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Optimization of Control Strategy Based on Soft Computing Approaches and Real Time Implementation in Cement Industries

C. Ramanadevi
Assistant Professor, Department of EEE, MAM School of Engineering, Trichy, Tamilnadu-621105
Email: ramanadevi4@gmail.com

***Abstract*— *This paper describes a control strategy for a nonlinear model of cement industry system and real time system designs are analyzed and their implementation in Labview simulation is outlined. Based on the Alopex evolutionary optimization algorithm with constrained T-S model, an intelligent fuzzy predictive controller to solve the control difficulties of industry process with multi-variables is approached. The application on cement rotary kiln control is discussed in detail. The rotary kiln calcinations 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. Parameters of the simulation model were set up based on the actual cement mill characteristics. The performances of the proposed control technique are compared with various conventional control techniques. The results of the proposed control technique indicate that this algorithm can prevent the cement industry effectively compared to the other control technique*.

***Keywords*— *FPC, T-S model, Alopex evolutionary optimization, Cement industry*.

I. INTRODUCTION

Many industrial process systems may not be as readily described mathematically due to the complexity of the components of the plant and the interaction between them. Cement mills are complex processing systems with interconnected processing and drive operations. It is well known that material grinding depends on many factors including mill geometry, speed, ball size distribution, mineral grind ability and granule geometry. Due to the inherent process complexivity development of an accurate model of the cement milling circuit is not a simple task. On some occasions, it is observed on real plants that intermittent disturbances like instance changes in the hardness of the raw material may drive the mill to a region where the controller cannot stabilize the plant.

In the process of cement production, the rotary kiln calcinations 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 cannot reach satisfied results with conventional control algorithms. 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.

II. 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. 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.

A. 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:

R^i : if x_1 is A_{1i} and … and x_m is A_{mi} , then

$$y^i = p^i{}_0 + p^i{}_1 x_1 + p^i{}_2 x_2 + \ldots + p^i{}_m x_m \quad (1)$$

where

$x_1 = y_1(k-1)$, … , $x_v = y_1(k-v)$, $x_{v+1} = y_2(k-1)$,…, $x_{(p-1)v+1} = y_p(k-1)$, …, $x_{pv} = y_p(k-v)$, $x_{pv+1} = u_1(k-l)$,…, $m=p(v+1)$, $u_p(k-l)$ denotes the p^{th} input component value of k-l time, $\{y_i\}$and $\{u_s\}$ are the input and output variables of object, $p^i_j = [p^i_{j1}\ p^i_{j2} \ldots p^i_{jp}]$ (j=0, 1, …, m) is the p^{th} dimensional column vector, A_{ji} is the fuzzy set of corresponding variables.

To a given generalized input vector $(x_{10} x_{20} \ldots x_{m0})$ the output of T-S fuzzy model on the k time is the weighted mean value of equation (1) y^i (i =1,2..., n) as

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$$y(k)=\sum_{i=1}^{n}\gamma^{k}{}_{i}y^{i},\gamma^{k}{}_{i}=\mu_i(\sum_{i=1}^{n}\mu_i)^{-1} \tag{2}$$

where, the weighted coefficient $\mu_i=\Pi^{m}{}_{j-1}A_{ji}(x_{j0})$ Π 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

$$A_k\ (z^{-1})y(k)\ =\ B(z^{-1})u(k\ -1)+C_k \tag{3}$$

A, B ,C are all related with k .

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

s.t. min max $\Delta u \le \Delta u(k+j-1) \le \Delta u$, min max $u \le u(k+j-1) \le u$, j =1,..., Nu

B. *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

$$x_i(t)\ =\ x_i(t-1)+\delta_i(t) \tag{4}$$

$$\delta_i(\mathrm{t})\ =\ \{\delta\, probability\ p_i(t) \\ -\delta\, probability 1-p_i(t) \tag{5}$$

$$P_i(t)=1/\left(1+e^{[\pm\Delta_i(t)/T]}\right) \tag{6}$$

$$\Delta_i(t)\ =\ \left[\mathrm{x_i}(\mathrm{t}-1)-\mathrm{x_i}(\mathrm{t}-2)\right]\times\left[\mathrm{F}(\mathrm{t}-1)-\mathrm{F}(\mathrm{t}-2)\right] \tag{7}$$

where F(x_1, x_2,…, x_n) is the objective function, x_i (t) is the ith 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 δ 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 δ and T in (1)-(4) should be determined. δ 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 cannot 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.

C. *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_1, x_2,…, x_n), and the flight speed is expressed as a vector V_i = (v_1, v_2,…, v_n). Each particle has a fitness value and knows that they found so far the best position (p best) 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 (g best) of all particles of the group (g best is the best value of p best). This can also be taken as peer particles' experience. The next step movement is decided on the best experience of own and companions.

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

Step 1. Initialize the particle swarm, the individuals are scattered into the solution space, then calculate the objective function value, giving the initial temperature T.

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Step 2. Two individuals are randomly selected among the swarm; calculate the differences between the two individual vectors and product of the objective functions.
Step 3. Calculate the probability vector p according to equation (6).
Step 4. According to equation (5), 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.
Step 5. Compare the changing of vector x_1, if the improvement is derived, the new individual x_1 is used for replacing the original one.
Step 6. Updating the temperature T with certain rules, the iteration number adds 1.
Step 7. When the finish condition is satisfied, the global optimal value can be outputted. The computation process ceased or returns to *Step 2*.

III. 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 cannot 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 cannot 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.

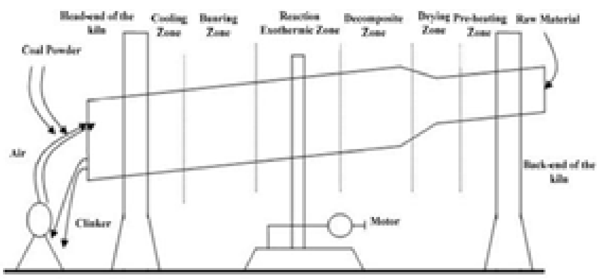


Fig. 1. Cement rotary kiln system.

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.

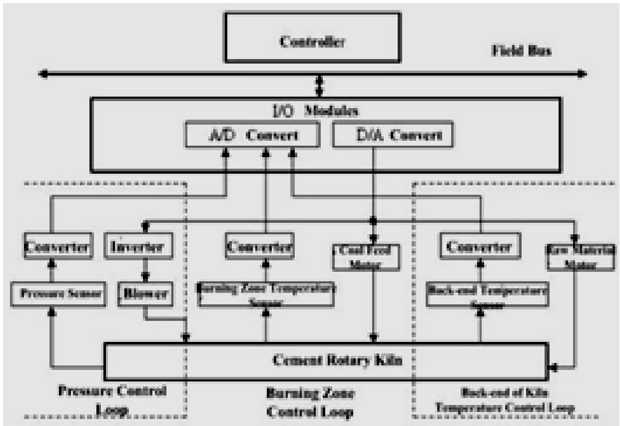


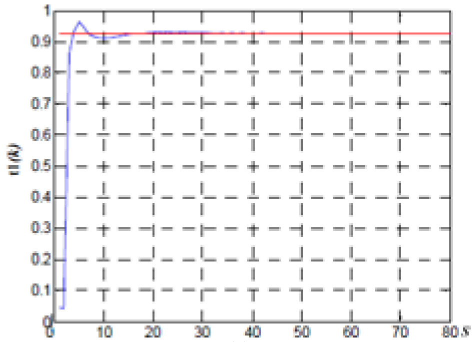
Fig. 2. Cement rotary kiln structure.

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 I.

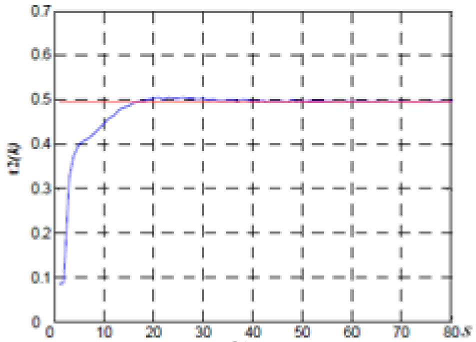
TABLE I. Some Parameters Data of Real Cement Rotary Kiln.

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

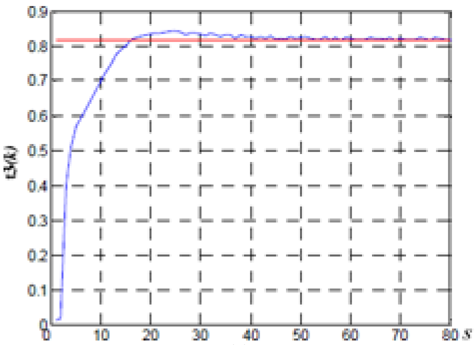
From the results, the presented control system operated steadily with satisfied response time and lower overshoot, also with small temperature and pressure deviation, which proves the effectiveness of the control scheme.



(a)



(b)



(c)

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

IV. Conclusion

This paper presents the application of fuzzy predictive control as main controller to control the cement industry. The T-S fuzzy predictive control model has been transformed into constrained optimization problem and solved by the Alopex based algorithm. Alopex algorithm helps to break out the local minimum points and enhances the precision of nonlinear optimization. Simulation is carried out in Labview platform 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 as cement industries.

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