Soft Sensor Model Based on IBA-LSSVM for Photosynthetic Bacteria Fermentation Process

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Abstract: *It is difficult to measure the key biological process variables of photosynthetic bacteria fermentation in real-time, and offline measurement has a large time lag and cannot meet the needs of real-time optimization control. In this paper, a soft sensor model based on least square support vector machine with an improved bat algorithm (IBA-LSSVM) was proposed. The velocity equation of the bat algorithm (BA) was improved and the random variation operation in differential evolution algorithm was introduced into BA algorithm. Thus, the diversity of the population can be increased, and the global and local searching ability of the BA algorithm can be enhanced. Furthermore, the IBA-LSSVM soft sensor model was established for the living cell concentration and compared with BA-LSSVM soft sensor model. Finally, the simulation results show that the improved model was the better learning ability and prediction performance than BA-LSSVM, the measurement error is 0.1358. The improved model could provide accurate guidance for the photosynthetic bacteria fermentation control optimization. This model has certain practical value.*

Keywords: *Process variables, Improved bat algorithm, Least squares support vector machine, Soft sensor model, Photosynthetic bacteria fermentation.*

Introduction

Photosynthetic bacteria are a prokaryotic organism with photosynthesis system, which is widely used in new energy development, environmental protection, breeding, medicine, and so on [6, 11-13, 25]. Photosynthetic bacteria have many functions such as phosphorus removal, denitrification, desulfurization, hydrogen production, oxidation of sulfides, and also have good decomposition and conversion of heavy metals and toxic organic substances. These excellent functional properties are of great value in the treatment of various wastewaters. The bacteria themselves are rich in a variety of high nutritional value substances, which has attracted people's attention. Due to the wide geographical area and a large population in our country, the demand for high-quality photosynthetic bacteria is extremely high. In the actual production fermentation process, to obtain high yield and quality of photosynthetic bacteria, it is necessary to optimize the fermentation process variables. However, the photosynthetic bacteria fermentation is a time-varying, non-linear, multi-variable, and strongly coupled complex process with many influencing factors. For some key biological variables (living cell concentration), it is currently difficult to measure in real-time by using some traditional physical sensors in the process of fermentation. Offline testing has a large time lag and cannot meet the needs of real-time optimization control.

Based on the above problems, this paper establishes a soft sensor model to predict the living cell concentration in the fermentation process of photosynthetic bacteria. Soft-sensing modeling is a new and popular method in the field of monitoring and control in recent years. Its principle is to realize the online estimation of key variables that are difficult to directly measure through easily measurable auxiliary variables and corresponding mathematical models [26, 27]. Generally, in the field of microbial fermentation, the commonly used soft-sensing modeling methods are mechanism modeling, data-driven modeling, and hybrid modeling. Since the fermentation process involves the growth and reproduction of living organisms, it is challenging to establish its accurate mechanism model, so it is more suitable for using data-driven method establishes its soft sensor model. Among the many methods based on data-driven soft measurement, the least square support vector machine (LSSVM) has been widely used due to a series of advantages such as of high fitting accuracy and strong generalization ability [18, 19].

Support vector machine (SVM) is an intelligent learning method. Based on statistical learning theory and the principle of structural risk minimization, it effectively avoids the possibility of neural network problems such as overfitting and local optimization. The LSSVM [2, 8, 20] is an improved version of SVM. Uses the least-squares linear system as the loss function, and replaces the inequality constraints in the SVM with equality constraints, transforming the solution of the quadratic programming problem into the solution of the linear equations. It simplifies the calculation complexity and improves the convergence speed of the algorithm [15, 21]. However, in LSSVM modeling, penalty factor and kernel parameter are hyper-parameters that must be optimized, and their values will directly affect the training and generalization performance of the model. Many scholars have been conducted their research on the selection of parameters, and commonly used parameter optimization techniques include grid search with cross-validation method, gradient descent method, particle swarm optimization (PSO) algorithm, genetic algorithm (GA), and bat algorithm (BA). Among them, the grid search and gradient descent are the earliest techniques of soft sensor model hyper-parameter optimization.

Nevertheless, accuracy and efficiency of these methods are very low and may fall into local optimum so that it is difficult to search the optimal global solutions. Due to the higher accuracy and the capability of finding global optimum solutions, other scholars have used various intelligent algorithms based on Biocomputing to the selection of hyper-parameters in LSSVM. Authors in [26] combine the PSO algorithm with LSSVM in the fermentation process and obtains fermentation prediction curve with small error; in [4] optimize LSSVM model parameters by PSO, improves the function approximation ability of the model, and achieves a good prediction effect; in [1] choose LSSVM model parameters by GA algorithm, which can effectively track variance. The complex non-linear relationship between quantities and predictive variables shows good prediction and generalization ability.

BA is a new intelligent algorithm proposed by Yang [22] based on the predation mechanism of bats. It has the characteristics of the simple model, strong search-ability, and faster convergence speed [23]. At present, it has been commonly employed in the field of motor operation monitoring [22], data mining [7], wind speed prediction [14], and hydroelectric power generation [5]. However, BA algorithm still has the problem of easily falling into a local minimum [10, 24]. To overcome the above issues, this paper improves the speed update formula of BA algorithm. It introduces the mutation mechanism of the differential evolution (DE) algorithm into BA, which enhances the global and local search ability of BA algorithm. Then the IBA was combined to optimize the model parameters of LSSVM, and the

IBA-LSSVM model for the concentration of living bacteria in the fermentation process of photosynthetic bacteria was established. The simulation results demonstrate that the soft sensor model has good generalization ability and prediction accuracy.

Materials and methods

Least square support vector machine

LSSVM is a machine learning method based on statistical learning theory and the principle of minimum structural risk [16]. It transforms the solution of quadratic programming problems of SVM into solving linear equations, which improves the speed, convergence accuracy and is a suitable method with small sample data. Its modeling principle is as follows.

There are l training samples: $\{(x_i, y_i) \mid i = 1, 2, \ldots, l\}$, in which the samples are dimension vectors of n $x_i \in R^n$ is an input and $y_i \in R^n$ is output. LSSVM which approximates the sample data can be expressed as:

$$\min_{\omega,b,\xi} J(\omega,\xi) = \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{g}{2}\sum_{i=1}^{n}\xi_i^2 , \tag{1}$$

$$\text{s.t.} \quad y_i = \omega^{\mathrm{T}}\varphi(x_i) + b + \xi_i, \ (i = 1, 2, ..., l), \tag{2}$$

where ω is weight vector; $g \in R^+$ is penalty parameter; ξ_i is error variable; b is deviation; $\varphi(\cdot)$ is a non-linear mapping, which can map from input space to high-dimensional feature space.

Lagrange method is used to optimize the above problems:

$$L(\omega,b,\xi,\alpha) = \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{g}{2}\sum_{i=1}^{l}\xi_i^2 - \sum_{i=1}^{l}\alpha_i(\omega^{\mathrm{T}}\varphi(x_i) + b + \xi_i - y_i), \tag{3}$$

where α_i is a Lagrange multiplier.

According to KKT condition, the optimization problem can be transformed into solving the linear equation:

$$\begin{bmatrix} 0 & 1_l^{\mathrm{T}} \\ 1_l & K + g^{-1}I_l \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}, \tag{4}$$

where $y = [y_1, y_2, \ldots, y_l]^{\mathrm{T}}$; $1_l = [1, \ldots, 1]^{\mathrm{T}}$; I_l is the unit matrix of order l, $\alpha = [\alpha_1, \ldots, \alpha_l]^{\mathrm{T}}$; K is the Kernel function matrix to satisfy mercer conditions, $K = K(x_i, x_j) = \varphi^{\mathrm{T}}(x_i)\varphi(x_j)$, $i, j = 1, \ldots, l$.

The radial basis function (RBF) is presented as the Kernel function:

$$K = K(x, x_i) = e^{\frac{-\|x - x_i\|^2}{2\sigma^2}} , \tag{5}$$

where σ is the Kernel function width.

Finally, the LSSVM function is estimated as:

$$y(x) = \sum_{i=1}^{l} \alpha_i K(x, x_i) + b. \tag{6}$$

Standard bat algorithm

BA is a non-linear global random search algorithm based on the predator-prey mechanism of bats. The algorithm includes three elements: pulse search frequency, pulse sound intensity and frequency of transmitting pulses.

Assume that the number of bat populations is N, the i bat's speed and position in time is v_i^t, v_i^{t-1}, z_i^t, z_i^{t-1}, z^* respectively, which represent the global optimum position in the current search process, the i Bats' status updates during a global search are as follows:

$$f_{\mathrm{i}} = f_{\min} \times (f_{\max} - f_{\min})\theta, \tag{7}$$

$$v_i^t = v_i^{t-1} + (z_i^t - z^*) f_i, \tag{8}$$

$$z_i^t = z_i^{t-1} + v_i^t, \tag{9}$$

where $\theta \in [0, 1]$ is the random numbers with uniform distribution, $f_i \in [f_{\min}, f_{\max}]$ is the I bat's search pulse frequency.

The local search of bat algorithm is realized by random perturbation, which randomly chooses a solution z_r in the current optimal solution set, and a new local solution z_{new} is generated near it, as shown in Eq. (10):

$$z_{new} = z_r + \mu A^t, \tag{10}$$

where A^t is the average pulse sound intensity of the current bat population; μ is the random numbers uniformly distributed on [-1, 1].

Bat i formula for search pulse frequency and pulse tone intensity update formula is as follows:

$$A_i(t+1) = \beta A_i(t), \tag{11}$$

$$R_i(t+1) = R_0[1 - \exp(-\gamma t)], \tag{12}$$

where R_0 is the maximum pulse frequency of bat population, γ is the frequency increase coefficient, β represents pulse intensity attenuation coefficient, $A_i(t)$ is the pulse intensity of t time, $A_i(t+1)$ is the pulse intensity of $t+1$ time, $R_i(t+1)$ is the pulse frequency of $t+1$ time.

Improved bat algorithm (IBA)

Because the BA algorithm still has the problem of easily falling into local minima on most of the multimodal test functions. Based on the above problem, this paper introduces the mutation mechanism of the DE algorithm and improves the speed update formula of the BA algorithm, which is as follow:

$$v_i^t = qv_i^{t-1} + \lambda_1(z_i^t - z^*) f_i + \lambda_2(z_i^t - z_r) f_i \ , \tag{13}$$

$$\lambda_2 = \frac{M_{\max} - M}{M_{\max}} \tau \ , \tag{14}$$

$$\lambda_1 = 1 - \lambda_2, \tag{15}$$

$$q = \frac{(q_{\max} - q_{\min})(M_{\max} - M)}{M_{\max}} + q_{\min} \ , \tag{16}$$

where M denotes the number of current iterations; $M_{\max}$ is the maximum number of iterations; τ is a real number of [0, 1], as the number of iterations increases, λ_2 decreases linearly, while λ_1 increases linearly $1 - \tau$ to 1, $q_{\max}$ and $q_{\min}$ are the maximum and minimum inertia weights.

The adaptive method makes the algorithm have a strong global search-ability in the early iteration stage; to jump out of local minimum, and in the later stage, local search is dominated by the current global optimal solution. Due to the lack of mutation mechanism in BA algorithm, the mutation mechanism in the DE algorithm is introduced into the BA algorithm to enrich the diversity of the population and enhance the local search ability of the algorithm. Mutation operations are as follows:

$$\eta = e^{1 - M_{\max}/(M_{\max} - M + 1)} \ , \tag{17}$$

$$F = F_0 \times 2^{\eta}, \tag{18}$$

$$z_{new} = z_{r1} + F(z_{r2} - z_{r3}), \tag{19}$$

where η is the mutation operator; F is the scaling factor; F_0 is the initial value of the scaling factor; z_{r1}, z_{r2}, z_{r3}, are three solutions randomly selected from the current local optimal solution set.

In summary, the IBA steps are as follows:

Step 1: initial population number, N; maximum number of iterations, $M_{\max}$; search accuracy, ε; search pulse frequency range, $[f_{\min}, f_{\max}]$; maximum pulse intensity, A; sound intensity attenuation coefficient, β; maximum pulse frequency, R_0; frequency increase coefficient, γ. Coefficients τ, weight range $[q_{\min}, q_{\max}]$ and initial scaling factor F_0 are used to initialize the population speed and position and calculate the fitness of each bat to find the current global optimal solution z^*.

Step 2: Generates a new generation of solution z_i^t based on the Eqs. (7), (9), (13)-(16) and calculates the fitness $f(z_i^t)$.

Step 3: Generate a random number *rand*1 if *rand*1 > R_i, then randomly select a solution in the current optimal solution set, Eq. (10) generate a new local solution z_{new}, and calculate its fitness $f(z_{new})$, if $f(z_{new}) < f(z_i^t)$, then replace the current bat individual's position, if *rand*1 > R_i, then three solutions z_{r1}, z_{r2}, z_{r3}, are randomly selected from the current local optimal solution set, Eqs. (17)-(19) generate a new individual z_{new}, and calculate its fitness $f(z_{new})$, if $f(z_{new}) < f(z_i^t)$, replace the current i^{th} bat individual's position.

Step 4: Generate a random number *rand*2, and if *rand*2 > A_i the updated position bat *i* is better than the current global optimal position, it accepts the new position as the current global optimal position, and the pulse tone intensity R_i, and plus frequency A_i are updated according to Eqs. (11) and (12).

Step 5: When the search accuracy satisfied or the maximum number of iterations is reached, the algorithm ends, and the output results are obtained; otherwise, it returns to Step 2. The *rand*1 and *rand*2 are random numbers uniformly distributed on [0, 1].

Results and discussion

Selection of auxiliary variables

In the process of photosynthetic bacteria fermentation, many potential auxiliary variables affect the key variables, such as light intensity, *E*; air flow rate, *H*; fermentation tank pressure, *p*; fermentation liquid temperature, *T*; fermentation liquid volume, *V*; ammonia flow acceleration rate, *S*; glucose flow acceleration rate, *C*; motor stirring speed, *U*; acidity and alkalinity of fermentation liquid, pH; and other environmental variables.

The accuracy of soft sensor model depends on the reasonable selection of measurable auxiliary variables [3, 9]. Therefore, the consistency correlation method [17] is used to obtain the correlation degree between the parameters and the concentration of live bacteria, and the top five variables with the highest correlation degree are selected as auxiliary variables. Table 1 shows the correlation between the potential auxiliary variables and the key parameters of viable bacteria concentration.

Table 1 shows that the light intensity, fermenter temperature, airflow rate, acceleration rate of glucose flow, acidity and alkalinity of fermentation broth are more closely related to the concentration of live bacteria, so these five variables are selected as auxiliary variables.

Soft-sensing modeling based on IBA-LSSVM

An offline training method was used to construct a soft-sensing model of viable bacteria concentration in photosynthetic bacteria fermentation process based on IBA-LSSVM. IBA was used to optimize the penalty parameters, and the width of the kernel function in the training process, and the best model parameters were obtained. Then the trained soft-sensing model was tested to verify the optimization performance of IBA. The whole software measurement model construction process is shown in Fig. 1.

Table 1. Relevance between environmental and dominant variables

External variables	**Correlation degree**
Fermenter temperature, *T*	0.819
Fermenter pressure, *P*	0.157
Motor agitation speed, *U*	0.231
Fermentation volume, *V*	0.132
Air flow rate, *H*	0.817
Intensity of illumination, *E*	0.951
Glucose flow rate, *C*	0.875
pH	0.796
Ammonia flow rate, *S*	0.525

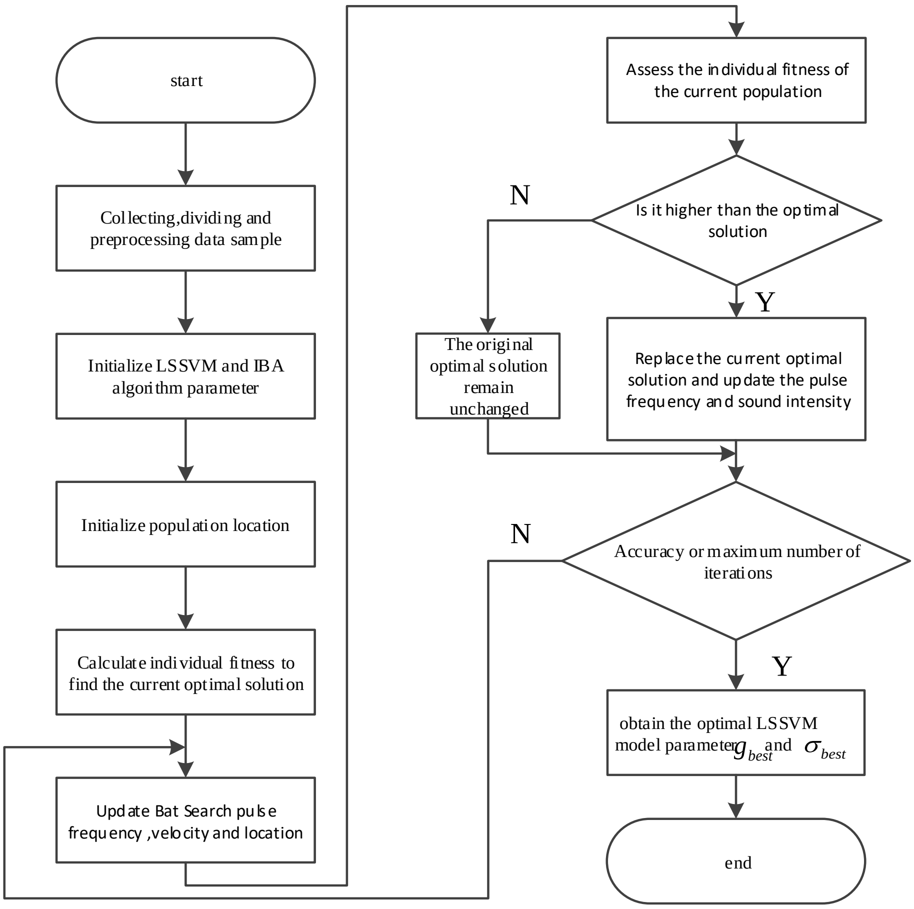

Fig. 1 Flow chart of a soft sensing model for photosynthetic bacteria fermentation

The specific steps of the algorithm are as follows:

(1) Sample data were collected and divided into two parts: training samples and test samples, and preprocessed.

(2) Set the search range of parameters g and σ, and initialize relevant parameters of IBA algorithm.

(3) The bat population is randomly generated, each bat position is composed of g and σ, the training samples are used for training, and the mean square deviation of training samples is taken as the fitness value.
(4) According to the rule of minimum fitness value, IBA algorithm is used to search iteratively and deal with the necessary cross-border processing to preserve the position with the best fitness value.
(5) Determine whether the search accuracy is satisfied or the maximum number of iterations is reached. If it is satisfied, the iteration ends and turns to (6); otherwise, it returns to (4) cycle for iteration.
(6) Selecting the best model parameters g_{best} and σ_{best} with global fitness and establishing LSSVM soft sensing model, the soft sensing model of viable bacteria concentration in photosynthetic bacteria fermentation process based on IBA-LSSVM was finally obtained.

Experimental research

Batch fermentation experiments were carried out according to the fermentation technology of photosynthetic bacteria. After sterilizing the fermentation tank at high temperature, the temperature of the fermentation process is controlled at 25-34 °C, pH is controlled at 6-8, illumination intensity is controlled at 2000-5000 Lux, the stirring speed of the motor is 350-450 $r \cdot min^{-1}$, the tank pressure is 0.04-0.06 MPa, ventilation rate is 0.2-0.6 $V \cdot (V \cdot min)^{-1}$. Acceleration rate of glucose flow was controlled at 0.01-0.015 $g \cdot (L \cdot h)^{-1}$ and the fermentation period was 48 hours. The illumination intensity, temperature, fermentation liquid value and acceleration rate of glucose flow were collected by the digital system every 1 min and then transferred from the lower computer to the upper computer to form a database. Under normal fermentation conditions, the fermentation broth was sampled every 2 h. After centrifugation and washing, the bacteria content was obtained after drying at 105 °C. The data of 10 fermentation batches were collected. Six batches of data (including 480 samples) were taken from the above batches as training samples, two batches (including 120 samples) as validation samples, and the remaining two batches (including 480 samples) as test samples.

In order to verify the feasibility of the above methods for soft-sensing modeling of photosynthetic bacteria fermentation process, IBA-LSSVM soft-sensing method was used to establish a soft-sensing model of viable bacteria concentration in photosynthetic bacteria fermentation process, and standard BA-LSSVM was selected to make a comparative analysis with it. The parameters of the model are as follows: population size N = 50, maximum iteration number $M_{\max} = 300$, search precision ε = 0.05, search pulse frequency range [0, 10], maximum pulse sound intensity A = 0.5, sound intensity attenuation coefficient β = 0.95, maximum pulse frequency R_0 = 0.5, frequency increase coefficient γ = 0.9, τ = 0.6, weight range [0.2, 0.9], initial scaling factor F_0 = 1, g and σ are set as [0.01, 1000]. The prediction results of the soft-sensing model based on IBA-LSSVM and BA-LSSVM are shown in Figs. 2 and 3, respectively.

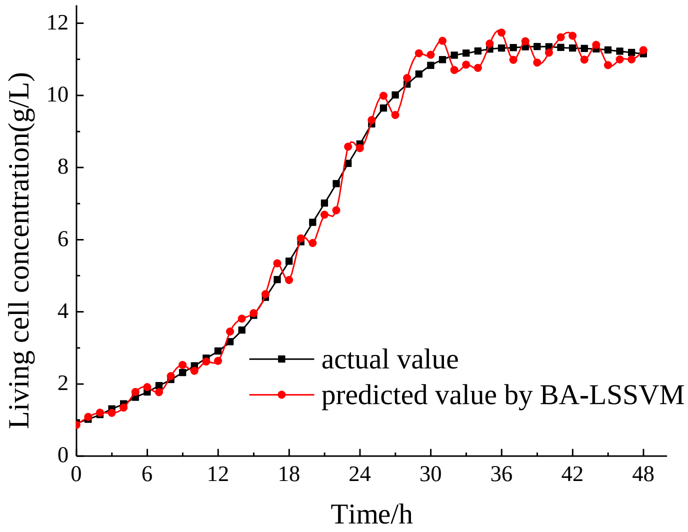

Fig. 2 Soft-sensing results based on BA-LSSVM model

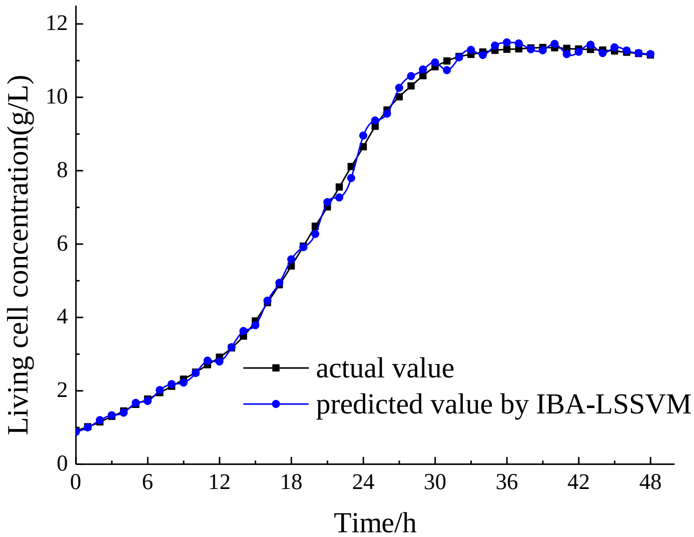

Fig. 3 Soft-sensing results based on IBA-LSSVM model

Comparing Figs. 2 and 3, we can find that the predictive curve of the IBA-LSSVM model in Fig. 3 is closer to the offline test value than that of BA-LSSVM model in Fig. 2. That is to say, the predictive effect of the IBA-LSSVM model is better than that of BA-LSSVM model.

The soft-sensing errors of the two models for the concentration of photosynthetic bacteria are shown in Fig. 4, and the root mean square error (RMSE) and the maximum relative error (MRE) of the two models are calculated as shown in Table 2, so that the prediction performance of the two models can be more intuitively reflected.

It can be seen from Fig. 4 and Table 2 that the soft measurement effect of IBA-LSSVM is better than that of BA-LSSVM, MSE is only 4.1%, which indicates that the prediction accuracy of the model is high. RMRE is 0.1358, which indicates that the model is feasible.

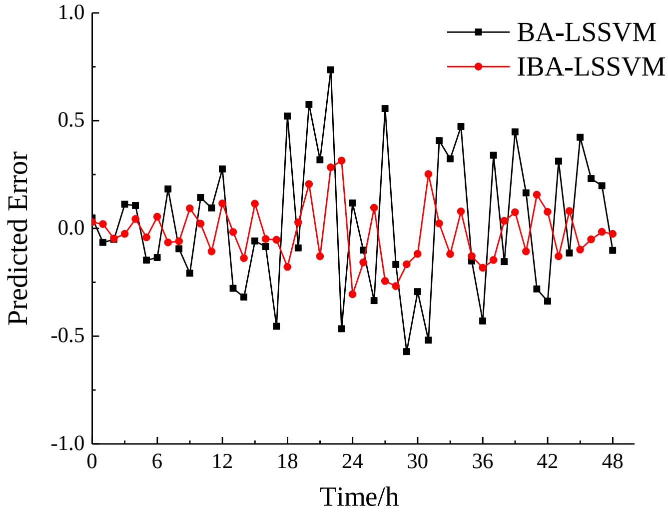

Fig. 4 Soft-sensing error diagram

Table 2. Error comparison of two soft sensor models

Model	**RMSE**	**MRE, (%)**
BA-LSSVM	0.3174	9.7
IBA-LSSVM	0.1358	4.1

Conclusion

The photosynthetic bacteria fermentation process is a complex time-varying, non-linear and strongly coupled process. The living cell concentration in the fermentation process is usually difficult to measure in real-time with traditional physical sensors. A soft sensor model based on IBA-LSSVM is proposed to deal with strong nonlinearity and dynamics of the process. The velocity equation of the BA algorithm was improved, and the random variation operation in the DE algorithm was introduced into BA algorithm. Thus, the diversity of the population can be increased, and the global and local searching ability of the BA algorithm can be enhanced. Furthermore, the IBA-LSSVM soft sensor model was established for the living cell concentration and compared with BA-LSSVM soft sensor model. The simulation results show that the learning ability and prediction performance of the soft sensor is better than those of BA-LSSVM, which provides a feasible measurement method for some industrial parameters that are difficult to be measured in real-time.

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References

1. Ahmadi M. A., M. Lee, A. Bahadori (2015). Prediction of a Solid Desiccant Dehydrator Performance Using Least Squares Support Vector Machines Algorithm, Journal of the Taiwan Institute of Chemical Engineers, 50, 115-122.
2. De Giorgi M. G., S. Campilongo, A. Ficarella, P. M. Congedo (2014). Comparison between Wind Power Prediction Models Based on Wavelet Decomposition with

Least-squares Support Vector Machine (LS-SVM) and Artificial Neural Network (ANN), Energies, 7(8), 5251-5272.
3. Fister Jr. I., D. Fister, I. Fister (2013). Differential Evolution Strategies with Random Forest Regression in the Bat Algorithm, Proceedings of the 15th Annual Conference Companion on Genetic and Evolutionary Computation, 1703-1706.
4. Gorjaei R. G., R. Songolzadeh, M. Torkaman, M. Safari, G. Zargar (2015). A Novel PSO-LSSVM Model for Predicting Liquid Rate of Two Phase Flow through Wellhead Chokes, Journal of Natural Gas Science and Engineering, 24, 228-237.
5. Gupta S., K. Sharma (2016). Optimization of Revenue Generated by Hydro Power Plant by Bat Algorithm (BA), Proceedings of the 3rd International Conference on Computing for Sustainable Global Development (INDIACom), 3576-3580.
6. Hallenbeck P. C., Y. Liu (2016). Recent Advances in Hydrogen Production by Photosynthetic Bacteria, International Journal of Hydrogen Energy, 41(7), 4446-4454.
7. Heraguemi K. E., N. Kamel, H. Drias (2015). Association Rule Mining Based on Bat Algorithm, Journal of Computational and Theoretical Nanoscience, 12(7), 1195-1200.
8. Li M., W. Chen, T. Zhang (2018). A Novel Seizure Diagnostic Model Based on Kernel Density Estimation and Least Squares Support Vector Machine, Biomedical Signal Processing and Control, 41, 233-241.
9. Lin Y., W. Yan (2015). Study of Soft Sensor Modeling Based on Deep Learning, Proceedings of the 2015 American Control Conference (ACC), 5830-5835.
10. Liu Y. (2016). Improved Bat Algorithm for Reliability-redundancy Allocation Problems, International Journal of Security and Its Applications, 10(2), 1-12.
11. Meng F., A. Yang, H. Wang, G. Zhang, X. Li, Y. Zhang, Z. Zou (2018). One-step Treatment and Resource Recovery of High-concentration Non-toxic Organic Wastewater by Photosynthetic Bacteria, Bioresource Technology, 251, 121-127.
12. Qi X., Y. Ren, P. Liang, X. Wang (2018). New Insights in Photosynthetic Microbial Fuel Cell Using Anoxygenic Phototrophic Bacteria, Bioresource Technology, 258, 310-317.
13. Sasaki K., M. Watanabe, Y. Suda, A. Ishizuka, N. Noparatnaraporn (2005). Applications of Photosynthetic Bacteria for Medical Fields, Journal of Bioscience and Bioengineering, 100(5), 481-488.
14. Sun W., M. Liu, Y. Liang (2015). Wind Speed Forecasting Based on FEEMD and LSSVM Optimized by the Bat Algorithm, Energies, 8(7), 6585-6607.
15. Sun Y.-M., N. Du, Q.-Y. Sun, X.-G. Chen, J.-W. Yang (2019). Research and Application of Biological Potency Soft Sensor Modeling Method in the Industrial Fed-batch Chlortetracycline Fermentation Process, Cluster Computing, 22(3), 6019-6030
16. Suykens J. A., J. Vandewalle (1999). Least Squares Support Vector Machine Classifiers, Neural Processing Letters, 9(3), 293-300.
17. Torgashov A., K. Zmeu (2015). Identification of Nonlinear Soft Sensor Models of Industrial Distillation Process under Uncertainty, IFAC-PapersOnLine, 48(28), 45-50.
18. Wang B., M. Shahzad, X. Zhu, K. U. Rehman, M. Ashfaq, M. Abubakar (2020). Soft-sensor Modeling for L-lysine Fermentation Process Based on Hybrid ICS-MLSSVM, Scientific Reports, 10(1), 1-15.
19. Wang B., M. Shahzad, X. Zhu, K. U. Rehman, S. Uddin (2020). A Non-linear Model Predictive Control Based on Grey-wolf Optimization Using Least-square Support Vector Machine for Product Concentration Control in L-lysine Fermentation, Sensors, 20(11), 3335, https://doi.org/10.3390/s20113335.
20. Wang Q., X. Tian (2011). Soft Sensing Based on KPCA and LSSVM, CIESC Journal, 62(10), 2813-2817.

21. Wang X., J. Chen, C. Liu, F. Pan (2010). Hybrid Modeling of Penicillin Fermentation Process Based on Least Square Support Vector Machine, Chemical Engineering Research and Design, 88(4), 415-420.
22. Yang X.-S. (2013). Bat Algorithm: Literature Review and Applications, arXiv preprint, arXiv: 1308.3900.
23. Yang X.-S., A. H. Gandomi (2012). Bat Algorithm: A Novel Approach for Global Engineering Optimization, Engineering Computations, 29(5), 464-483.
24. Yuan Y., X. Wu, P. Wang, X. Yuan (2018). Application of Improved Bat Algorithm in Optimal Power Flow Problem, Applied Intelligence, 48(8), 2304-2314.
25. Zhang J., X. Feng, X. Liu, G. Xie, Q. Fang, H. Luo (2011). Process Optimization of Brewers' Grains Fermentation Using Photosynthetic Bacteria to Make Fish Feed, Transactions of the Chinese Society of Agricultural Engineering, 27(8), 387-392.
26. Zhu X., K. U. Rehman, B. Wang, M. Shahzad (2020). Modern Soft-sensing Modeling Methods for Fermentation Processes, Sensors, 20(6), 1771, https://doi.org/10.3390/s20061771.
27. Zhu X., X. Ji (2014). Soft Sensing of Key State Variables in Fermentation Process Based on Relevance Vector Machine with Hybrid Kernel Function, Sensors & Transducers, 173(6), 237-243.

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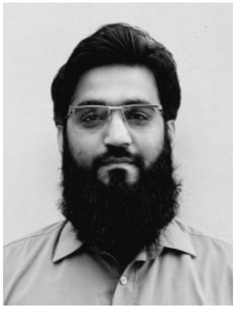

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