The Study of Multivariate Fuzzy Neural Scheme in Controlling Temperature during Beer Fermentation

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Abstract. The brewery fermentation process has inherence characteristics of multivariable, seriously nonlinear, uncertain, time-variant and large delay. The given process parameters aren’t traced very well. In this paper, segmented control strategy is used, which is dividing the ferment process into pre-fermentation and post-fermentation period. In each ferment period, strategy of fuzzy neural control based on Multivariate –decoupling is adopted and simulated in MATLAB, the results show the strategy’s validity and practicability in controlling beer ferment.

1. Introduction
Beer fermentation is a complex biochemical process with a large amount of heat generation. During the fermentation process, the required parameters are gotten by controlling temperature and pressure. At present, Conical Fermentor without stirring device, whose effective volume is generally between 50 m\(^3\)~ 1000m\(^3\), is widely used. For heat exchange, it has to convect with the cooling medium in the outside coil. Therefore, large time delay, strong coupling and time variability are the main characteristics of this process. So, effective control strategies should be adopted to control the biochemical reaction to improve the fermentation ability and improve and stabilize the quality of beer.

2. Beer fermentation process
Beer fermentation process is divided into pre-fermentation and post-fermentation period (beer storage and maturation). The pre-fermentation period, with yeast in the bottom, the temperature is relatively low and the fermentation process is slow. The post-fermentation period and storage period is relatively long. During this period, the yeast is growing quickly. The releasing heat makes temperature rise, so it needs to be cooled. The entire fermentation process is shown in Figure 1.

![Fermentation process curve](image)
2.1. Pre-fermentation period

2.1.1. Cool the wort to inoculation temperature (about 6°C shown in figure 1.).
2.1.2. After the yeast has been propagated for about 20 hours, the fermentation temperature and hypoglycemic condition should be checked regularly.
2.1.3. Fermentation takes about 2-3 days, and the temperature rises to the specified maximum temperature T2, generally 12°C. At this time, the fermentation broth should be properly cooled to maintain it at the specified maximum temperature. The opening of middle and valves are the controlled parameters, and the temperature should be maintained.

2.2. Post-fermentation period and storage period

In the post-fermentation period, temperature is first high and then low. When the liquor temperature drops to 5-6°C, keep it for 24 hours (t3–t4 incubation period in Figure 1), and recover the yeast. Finally, the temperature is reduced to 0 to -1°C, and the beer is stored for 7 to 14 days. During the post-fermentation, in order to lower the temperature, the opening of the middle valve and the lower valve is the controlled parameters.

3. Multivariate fuzzy neural system in controlling temperature during beer fermentation

The system diagram is shown in figure 2. The control strategy is the embodiment of the combination of the idea of multivariable decoupling control and fuzzy nerve, using the fuzzy nerve controller to adjust the parameters online to adapt to the real operating conditions.

![Figure 2. Multivariate fuzzy neural system in controlling temperature during beer fermentation](image)

3.1. Details of multivariable decoupling fuzzy neural control strategy

3.1.1. Decoupling

According to the literature [4], in the decoupling part, let s = 0 to get the static decoupling part. Based on the model of the fermentation, the initial static decoupling matrix is:

\[
W_F = \begin{bmatrix}
1 & -g_{12} \\
-g_{21} & 1
\end{bmatrix} = \begin{bmatrix}
1 & \lambda_1 \\
\lambda_2 & 1
\end{bmatrix}
\]

(1)

g_{ij} (i, j=1,2) is the element of the steady-state gain matrix.

The decoupling compensation matrix can completely eliminate the coupling. In order to minimize the impact caused by coupling, fuzzy control strategy is adopted to adjust the decoupling matrix online. As shown in Figure 3.

![Figure 3. Multivariable decoupling control](image)
The output is:
\[
\begin{bmatrix}
y_1 \\
y_2
\end{bmatrix} =
\begin{bmatrix}
a_{11} & a_{12} \\
a_{21} & a_{22}
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2
\end{bmatrix}
\]
(2)

Where \( u \) and \( y \) respectively represent the output of the controller and the output of the system, and \( a_{ij} \) is the element of the decoupling matrix. According to the above formula, the output increments at time \( n-1 \) and \( n \) are:
\[
y_1(n-1) = a_{11}u_1(n-2) + a_{12}u_2(n-2)
\]
(3)
\[
y_1(n) = a_{11}u_1(n-1) + a_{12}u_2(n-1)
\]
(4)

From the above two:
\[
a_{12} = \frac{y_1(n-1)u_1(n-1) - y_1(n)u_1(n-2)}{u_2(n-2)u_1(n-1) - u_2(n-1)u_1(n-2)}
\]
(5)

By the purpose of decoupling, in order to eliminate the effects of loop 2 to loop 1, it must be \( a_{12} \neq 0 \). If \( a_{12} = 0 \), it shows that the current decoupling coefficient is not perfect and needs modification. Based on the Unit Matrix Synthesis method, the modification is:
\[
\begin{bmatrix}
w_{d11}(s) & w_{d12}(s) \\
w_{d21}(s) & w_{d22}(s)
\end{bmatrix}
\begin{bmatrix}
w_{F11}(s) & w_{F12}(s) \\
w_{F21}(s) & w_{F22}(s)
\end{bmatrix} =
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\]
(6)

Where \( w_d(s) \) is the transfer function matrix of the controlled object, \( w_F(s) \) is the decoupling compensation matrix, and its expression is (1) when it is statically decoupled, then:
\[
w_d(s)w_F(s) =
\begin{bmatrix}
w_{d11}(s) & w_{d12}(s) \\
w_{d21}(s) & w_{d22}(s)
\end{bmatrix}
\begin{bmatrix}
1 & 1 \\
\lambda_1 & \lambda_2
\end{bmatrix} =
\begin{bmatrix}
1 & 0 \\
0 & 1
\end{bmatrix}
\]
(7)

From(7)and(2):
\[
w_{d11} \cdot \lambda_1 + w_{d12} = a_{12}
\]
(8)
\[
w_{d21} \cdot \lambda_2 + w_{d21} = a_{21}
\]
(9)

From(8),(9)and(1)it can show that \( \lambda_1, \lambda_2 \) are Negative. When \( a_{12} \) deviates from 0 and is changing towards the direction of greater than zero, \( \lambda_1 \) should change towards the negative direction to make \( a_{12} \) return to the 0. And when \( a_{21} \) is changing towards negative direction, \( \lambda_2 \) should change towards the direction of greater than zero. Similarly, the relationship between \( a_{21} \) and \( \lambda_2 \) is as above. If a fuzzy subset expresses the relationship between \( a_{12} \) and \( \lambda_1 \), then a table of fuzzy rules is:

| Table 1. The fuzzy control rule for decoupling matrix element modification |
|------------------|---|---|---|---|---|
| \( a_{12} \) | NB | NS | O | PS | PB |
| \( \lambda_1 \) | PB | PS | O | NS | NB |

Similarly, according to the expression of \( a_{21} \), the modified rule table of \( \lambda_2 \) can be obtained.
\[
a_{21} = \frac{y_2(n-1)u_2(n-1) - y_2(n)u_2(n-2)}{u_1(n-2)u_2(n-1) - u_1(n-1)u_2(n-2)}
\]
(10)

3.1.2. Fuzzy neural network (Figure 2.)

In the pre-fermentation period, the inputs of the fuzzy controller No.1 are E1 and EC1. E1 is the deviation of the measured temperature of the upper temperature from the given temperature and EC1 is the E1’s variation. The output is U1 that is the opening degree of the upper cooling valve. In the same way, for the fuzzy controller No.2. Usually, the domain of error and its variation is [-6, 6]. the fuzzy subset is divided into seven levels, that is {PB, PM, PS, ZE, NS, NM, NB}={"Positive large", "Positive middle", "Positive small", "Zero", "Negative small", "Negative middle", "Negative large"}, The membership function uses a Gaussian function, that is:
\[
f(x_i) = \frac{-(x_i-a_{ik})^2}{b_{ik}}
\]
(11)

Where \( x_i \) is the input variable, \( i \) is the serial number of the inputs, and \( a_{ik} \) and \( b_{ik} \) are the center position and width of the function, respectively. So, each fuzzy subsystem has a two inputs and one output. According to the grid method of fuzzy subsets, the fuzzy rules are a combination of fuzzy subsets. Each subsystem has 49 rules. As shown in table 2.
Table 2. Fuzzy control rules table

| E   | EC   | NB  | NM  | NS  | ZE  | PS  | PM  | PB  |
|-----|------|-----|-----|-----|-----|-----|-----|-----|
| NB  | PB   | PB  | PB  | PB  | PB  | PM  | ZE  | ZE  |
| NM  | PB   | PB  | PM  | PM  | PS  | ZE  | ZE  | ZE  |
| NS  | PM   | PM  | PS  | ZE  | NS  | NM  | NM  | NM  |
| ZE  | PS   | ZE  | NS  | NM  | NB  | NB  | NB  | NB  |
| PS  | ZE   | ZE  | NS  | NM  | NB  | NB  | NB  | NB  |

After the fuzzy control rule is established, the output can be obtained by using the approximate reasoning synthesis rule proposed by L.A. Zaden. When the weighted average method is used for defuzzification, it has the following form:

$$u^* = \frac{\sum_{i=1}^{m} \left( \mu_{A_1}(x_1) \land \mu_{A_2}(x_2) \land \cdots \land \mu_{A_n}(x_n) \right) w_i}{\sum_{i=1}^{m} \left( \mu_{A_1}(x_1) \land \mu_{A_2}(x_2) \land \cdots \land \mu_{A_n}(x_n) \right)}$$

where $m$ is the number of fuzzy rules. In this paper, the number of fuzzy separations is 7, so the number of rules $m = 49$, $n$ is the number of controller inputs, where $n = 2$, and $w$ is center value of the membership function of the fuzzy output. $\mu$ is the membership function of each input fuzzy set. The neural network representing the above fuzzy controller is shown in Figure 4 below. A hierarchical neural network is used to represent the fuzzy controller and the central value and width of the membership function of the input and output can be adjusted online to control the system effectively.

Figure 4. Fuzzy neural network controller

3.1.3. Online learning algorithm of fuzzy neural network

As shown in Figure 4, the fuzzy divisions of each input variable is predetermined. The parameters that need to learn are the connection weight $w_i$ of the last layer, the center value $a_{ik}$ and width $b_{ik}$ of the membership function of the second layer. According to experience, the initial values are determined as follows. The initial center values of each fuzzy variable membership function are $\{6, 4, 2, 0, 2, 4, 6\}$, the Quantification factors are $k_1 = x_m / x$, $k_2 = y_n / y$, $[-x, x]$ and $[-y, y]$ are the actual range of errors and its variation. It can be estimated that $[-x_m, x_m]$ and $[-y_n, y_n]$ is the domains of the corresponding linguistic variables, which are $[-6, 6]$ in this paper. Performance index is defined as:

$$E = \frac{1}{2} (y_d - y)^2$$

$y_d$ is the expected output value, here is the given process temperature, and $y$ is the real measured temperature. $\frac{\partial E}{\partial w_i}$, $\frac{\partial E}{\partial a_{ij}}$ and $\frac{\partial E}{\partial b_{ij}}$ are calculated with the error back propagation algorithm. The first order gradient optimization algorithm is employed to adjust $w_i$, $a_{ij}$ and $b_{ij}$. In order to derive the iterative algorithm of error back propagation, it is necessary to formally describe the relationship between input and output of each neuron.
4. Simulation of multivariate decoupling fuzzy nerve control strategy of fermentor

4.1. Mathematical models and flowcharts for simulation

Because of the conditions, the mathematical model used in this paper is provided by the literature [6]. An open fermentor with a height of 8m and a diameter of 5m is used as the model. The outer wall of the fermentor is provided with three cooling sleeves, upper, middle and lower, and three temperature measuring points and three regulating valves are set up correspondingly. Mathematical models for pre-fermentation period and post-fermentation period are respectively G1 and G2:

\[
G_1(s) = \begin{bmatrix}
-1.43044e^{-240s} \\
7466.7s^2+435.89s+1 \\
-0.2301e^{-540s}
\end{bmatrix}
\begin{bmatrix}
-0.615915e^{-240s} \\
7466.7s^2+435.89s+1 \\
-0.914839e^{-480s}
\end{bmatrix}
-0.615915e^{-240s}
\begin{bmatrix}
2949.87s^2+139.08s+1 \\
7466.7s^2+435.89s+1 \\
8147.96s^2+515.95s+1
\end{bmatrix}
\]

(14)

\[
G_2(s) = \begin{bmatrix}
-0.615915e^{-240s} \\
484.118s^2+286.25s+1 \\
-0.914839e^{-540s}
\end{bmatrix}
\begin{bmatrix}
-0.859148e^{-240s} \\
6241.2s^2+450.76s+1 \\
-0.416558e^{-540s}
\end{bmatrix}
-0.859148e^{-240s}
\begin{bmatrix}
8147.96s^2+575.95s+1 \\
7466.7s^2+435.89s+1 \\
7679.75s^2+444.95s+1
\end{bmatrix}
\]

(15)

The main simulation diagram is:

![Simulation Diagram](image)

4.2. The simulation results

On the normal conditions of the fermentor, the simulation results are shown in Figure 6. From the simulation results, in the pre-fermentation period, the temperature of the middle and upper parts is basically the same, which meets the process requirements, that is, the upper and middle temperatures are kept in balance. In the post-fermentation period, the middle and lower temperatures are the controlled parameters, and the simulation results are in Figure 7.

![Pre-fermentation Temperature Curve](image)

**Figure 6. Pre-fermentation temperature curve**

![Post-fermentation Temperature Curve](image)

**Figure 7. Post-fermentation temperature curve**

The simulation results show the difference between the middle and lower temperature is about 0.3°C, which can meet the process requirements. The control strategy proposed in this paper basically meets the fermentation process requirements, which confirms the practicability and effectiveness of the control strategy.
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