An Improved Method of HDP for Optimal Control in Wiped Film Molecular Distillation Systems

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Abstract—For the wiped film molecular distillation system which has the characteristics of multiple parameter, large inertia, large time delay, nonlinearity and others, adjustment it’s parameters mainly bases on human experience. In order to stabilize the production process, Extreme Learning Machine network is used to model the molecular distillation system and proposes heuristic dynamic programming algorithm based on extreme learning machine. For the purpose of verifying the effectiveness of the algorithm, the algorithm is used to control the wiped film molecular distillation system and the optimizing control results show that the heuristic dynamic programming algorithm has good control effect and improves the stability of the molecular distillation process. At the same time, the convergence rate of Heuristic Dynamic Programming based on the Extreme Learning Machine is faster than the Heuristic Dynamic Programming based on the BP network by analyzing experiment result.

Keywords—wiped film molecular distillation; extreme learning machine; heuristic dynamic programming; optimizing control

I. INTRODUCTION

Molecular distillation technology, also known as the short path distillation technology, breaks through the conventional evaporator principle that using the deference of boiling point among the deferent material. And it implements material purification and separated by using the different of different molecular mean free path, which is widely used in the field of pharmaceutical, chemical, medical and other industries [1]. Wiped film molecular distillation is a kind of molecular distillation technology. It makes film and the heating surface having sufficient contact, enhances the effect of evaporation by using high-speed rotating blade installed in the evaporation surface, forms and updates the thin film, when the material enters from the feed inlet into the. The obtained rate and purity of purified product are affected by evaporation temperature, feed flow rate, operating pressure, the speed of the wiped film motor and so on. And because of the coupling among the different parameters, it is difficult to establish an effective model to achieve stable control, which directly affects the separation efficiency and purification of molecular distillation system.

In order to stabilizing and improving the separation effect of wiped film molecular distillation system and reducing energy consumption, domestic and foreign scholars have done a lot of research into the molecular distillation. Cvengros et al who use Boltzmann equations, Navier-Stokes equations and the heat balance relationship to describe the mass transfer in the gas phase process, the film flow process and heat transfer process under gravity and establish corresponding mathematical model. And literature [1] points out that before the material into the evaporation apparatus, it is need to be preheated so that the material temperature closes to heating wall temperature and improves equipment efficiency. Otherwise, when the material enters into the evaporator, the part of the evaporation wall is used to preheat material and reduce the evaporation rate of the evaporator [2, 3]. Batistella et al establish the corresponding mass, energy, momentum, and the evaporation rate equation to describe the transfer process in falling film and centrifugal molecular distillation process [4]. Xu Chang et al establish a three-dimensional model of the evaporator and analyze the influence of the feed rate, rotor speed and viscosity of the material for residence time distribution through using the CFD simulation software which is used to simulate study the residence time distribution of material in wiped film molecular distillation equipment inside [5]. In the literature [6], GA-BP neural network is used to build the model of wiped film molecular distillation system, but it still needs a long time to adjust weights of network and control effect is not ideal because of not considering the multi-parameter coupling. To solve the above optimal control problem, an algorithm of heuristic dynamic programming (HDP) based on extreme learning machine (ELM) is proposed in this paper.

In 1977, Werbos proposed a new optimization method - Heuristic Dynamic Programming concept and then gave its basic structure made up by the action network, the critic network and the model network in 1990 [7, 8]. In 1997, Prokhorov and Wunsch proposed the design method and design procedures based on BP neural network for HDP and DHP [9, 10]. This method is suitable for complex, nonlinear and time-varying environment. Although the HDP consisted by BP neural network can solve the problem of "curse of
dimensionality", but there exists some problem such as training time too long, easy to fall into local optimal solution, over-fitting problems et al. In some highly real-time occasion, its application is limited and its control effect cannot meet the system requirements due to the BP neural network need long time to train its weights. So, the Heuristic Dynamic Programming algorithm based on Extreme Learning Machine (HDP/ELM) is proposed in this paper. The action network, critic network and model network are all formed by ELM.

For optimal control problem of wiped film molecular distillation, its system model established by ELM, and the HDP/ELM is applied to the wiped-film molecular distillation production control in order to achieving optimal control of wiped film molecular distillation. At last, the conclusion will be given by analysis the simulation result.

II. WIPED FILM MOLECULAR DISTILLATION SYSTEM AND ITS MAIN PARAMETERS ANALYSIS

Internal structure of wiped film molecular distillation device is shown in Fig. 1.

![Figure 1. Wiped film molecular distillation structure.](Image 127x384 to 230x500)

As shown on the Fig. 1, rotation axis and roll installed on the rotation axis compose the film scraper. Under the action of centrifugal force, the roll closes to the evaporator surface. And in the roll and the evaporation surface together action, material will form a thin film on the surface of the evaporator when the axis rotates. When the liquid enters enough, it will form the head wave at front of the roller. With the head waves mix with the film formed before, it makes the concentration of the film uniform distribution and the film will be updated. Also, along with the rotation of the roller rotates itself, the head waves of the liquid will be updated, which increases the heat and mass transfer effects. Besides, maintaining the vacuum between the evaporation surface and condensation surface or filled with rare gas can make molecules easier to escape from the film [11, 12]. Therefore, the introduction of wiper rolling speeds up the relative velocity of the molecular movement and improves the efficiency of molecular distillation.

A well purification effect and stable operation system of the molecular distillation is not only associated with the manufacturing process, such as the distance between the geometry of the evaporator space size, the evaporation surface to the condensation surface, condenser type and et al., also related with operating parameters, such as pressure within the evaporator, feed flow rate, evaporator temperature, wiped film motor speed and so on [13]. The process of molecular distillation has the characteristics of multiple variables, nonlinear, and strong coupling. Since the material flow duct is long, and the intermediate container and the inertia parameters are large, the system of molecular distillation also is a large delay system. So far, researchers have not yet established a general mathematical model about the system of molecular distillation.

From the above analysis, the main parameters affecting the effect of molecular distillation evaporation are temperature, evaporation pressure, feed rate and speed of wiped film motor. In order to verify the control effect of HDP/ELM algorithm for complex, nonlinear systems, this paper will take three grades molecular distillation system as the research object, where the parameters of first two grade are fixed, which are used to remove moisture and impurity in crude oil of schisandra. The parameters of the third-grade will be taken as the control variable include evaporation pressure, evaporator temperature, feed speed and wiped film motor speed and the purity and yield of schisandra is used as the state variable.

III. ESTABLISHMENT THE ELM MODEL FOR MOLECULAR DISTILLATION SYSTEM

In 2006, Nanyang Technological University Professor Huang GB proposed feedforward neural network ELM (Extreme learning machine, ELM) concept [14]. This method randomly gives input weights and thresholds of input neurons, and then through regularization principle calculates output weights. Through this method, the neural network is still able to approximate any continuous system. Because of its learning speed improves nearly a thousand times compared with BP, SVM, so it is named as "extreme learning machine."

Since the parameters of molecular distillation system are mutual coupling among the various parameters, as well as a large inertia, large time delay, nonlinear characteristics, which make it difficult to establish their precise and efficient mathematical models. Neural network has abilities of learning, memory, self-organizing and adaptive, which provides a new means for establishment model of molecular distillation. In this paper, the third-grade model of molecular distillation is built by fix ELM. The input weights and hidden layer node thresholds of the fix ELM are randomly generated, and the output weights of the hidden layer are generated through once calculation.

For the different sample \((x_i, t_i)\), where the number of the sample is N, and \(X_i = [x_{i1}, x_{i2}, ..., x_{in}]^T \in R^n, t_i \in R\), the single hidden layer feed-forward network having a hidden layer neurons, can be written as [11]

\[
\sum_{i=1}^{L} \beta_j g(a_j \cdot X_j + b_j) = t_j
\]

\[j=1,2,\cdots,L, b, \beta \in R, a, \beta \in R\]

where \(a_i\) represents the input weights between input layer neurons and the number \(i\) neurons of hidden layer, \(\beta_j\) represents the output weights between the hidden layer neurons and the number \(i\) neurons of output layer, \(b\) represents the
threshold of hidden layer neurons, and \( X_j \cdot a_i \) represents the inner product of \( a_i \) and \( X_j \).

For the standard single hidden layer feed-forward neural network having \( L \) hidden layer neurons, the activation function is \( g(x) \), it can approach input samples from the same continuous system with zero error, i.e.

\[
\sum_{j=1}^{N} \beta_j g(a_i \cdot X_j + b_i) = t_j
\]

(2)

where, \( j = 1,2,\ldots,N \) is the number of sample. Also, the above equation can be rewritten as follows

\[
H\beta = T
\]

(3)

\[
H(a_1,\cdots,a_N,b_1,\cdots,b_N,X_1,\cdots,X_L) = \begin{bmatrix}
  g(a_1 \cdot X_1 + b_1) & \ldots & g(a_L \cdot X_L + b_L)
\end{bmatrix}
\]

(4)

\[
\beta = \frac{1}{L} \beta_{1}^{T} \Lambda
\]

(5)

where \( H \) is called the output matrix of hidden layer neural network [15]. Therefore, the training of ELM is equivalent to find the value of \( \hat{\beta} \), which is the least squares solutions of linear systems \( H\beta = T \). It can be written as

\[
\| H(a_1,\cdots,a_L,b_1,\cdots,b_L) \hat{\beta} - T \| = \min_{\beta} \| H(a_1,\cdots,a_L,b_1,\cdots,b_L)\beta - T \|
\]

(6)

Huang has been demonstrated that the least squares solution of above linear systems contain the characteristics of minimum training error, the minimum weight, the best generalization ability and uniqueness [15]. The process of building the neural network modeling molecular distillation system can be summarized as the following steps:

- Determine the number of input and output, which are the number of input layer neurons in the output layer. According to the last paragraph of part 2, the input number 4 and the output number are 2.

- Determine the neurons number of hidden layer. The number of hidden nodes depends on the number of training samples the size of the noise and the complexity of laws contained in the sample. In this paper, the number of the hidden layer is determined by cut-and-trial method and the final number is 8.

- Generate the input weights \( a_i \) and hidden layer node threshold \( b_i \) by the method of random generated, where \( i = 1,2,\ldots,N \).

- Calculate the hidden layer output matrix \( H \).

- Calculate the output weights \( \hat{\beta} \).

Finally, the structure of ELM is 4-8-2, and set the hidden layer activation function is symmetric Sigmoid function.

The trained model of ELM has a very good prediction and generalization ability, as shown in Fig. 2.

![Figure 2. Generalization ability test of ELM.](image)

Analyzing the simulation results, the molecular distillation model based on ELM can accurately predict the next time output when the input set of molecular distillation system is given. The error between forecast and real output is shown as Fig. 3. According to the simulation results, the absolute error is very smell that approximate equals a thousandth, which meet s the need of the train goal.

![Figure 3. Error of forecast output and actual output.](image)

**IV. THE PRINCIPLE OF HDP**

Optimal control variable of the HDP is obtained by calculating the optimal performance function. When the dimension of the state variable and the control variable are large, solving optimal control variable about the dynamic programming will emerge the problem of "curse of dimensionality" due to the rapid growth of the amount of calculation and the storage. Using the function to approximate the performance index function and control strategies, in order to meeting the principle of optimality, obtaining optimal control variable and getting optimal performance, HDP can effectively avoid the "curse of dimensionality" appearance.

For discrete-time nonlinear dynamic systems, it can be expressed as

\[
\begin{align*}
\sum_{j=1}^{N} \beta_j g(a_i \cdot X_j + b_i) &= t_j \\
H\beta &= T \\
H(a_1,\cdots,a_N,b_1,\cdots,b_N,X_1,\cdots,X_L) &= \begin{bmatrix}
  g(a_1 \cdot X_1 + b_1) & \ldots & g(a_L \cdot X_L + b_L)
\end{bmatrix} \\
\beta &= \frac{1}{L} \beta_{1}^{T} \Lambda \\
\| H(a_1,\cdots,a_L,b_1,\cdots,b_L) \hat{\beta} - T \| &= \min_{\beta} \| H(a_1,\cdots,a_L,b_1,\cdots,b_L)\beta - T \|
\end{align*}
\]
\[ x(k+1) = F[x(k),u(k),k] \quad (k = 0,1,...) \]  
(7)

where \( x(k) \in R^n \) is state variable, \( u(k) \in R^n \) is control variable, and \( F \) is the function of system.

The performance index function corresponding to the system (also known as cost function) is

\[ J[x(k),k] = \sum_{i=1}^{\infty} \gamma^{i-k} U[x(i),u(i),i] \]  
(8)

where \( U \) is named as utility function, \( \gamma \) is discount factor and \( 0 < \gamma \leq 1 \), and \( J \) is the cost function of \( x(k) \) at time of \( k \).

HDP is a kind of adaptive programming and the structure is shown as Fig. 4.

![Figure 4. The structure of HDP.](image)

The network of action, model, and critic are implemented by neural networks. Network model is used to predict the next state of the controlled object. The output of the critic network \( \hat{J} \) is an estimated value of (8), which can be realized by minimized error over time. That can be written as

\[ ||E_i|| = \sum_k E_i(k) \]  
(9)

If the \( E_i(k) = 0 \) for all the times of \( k \), then the (9) can be written as

\[ J(k) = U(k) + \gamma J(k+1) \]  
(10)

\[ = U(k) + \gamma [U(k+1) + \gamma J(k+2)] \]

\[ = \sum_{i=1}^{\infty} \gamma^{i-k} U(i) \]

The function defined in (8) and (10) are same, so an accurate critic network can be obtained through the principle of minimizing. Goal of training the action network is to produce optimal control signal \( u(k) \), which makes the value of \( \hat{J}(k) \) minimizing [16].

V. ACHIEVEMENT OF HDP CONTROLLER BASED ON ELM

According to the input and output characteristics of the molecular distillation system, network structure of action, critic, and model are 2—14—4, 2—4—1, 6—20—2 respectively. All the hidden layer neuron activation functions are bipolar transfer functions, and the output layers function are linear function.

To facilitate the derivation, make the following definition: at times \( k \), \( u(k) \) is the system inputs and it has \( m \) components; \( x(k) \) is the system output at times \( k-1 \), and it has \( n \) components; matrices \( A \) and \( B \) are respective 2 and 4 unit matrix.

A. The Implementation of Model Network

The training of model network is off-line. First, generate the input weights \( w_{ml} \) and threshold of hidden layer node \( h_i \), where \( i \) equals the number of hidden node.

Then, define the input and output matrices \( M(k) \) and \( T(k) \) at times of \( k \).

\[ M(k) = [u_1(k),u_2(k),...,u_m(k),x_1(k),x_2(k),...,x_n(k)] \]  
\[ T(k) = x_1(k),x_2(k),...,x_n(k) \]

Next, calculate the output matrix of hidden layer \( H \).

\[ H = M(k) \ast w_{ml} + h_i \]  
(11)

Finally, calculate the output weight of model network \( \beta \).

According to the (3), \( \beta \) is the least squares solutions \( \tilde{\beta} \).

\[ ||H \ast \beta - T|| = \min_\beta ||H \ast \beta - T|| \]  
(12)

Model network structure is shown as Fig. 5.

![Figure 5. The structure of model network.](image)

B. The Implementation of Critic Network

Firstly, randomly generate the input weights \( w_{c1} \), output weights \( w_{c2} \) and hidden layer node threshold of critic network \( c_i \), where \( i \) equals the hidden node number of critic network.

Then calculate the output matrix of hidden layer \( H_c(k+1) \) and evaluation index \( J(k+1) \) according to output of model network \( x(k+1) \).

\[ h_i(k+1) = x(k+1) \ast w_{c1} + c_i \]  
(13)

\[ H_c(k+1) = \frac{1 - e^{-c_i(x(k+1))}}{1 + e^{-c_i(x(k+1))}} \]  
(14)

\[ J(k+1) = H_c(k+1) \ast w_{c2} \]  
(15)

Next, calculate the evaluation index \( J(k) \) and performance \( U(k) \).

\[ U(k) = x \ast A \ast x' + u \ast B \ast u' \]  
(16)

\[ J(k) = \gamma J(k+1) + U(k) \]  
(17)

Then calculate the hidden layer output \( H_c(k) \).

\[ H_c(k) = x(k) \ast w_{c1} \]  
(18)

Finally, solve the output weights \( w_{c2} \), according to the equation \( H_c(k) \ast w_{c2} = J(k) \), i.e.

\[ ||H_c(k) \ast w_{c2} - J(k)|| = \min_\beta ||H \ast \beta - T|| \]  
(19)

2016 Prognostics and System Health Management Conference (PHM-Chengdu)
C. The implementation of action network

First, calculate the value of \( \hat{J}(k+1) \) and \( J(k) \) according to the new weights \( wc1, wc2 \).

\[
\hat{J}(k+1) = H\gamma (k+1) * wc \ 22
\]
\[J(k) = \gamma * J(k+1) + U(k)
\]

Then randomly generate the weight value \( wa1 \), calculate the hidden layer output \( H_a(k) \) and the output of action network output \( u \).

\[
h_a(k) = x(k) * wa1
\]
\[
H_a(k) = \frac{1 - e^{k_x(k)}}{1 + e^{k_x(k)}}
\]
\[
u = H_a(k) * wa2
\]

According to the thinking of adjusting the ELM’s output weights, the output weights of the action network can be expressed as

\[
wa2 = H^{-1}_a(k) * \tilde{\nu}
\]

Where \( \tilde{\nu} \) is the desired output of the action network, which makes the value of the \( J(k) \) minimum. Thus, if the \( \tilde{\nu} \) is obtained, the value of \( wa2 \) will be obtained.

Then, the inverse function of sigmoid is defined as \( g(\bullet) \). The steps to solve the value \( \tilde{\nu} \) are as follows

\[
A = [\hat{J}(k+1) + U(k)] * wc \ 22^{-1}
\]
\[
B = g(A) * w_{c1}^{-1} * wm \ 2^{-1}
\]
\[
\frac{um}{} = \begin{bmatrix} u(k) \\ x(k) \end{bmatrix} = g(B) * wm \ 1^{-1}
\]
\[
\tilde{\nu}(k) = um(1:m,\cdot)
\]

where \( um(1:m,\cdot) \) expresses the first \( m \) rows of the matrix \( um \).

Therefore, combined the (25) and (29), the estimated value of the output weights \( wa2 \) can be obtained, which is written as \( wa2 \).

So, when having a trained model network, the steps to implement the HDP controller based on ELM are as follows

Step 1: Initializing the action and critic network weights \( wa1, wa2, wc1, wc2 \) and discount factor \( \gamma \).

Step 2: Taking \( x(k) \) into the action network, \( u(k) \) will be obtained. And putting the matrix \([u(k) \ x(k)]\) into the model network, \( x(k+1) \) will be obtained.

Step 3: Taking \( x(k+1) \) into the critic network, \( J(k+1) \) will be obtained.

Step 4: According to step 2 and step 3, calculating \( J(k) \) and solving the output weights of \( wc2 \), where

\[
J(k) = \gamma * J(k+1) + U(k)
\]

Step 5: Making \( wc2 = wc2 \), and calculating \( J(k+1) \) and \( J(k) \).

Step 6: Calculating \( \tilde{\nu}(k) \), solving the output weight \( wa2 \) and making \( wa2 = wa2 \).

Step 7: Judgment whether the training times is reaching, if reaching, skips to step 8, otherwise jumps to step 2.

Step 8: Ending training.

VI. SIMULATION AND ANALYSIS

The simulation results are shown as Fig. 6 to Fig. 10. The simulation results show that HDP controller based on ELM can achieve effective control for molecular distillation systems.
According to the Fig. 6 to Fig. 10, all the control variable and state variable are at a reasonable range. Besides, evaporation temperature, feed rate, the wiped film motor speed and operating pressure are stable after six steps, which is beneficially stable the produce process of molecular distillation system. From the simulation results, when the yield and purity of molecular distillation system is stable at a reasonable range, compared the control variable value obtained by ELM/HDP with manually setting, the value of control variable is smaller, which means small energy consumption. And the time required for stable control variable is greatly shortened than the time for manual adjustment.

To convenience compare the control effect about the algorithm HDP based on ELM with HDP based on BP network, the simulation result yield of schisandra and purify of schisandra about HDP based on BP network are given as Fig. 11.

Comparing the Fig. 6 with Fig. 11, it can be found that the control effect of ELM/HDP is better than the algorithm HDP which is implemented by BP network. According to the simulation result, the both stable value of Fig.6 is larger than the Fig. 11, which means the ELM can find better neural network weight than the BP network. Besides, Fig.6 only needs six steps to arrive at stability and the Fig.11 needs fifteen steps.

VII. CONCLUSION

In this paper, for problem of the molecular distillation system parameters adjustment dependent on experience, the ELM prediction model for molecular distillation system is set up and the HDP control algorithm based on ELM is proposed. The method achieves effectively control for molecular distillation system, and its main parameters are controlled within a range of process requirements, which improve the stability of molecular distillation process.

In this paper, three works is finished. First, ELM is used to build the third grade model of the molecular distillation system. Second, the algorithm HDP based on BP network has been improved, which using the ELM replaces the BP network to implement the HDP. Third, the improved algorithm HDP is used in the file of the molecular distillation and achieves well simulation result.

REFERENCES

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