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Biomass concentration prediction via an input-weighed model based on artificial neural network and peer-learning cuckoo search

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ABSTRACT

Biomass concentration (BC) is considered as one of the most important biochemical parameters. Its reliable on-line estimation is crucial in the real-time status monitoring and quality control of fermentation processes. Considering that each input variable may have different influence on BC in actual fermentation processes, a novel input-weighted empirical model based on the radial basis function neural network (RBFN) and a new peer-learning cuckoo search (PLCS) algorithm, is proposed in this paper to predict BC. The determination of input variable weights and RBFN parameters for the proposed BC prediction model is framed as one and the same optimization problem. Inspired by a common social phenomenon that the mutual learning between team members (peers) would be extremely helpful for their team to accomplish a work efficiently, a PLCS algorithm is proposed to solve the resulting optimization (RO) problem, and thereby accomplish the development of the proposed BC prediction model. The effectiveness and superiority of this new prediction model is validated using the production data from a lab-scale nosiheptide fermentation process. Moreover, the performance of PLCS is also demonstrated on the RO problem with these data and some benchmark functions.

1. Introduction

Recent decades have witnessed the widespread use of fermentation products in the fields of pharmaceuticals, chemicals, foods, energy resources, and so on [1–4]. Biomass concentration (BC) is one of the most important biochemical parameters, which can reflect the status of fermentation and affect the quality and yield of fermentation products. But it is usually measured offline in the laboratory with an analytical procedure, which is not only costly but also time-consuming (several hours) [5], leading to the risk of sample contamination and bringing difficulties to real-time status monitoring and quality control of fermentation processes. Therefore, the development of an on-line BC prediction model is of considerable practical significance.

Models that can be used for predicting BC are classically developed on the basis of balance equations together with rate equations for microbial growth, substrate consumption, product formation, and so on [6–8]. However, due to the inherent complexity of many fermentation processes, the underlying physicochemical phenomena are seldom fully understood, and the development of mechanistic models is costly, time-consuming and tedious. Therefore, to develop a BC prediction model via mechanistic methods has considerable practical difficulties for most fermentation processes. As a result, empirical methods have been widely employed to develop BC prediction models [9–17]. In empirical modeling, the model is developed exclusively from the historical input–output data without invoking the process phenomenology. Thus, the expensive, time-consuming and tedious search for a suitable mechanistic prediction model can be avoided.

Through observation, it can be found that the above mentioned empirical modeling methods share one common characteristic, which is that they treat all the input variables equally during the course of modeling. However, for actual fermentation processes, each input variable may have different influence on BC. So here, using the feature-weighted idea in classification field for reference [18,19], we propose an input-weighed empirical method to develop the BC prediction model. Artificial neural networks are often employed for empirical modeling of various industrial processes or systems [20–25], due to their powerful nonlinear mapping ability. In this study, we utilize radial basis function neural networks (RBFNs) to develop the empirical BC prediction model, since such neural networks are capable of approximating any continuous function to any prescribed degree of accuracy [26] and have been successfully applied in a number of fermentation processes [10,12,17,27,28]. Furthermore, in this study, the weight of each input variable

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together with the RBFN parameters (i.e., the center and the width of each hidden neuron, the weight of the link between each hidden neuron and the output neuron) of the empirical BC prediction model is to be obtained simultaneously, by framing the determination of their values as one and the same optimization problem.

Cuckoo search (CS) is one of the latest nature-inspired optimization algorithms, initially introduced by Yang and Deb in 2009 [29]. This algorithm is based on the brood parasitic behavior of some cuckoo species in combination with the Lévy flight behavior of some birds and fruit flies. And recent studies have shown that CS is potentially far more efficient than the genetic algorithm (GA), particle swarm optimization (PSO) and some other nature-inspired optimization algorithms [30,31]. This warrants us to try solving the above resulting optimization (RO) problem through CS. In the basic CS (BCS) algorithm, there is no information exchange between individuals (namely cuckoos) and, essentially, the searches are performed independently. To some extent, this would limit the algorithm's search capability. So, here we propose a new peer-learning CS (PLCS) algorithm. To be specific, we propose a peer-learning strategy which allows each individual to learn from an exemplar that is selected randomly among its peers, and introduce this strategy into BCS. The new PLCS algorithm is inspired by the social collective idea that the mutual learning between team members (peers) would be extremely helpful for their team to accomplish a work efficiently. In addition, the roulette wheel selection technique is used to ensure better individual has higher probability to be selected as the exemplar, and thereby provide a more promising search direction. Further, PLCS is employed to solve the RO problem in order to obtain the input variable weights and RBFN parameters of the proposed empirical BC prediction model simultaneously.

The rest of this paper is organized as follows. Section 2 describes the development of the proposed input-weighted BC prediction model based on RBFN and PLCS, named the PLCS-IW-RBFN prediction model, mainly including the basic idea of input-weighted modeling, the new PLCS algorithm, and the implementation of PLCS for solving the optimization problem resulting from the input-weighted modeling. A case study is presented and discussed in Section 3. Finally, Section 4 concludes this paper with a brief discussion on the scope for future studies.

2. Methodology of developing the PLCS-IW-RBFN prediction model

2.1. Input-weighted modeling method based on RBFN

As research continues, we find that the interaction between each process variable and BC is different in actual fermentation processes. On the one hand, the influence of each control variable (e.g., the temperature, pH and dissolved oxygen concentration) on BC is different; to be specific, BC is more sensitive to the changes of some control variables, while relatively insensitive to the changes of others. On another hand, the influence of BC on each display variable (e.g., the contents of oxygen and carbon dioxide in end gas) is also different; to be specific, some display variables are more sensitive to the change of BC, while some others are relatively insensitive. Whereas the input variables needed for developing the BC prediction model are composed of some control and display variables. So it can be concluded that different input variable has different influence on BC.

Just based on the above, and using the feature-weighted idea in classification field for reference [18,19], this paper proposes an input-weighed empirical method and use it to develop the BC prediction model. For this new modeling method, the reasonable selection of the weight of each input variable is the key. Here, we determine them together with other parameters (i.e., the corresponding RBFN parameters) of the empirical BC prediction model simultaneously, as described below.

As is stated in Introduction, this paper uses RBFNs to develop the input-weighed empirical BC prediction model. RBFNs are generally composed of three layers, namely the input, hidden and output layers. The input layer is only used to connect the network to its environment. The neurons in the hidden layer are associated with centers, which are vectors with dimension equal to the number of inputs to the network. The response from a hidden neuron is produced by passing the neuron activity (the Euclidean distance between the input vector and the neuron center) through a radial basis function, such as the Gaussian function [32] which is used in this study. Finally, the output layer is linear and serves as a summation unit. For the proposed input-weighed empirical BC prediction model, weighed values of the input variables are used as inputs to the network (see Fig. 1), and it can be formulated as

$$X = \sum_{k=1}^{hid} \omega_k^{\mathrm{L}} \phi_k(\boldsymbol{v}) \tag{1}$$

where X is BC; hid is the number of hidden neurons; ω_k^{L} is the weight of the link between the kth hidden neuron and the output neuron; $\phi_k(\boldsymbol{v}) = \exp\left(-{}^{1}/_{2\sigma_k^2}\|\boldsymbol{v}-\boldsymbol{c}_k\|^2\right)$ in which $\boldsymbol{c}_k = (c_{k1}, c_{k2}, \cdots, c_{kn})$ and σ_k are the center and the width of the kth hidden neuron, respectively, and $\|\boldsymbol{v}-\boldsymbol{c}_k\|$ denotes the Euclidean distance between $\boldsymbol{v}$ and $\boldsymbol{c}_k$; $\boldsymbol{v} = \boldsymbol{u}\circ\boldsymbol{\omega}^{\mathrm{I}}$ in which $\boldsymbol{u} = (u_1, u_2, \cdots, u_n)$ is the input variable vector, $\boldsymbol{\omega}^{\mathrm{I}} = (\omega_1^{\mathrm{I}}, \omega_2^{\mathrm{I}}, \cdots, \omega_n^{\mathrm{I}})$ is the corresponding weight vector of input variables, and $\circ$ denotes the entry-wise multiplication; and n is the number of input variables.

The development of the above prediction model is essentially the determination of $\boldsymbol{\omega}^{\mathrm{I}} = (\omega_1^{\mathrm{I}}, \omega_2^{\mathrm{I}}, \cdots, \omega_n^{\mathrm{I}})$ and the RBFN parameter vector $\boldsymbol{\theta} = (c_{11}, c_{12}, \cdots, c_{1n}, c_{21}, c_{22}, \cdots, c_{2n}, \cdots\cdots, c_{hid1}, c_{hid2}, \cdots, c_{hid\,n}, \sigma_1, \sigma_2, \cdots, \sigma_{hid}, \omega_1^{\mathrm{L}}, \omega_2^{\mathrm{L}}, \cdots, \omega_{hid}^{\mathrm{L}})$. Assuming that B batches of training data pairs ($\boldsymbol{u}_{bh}$, X_{bh}) (here $b = 1, 2, \cdots, B$ denotes the bth batch of training data; $h = 1, 2, \cdots, H_b$ denotes the hth set of training data pairs and H_b is the total number of training data pairs in batch b) are available, the problem of determining $\boldsymbol{\omega}^{\mathrm{I}}$ and $\boldsymbol{\theta}$ can be formulated as an optimization problem, where an objective function that can reflect the errors between the true outputs (i.e., the measured values of BC X_{bh}) and the model predictions (i.e., the predicted values of BC $\widehat{X}_{bh}$) must be minimized with respect to both $\boldsymbol{\omega}^{\mathrm{I}}$ and $\boldsymbol{\theta}$. Considering that (1) for measurement instruments, which include hardware instruments (e.g., the temperature-measuring thermocouple) and soft instruments (e.g., the proposed BC prediction model), the relative error is an important index for evaluating their measurement precision, and (2) the increase of BC is often ten times or even several dozen times during the fermentation process–in other words, BC can vary in a wide range through the fermentation process from start to finish, this paper accomplishes the development of the above BC prediction model by minimizing the mean relative error as given in Eq. (2), in order that the

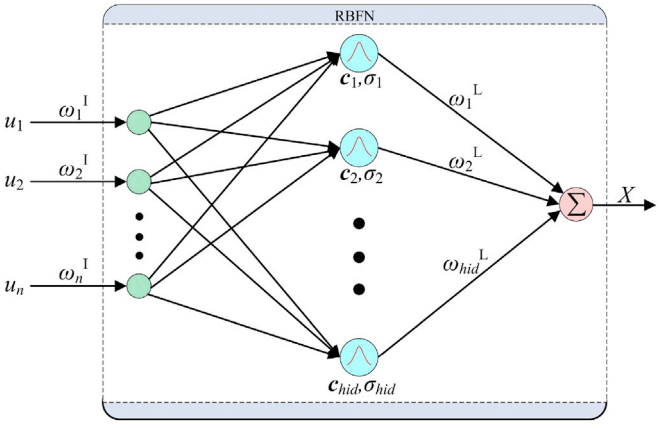

Fig. 1. Schematic representation of the PLCS-IW-RBFN prediction model of BC.