Decoupling Control Based on Fuzzy Neural-Network Inverse System in Marine Biological Enzyme Fermentation Process

XIANG LIN ZHU¹, ZHE YU JIANG¹, BO WANG¹, AND YU JUN HE²

¹School of Electrical and Information Engineering, Jiangsu University, Zhenjiang 212013, China
²China Machinery Industry Suzhou Senior Technical School, Suzhou 215101, China

Corresponding author: Bo Wang (wangbo@ujs.edu.cn)

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ABSTRACT The marine biological enzyme fermentation process is a time-varying, nonlinear, uncertain, and multivariable system, so high performance decoupling control is a target to seek. A decoupling control method based on a fuzzy neural-network inverse system for the marine biological enzyme fermentation process is proposed, in which the inverse system linearizing method of the nonlinear system is combined with the nonlinear identifying technology of the fuzzy neural network. First, based on the characteristics of the fermentation process, the model of a fermentation system is obtained, and the reversibility of the system is proved. Second, the $a$th-order inverse system of the fuzzy neural network is constructed and connected in series with the fermentation system to be a pseudo-linear compound system. Finally, closed-loop control is carried out to obtain good control performance by introducing an expert controller. The simulation experiments demonstrate that good control performance (high accuracy and good robust) can be obtained in the multivariable fermentation process based on the fuzzy neural-network inverse system.

INDEX TERMS Marine biological enzyme fermentation process, fuzzy neural-network, inverse system method, decoupling control.

I. INTRODUCTION

Marine biological enzyme fermentation process is a multi-variable coupling system with time-varying, nonlinear and stochastic characters [1], [2]. For involving complex process of microbial cells growth and metabolism, the system could be influenced by many complicated factors, and the parameters are exactly related to it. How to realize decoupling control about the nonlinear, multi-variable and strong coupling bioprocess has been attracted by biological academic circles [3]. Decoupling control can limit the coupling at some degree or decouple a multi-input multi-output control system into several independent single-input single-output system through cascading an appropriate compensation device. A relatively integrated design theory of inverse system method has been constructed for the general nonlinear system [4]–[6]. However, as is known to all, this method is based on an accurate mathematical model of the controlled system. In many practical cases, the accurate mathematical description of the marine biological enzyme fermentation process is almost unknown. Even if the complex nonlinear mathematical model is completely known in advances, the nonlinearities and complex coupling relationships contained in the model still make it difficult to deduce the inverse system. So how to identify the structure of $a$th inverse system without accurate mathematical model has played a crucial role to the practical application and promotion about inverse system in bioprocess [7]–[10].

In recent years, new theories have appeared and developed rapidly, such as the intelligent control, artificial neural networks, fuzzy logic and so on. People found that these novel techniques possess some new features which traditional methods didn’t have, especially that they have high ability in solving the complexity, uncertainty and a high standard requirements performance for the modern industrial system. As a organic combination of fuzzy logic and neural network, fuzzy-neural network has advantages both of fuzzy logic and neural network. It can not only deal with the fuzzy information but also carry out fuzzy reasoning. Besides that it introduces in neural network learning mechanism to enhance the adaptive capacity of the network, all of the above
advantages make the fuzzy-neural network posses reasoning capability and adaptive ability. At the same time, because fuzzy-neural network can approximate any continuous nonlinear mapping like the neural network do, it has been widely used in system identification [11]–[13].

A multivariable decoupling control method based on fuzzy-neural network inverse system was proposed by combining the inverse system with fuzzy-neural network for marine biological enzyme fermentation process. According to the characteristics of fermentation process, the method establishes the corresponding mathematical model and analyzes the reversibility firstly. Then the fuzzy neural network inverse system is constructed based on the function fitting properties of fuzzy-neural network and connected in series with fermentation system to be a pseudo-linear compound system. At last, it carries out closed-loop control by introducing expert controller into pseudo-linear system and obtains high-performance decoupling control.

II. MATHEMATICAL MODEL AND REVERSIBILITY ANALYSIS

There are a number of complex kinetic model used to describe the time-varying dynamic behavior for marine biological enzyme fermentation process. Mathematical model of the marine biological enzyme fermentation process refers to the mass balance conditions in bioreactor, which has the following generalized structure [1]:

\[
\begin{align*}
\frac{dX}{dt} &= \phi \times X - \frac{X}{V} \frac{dV}{dt} \\
\frac{dS}{dt} &= \varphi \times X + \frac{k_3}{V} f_c - \frac{S}{V} \frac{dV}{dt} \\
\frac{dP}{dt} &= \sigma \times X - k_2 p + \frac{k_3}{V} f_n - \frac{P}{V} \frac{dV}{dt} \\
\frac{dV}{dt} &= \alpha x_1 - x_2 \end{align*}
\]

(1)

Where \( X \), \( S \) are mycelia concentration and substrate concentration[g/L]; \( P \) is relative enzyme activity [%]; \( V \) is volume of cultivation broth in bioreactor [L]; \( f_{am} \) is flow(supply) rate of ammonia, \( f_c \) is flow(supply) rate of carbon source, \( f_n \) is flow(supply) rate of nitrogen source [l/h]; \( t \) is time[h]; \( k_i (i = 1, 2, 3) \) is non-zero constant; \( \phi , \varphi , \sigma \) are all the analytic functions of state variables.

For the convenience and concision of the form, let state variables \( x = (x_1, x_2, x_3, x_4)^T \), \( u = (u_1, u_2, u_3) \), and then Eq.(1) would be rewritten as the following nonlinear system:

\[
\begin{align*}
\dot{x}_1 &= \phi x_1 - \frac{x_1}{x_4} (u_1 + u_2 + u_3) = f_1(x, u) \\
\dot{x}_2 &= \varphi x_1 + \frac{k_1}{x_4} u_2 - \frac{x_2}{x_4} (u_1 + u_2 + u_3) = f_2(x, u) \\
\dot{x}_3 &= \sigma x_1 - k_2 x_3 + \frac{k_3}{x_4} u_3 - \frac{x_3}{x_4} (u_1 + u_2 + u_3) = f_3(x, u) \\
\dot{x}_4 &= u_1 + u_2 + u_3 = f_4(x, u)
\end{align*}
\]

(2)

The Eq. (2) can be simply described as:

\[
\begin{align*}
\dot{x} &= h(x) + g(x) u \leftrightarrow \dot{x} = f(x, u) \\
h(x) &= \begin{bmatrix} \alpha x_1 \\ \beta x_1 \\ \sigma x_1 - k_2 x_3 \\ 0 \end{bmatrix} g(x) = \begin{bmatrix} \frac{x_1}{x_4} \\ \frac{x_1}{x_4} \\ \frac{x_4}{x_4} \\ 1 \end{bmatrix} \\
\end{align*}
\]

(3)

For the marine biological enzyme fermentation process expressed as the nonlinear system (2), the flow rate \( u_1 \sim u_3 \) are regarded as the control variables, \( X(x_1), S(x_2), P(x_3) \) as the controlled variables, \( V(x_4) \) as state variable. The mathematical model of the Marine biological enzyme fermentation process is established as follows:

\[
\begin{align*}
\dot{x} &= f(x, u) \\
y &= (y_1, y_2, y_3)^T = (x_1, x_2, x_3)^T
\end{align*}
\]

(4)

(5)

As the marine biological enzyme fermentation process is a time-varying, nonlinear, multivariable and strong coupling system, conventional control method is very difficult to achieve decoupling control and get good control effect. It is hard and even impossible to use the inverse system method based on the theory of differential geometry to get the analysis inverse strictly, so inverse system method still not fit to put into practice. If combining the nonlinear identifying technology of fuzzy-neural network with the inverse system method, the fuzzy-neural network can be used to construct inverse system, which avoids the problem that is difficult to get the inverse analysis, and makes the application of complex nonlinear inverse control method possible.

In order to provide a theoretical basis for using the fuzzy-neural network inverse system method in the marine biological enzyme fermentation process, testifying the reversibility of original system is the primary task. The integrity mathematical description of the original system are:

\[
\begin{align*}
x &= x_4 \\
y &= (y_1, y_2, y_3)^T = (x_1, x_2, x_3)^T \\
\dot{x} &= u_1 + u_2 + u_3
\end{align*}
\]

(6)

According to Interactor algorithm[5](The algorithm is put forward by X. Z. Dai professor of southeast university to deduce the inverse system of MIMO system), it can get the first derivative of the outputs \( y = (y_1, y_2, y_3) \) to make it explicit express with the inputs \( u = (u_1, u_2, u_3) \).

\[
\begin{align*}
\dot{y}_1 &= \phi y_1 - \frac{y_1}{x} (u_1 + u_2 + u_3) \\
\dot{y}_2 &= \varphi y_1 + \frac{u_1}{x} y_2 - \frac{y_2}{x} (u_1 + u_2 + u_3) \\
\dot{y}_3 &= \sigma y_1 - k_2 y_3 + \frac{k_3}{x} u_3 - \frac{y_3}{x} (u_1 + u_2 + u_3)
\end{align*}
\]

(7)
Apparently the first derivative of the outputs $y = (y_1, y_2, y_3)^T$ meets the requirements, the rank of Jacobean matrix is as Eq. (8):

$$\text{rank} \left[ \frac{\partial y}{\partial u} \right] = \text{rank} \left[ \begin{bmatrix} \frac{\partial y_1}{\partial u_1} & \frac{\partial y_1}{\partial u_2} & \frac{\partial y_1}{\partial u_3} \\ \frac{\partial y_2}{\partial u_1} & \frac{\partial y_2}{\partial u_2} & \frac{\partial y_2}{\partial u_3} \\ \frac{\partial y_3}{\partial u_1} & \frac{\partial y_3}{\partial u_2} & \frac{\partial y_3}{\partial u_3} \end{bmatrix} \right] = \text{rank} \left[ \begin{bmatrix} k \, 1 & 1 & 1 \\ k_1 & 0 & 0 \\ 0 & k_3 & 0 \end{bmatrix} \right] = 3$$

(8)

In the actual marine biological enzyme fermentation process, the mycelia concentration, substrate concentration, chemical potency and the volume of cultivation broth in bioreactor is separately more than zero and the constant $k_i (i = 1, 2, 3)$ is separately not zero. Then

$$\det \left( \frac{\partial y}{\partial u} \right) = \det \left[ \begin{bmatrix} \frac{\partial y_1}{\partial u_1} & \frac{\partial y_1}{\partial u_2} & \frac{\partial y_1}{\partial u_3} \\ \frac{\partial y_2}{\partial u_1} & \frac{\partial y_2}{\partial u_2} & \frac{\partial y_2}{\partial u_3} \\ \frac{\partial y_3}{\partial u_1} & \frac{\partial y_3}{\partial u_2} & \frac{\partial y_3}{\partial u_3} \end{bmatrix} \right] = \frac{x_1}{x^3} \left[ \begin{bmatrix} 1 & 1 & 1 \\ k_1 & 0 & 0 \\ 0 & k_3 & 0 \end{bmatrix} \right] = -\frac{y_1 k_1 k_3}{x^3} \neq 0$$

(9)

The relative degree of the system is $a = (a_1, a_2, a_3)^T = (1, 1, 1)^T$ and $a_1 + a_2 + a_3 = 1 + 1 + 1 = 3 < 4 = n$, it indicates that the system is reversible. By existence theorem of implicit function, the inverse system of original system can be expressed as Eq. (11):

$$u = [u_1, u_2, u_3]^T = \phi(x, y_1, y_2, y_3)$$

(10)

### III. SYSTEM IDENTIFICATION

To a MISO(Multiple Input and Single Output) nonlinear system as $y = f(x)$, $f$ is unknown and $x \in X \subset R^n$, $x = (x_1, x_2, \ldots, x_m), y \in Y \subset R$. If $n$ groups input-output sample data were offered as $(x_1, y_1), (x_2, y_2) \cdots (x_n, y_n)$, a model of fuzzy rules can be built as follows [14]:

$$R^i : \text{if } x_1 \in A_1^i \text{ and } x_2 \in A_2^i \text{ and } \cdots \text{ and } x_m \in A_m^i \text{ then } y \in B^i \quad i = 1, 2, \cdots, W$$

(11)

In the Eq. (11), $W$ shows the number of fuzzy rules; $A_i^i$ is a fuzzy set in the universe of $x_i$ and its membership function is $\mu_{A_i^i}(x_i), i = 1, 2, \cdots, m; B_i^i$ is a fuzzy set in the output universe of $y$. The model not only approximate the $n$ groups sample data accurately, but also has enough generalization power.

Before constructing a model of fuzzy Eq. (11), two steps of optimization have to be finished, such as structure identification and parameters learning. Structure identification is to determine the number of fuzzy rules from the known input-output sample data set, and also determine the initial parameters of each rule. Parameter learning is to construct a 4-layer fuzzy-neural network model that matches the fuzzy inference mechanism based on the given initial fuzzy inference system. Through adaptive network training and using gradient descent mixed least squares method to learn and optimize the parameters, so that the model will possess a higher approximation accuracy [15].

### A. STRUCTURAL IDENTIFICATION

The research adopted clustering method to construct the initial fuzzy inference model. Thoughts and steps of the method are as follows: if given $n$ data samples $(x_1, x_2, \cdots, x_n)$ of $m$-dimensional space and each sample can be regarded as a cluster center [13], the density indicator at the $x_k$ points is defined as:

$$D_k = \sum_{i=1}^n \exp \left( -\frac{\|x_k - x_i\|^2}{(\sigma 1/2)^2} \right)$$

(12)

The sample data points have a high density if it contains a number a neighboring data points. Nominal range defines an area from the point, other data points outside of the nominal range contribute very little to density index. After calculating each sample data’s index, it chooses the sample data with the highest index as the first cluster center. Let $x_{c_1}$ be the selected points, $D_{c_1}$ be the density index for $x_{c_1}$. The density index for $x_k$ can be amended by following formula:

$$D_{k'} = D_k - D_{c_1} \exp \left( -\frac{\|x_k - x_{c_1}\|^2}{(\sigma 2/2)^2} \right)$$

(13)

In Eq. (13), $\sigma 2$ is a positive number. Obviously, the density index of sample data points near the first cluster center $x_{c_1}$ will be significantly reduced, so these points cannot be selected as the next cluster center.

It selects the next cluster center after amending the density index for each data point, and then amends the density index for all data points again. This process is repeated until the density index $D_{c_l}$ which corresponds to the new cluster center $x_{c_l}$ is smaller than the given value $\alpha$. The above clustering algorithm has divided the known sample set into $W$ categories and receives corresponding cluster center $x_{ci} = \{x_{c_1}, x_{c_2}, \cdots, x_{cw}\}$. At the same time, it has received corresponding fuzzy rules number and initial parameters in each rule.

### B. PARAMETER LEARNING

A MISO nonlinear system is expressed by $W$ categories fuzzy rules with singleton, and the product operator and weighted average of anti-fuzzy are shown as Eq. (11). Then the output is to be:

$$y = f(x) = \sum_{i=1}^w \sum_{j=1}^m w_i \prod_{i=1}^m \exp \left( -\frac{(x_i - a_i^j)^2}{b_i} \right)$$

(14)
In Eq. (14), fuzzy rules \( W \) are fixed, \( a_i' \), \( b_i' \) and \( w_i \) are freely parameters. The rules number and initial parameter \( a_i'(0), b_i'(0), w_i(0) \) are determined by the front Structural identification.

However, each of the two prerequisites is very difficult or even impossible to satisfy in the actual control of biological processes. Because fuzzy-neural network can approximate any continuous nonlinear mapping, it can be used to approach the inverse system (Eq. (10)). In the case of knowing the relative rank of the inverse system \( a = (a_1, a_2, a_3)^T = (1, 1, 1)^T \), the fuzzy-neural network at inverse system is comprised with three fuzzy-neural topology and three integrators, in which they respectively represent the nonlinear mapping relationship and the dynamic characteristics of the inverse system. Connecting it before the marine biological enzyme fermentation process could be gotten three decoupling pseudo-linear sub-systems. The pseudo -linear composite system is shown in fig.2.

The pseudo-linear system is used to connect the fuzzy-neural network \( a_th \) inverse system with the fermentation system, and it is constituted by the first-order mycelia concentration sub-system, the first-order substrate concentration sub-system and the first-order chemical potency sub-system. In this way, the complex control turns into three simple controls of integral linear system. And the effective control of fermentation system will be realized by using the additional linear close-loop controller. Controlling method of linear closed-loop controller can be selected from classical control theory, modern control theory, advanced control theory, etc. The system introduces expert controllers based on PID technology and expert experience to achieve closed-loop control. Fig.3 shows the principle of the expert controller.

IV. INVERSE SYSTEM DECOUPLING CONTROL METHOD

By knowing the inverse system theory, the realization of the inverse system method must meet two preconditions that are:

1) Mathematical model of original system is accurately known;
2) Analysis expression of the inverse system can be gotten from the original system’s mathematical model.

Inference engine deals with the current problems through knowledge obtained from the fermentation experts. Inference is stored from professional experience, common sense and expert experience to achieve closed-loop control.
certain reasoning strategies, which is based on the current input data information and the knowledge in the knowledge base [16].

PID (Proportional Integral Differential control method) controller applies the difference equation:

\[ u(k) = K_p(e(k)) + \frac{T_i}{T} \sum_{j=0}^{k} e(j) + \frac{T_d}{T} (e(k) - e(k-1)) \]  \hspace{1cm} (17)

Where \( T_i \), \( T_d \) are integration time constant, differential time constant; \( k \) is the sampling sequence number, \( k = 0, 1, 2 \cdots \); \( u(k) \) is output at the \( k \)-th sampling time, \( e(k) \) is the input deviation at the \( k \)-th sampling time, \( e(k-1) \) is the input deviation at the \( (k-1) \)-th sampling time.

Combing the PID algorithm with the expert control rules to compensate, it can bring control rules as follow:

1) IF \( |e(k)| < m_1 \) AND \( |De(k)| < m_2 \) THEN \( K_p(k) = K_p(k-1) \) AND \( T_i(k) = T_i(k-1) \) AND \( T_d(k) = T_d(k-1) \)

   The original parameters \( K_p, T_i \) and \( T_d \) will be maintaining unchanged if the deviation and deviation change rate are remaining in allowable scope.

2) IF \( |e(k)| \geq m_1 \) AND \( |De(k)| \geq m_2 \) THEN \( K_p(k) = \varepsilon_1 \cdot K_p(k-1) \) AND \( T_i(k) = \varepsilon_2 \cdot T_i(k-1) \) AND \( T_d(k) = \varepsilon_3 \cdot T_d(k-1) \)

   The proportion, integral and differential action will be reduced, if the deviation and deviation change rate are too large.

3) IF \( |De(k)| \geq m_3 \) AND \( De(k) \cdot e(k) \geq 0 \) THEN \( K_p(k) = K_p(k-1)/\varepsilon_1 \) AND \( T_i(k) = T_i(k-1)/\varepsilon_2 \) AND \( T_d(k) = T_d(k-1)/\varepsilon_3 \)

   The proportion and integral action will be enhanced, if the deviation change rate is slow and to be a monotone process.

   In the rules, \( m_1, m_2, m_3 \) are the empirical index, \( \varepsilon_1, \varepsilon_2, \varepsilon_3 \) are the weighted factor which are available to be amended online.

\[ g = \text{input deviation at (} k \text{-th sampling time)} \]

\[ k \text{ is the input deviation at the (} k-1 \text{-th sampling time)} \]

\[ k \text{ is the sampling sequence number} \]

\[ T \text{ is the input deviation at the (} k \text{-th sampling time)} \]

\[ T \text{ is the input deviation at the (} k-1 \text{-th sampling time)} \]

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requirement of alkaline protease MP fermentation, the temperature is controlled at 28°C, pH is 9.5, the fermentation pressure is 0.04Mpa, the aeration amount is 1000L/h, the stirring speed is 250r/min, the dissolved oxygen is controlled in 45~75%, and the optimum fermentation time is 90h. The measurement of mycelia concentration, substrate concentration and relative enzyme activity are obtained by the method of cell wet weight, saccharimeter and spectrophotometer. At the same time, in order to eliminate various errors in the measurement fermentation process, the data obtained above are processed by digital filtering, and eliminated the error by adopting the clustering analysis method, so that the training of fuzzy neural network has better performance and all data are normalized.

The input sample set is \( u = (f_{\text{am}}, f_{c}, f_{\text{f}})^T \), state sample set is \( x = (X, S, P, V)^T \). Then by using the seven-digit decimal high-precision numerical algorithms to obtain the corresponding derivative offline, the input and output set will be constituted. Sample sets are \( \{\dot{X}, X, \dot{S}, S, \dot{P}, P\} \), \( \{u_1, u_2, u_3\} \), the former is input of fuzzy-neural network, the latter is the output of fuzzy-neural network. For the implicit dynamic \( V \), volume of cultivation broth), the corresponding implicit dynamic equation is the relationship between the \( V \) which is the fourth equation of the formula (1) and the three input variables. As long as the input is conformed, \( V \) is stable.

The input sample data sets \( \{\dot{X}, X, \dot{S}, S, \dot{P}, P\} \) and output sample data sets \( \{u_1, u_2, u_3\} \) are divided into five batches, each of them contains 70 data samples. The former four batches are taken as a training set to train the fuzzy-neural network and obtain the corresponding free parameters \( a_l, b_l \) and \( w_i \). The last batch serves as a test set to identify the established fuzzy-neural network topology model. Fig.5 is the identification result of fuzzy-neural network topology model. The identified fuzzy-neural network \( a \)th inverse system will be in series with the original system to constitute a
pseudo-linear composite system, whose transfer function are \( G_x(s) = s^{-1} \), \( G_y(s) = s^{-1} \) and \( G_z(s) = s^{-1} \) respectively. Since every independent circuit corresponds to a first-order dynamic block, the expert controller is used to carry out closed-loop control for the system.

In order to verify the advantage of inverse system control method, the inverse system method and the PID closed-loop control method are compared, the decoupling effect are shown in Fig.6 and Fig.7. It can be seen from the Fig.6 and Fig.7, in the case of PID control, the mycelia concentration and relative enzyme activity have great fluctuation with the strong coupling when the substrate concentration is changed from 120 step jump to 160. The steady-state error of the mycelia concentration and substrate concentration in the PID control method is 2.8% and 3.1% respectively, while the steady-state error of the mycelia concentration and substrate concentration in the FNN algorithm decreases to 1.2% and 1.4%. In the case of inverse system method, the steady-state error is eliminated and the decoupling effect is satisfactory. It indicates that marine biological enzyme fermentation process using the decoupling control method based on fuzzy-neural network inverse system is effective and have a good control characteristic.

VI. CONCLUSIONS

Through the simulation of the three-input and three-output strong coupling marine biological enzyme fermentation process with nonlinear, the results show that using the fuzzy-neural network to fit the inverse system of the MIMO(Multiple Input and Multiple Output) nonlinear system has a good approximation performance. It does not require prior knowledge of the model, but it can achieve the ideal identification effect by only using a small amount of input/output data. Connecting the inverse system before the original system can make the system decoupled and to be a pseudo-linear composite system. Thus the MIMO nonlinear coupling problem of the marine biological enzyme fermentation process can be solved by adding the controller in the pseudo-linear composite system that is closed-loop controlled. The fuzzy-neural network inverse system decoupled control method has clear physical concept, which can realize the decoupling and linearization of general nonlinear reversible systems, and it can be widely used. It supplies a new way for MIMO nonlinear decoupling control.

The fuzzy-neural network inverse system decoupling control method combines the inverse system theory with the intelligent control method, which has a large computational complexity compared with the traditional PID control, neural network and other single control methods. The follow-up will carry out the related research on the computational complexity of the algorithm.

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Xiang Lin Zhu received the B.Sc. degree from the Hu Nan Institute of Engineering in 1984. He is currently a Professor and a Supervisor of postgradu- 
ates at Jiangsu University. His research interests include microbial fermentation intelligent control technology and optimization control of industrial 
processes.

Zhe Yu Jiang received the B.Sc. degree from the University of Electronic Science and Technol- 
ogy of China, Zhongshan Institute, in 2015. He is currently pursuing the M.Sc. degree in electrical and information engineering with Jiangsu University. His main research interests include micro- 
bral fermentation intelligent control technology, along with fermentation equipment and its detec- 
tion technology.
BO WANG received the Ph.D. degree from Jiangsu University in 2010. He is currently a Professor with Jiangsu University. His research interests include soft measurement and optimal control of biochemical reaction processes.

YU JUN HE received the master’s degree from Jiangsu University in 2005. He is currently a Teacher with the China Machinery Industry Suzhou Senior Technical School. His research interests include the control of fermentation processes.

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