

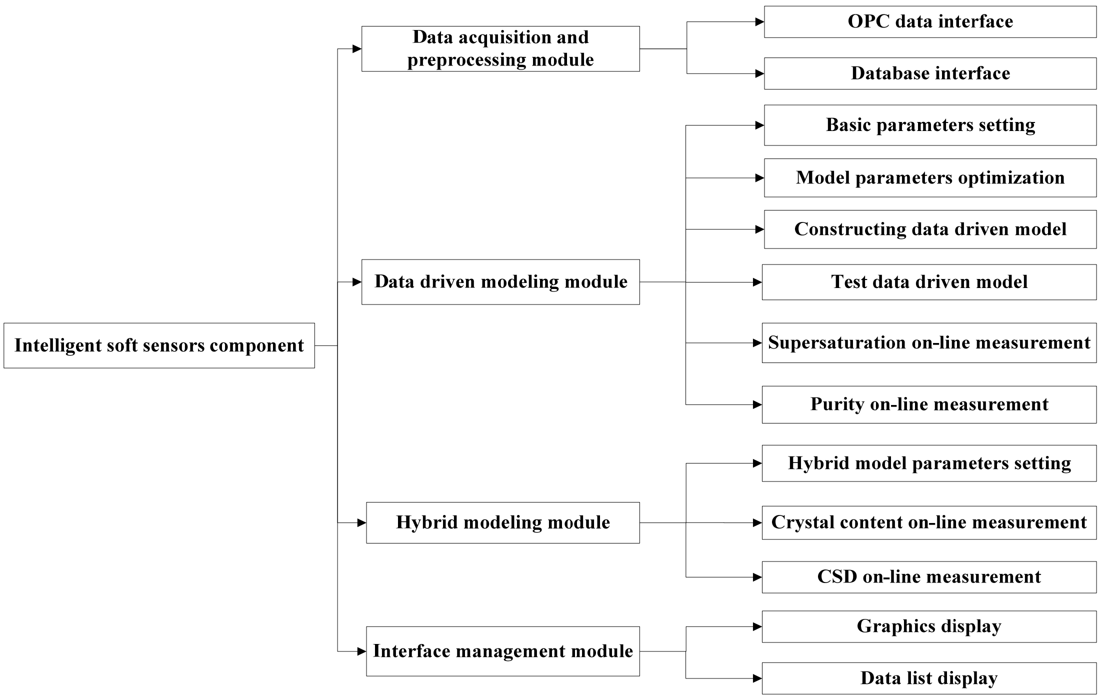


Figure 5. Architecture of soft-sensors component for sugar cane crystallization process

The intelligent soft-sensors component can be divided into four modules, which are shown as Figure 5.

b.ii Design of data acquisition and preprocessing module

Real-time data of process parameters is collected and stored by data acquisition program of PC monitoring system [23]. And intelligent soft-sensors component can read real-time data periodically through the OPC interface or historical data through the database access interface. In order to avoid the deviation caused by different magnitude, real-time data and historical data must be preprocessed, namely scale transformation, which is aimed at transforming the input and output sample data into range [0, 1] or [-1, 1]. After preprocessing of original data, they will be sent to the data driven modeling module as data sample.

b.iii Design of data driven modeling module

Data sample after normalizing will be divided into training set and testing set. A data-driven model based on twin support vector regression (TSVR) is constructed by using training set, the parameters of which are optimized by particle swarm optimization algorithm (PSO). This optimized model is tested and evaluated by testing set [24-25]. Finally, key parameters including mother liquor supersaturation and purity will be predicted on-line.

b.iv Design of hybrid modeling module

Hybrid modeling solution for sugar cane crystallization is shown as Figure 6. Hybrid model includes data-driven model and simplified mechanism model, which are mixed by serial mode. Seven easy-to-measure variables are chosen as input of data-driven model, including vacuum degree, massecuite temperature, massecuite level, steam pressure, steam temperature, feeding rate and massecuite brix, and two difficult-to-measure variables are chosen as output, including mother liquor supersaturation and mother liquor purity.

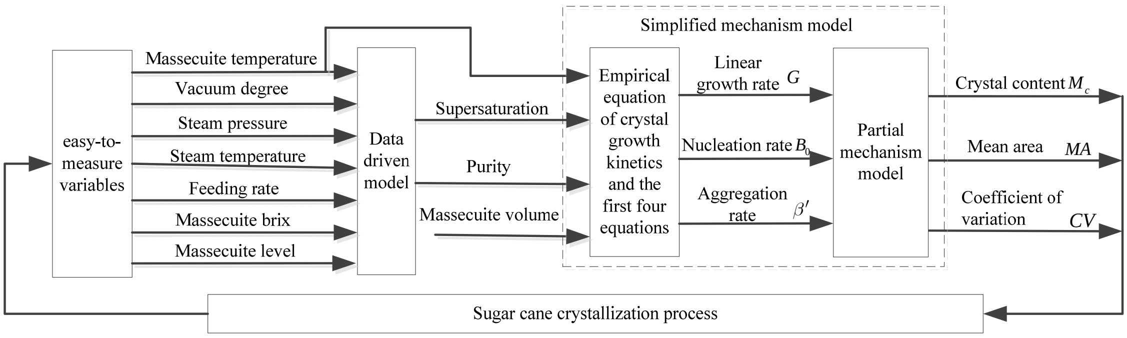


Figure 6. Overall scheme for the hybrid modeling in sugar cane crystallization

Simplified mechanism model includes a series of nonlinear algebraic differential equations, and forms the desired quality, energy and material balance equation. Material balance equation, including a four order equations, can be expressed by particle volume coordinate system. And the crystal size distribution (CSD) can be obtained by order equations.

According to the identification of International Sugar Analysis and Unified Approach Committee, crystal size distribution parameters can be expressed by CV and MA, which are parameters of mass distribution function. However, there isn't any technology to measure these parameters on line.

From crystallization mechanism, distribution distance of the mass can be defined as:

$$\eta_j(L) = \int_0^\infty L^j m(L) dL, \quad j = 0,1,2,3,\cdots, \tag{1}$$

Average size of crystal is:

$$\mathrm{MA} = \bar{L} = \int_0^\infty L m(L) dL \Big/ \int_0^\infty m(L) dL \tag{2}$$

Namely:

$$\mathrm{MA} = \eta_1 / \eta_0 \tag{3}$$

$$CV = \frac{\sigma}{\bar{L}} \tag{4}$$

Among them:

$$\sigma^2 = \frac{1}{\eta_0} \int_0^\infty \left(L - \bar{L}\right)^2 m(L) dL \tag{5}$$

Therefore, the variation coefficient of crystal size distribution is:

$$\mathrm{CV} = \left(\eta_0 \eta_2 / \eta_1^2 - 1\right)^{1/2} \tag{6}$$

Material balance equation is constructed by number-volume distribution distance function, and the predictive validation process of CSD needs to establish mass-size distribution and number-volume distribution function, the relationship of which is shown as followings:

$$v = k_v L^3 \tag{7}$$

$$n(L) = n(v) dv \tag{8}$$

$$m(L) = \rho_c k_v L^3 n(L) / M_c \tag{9}$$

Among them, M_c , ρ_c , v , k_v $n(L)$, $m(L)$ represents crystal content, crystal density, crystal volume, volume coefficient, quantity function and quality function relatively. Relate Eqs. (7), (8), (9) and (1), new formula can be set as followings:

$$\eta_j = \frac{1}{M_c}\left(\frac{\rho_c}{k_v^{k-1}}\tilde{v}_k\right)$$
$$k = \frac{j}{3}+1,\ j = 0,3,6,\cdots \tag{10}$$

Among them, $\tilde{v}_k$ represents the crystal volume of any time.

According to the theory of Randolph and Larson, the mass distribution distance equation is formed as crystal mean size ($\bar{L}$) and distribution variables (σ), which is:

$$\eta_j(L) = \sum_r \left[\left(2^{1/2}\sigma\right)^{j-r}\left(\bar{L}\right)^r \frac{j!\times 1\times 3\times ...\times (j-r-1)}{\left(j-r\right)!2^{(j-r)/2}}\right] \tag{11}$$

Among them, *when j is even*, $r = 0,2,4,...,j$; *when j is odd*, $r = 1,3,5,...,j$ 。

According to Eq. (11), the 3 order and 6 order of mass distribution distance is obtained as:

$$\eta_3/\bar{L} = 1+3\left(\frac{\sigma}{\bar{L}}\right)^2 \tag{12}$$

$$\eta_6/\bar{L} = 1+15\left(\frac{\sigma}{\bar{L}}\right)^2 + 45\left(\frac{\sigma}{\bar{L}}\right)^4 + 15\left(\frac{\sigma}{\bar{L}}\right)^6 \tag{13}$$

Set:

$$X = \left(\frac{\sigma}{\bar{L}}\right)^2 \tag{14}$$

Joint Eqs. (4), (12), (13) and (14), new equation can be obtained:

$$MA = \bar{L} = \left(\frac{\eta_3}{1+3X}\right)^{1/3} \tag{15}$$

$$\mathrm{CV} = \sqrt{X} \tag{16}$$

$$15\eta_3^2 X^3 + \left(45\eta_3^2 - 9\eta_6\right)X^2$$
$$+\left(15\eta_3^2 - 6\eta_6\right)X + \eta_3^2 - \eta_6 = 0 \tag{17}$$

Sugar cane crystallization is a nonlinear and non-stable process, which is accompanied by nucleation, growth and aggregation mechanism. What' more, the operation conditions, the process state and their relation is not clear, which will lead to underestimate of CSD. Therefore, the linear growth rate G_v, the nucleation rate B_0 and the aggregation rate $\beta^{'}$, which are related to the construction of the simplified mechanism model, are excellently important. This paper will characterize the changes of these three parameters by following empirical formulas.

$$G_v = K_g \exp\left[-\frac{57000}{R\left(T_m + 273\right)}\right]\left(S - 1\right) \times \exp\left[-13.863\left(1 - \mathrm{Pur}_{sol}\right)\right]\left(1 + \frac{6.8}{V_m}\right) \tag{18}$$

$$B_0 = K_n \times 2.894 \times 10^{12} G_v^{\ 0.51}\left(\frac{\tilde{\mu}_1}{k_v V_m}\right)^{0.53} V_m \tag{19}$$

$$\beta' = K_{ag} G\left(\frac{\tilde{\mu}_1}{k V_m^2}\right) \tag{20}$$

Among them, K_g, K_n and K_{ag} are obtained from the optimization value of factory, the value of which are: $K_g = 265$, $K_n = 0.721$ and $K_{ag} = 1.36 \times 10^{-5}$. T_m, R, Pur_{sol}, S and V_m represents massecuite temperature, temperature coefficient, mother liquor purity, mother liquor supersaturation and massecuite volume.

Taking mother liquor supersaturation, mother liquor purity, massecuite temperature and massecuite volume as input, and initializing $K_g, K_n, K_{ag}, \rho_c, k_v$ and R, the 0, 1, 2, 3 order distance $\tilde{\mu}_0, \tilde{\mu}_1, \tilde{\mu}_2$ and $\tilde{\mu}_3$ can be calculated by substituting Eqs. (18), (19) and (20) into Eqs. (21), (22), (23) and (24).

$$\frac{d\tilde{\mu}_0}{dt} = B - \frac{1}{2}\beta' \tilde{\mu}_0^2 \tag{21}$$

$$\frac{d\tilde{\mu}_1}{dt} = G_v \tilde{\mu}_0 \tag{22}$$

$$\frac{d\tilde{\mu}_2}{dt} = 2G_v \tilde{\mu}_1 + \beta' \tilde{\mu}_1^2 \tag{23}$$

$$\frac{d\tilde{\mu}_3}{dt} = 3G_v \tilde{\mu}_2 + 3\beta' \tilde{\mu}_1 \tilde{\mu}_2 \tag{24}$$

G_v, B_0 and β' can be calculated by the 1 order distance. According to the linear growth rate G_v and the 0 order distance, crystal content can be obtained by differential Eqs. (25) and (26):

$$J_{cris} = 3\left(k_v \rho_c \tilde{\mu}_0\right)^{1/3} M_c^{2/3} G_v \tag{25}$$

$$\frac{dM_c}{dt} = J_{cris} \tag{26}$$

According to the crystal content $M_c, \tilde{\mu}_2$ and $\tilde{\mu}_3$, η_3 and X can be calculated by Eqs. (11) and (17). According to η_3 and X, the mean area MA and coefficient of variation CV can be calculated by Eqs. (15) and (16).

Simplified mechanism model uses mother liquor supersaturation, mother liquor purity, massecuite temperature and volume as input, and predicts CSD accurately. Among them, CSD parameters mainly refers to mean area MA and coefficient of variation CV.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

a. Experiment conditions

As is shown in Figure 7, an intelligent comprehensive experimental platform is developed. Taking a-massecuite as an example, experimental conditions are shown as followings.

(1) Time of sugar boiling process is between 2.0~2.5 hours.

(2) Volume of sugar boiling is 1 m^3.

(3) Initial brix is 62 $^o Bx$, the purity is 85 *AP*, and the temperature is 65℃.

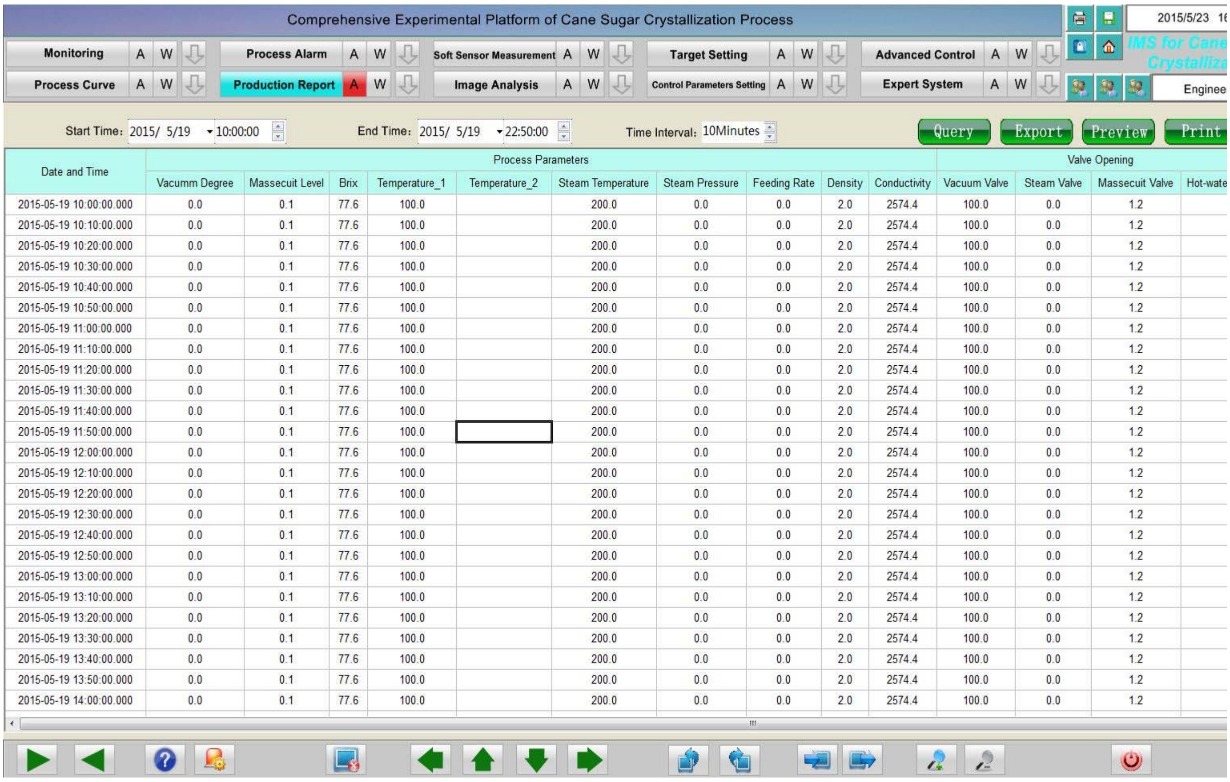
(4) Temperature of hot water is 68℃.

(5) Boiling stage is divided into 6 stages: the beginning stage, the material stage, the sorting stage, the feeding stage, the concentration stage and the release stage.

Figure 7. Intelligent comprehensive experimental platform for sugar cane crystallization process

b. Experimental results and analysis

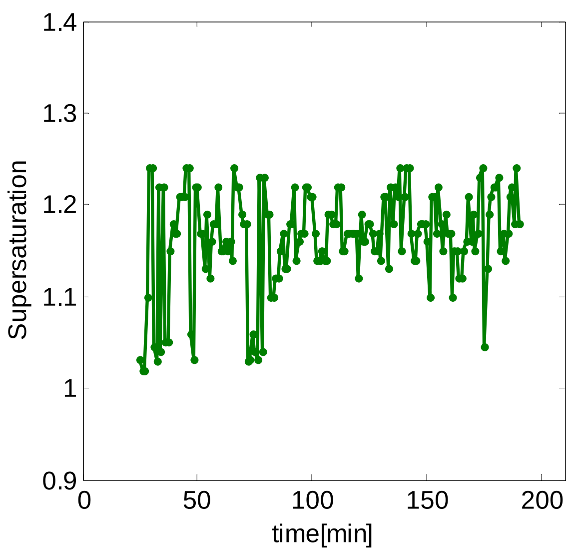
The PC monitoring system based on SCADA monitoring software realizes real-time monitoring of sugar cane crystallization, which is shown as dynamic monitoring screen, process curve, report and other ways. Data report of designed system is shown as Figure 8.



Date and Time	Process Parameters										Valve Opening			
	Vacumm Degree	Massecuit Level	Brix	Temperature_1	Temperature_2	Steam Temperature	Steam Pressure	Feeding Rate	Density	Conductivity	Vacuum Valve	Steam Valve	Massecuit Valve	Hot-wate
2015-05-19 10:00:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 10:10:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 10:20:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 10:30:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 10:40:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 10:50:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:00:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:10:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:20:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:30:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:40:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 11:50:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:00:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:10:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:20:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:30:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:40:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 12:50:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:00:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:10:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:20:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:30:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:40:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 13:50:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	
2015-05-19 14:00:00.000	0.0	0.1	77.6	100.0		200.0	0.0	0.0	2.0	2574.4	100.0	0.0	1.2	

Figure 8. Data report of PC monitoring system

Intelligent soft-sensors component predicts mother liquor supersaturation and purity by obtaining real-time parameters data and using off-line model. Experiments have achieved good prediction effect. Figure 9 shows the on-line measurement of mother liquor supersaturation, and Figure 10 shows the on-line measurement of mother liquor purity.



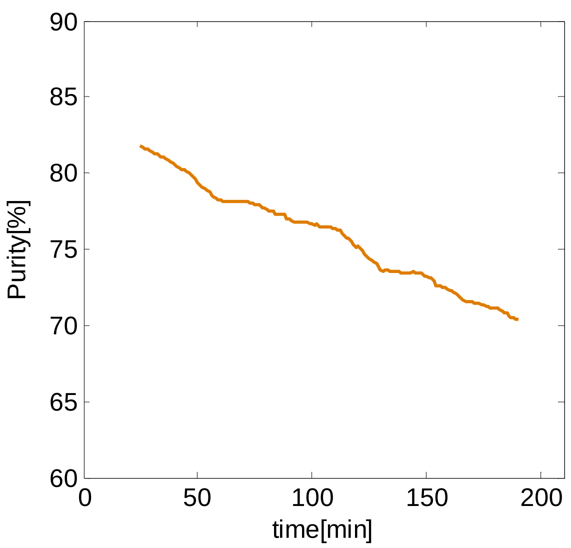


Figure 9. On-line measurement of mother liquor supersaturation

Figure 10. On-line measurement of mother liquor purity

Intelligent soft-sensors component realizes on-line measurement of crystal content and crystal size distribution (CSD) by using hybrid modeling method, the predicted mother liquor supersaturation and mother liquor purity. Figure 11 shows on-line measurement of crystal content, and Figure 12 shows on-line measurement of crystal size distribution.

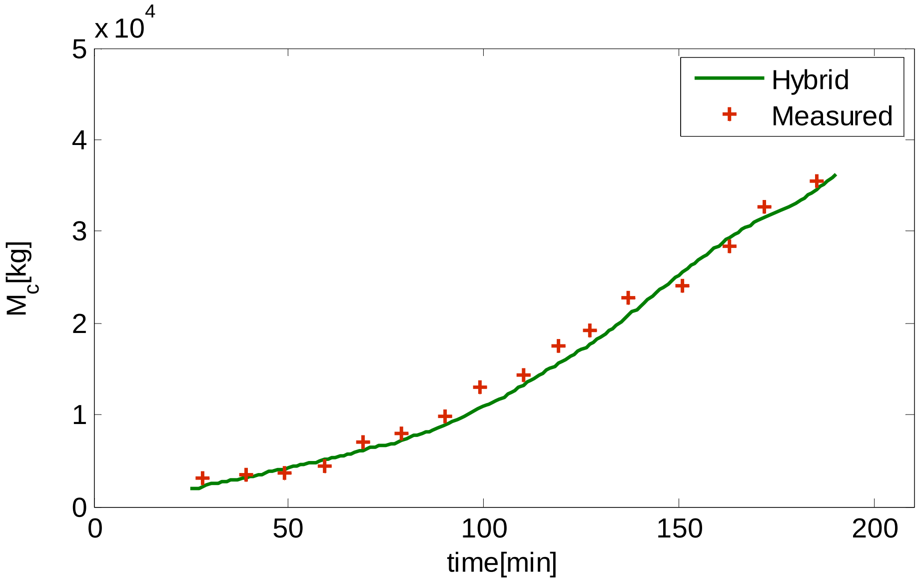


Figure 11. On-line prediction of crystal content for sugar cane crystallization

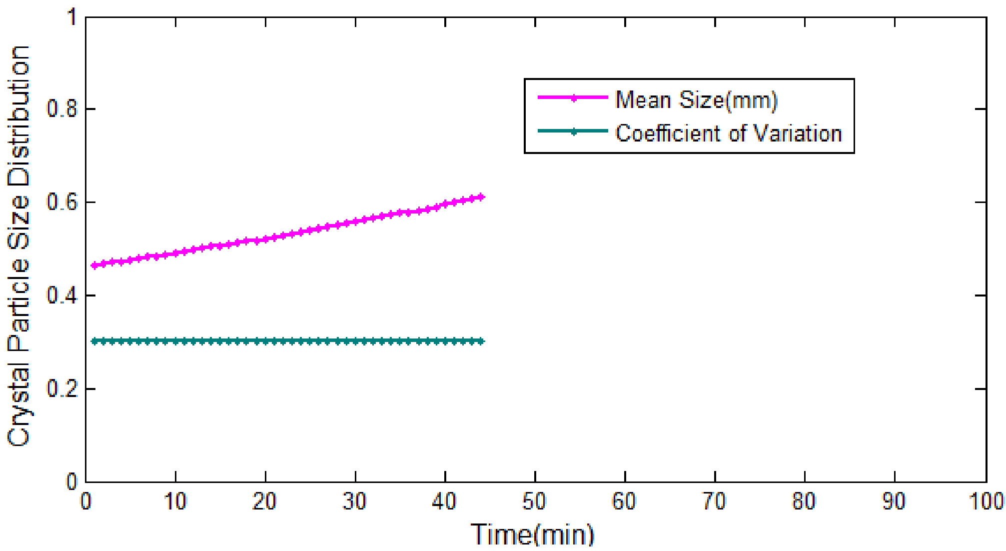


Figure 12. On-line prediction of CSD for sugar crystallization

From Figure 11, crystal content obtained by hybrid model can fit with the experimental values well, which shows that hybrid model combined with data-driven model and simplified mechanism model has a good prediction result and is able to predict the change trend of crystal content. From Figure 12, the coefficient of variation (CV) ranges from 0.25 to 0.30, which is in agreement with views that CV of sugar cane products is more than 0.20. Meanwhile, the mean size of final crystal is about 0.8511 mm, which belongs to the range of medium white sugar. In a word, crystal size distribution detection based on hybrid model achieves satisfactory results, which indicates that intelligent integrated measuring and controlling system is feasible and effective. This designed system can solve the problem that traditional sensors can't measure crystal size distribution (CSD), and provide the basis for realization of process optimization and practical automatic controlling strategy for sugar cane crystallization.

V. CONCLUSION

An intelligent integrated measuring and controlling system is researched on the basis of analyzing the deficiencies in existing sugar cane crystallization automatic control system. The overall structure is researched at first. And PC monitoring system is developed, including multi-task process management and process monitoring picture. At the same time, intelligent soft-sensors component is designed and implemented by combining data-driven model and simplified mechanism model. Experimental results show that this designed system has not only achieved great on-line prediction for immeasurable parameters, but also has good openness and scalability, which can provide complete parameter detection for the implementation of sugar cane crystallization automatic control system.

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REFERENCES

[1] Y. Meng, J. Chen, G. Lu, et al. "Detecting syrup brix in cane sugar crystallization using an improved least squares support vector machine", International Journal of Control and Automation, Vol. 8, 2015, pp. 171-184.

[2] Y. Meng, X. Yu, H. He, et al, "Knowledge-based modeling for predicting cane sugar crystallization state", International Journal on Smart Sensing and Intelligent Systems, Vol. 7, 2014, pp. 942-965.

[3] ZK. Nagy, G. Fevotte, H. Kramer, et al, "Recent advances in the monitoring, modelling and control of crystallization systems", Chemical Engineering Research and Design, Vol. 91, 2013, pp. 1903-1922.

[4] T. Diringer, BC. Nielsen, "Importance of in-line colour measurement of sugar for product quality and factory performance", International Sugar Journal, Vol. 34, 2012, pp. 1-9.

[5] W. Paengjuntuek, A. Arpornwichanop, P. Kittisupakorn, "Product quality improvement of batch crystallizer by a batch-to-batch optimization and nonlinear control approach", Chemical Engineering Journal, Vol. 139, 2008, pp. 344-350.

[6] J Yu, "A Bayesian inference based two-stage support vector regression framework for soft sensor development in batch bioprocesses", Computers and Chemical Engineering, Vol. 41, 2012, pp. 134-144.

[7] P. Kadlec, B. Gabrys, S. Strandt, "Data driven soft sensor in the process industry", Computers and Chemical Engineering, Vol. 33, 2009, pp. 795-814.

[8] M. Kano, M. Ogawa, "The state of the art in chemical process control in Japan: Good practice and questionnaire survey", Journal of Process Control, Vol. 9, 2010, pp. 969-982.

[9] M. Kano, Y. Nakagawa, "Data-based process monitoring, process control, and quality improvement: Recent developments and applications in steel industry", Computers and Chemical Engineering, Vol. 32, 2008, pp. 12-24.

[10] R. Grbic, D. Sliskovic, P. Kadlec, "Adaptive soft sensor for online prediction and process monitoring based on a mixture of Gaussian process models", Computers and Chemical Engineering, Vol. 58, 2013, pp. 84-97.

[11] P. Georgieva, SF. de Azevedo, "Application of artificial neural networks in modeling and optimization of batch crystallization processes", Electronics and Telecommunications, Vol. 4, 2006, pp. 697-706.

[12] P. Georgieva, SF. de Azevedo, M. J. Goncalves, "Modeling of sugar crystallization through knowledge integration", Engineering in Life Sciences, Vol. 3, 2003, pp. 146-153.

[13] LA. Suarez, P. Georgieva, SF. de Azevedo, "Nonlinear MPC for fed-batch multiple

stages sugar crystallization", Chemical Engineering Research and Design, Vol. 89, 2011, pp. 753-767.

[14] A. Andrasik, A. Meszaros, SF. de Azevedo, "On-line tuning of a neural PID controller based on plant hybrid modeling", Computers & Chemical Engineering, Vol. 28, 2004, pp. 1499-1509.

[15] M. von Stosch, J. Peres, SF. de Azevedo, et al, "Modelling biochemical networks with intrinsic time delays: a hybrid semi-parametric approach", BMC Systems Biology, Vol. 4, 2010, pp. 131.

[16] J. F. Yu, H. R. Wang, "The implement of hydraulic control system for large-scale railway maintenance equipment based on PLC", Sensors and Transducers, Vol. 170, 2014, pp. 222-226.

[17] YI. Al. Mashhadany, "Design and implement of a programmable logic controller (PLC) for classical control laboratory", Intelligent Control and Automation, Vol. 3, 2012, pp. 44-49.

[18] X. D. Miao, S. M. Li, H. Shen, "On-board lane detection system for intelligent vehicle based on monocular vision", International Journal on Smart Sensing and Intelligent Systems, Vol. 5, No. 4, 2012, pp. 957-972.

[19] G. Gelen, M. Uzam, "The synthesis and PLC implementation of hybrid modular supervisors for real time control of an experimental manufacturing system", Journal of Manufacturing Systems, Vol. 33, 2014, pp. 313-326.

[20] R. Bayindir, Y. Cetinceviz, "A water pumping control system with a programmable logic controller (PLC) and industrial wireless modules for industrial plants—An experimental setup", ISA Transactions, Vol. 50, 2011, pp. 321-328.

[21] M. Q. Vollema, H. Hoijtink, "The Multidimensionality of Self-Report Schizotypy in a Psychiatric Population: An Analysis Using Multidimensional Rach Models", Schizophr Bull, Vol. 26, 2000, pp. 565-575.

[22] I. Richardson, V. Casey, F. McCaffery, "A Process Framework for Global Software Engineering Teams", Information and Software Technology, Vol. 54, 2012, pp. 1175-1191.

[23] Y. M. Luo, P. Z. Liu, M. H. Liao, "An artificial immune network clustering algorithm for

mangroves remote sensing image", International Journal on Smart Sensing and Intelligent Systems, Vol. 7, No. 1, 2014, pp. 116-134.

[24] Y. Q. Wang, L. Liu, "New intelligent classification method based on improved meb algorithm", International Journal on Smart Sensing and Intelligent Systems, Vol. 7, No. 1, 2014, pp. 72-95.

[25] N. Samanta, A. K. Chanda, C. RoyChaudhuri, "An energy efficient, minimally intrusive multi-sensor intelligent system for health monitoring of elderly people", International Journal on Smart Sensing and Intelligent Systems, Vol. 4, No. 2, 2014, pp. 762-780.