Intelligent Fuzzy Predictive Controller Design for Multivariable Process System

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Abstract

Based on the Alopex evolutionary optimization algorithm with constrained T-S model, this paper presents an intelligent fuzzy predictive controller to solve the control difficulties of industry process with multi-variables. The T-S model is firstly established for nonlinear multivariable systems and its sequence parameters of fuzzy rules are identified by local recursive least square method. Then the generalized predictive control can be adopted to realize the nonlinear multivariable system adaptive predictive control. The application on cement rotary kiln control was discussed in detail as an example. The rotary kiln calcination is the most important part of cement production including complicated physical and chemical reaction processes with large inertia, pure hysteresis, nonlinearity and strong coupling characteristics and multi-variables. The main control system structure includes three control loops as the pressure control loop, the burning zone control loop and the back-end of kiln temperature control loop. The simulation results show the effectiveness of the optimization and control schemes with satisfied performance on response time.

Keywords: Cement Rotary Kiln; Fuzzy Predictive Control; Alopex; Multivariable System

1. Introduction

In modern industrial process control, the plant usually has the characteristics of many complex variables, serious nonlinear, strong inertia, time-delay, distributed parameters, time-varying and classes of interferences. The fuzzy model is fit for application in the modeling, identification and predictive control of nonlinear systems. Based on T-S model, fuzzy generalized predictive control of constrained nonlinear programming problem is usually planning problem, the traditional nonlinear optimization algorithms (such as quadratic programming) on the initial sensitive calculations and can not effectively find the global optimal solution [1-3]. The key problem for solving in the optimization is to avoid falling into local minimum, improve the convergence speed. Thus, new optimization techniques are used to solve the constrained problem. In this paper, the intelligent optimization algorithm of Alopex is introduced to the constrained T-S model based fuzzy predictive control solving process and its application to multivariable process system. Simulation studies show the effectiveness of the scheme.

In practice, a majority of systems are multivariable and their inputs and outputs are often cross-couple strongly. Although multivariable GPC algorithms have controlled these systems effectively, it is difficult to tune the parameters of the controller to achieve desired control performance. In order to control...
multivariable system better, it is advisable to study proper predictive control methods. Some constrained predictive controllers have been designed, but they all can not attain the desired performance. The evolutionary algorithm is a kind of basic computation method based on the natural evolution process. Compared with the traditional conjugate gradient method, exhaust algorithm, it is a global optimization method with high robustness and widely application. Evolutionary algorithm is with self-organizing, adaptive, self-learning specialties, and can not be limited by the nature of the problem, which can effectively solve complex optimization problems the traditional optimization methods with difficulties. The evolutionary algorithms developed rapidly in recent years are genetic algorithm, PSO algorithm, differential evolution operator method etc. There are many researchers carried out extensive research and various improvements. This paper focuses on the Alopex based improvement for PSO and used for multivariable system.

Automatic control of cement kiln has been paid much attention up to now. In the process of cement production, the rotary kiln calcination is the most important technology link which includes complicated physical and chemical reaction process with large inertia, pure hysteresis, nonlinearity, time-varying, distributed parameters and strong coupling characteristics. It is hard to derive the exact mathematical model and can not reach satisfied results with conventional control algorithms [4-8]. Now, the cement rotary kilns are mainly controlled manually or semi-automatically, which is based on the experience of operators to attain acceptable performances with low production rate. The most used forms of advanced cement kiln automation are made of fuzzy logic and expert systems with the past twenty years. Recent years, there are some partly successful reports on trying other control strategies such as model predictive control. This paper presents the application of fuzzy predictive control based on the Alopex evolutionary optimization algorithm to implement the monitoring, analysis and optimization based on the field bus technology to the conventional cement production defects.

2. Control Algorithm Design

Generalized predictive control (GPC) has been successfully applied to the industrial processes. However, there are usually physical constraints on the input variables, so the research for input-constraint GPC is very meaningful [9-12]. The conventional nonlinear planning methods are with the problems of high computation load along with the number of constraint conditions by exponential law. T-S fuzzy model has the ability of enough approximation to nonlinear functions in essence, and the frequent item sets can thus be expressed by linear equations which is easy for application of common control strategies.

2.1. Intelligent Fuzzy Predictive Control Algorithm

For the \( p \times p \) system, the T-S fuzzy system can be approximated. Suppose the \( i \) th rules of T-S model can be written as [2]:

\[
R^i: \text{if } x_1 \text{ is } A_{i1} \text{ and } \ldots \text{ and } x_m \text{ is } A_{im}, \text{ then }
\]

\[
y^i = p_0^i + p_1^i x_1 + p_2^i x_2 + \ldots + p_m^i x_m
\] (1)
where \( x_i = y_1(k-1), \ldots, x_p = y_p(k-v), x_{i+1} = y_2(k-1), \ldots, x_{p+v} = y_2(k-v), \ldots, \)

\( x_{(p-1)v+1} = y_p(k-1), \ldots, x_{pv} = y_p(k-v), x_{pv+1} = u_1'(k-1), \ldots, x_{m} = u_p'(k-l), \ m = p(v+l), \)

\( u_p'(k-l) \) denotes the \( p \)th input component value of \( k-l \) time, \( \{y_i\} \) and \( \{u_i\} \) are the input and output variables of object, \( p_j = [p_{j1} \ p_{j2} \ldots p_{jm}] \) \((j=0,1,\ldots,m)\) is the \( p \)th dimensional column vector, \( A_{ji} \) is the fuzzy set of corresponding variables.

To a given generalized input vector \( (x_{10} x_{20} \ldots x_{n0}) \), the output of T-S fuzzy model on the \( k \) time is the weighted mean value of equation (1) \( y^i(i=1,2,\ldots,n) \) as

\[
y(k) = \sum_{i=1}^{n} \gamma^i y^i, \ \gamma^i = \mu_i \left( \sum_{i=1}^{n} \mu_i \right)^{-1}
\]

(2)

where the weighted coefficient \( \mu_i = \prod_{j=1}^{m} A_{ji}(x_{j0}) \), \( \prod \) is the fuzzy operator, usually is minimax or product calculation.

T-S fuzzy model uses linear equations to describe and is a nonlinear model in essence. First it gets the final output value, deriving the center of the fuzzy clustering, and then the control parameters of T-S model can be identified, finally the predictive control based on T-S model can be performed. Based on the results of identification, the expressions of system model can be developed. The input-output relations model can be written as

\[
A_k(z^{-1})y(k) = B(z^{-1})u(k-1) + C_k
\]

(3)

\( A, B, C \) are all related with \( k \). Where

\[
\begin{cases}
A_k(z^{-1}) = 1 + a_1(k)z^{-1} + \ldots + a_m(k)z^{-nv} \\
B_k(z^{-1}) = b_0(k) + b_1(k)z^{-1} + \ldots + b_m(k)z^{-nu}
\end{cases}
\]

(4)

\[
\begin{align*}
a_i(k) &= -\sum_{j=1}^{i} \theta_{ij} \beta_{ij}^i, i = 1,2,\ldots,nv \\
b_i(k) &= \sum_{j=i}^{i+nu} \theta_{ij} \beta_{ij}^i, i = 0,1,\ldots,nu \\
C_i &= \sum_{j=1}^{i} \theta_{ij} \beta_{ij}^i
\end{align*}
\]

(5)

Based on model (3), the generalized predictive control (GPC) is applied.

Under the conditions of constraints, the control algorithm optimization problem can be shown as
2.2. Alopex Algorithm for Optimization

Alopex is a kind of algorithm with combination of innovative and random optimization. It changes from the previous argument the impact of the objective function and be inspired, with the process control parameters to control the direction of travel of the probability of use of “noise” to get rid of local optimum, the algorithm has some climbing ability. It is not only to some extent overcomes the traditional heuristic operator’s shortcomings of easily trapped into local minima, but also overcome the insufficient of simulated annealing algorithm from completely random search to gradient search very slow convergence. It does not require the objective function differentiable, and can guarantee the solution obtained to meet a given accuracy with the main features of rapid search capability.

For a practical optimization problem, it can usually be transformed into solving an object function \( F(x_1, x_2, ..., x_N) \) general extreme value, where \( x_1, x_2, ..., x_N \) are the independent variable to be determined. The Alopex algorithm can be written as

\[
x_i(t) = x_i(t-1) + \delta_i(t)
\]

\[
\delta_i(t) = \begin{cases} 
\delta & \text{probability } p_i(t) \\
-\delta & \text{probability } 1 - p_i(t) 
\end{cases}
\]

\[
p_i(t) = \frac{1}{1 + e^{[\Delta_i(t) - \mathcal{T}]}}
\]

\[
\Delta_i(t) = [x_i(t-1) - x_i(t-2)] \times [F(t-1) - F(t-2)]
\]

where \( F(x_1, x_2, ..., x_N) \) is the objective function, \( x_i(t) \) is the \( i \)th independent variable value on the time of \( t \), \( \delta_i(t) \) is the random step length of variable \( x_i \) on the time of \( t \), \( p_i(t) \) is the probability of \( t \) time along with the direction of \( \delta \) increasing. The positive and negative sign are depended on the practical problem, with the positive sign making \( F \) minimizing and negative sign making \( F \) maximizing. \( F(t-1) \), \( F(t-2) \) are the values of \( F \) on the time of \( t-1 \) and \( t-2 \).

When applying Alopex algorithm to a certain problem, the parameter \( \delta \) and \( \mathcal{T} \) in (1)-(4) should be determined. \( \delta \) is depended on the range of variable with usually taken as one percent of dynamics variable space or less.

Alopex algorithm in the iteration process, each independent variable not only changes to the positive, but also to a certain degree of probability to the reverse direction, with purpose of making the algorithm out of
local optimum. From the test it can be learn that in order to get global optimal solution, the change of variable step forward should be smaller to avoid the step is too large to miss the global optimum. And the reverse step size should be large, because the purpose of the reverse change in the objective function is to get rid of local optimal value. If the reverse step is too small, the probability of the objective functions out of local optimum will not be large, this may lead to the objective function in swing back and forth on one side and can not jump out of the local optimum value or even those who can jump out of local optimal values, but requires several iterations, resulting in income convergence speed decreases. So the improvements for this algorithm are needed.

2.3. Alopex Based Evolutionary Optimization Algorithm

PSO algorithm is established from the 2D space model to the graphical movement of the flock. The birds are abstracted for particles without quality and volume and extended to N-dimensional space. The location of the particle can be expressed as a vector \( X_i = (x_{i1}, x_{i2}, ..., x_{in}) \), and the flight speed is expressed as a vector \( V_i = (v_{i1}, v_{i2}, ..., v_{in}) \). Each particle has a fitness value and knows that they found so far the best position (pbest) and the present position \( X_i \). This can be taken as self-flying experience. In addition, each particle is also aware of the found best positions (gbest) of all particles of the group (gbest is the best value of pbest). This can also be taken as peer particles’ experience. The next step movement is decided on the best experience of own and companions.

To the \( k \)th iteration, the particle of PSO changes as following mode:

\[
\begin{align*}
\text{v}_{id}^{k+1} &= w \times \text{v}_{id}^k + c_1 \times \text{rand}() \times (p_{id} - x_{id}^k) + c_2 \times \text{rand}() \times (p_{gd} - x_{id}^k) \\
\text{x}_{id}^{k+1} &= \text{x}_{id}^k + \text{v}_{id}^{k+1}
\end{align*}
\]

where \( i = 1,2, ..., M \), \( M \) is the total number of the swarm, \( \text{v}_{id}^k \) denotes the \( d \)th element of flying speed vector of the \( k \)th iteration particle \( i \). \( x_{id}^k \) is the \( d \)th element of position vector of the \( k \)th iteration particle \( i \). \( p_{id} \) is the \( d \)th element of the best position pbest of particle \( i \). \( p_{gd} \) is the \( d \)th element the best position of swarm gbest. \( c_1 \) and \( c_2 \) are the weighted factors. \( \text{rand}() \) is the random function, producing random number between \([0,1]\). \( w \) is the inertia weighted function.

The basic PSO algorithm has the advantage of less parameter to be determined for the user with simple operation. The disadvantages lie in the its easily fall into local minimum and the searching precision is relatively low. It is necessary to improve this algorithm.

Based on the presented Alopex algorithm, the combination with the evolutionary optimization algorithm can be performed. The algorithm using real number coding for calculation, the calculation steps are: randomly select two individuals \( x_1 \) and \( x_2 \), assume that two individuals as \((t - 2)\) and \((t - 1)\) times
vectors, then the probability of further iteration direction can be derived by the differences of these two vectors and with the objective function. Once the direction is determined, some steps should be added or lessened to derive the new individual. Comparing the new and original individuals, if the performance is enhanced, the original one should be replaced, or preserving the original one.

The whole algorithm has the characteristics of simple process, randomness and parallelism using the advantages of evolutionary algorithm and Alopex. The detailed process can be shown as

**Step1.** Initialize the particle swarm, the individuals are scattered into the solution space, then calculate the objective function value, giving the initial temperature $T$.

**Step2.** Two individuals are randomly selected among the swarm; calculate the differences between the two individual vectors and product of the objective functions.

**Step3.** Calculate the probability vector $p$ according to equation (9).

**Step4.** According to equation (8), determine the running direction of individual $x_1$, update every variables of $x_1$, using evaluation function to compute the objective function value by its position in the solution space.

**Step5.** Compare the changing of vector $x_1$, if the improvement is derived, the new individual $x_1$ is used for replacing the original one.

**Step6.** Updating the temperature $T$ with certain rules, the iteration number adds 1.

**Step7.** When the finish condition is satisfied, the global optimal value can be outputted. The computation process ceased or returns to **Step2**.

### 3. Application for Cement Rotary Kiln Multivariable Process Control

To test the effectiveness of the presented method, an example of multivariable system is adopted and simulated. Cement rotary kiln thermal system decides the production, quality and energy consumption. There are several factors impact the thermal system of rotary kiln, including the rotation speed, the feed volume of coal, the feed volume of raw material and inner pressure of rotary kiln. When the kiln rotation speed increases, the temperature drops slightly and usually the speed is kept constantly. When the feed volume of coal increases, the reaction of decomposition furnace can be exacerbated to make the temperature higher; and when the feed volume of raw material increases, the reaction material in the kiln is added to make the temperature higher. But when the temperature increases to a certain value, since the material can not get a fully reaction, the temperature of inner kiln drops. So the input volume of inner kiln material should be in a certain proportional relationship with the feed volume of coal to make them in a fully reaction state. The feed volume of coal and raw material are controlled by the speed of coal feed motor and raw material motor respectively. The rotary kiln should be remaining a micro-negative pressure state, because in the positive pressure state, the ventilation is poor and the fuel can not be burned completely; in the large negative pressure state, the fast ventilation will take away the heat. The inner pressure of kiln is controlled by the speed of flue blower. The whole system can be shown as figure 1.

Figure 2 denotes the control system of cement rotary kiln. The control links contain the burning zone temperature (feed volume of coal control), back-end of kiln temperature (feed volume of raw material control), and the inner pressure (blower speed control) three parts. The control system contains A/D, D/A converter and I/O modules together with a number of sensors or transformers. There are three control loops
in the system, which are the pressure control loop, burning zone control loop and back-end of kiln temperature control loop. The advanced control algorithm is implemented by the IPC of the highest level in the system.

In the previous section, Alopex based evolution method and fuzzy predictive controller for the multivariable system such as rotary cement kiln has been developed. In this section, it is tested on the simulation model. Choosing 8 fuzzy rules, using given signals as input signals for tracking. Based on the above training data of real system, 1000 sets data points are used for fuzzy rules construction and modeling process as shown in Table 1.

In the control simulation, the controlled object deal with quantization (normalization), the back-end temperature of the kiln is $0^\circ C \sim 600^\circ C$, corresponding to 0~1, with sampling period of $T=2ms$; the burning zone temperature is $0^\circ C \sim 1400^\circ C$, corresponding to 0~1, with sampling period of $T=2ms$; the inner pressure $0P \sim 20000P$, corresponding to 0~1, with sampling period of $T=2ms$. In the condition, the initial step response is $T_1=[t_1(k),t_2(k),t_3(k)]^T=[0.92,0.5,0.81]^T$ as the given signals. The response curves of the system can be shown as figure 3.
Table 1 Some Parameters Data of Real Cement Rotary Kiln

<table>
<thead>
<tr>
<th>NO.</th>
<th>Wind Speed (m/s)</th>
<th>Rotation speed of coal motor (r/m)</th>
<th>Burning zone temperature (°C)</th>
<th>Raw material motor speed (r/m)</th>
<th>Back-end of kiln temperature (°C)</th>
<th>Kiln rotation speed(r/m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24.13</td>
<td>643.15</td>
<td>1378.23</td>
<td>1234.61</td>
<td>670.12</td>
<td>464</td>
</tr>
<tr>
<td>2</td>
<td>22.69</td>
<td>638.26</td>
<td>1363.21</td>
<td>1219.86</td>
<td>659.36</td>
<td>471</td>
</tr>
<tr>
<td>3</td>
<td>23.88</td>
<td>651.76</td>
<td>1354.47</td>
<td>1310.37</td>
<td>671.23</td>
<td>479.43</td>
</tr>
<tr>
<td>4</td>
<td>24.35</td>
<td>649.38</td>
<td>1321.83</td>
<td>1287.69</td>
<td>668.32</td>
<td>473.24</td>
</tr>
<tr>
<td>5</td>
<td>25.23</td>
<td>658.36</td>
<td>1409.91</td>
<td>1269.71</td>
<td>672.43</td>
<td>469.56</td>
</tr>
<tr>
<td>6</td>
<td>24.76</td>
<td>652.82</td>
<td>1405.68</td>
<td>1295.62</td>
<td>668.85</td>
<td>472.11</td>
</tr>
</tbody>
</table>

From the results, the presented control system operated steadily with satisfied response time and lower overshoot, also with small temperature and pressure deviation, which proves the effectiveness of the control scheme.

Fig.3 System Response Curves of Three Controlled Variables (a) t1(k), (b) t2(k), (c) t3(k)

4. Conclusions and Future Work

This paper presents the application of fuzzy predictive control as main controllers to control the multivariable systems. The T-S fuzzy predictive control model has been transformed into constrained optimization problem and solved by the Alopex based evolutionary algorithm. Alopex algorithm helps to break out the local minimum points and enhances the precision of nonlinear optimization. Simulation is carried out on the cement rotary kiln system as an example with controlling the temperature and pressure of the cement rotary kiln, and simulation results were derived. The results show that the presented control and optimization scheme can reach satisfied performance and the solution algorithm for T-S model predictive control is effective with potential applications for multivariable process system.

In the future work, we will study the more effective algorithm to improve the control performances; in
addition, the application objects of the presented method should be further expanded and investigated.

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References