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Control System with Neural Networks for Product Crystal Size of Sodium Chloride

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ABSTRACT

A sodium chloride crystallizer shows oscillatory and nonlinear characteristics under its nucleating and growing process. Because these characteristics vary with operational condition, we can't control the product crystal size exactly with a PID controller or a sequence controller. Then, we make a model with threefold neural networks for the laboratory equipment that is a jet mixing crystallizer. We try to control the product crystal size with its neuro-model, and we reach the conclusion that our neuro-model is applicable to the practical crystallizer.

1. INTRODUCTION

Japanese salt manufacturing process may be composed of two stages. First stage is for concentrating seawater with the ion-exchange membrane electrodialysis system. Second stage is for concentrating the brine into crystal salt by heating with vapor.

The core of the problem for producing the desired size crystal is oscillatory and nonlinear characteristics of crystallizer under its nucleating and growing process. Because these characteristics vary with operational conditions, we can't control the product crystal size exactly with a PID controller or a sequence controller.

The conventional way for producing the desired crystal size is as follows: (1) we design and make the specified crystallizer matched with the desired crystal size. (2) An expert operator adjusts operational condition of the crystallizer with his experience and intuition.

However, as the stable range of the crystallizer depends on operational condition, it is difficult to produce the irregular crystal size with the unknown single crystallizer. So, it is indispensable to getting the exact characteristics of the crystallizer to estimate exact operational condition for producing the irregular crystal size.

The purpose of this paper is to propose a neuro-model of the crystallizer for producing the irregular crystal size with altering the operational conditions. We find that this neuro-model can cancel the effect of the known disturbance in the experiment. Then, we choose seeding rate as a new operational factor. This rate concerns the nucleating process and can suppress the oscillatory characteristic phenomenon of the product crystal size. We make a model for controling the product crystal size with measuring it and operational condition of the laboratory equipment.

Here, what has to be noticed is that the measured data of the product crystal size shows asymmetrical distribution for axis of time base. If we make a model with the average of asymmetrical distribution data, we can't obtain accurate it. However, our neuro-model uses the maximum data, the representative data, and the minimum data in the asymmetrical distribution of the crystal size. Therefore, we can obtain accurate it using the distribution data.

2. CONFIGURATION OF CONTROL SYSTEM

2.1 LABORATORY EQUIPMENT

We used an evaporating jet-mixing type crystallizer of 500 liters capacity, shows in Figure 1. We control individual local loops on the laboratory equipment using DDC system and sequence controler for making its local loops stationary state and total system stable state.

The point to control crystal size is how to match growing process with nucleating process. The grown crystal is easy to nucleate. The nucleated crystal is easy to grow. Then, we use seeding rate because of this rate can suppress the oscillatory process of the product crystal size. Moreover, we use neuro-model becase of getting the exact characteristic of the crystallizer simply using its learning function. Configration of control system is shown in Figure 2.

The operational conditions for producing the crystals of 400 micrometer are as follows: (1) Seed crystals are prepared mean size of 100, 200, and 270 micrometer, (2) and are fed into the crystallizer at a constant rate between 2 and 36 kilogram per hour. (3) An aqueous solution of sodium chloride evaporates at aconstant rate of 50 or 100 kilogram per hour. (4) Product crystals are removed from the crystallizer to maintain a constant suspension density of 4, or 7. (5)The composition ratio of sodium chloride in the aqueous solution is between 14.00 and 27.81.

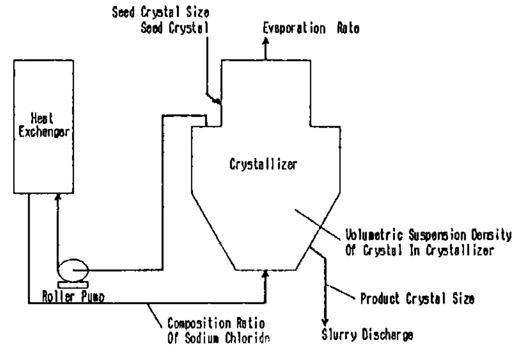

Figure 1 A sodium chloride cristallizer

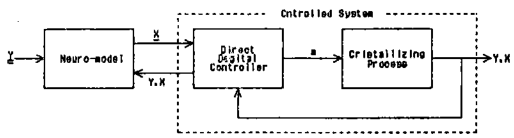

Figure 2 Configration of control system

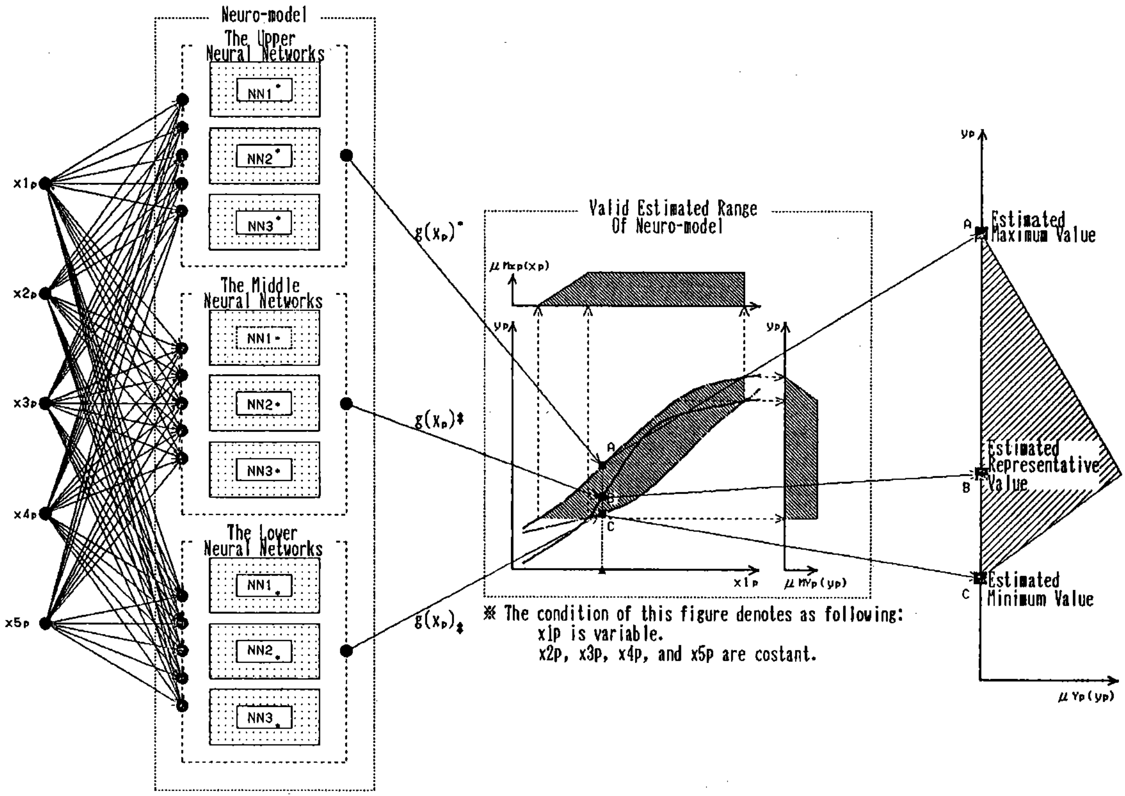

Figure 3 Configration of neuro-model with threefold neural networks

2.2 CONTROL SYSTEM WITH NEURAL NETWORKS

It is the problem of estimation using models that there is not a standard to judge the matched range between models and objects. If we try to estimate out of the valid range of the model, it is likely that estimated accuracy of models goes down. Therefore, we can't believe estimated value using models without checking the valid range of the model.

Our neuro-model for producing the desired size crystal is shown in Figure 3. This model is composed of the threefold neural networks. Also, individual onefold neural networks are composed of several multilayer neural networks. Since multilayer neural networks have height capability as an approximate realization tool of nonlinear mappings, we find that our neuro-model has higher flexibility than linear regression models.

The measured data of the product crystal size are distributed asymmetrically for axis of time base because of the oscillatory and nonlinear characteristics of the crystallizer. Our neuro-model uses the measured data of the product crystal size (the maximum data, the representative data, and the minimum data in the asymmetrical distribution), and five operational factors(evaporation rate, seeding rate, seed crystal size, volumetric suspension density of crystal in crystallizer, and composition ratio of sodium chloride).

Our neuro-model can include the asymmetrical distribution of the measured crystal size with the lower neural networks NN_* and the upper neural networks NN^* in threefold neural networks, so that it is possible to get the lower and upper characteristics (the interval characteristic) for the asymmetrical distribution of the measured crystal size with made neuro-model. Also, this neuro-model can get representative characteristic as the most dense data in the asymmetrical distribution with the middle neural networks NN* in threefold neural networks.

We must make our neuro-model on condition that we satisfy as follows:

$$g_*(x_p) \leq y_p \qquad \cdots(1)$$

$$g^*(x_p) \geq y_p \qquad \cdots(2)$$

$$g_*(x_p) \leq g*(x_p) \leq g^*(x_p) \qquad \cdots(3)$$

$$x_p=[x_{1p}, x_{2p}, \cdots, x_{np}], \quad (p=1, 2, \cdots, m)$$

where $g_*(\cdot)$, $g*()$, and $g^*(\cdot)$ as inputs and outputs function correspond to NN_*, NN*, and NN^*. x_p denotes n inputs as a vector under the pattern p, y_p denotes targets.

Learning law is denoted as follows:

$g_*(\cdot)$:

$$\min \Sigma E_{p*} \qquad \cdots(4)$$

if $y_p \geq g_*(x_p)$

$$E_{p*} = \gamma\,(g_*(x_p)-y_p)^2/2 \qquad \cdots(5)$$

$$\delta_p = \gamma\,(y_p-o_p)f'(i_p) \qquad \cdots(6)$$

if $y_p < g_*(x_p)$

$$E_{p*} = (g_*(x_p)-y_p)^2/2 \qquad \cdots(7)$$

$$\delta_p = (y_p-o_p)f'(i_p) \qquad \cdots(8)$$

$g*(\cdot)$:

$$\min \Sigma E_p* \qquad \cdots(9)$$

$$E_p* = (g*(x_p)-y_p)^2/2 \qquad \cdots(10)$$

$$\delta_p = (y_p-o_p)f'(i_p) \qquad \cdots(11)$$

$g^*(\cdot)$:

$$\min \Sigma E_p^* \qquad \cdots(12)$$

if $y_p > g^*(x_p)$

$$E_p^* = (g^*(x_p)-y_p)^2/2 \qquad \cdots(13)$$

$$\delta_p = (y_p-o_p)f'(i_p) \qquad \cdots(14)$$

if $y_p \leq g^*(x_p)$

$$E_p^* = \gamma\, g^*(x_p)-y_p)^2/2 \qquad \cdots(15)$$

$$\delta_p = \gamma\,(y_p-o_p)f'(i_p) \qquad \cdots(16)$$

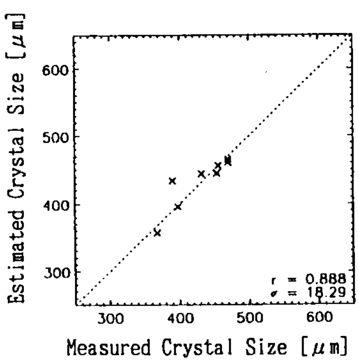

Figure 4 Simulation results using linear regression model

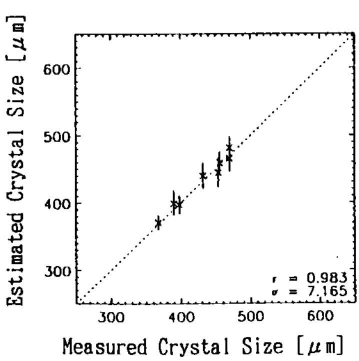

Figure 5 Simulation results using neuro-model with twofold neural networks

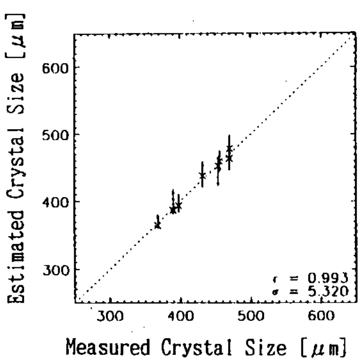

Figure 6 Simulation results using neuro-model with threefold neural networks

where i_p and o_p are the input and output, E_p is the evaluation function, $f'(\cdot)$ is the derivative of the semilinear activation function. γ is weight parameter for the error signal δ_p that varies inversely as the learning time.

The weight of the networks is adjusted by the backpropagation:

$$\triangle w = \alpha \triangle w + \eta \delta_p o_p \qquad \cdots(17)$$

where w denotes weights, $\triangle$ is its deviation, η is the learning rate, and α is a constant which determines the effect of past weight changes on the current direction of movement in weight space.

This model can judge the validity of the estimated representative data $g(x_p)*$ between the estimated maximum data $g(x_p)^*$ and minimum data $g(x_p)_*$ according to their sequence relationship :

the capacity of this model is shown in Figure 4, Figure 5, and Figure 6. These figure show the correlation between the measured crystal size and the estimated crystal size under the same operational condition. Figure 4 shows that the linear regression model does not fit the crystallizer that has nonlinear characteristic. Because the distribution of crystal size is asymmetry, we find that Figure 6 fits the measured crystal size compared with Figure 5.

3. EXAMPLES OF CONTROL FOR PRODUCT CRYSTAL SIZE

3.1 ESTIMATION OF CRISTAL SIZE UNDER CERTAIN OPERATIONAL CONDITION

In case the set value of the evaporation rate varies from day running to night runing, an expert operator estimates the product crystal size according to the variation of operational condition with his experience and intuition. Each operator has individual experience for the trouble or the variation of the running state, so that he has individual standard judgment to estimate the product crystal size. It is likely that operators do individual operation with the individual standard judgment under the same condition. There is not an absolute proof to operate efficiently for all operators.

Then, we make a model with inputs and outputs for the object, and estimate outputs for unknown inputs, as shown block chart in Figure 7. Here, we suppose that transfer function $G_1(s)$ is first order lag and dead time:

$$G_1(s) = \frac{K_1}{1+T_1 s} e^{-L_1 s} \qquad \cdots(18)$$

where k is a gain, T is time constant, s is Laplace operator, L is dead time. Resultingly, this figure shows that we can estimate a gain k1 of transfer function $G_1(s)$ using a model.

The result of the experiment is shown in the Figure 8 under the experiment condition that is listed in Table 1. We estimate the product crystal size for the variation of evaporation rate. Because result, the maximum value, the representative value, and the minimum value is 493, 463, and 421 micrometer. This model is made with much data about 400 micrometer. Therefore, a valid range about 463 micrometer in figure 7 tends to be wide, as compared to its about 400 micrometer. Because the measured product crystal size after the variation is about 470 micrometer, we find that the estimated representative value matched the measured crystal size, and that we can estimate the product crystal size exactly using our neuro-model.

3.2 ESTIMATION OF OPERATIONAL CONDITION FOR DESIRED CRISTAL SIZE

We must have the ability to estimate operational condition exactly to produce many kinds of the product crystal size. However, an expert operator searches the optimal operational condition with trial-and-error, so that it is difficult to control the product crystal size exactly.

Then, we make a model, and estimate an optimal input for a desired output, as shown block chart in Figure 9. Here, we suppose that transfer function $G_2(s)$ is first order lag and dead time:

$$G_2(s) = \frac{K_2}{1+T_2 s} e^{-L_2 s} \qquad \cdots(19)$$

Resultingly, this figure shows that we can estimate an inverse gain $1/K_2$ of transfer function $G_2(s)$ using a model.

The result of the experiment is shown in the Figure 10 under the experiment conditions that is listed in Table 2. We estimate seeding rate for producing crystal of 400 micrometer. As a result, seeding rate is 9.6 kilogram per hour. The measured product crystal size after the variation is about 390 micrometer. The desired crystal size matched the measured crystal size on steady state. Therefore, we find that we can estimate optimal operational condition for obtaining the desired crystal size using our neuro-model.

3.3 DISTURBANCE COMPENSATION WITH VARIATION OF OPERATIONAL CONDITION

For keeping steady-state on the crystallizer, it is necessary to have the ability to obtain the characteristic crystallizer exactly, to estimate the effect of the known disturbance exactly, and to estimate the optimal operational condition exactly to compensate it. An expert operator does those with his experience and his intuition, and searches optimal operational condition with trial-and-error. However, it takes long time to do these, and it is difficult to control it efficiently.

Then, we make a model, and estimate the optimal input to compensate the known disturbance, as shown block chart in Figure 11. Resultingly, this figure shows that we can estimate a gain rate K_1/K_2 of two transfer functions. We must obtain dead times of two transfer functions to cancel dead times.

The result of the experiment is shown in Figure 12 under the experiment conditions that is listed in Table 3. We estimate operational condition to compensate the known disturbance. As a result, seeding rate is 6.4 kilogram per hour because of keeping the product crystal size about 454 micrometer under the variation of the evaporation rate that varies from 80 to 100 kilogram per hour. The measured crystal size after the variation is about 456 micrometer. The desired crystal size matches the measured crystal size on steady state. Therefore, we find that we can estimate optimal operational condition for keeping the desired crystal size using our neuro-model.

4. CONCLUSIONS

We control the product crystal size of the sodium chloride crystallizer with a neuro-model that composed of the threefold neural networks. Our neuro-model is made of asymmetrical distribution data, and can estimate interval data and representative data of it, which is the feature of this model. We find that our neuro-model is useful for a crystalling process.

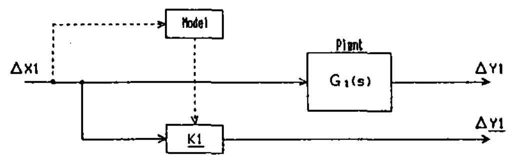

Figure 7 Block chart for estimating the crystal size under certain operational condition

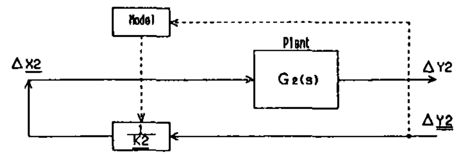

Figure 8 Block chart for estimating operational condition for the desired crystal size

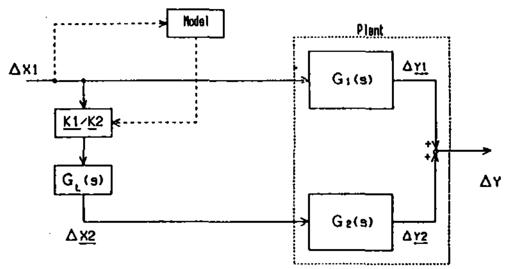

Figure 9 Block chart for compensating disturbance with the variation of operational condition

Table 1 Experiment condition for estimating the product crystal size

Operational foctors		Before		After		Model
evaporation rate	[kg/h]	*80*	→	*100*		
seeding rate	[kg/h]	4.8		4.8		
seed crystal size	[μm]	202		202		
suspension density	[-]	7.0		7.0		
composition ratio of NaCl	[%]	22.6		22.6		
product crystal size	[μm]	*432*	→	*470*	⇄	*463*

Table 2 Experiment condition for estimating the seeding rate

Operational foctors		Before		After		Model
evaporation rate	[kg/h]	100		100		
seeding rate	[kg/h]	*5.2*	→	*9.6*	←	*9.6*
seed crystal size	[μm]	198		198		
suspension density	[-]	7.0		7.0		
composition ratio of NaCl	[%]	22.6		22.6		
product crystal size	[μm]	*470*	→	*390*	⇄	*400*

Table 3 Experiment condition for estimating the seeding rate under the variation of evaporation rate

Operational foctors		Before		After		Model
evaporation rate	[kg/h]	*80*	→	*100*		
seeding rate	[kg/h]	*4.8*	→	*6.4*	←	*6.4*
seed crystal size	[μm]	202		202		
suspension density	[-]	7.0		7.0		
composition ratio of NaCl	[%]	22.6		22.6		
product crystal size	[μm]	*454*	→	*456*	⇄	*454*

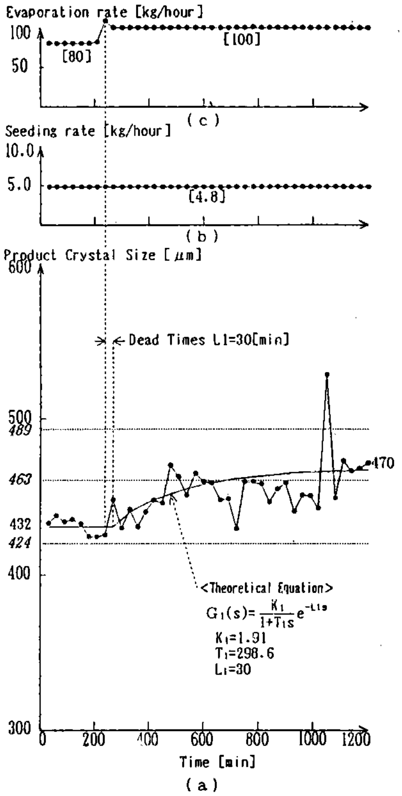

Figure 10 Estimated crystal size under the variation of evaporation rate

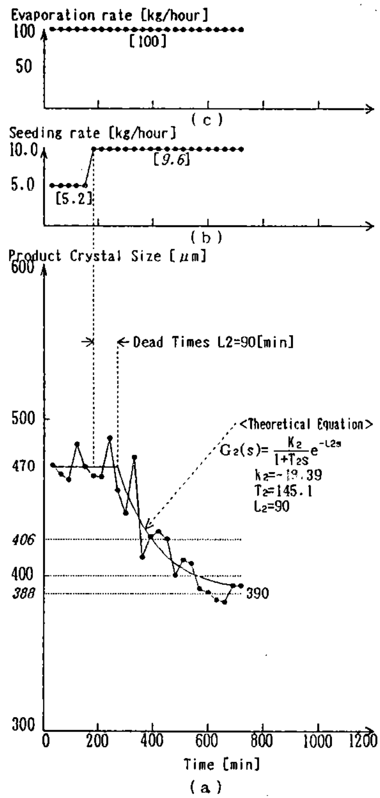

Figure 11 Estimated seeding rate for producing the desired crystal size

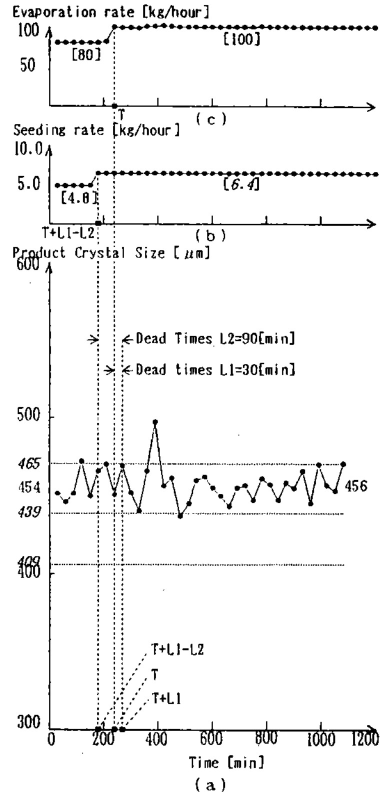

Figure 12 Controlled crystal size with the estimated seeding rate under the variation of evaporation rate

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