Modelling and Control of Chemical Process in Sugar Industry

Karthik.C*
M.Tech (C & I)
Kalasalingam University
Tamilnadu, India

Valarmathi.K
Professor & Head/ICE
Kalasalingam University
Tamilnadu, India

Prasanna.R
M.Tech (C & I)
Kalasalingam University
Tamilnadu, India

ABSTRACT
Neutralizing pH value of sugar cane juice is the important craft in the control process in the clarifying process of sugar cane juice, which is the important factor to influence output and the quality of white sugar. On the one hand, it is an important content to control the neutralized pH value within a required range, which has the vital significance for acquiring high quality purified juice, reducing energy consumption and raising sucrose recovery. On the other hand, it is a complicated physical-chemistry process, which has the characteristics of strong non linearity, time-varying, large time-delay, and multi- input. Therefore, there has not a very good solution to control the neutralized pH value. Firstly, in this paper, neural network model for the clarifying process of sugar juice is established based on gathering 1200 groups of real-time sample data in a sugar factory.

Keywords: Clarifying process of sugar cane juice, Neural Network, System Identification, Neutralized pH value, Diagnosis, LabVIEW.

1. INTRODUCTION
Clarifying process is a core link in the course of sugar production, it has the characteristics of strong non-linearity, multi-constraint, strong coupled, time-varying, large time-delay, and multi-input. The technology is complicated, which results in great difficulty in the course of modeling and optimization control. With the existing technological process and equipment, it is a key problem how to utilize directional information and adjust processing parameters in real time on site to keep the optimum state of production, improving the quality of the purified juice. It is a complicated physical-chemistry process to neutralize the juice, and the pH value needs the manual regulation in the actual production process, so its control effect is insufficiently stable, i.e. sometimes pH excessively is high and sometimes it excessively is low, and the result is not good. The retention time of juice in the clarifiers has a great effect on the juice and its components. If the juice is refractory or contains a large proportion of suspended matter it may be logical to hold the juice in the clarifier for a longer period of time. However excessive capacity clarifiers that hold juice for long periods result in higher levels of inversion (Baikow 1982)

2. CLARIFYING PROCESS OF SUGAR JUICE
At present, sulfurous acid method is very popularly used in most sugar factories in China. In this craft the process of neutralizing the pH value is very important and it directly influences the output and the quality of white sugar. The mixed juice coming from the milling section is processed by working procedures such as predefecation, heating, neutralization reaction, sedimentation and filtering and so on. The aim is to put out the high-quality sugar in the course of crystallization by eliminating the non-sugar elements and eventually obtain the high quality of the granulated sugar. The sulphitation process is mainly adopted at present. It is a complicated physical-chemistry process to clarify the juice, and is divided into four stages which are predefecation, heating, neutralization reaction, sedimentation put into the mixed juices to adjust pH to a low-grade acidity or neutralization. And then the mixed juice is heated, for the first time, with the temperature controlled within the range of 55-70□. After that the mixed juice is sent into the neutralization device. In neutralization device, the lime liquid and sulfur dioxide gases are added to mixed juices. Then sulfurous acid and calcium hydroxide neutralize in the join, which produces calcium sulfurous to be separated out, synchronously colloid is coagulated. Then the neutralized juice is heated for the second time to accelerate reaction of phosphoric acid and sulfurous acid. Finally the neutralized juice is going to the subsider for subsiding. The main factors affecting the sulphitation neutralization are:

(1)The instability of flow of juice will directly influence the following operations such as adding lime, sulfur dioxide and the phosphoric acid.
(2) Either pre-ash's pH value too high or too low will result in the increased difficulty of the sulphitation neutralization control.
(3)Influence of the lime milk and sulpher dioxide flow. If the amount of lime put into the juice is too small or the amount of sulfur dioxide is too large, pH value in the sugarcane juice will become acid, which will affect neutralization reaction and cause high SO_2 and calcium contents in the purified juice, and inevitably decrease the purity of juice. If too large amount of lime or too small

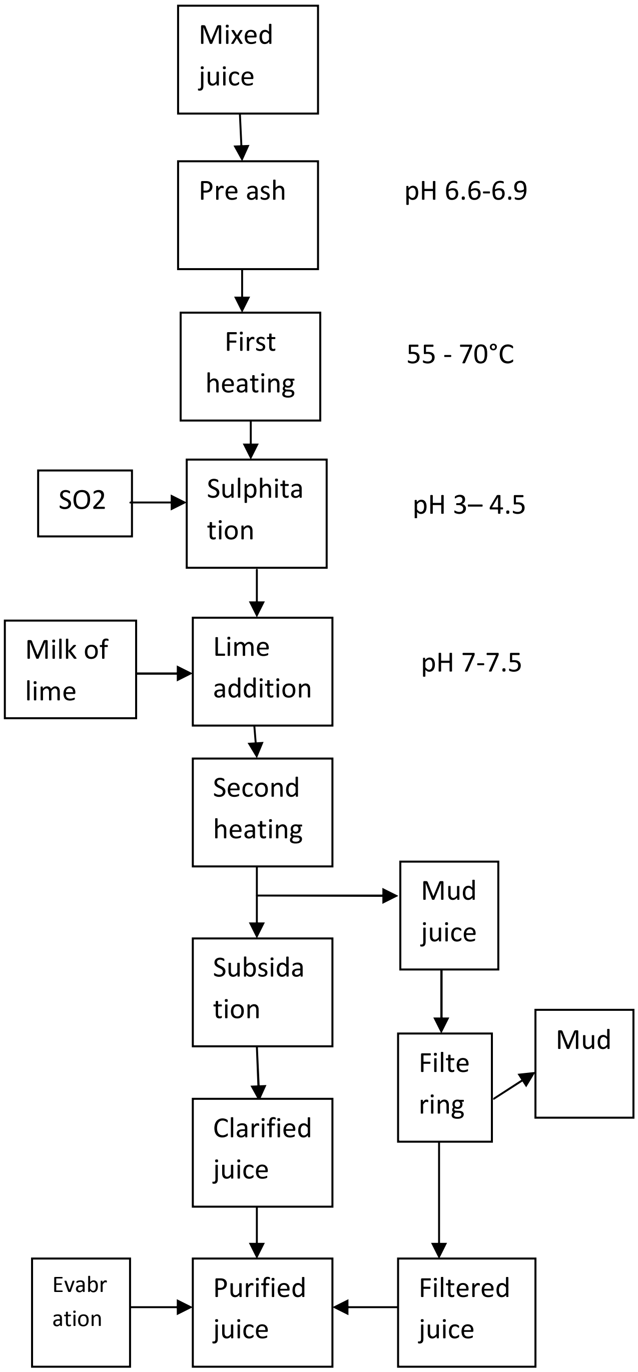

Fig.1. Clarifying process flow diagram

amount of sulpher dioxide is put into the juice, it will cause the reducing sugar, resolving and increase Color Value of the purified juice, and inevitably decrease the purity of juice. It has the vital significance to control pH value stability in the clarifying process of sugar juice, which affects directly the quality of the purified juice, and inevitably the product's quality. If the neutralized pH value is too low, this will speeds up the sucrose transformation, which results in loss of sucrose and cause the juice containing higher dissoluble calcium,
and inevitably cause a lot of scale formed in the evaporation station and boiling house, thus it increases energy wastage. Contrarily, when the neutralized pH value is too high, the original sugar decomposes the new pigment so that its color becomes depth, these can increase color value of the
product sugar, and affects the quality of the granulated sugar. Moreover, instability of the pH value can increase the amount of use of the clarifying agent, and increase the cost.

3. NEURAL NETWORK MODELING OF CLARIFYING PROCESS

Artificial Neural Network (ANN) is used in this work for system identification. The data required to develop the ANN model for system identification are collected by conducting experiments in the laboratory grade pH process and through MATLAB simulation. The collected data is divided into training and test data. The sampling instant k is equivalent to t and the neural network structure used. Network training is first carried out offline in batch form using the Levenberg-Marquadt optimization. The algorithm essentially seeks to minimize the prediction error over the training data set. The input and output data sets used for training are obtained by adding a random generator with step input and then applying this to the trained to minimize the cost function The neural network modeling mainly has several important links: sample data pretreatment, data normalization, network design, network training and network test and so on. When processing the sample data, summarizing the operation range of sampled variables based on technical requirements and operation experiences, parts of the data can be primarily eliminated. After being processed, 800 sets of data are used as training samples, and 200 sets of data are used as testing samples, the data become numerical values between (-1,1) after a naturalized process. Our designed neural network is chosen as a 4-25-1 structure with 4 input neutrons, 25 hidden neutrons and 1 output neutron. For this neural network, the hidden layer and output layer use the sigmoidal function. We have applied trainlm (the Levenberg-Marquardt algorithm) for the training of the network, and the trained model is shown in Fig. 2 Different type of system identification methods are analyzed and suitable method were underlined to the process. Neural network model were adapted to the clarifying process.

4. FUZZY MODELING

Fuzzy modeling often follows the approach of encoding expert knowledge expressed in a verbal form in a collection of if–then rules, creating a model structure. Parameters in this structure can be adapted using input-output data. When no prior knowledge about the system is available, a fuzzy model can be constructed entirely on the basis of system measurements. Note that the fuzzy observers used in the architecture. In the following, we consider data-driven modeling based on fuzzy clustering. This approach avoids the well-known bottleneck of knowledge acquisition. The fuzzy model is acquired from sampled process data, utilizing the functional approximation capabilities of fuzzy systems. Assume that data from an unknown system $y = F(\mathbf{x})$ is observed. The aim is to use this data to construct a deterministic function $y = f(\mathbf{x})$ that can approximate $F(\mathbf{x})$. The function f is represented as a collection of fuzzy if–then rules. Depending on the form of the propositions and on the structure of the rule base, different types of rule-based fuzzy models can be distinguished TSK fuzzy modeling of clarifying process

We consider rule-based models of the Takagi-Sugeno (TS) type .It consist of fuzzy rules which each describe a local input output relation, typically in an affine form. The representation as a TS model is given by

Ri : **If** *x*1 is *Ai*1 **and** . . . **and** *xn* is *Ain* **then** *yi* = **a***i***x** + *bi*

with *i* = 1, 2, . . .,*K*. Here, *Ri* is the *i*th rule, *Ai*1, . . ,*Ain* are fuzzy sets defined in the antecedent space,

x = [*x*1, . . . , *xn*]*T*

is the antecedent vector, and *yi* is the rule output variable. *K* denotes the number of rules in the rule base, and the aggregated output of the model, ˆ*y*, is calculated by taking the weighted average of the rule consequents.

5. INTELLIGENT CONTROLLER

The Intelligent Controller consists of two major parts that predict the performance of the plant for specific time horizon - (i) the Neural Network System Identification and (ii) the Intelligent Controller. Neural network is used to represent the forward dynamics of the plant. The prediction error between the plant output, *yp*, and the neural network output, *ym* is used as the neural network training signal. The neural control perform the modeling as shown in the Fig-2 using Labview software as well as in Matlab and it is performed over a specific time horizon. This time horizon is being shifted forward, thus, the model predictive control is called receding horizon control. The result of pH value control in clarifying process is shown in Fig. 4. The performance were analyzed and compared with the conventional controller.

5.1 PID controllers

In general, a classical PID control system can be depicted, in which the input–output relation of the PID controller is expressed as,

$$u = K_c e + 1/T_t \int_0^t edt + T_d e$$

where u is the control signal, e is the error signal, and Kc, Ti and Td denote the proportional gain, the integral gain and derivative gain, respectively.

The PID controller tuning synchronizes the controller with the controlled variable, thus allowing the process to be kept at its desired operating conditions.

6. INTELLIGENT TUNING

6.1 GENETIC ALGORITHM

GAs and searching algorithms imitate some of the processes of natural evolution. The searching process is similar to the natural evolution of biological creatures, in which successive generations of organisms are born and raised until they themselves are able to breed. In such algorithms, the fittest among a group of artificial creatures can survive and form a new generation. e.g., tournament selection is computationally more efficient than the other selection methods.

6.2 BASIC PSO ALGORITHM

In a PSO system, a swarm of individuals (called particles or intelligent agents) fly through the search space. Each particle represents a candidate solution to the optimization problem. The position of a particle is influenced by the best position visited by itself (i.e. its own experience) and the position of the best particle in its entire population. The best position obtained is referred to as the global best particle. The performance of each particle (i.e. how close the particle is from the global optimum) is measured using a fitness function that varies depending on the optimization problem. Each particle traverses the XY coordinate within a two-dimensional search space. Its velocity is expressed by vx and vy (the velocity along the X-axis and Y-axis, respectively). Modification of the particles position is realized by the position and velocity information (Kennedy et al., 2001). Each agent knows its best value obtained so far in the search (pbest) and its XY position. This information is an analogy of the personal experiences of each agent. Individual particles also have knowledge about the best value achieved by the group (gbest) among pbest. Each agent uses information relating to: its current position (x, y), its current velocities (vx, vy), distance between its current position and its pbest and the distance between its current position and the group's gbest to modify its position. The velocity and position of each agent is modified according (5.1) and (5.2) respectively (Kennedy and Eberhart, 1995)

The velocity modifications of the particle position is realized by,

$$v_t^{k+1} = v_t^k + c_1 rand_1{}' \ (pbest_t - s_t^k) + c_2 rand_2{}' \ (gbest - s_t^k)$$

The position modifications of the particle is realized by,

$$s_t^{k+1} = s_t^k + v_t^{k+1}$$

A problem with the early version of the PSO algorithm as represented by (5.1) is that the system has a tendency to explode as oscillations become wider (Kennedy et al., 2001). To damp the velocity and limit uncontrollable oscillations of the particles, a method of limiting the velocity to a predetermined value with a maximum velocity parameter. The effect of this code allows particles to oscillate within bounds with no tendency for the swarm to converge (Kennedy et al., 2001). The max V parameter thus improves the resolution of the search and arbitrarily limits the velocities of each particle (Carlisle and Dozier, 2001).

The transfer function of the clarifier system is given by,

$$G(s) = \frac{0.00416}{s^2 + 0.5083\,s + 0.00416}$$

The kp, ki, kd values are taken by trail and error method. The values taken for Kp, ki and kd are, kp =3.00, ki =0.05, kd=0. The open and closed loop responses are obtained for the given values and the comparison between conventional and evolutionary algorithms is given in the table 1.

Table.1.Comparison between conventional and evolutionary algorithms

Characteristics	Conventional method	Evolutionary algorithm	
		GA	PSO
Settling time	Large(above 250s)	0.742s	3.04s
Rise time	75s	0.632s	0.632s
Peak amplitude	1.1	1.04	1.14

7. CONCLUSION

To overcome the difficulty of neutralized pH value stable control for the clarifying process in the sugar refineries, a Neural controller used to control neutralized pH value is designed in this paper. In this method, with model network, is able to guide the controller to learn and train better with partial prior knowledge of the controlled system known. Neural combining the concepts of reinforcement learning is used to optimize and control the neutralized pH value for sugar clarifying section. The research indicates that this method has good control results and abilities for anti-disturbances. This will build a good foundation for implementation in real-time control in the future.

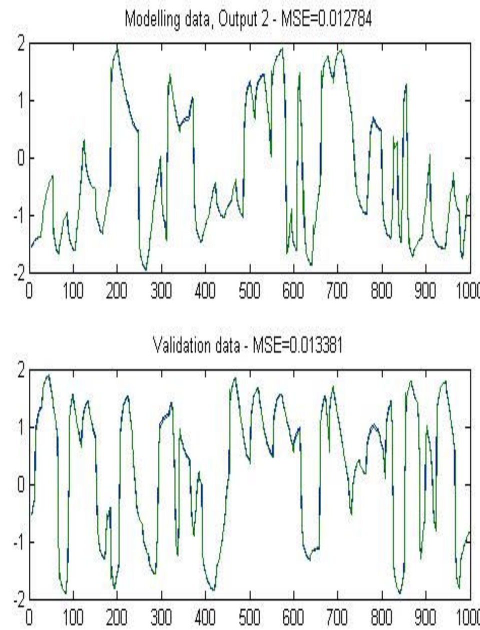

Fig: 2 Neural Network model for clarifying process

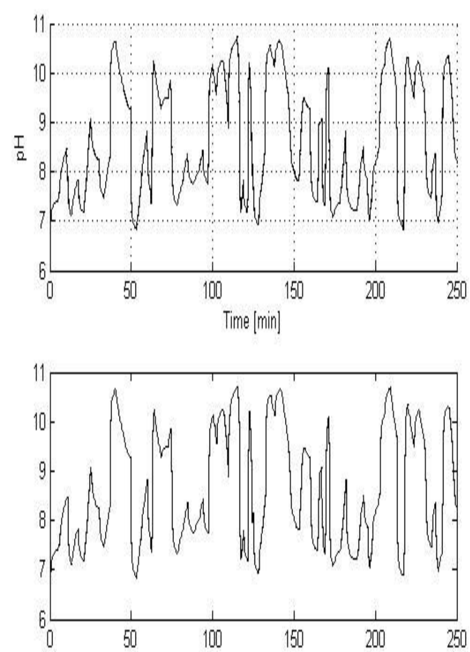

Fig 3. Fuzzy Modelling output

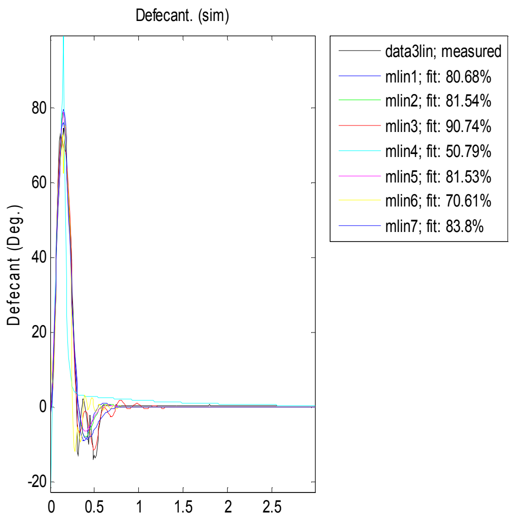

Fig:4 Comparison of different methods of modeling

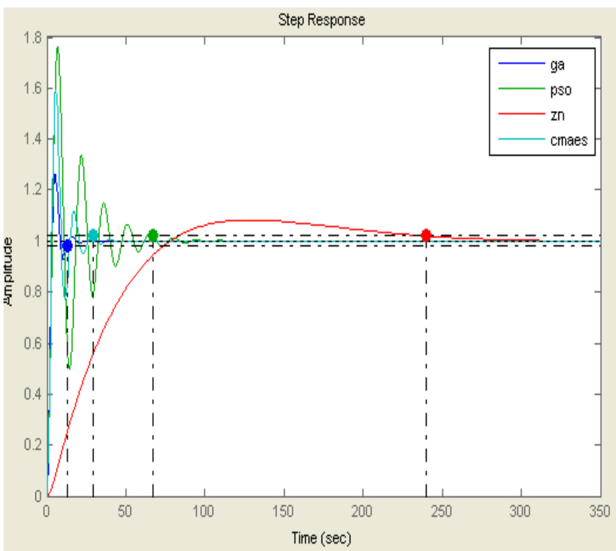

Fig:5 Comparison of GA,PSO, ZN and CMES based PID tuning

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