Modeling of Fluid Industry Based on Flexible Neural Tree

QU Shou-ning, LIU Zhao-lian, CUI Guang-qiang, and FUAi-fang

***Abstract*—Realizing optimal control of fluid industry is a difficult problem due to its features of complexity, strong correlation, non-linear and uncertainty. For solving the problem, we propose build the whole model for it. Cement production process is taken as an instance, and its production process model is gotten by evolving flexible neural tree (FNT). The FNT model's structure and parameters are optimized by probabilistic incremental program evolution (PIPE) and simulation annealing (SA) respectively. The result demonstrates that the put forward method is effective and feasible for solving the problem.**

***Index Terms*—fluid industry, flexible neural tree, probabilistic incremental program evolution, simulation annealing**

I. Introduction

An important characteristic of modern industry is that direction develops to good-sized and automatization. with the development of market economy and annexation and combination between corporations, More and more large-scale, exceptional large enterprises appear unceasingly in the fluid industry, which holds leading post in the field of national economy, such as Petroleum and Chemical, Metallurgy, Paper making, Chemical industry, Electric power, Medicine and so on. In the recent years especially, fluid industry is growing greatly in every country in the background of ceaseless development of economic globalization. At the same time, fluid industry's production takes on high complexity, strong association, non-linear and indeterminacy [1], [2]. The expansion of producing scale will definitely make the process and their associations more complex, and at the same time it makes automatic control of fluid industry more difficult. Building accurate and effective model of production process will afford great help for automatic and optimal control of fluid industry. But at moment most research about fluid industry production process focuses on single process, and ignores the strong correlation between different processes as a whole. For example, the research on cement production process often focuses on decomposing furnace and rotary calciner. In this paper, we apply flexible neural tree (FNT) model [3] for resolving it.

According to the model, the whole model of fluid industry production process can be built. On one hand, the method provides theoretical basis for producing control of fluid industry, and makes the process control more scientific and pertinent; on the other hand, it establishes a good basis for process optimal control of fluid industry. The FNT structure is developed using probabilistic incremental program evolution (PIPE) [4] and the parameters are optimized by simulation annealing algorithm (SA) [5].

In this paper, we take cement production process as an example and build its process model. Cement production process mainly includes decomposing furnace, rotary calciner and grate cooler. Decomposing furnace is principally responsible for the decomposition of the raw material, and the decomposition rate could reach 80% -90%; then decomposed material flows into rotary calciner, which takes on two task: one is decomposing the remaining raw material, and the other is calcine the decomposed raw material; at last the calcined material will be cooled in the grate bed. So the three processes are closely linked each other as a whole. The quality of cement is not only dependent on one single process, but depends on the overall operation of the three courses.

The paper is organized as follows: Section 2 gives the representation and calculation of the flexible neural tree model and narrates a hybrid learning algorithm (PIPE and SA) for evolving the neural tree model. Section 3 presents the final model for cement production process. Some concluding remarks are presented in Section 4.

II. FNT Model and Its Application

A. Introducing FNT model

Based on the pre-defined instruction operator sets, a flexible neural tree model (see figure 1) can be created and evolved. This framework allows input variables selection, over-layer connections and different activation functions for different nodes. The hierarchical structure is evolved using PIPE algorithm with specific instructions. The fine tuning of the parameters encoded in the structure is accomplished using SA. In this paper, the proposed method interleaves both optimizations [3].

DOI: 10.7763/IJCTE.2009.V1.15

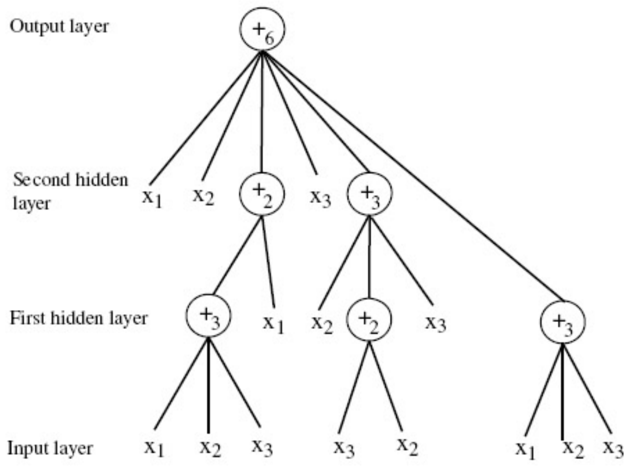

Fig. 1 flexible neural tree model

The structure optimization of the FNT model is completed by PIPE [4]. PIPE combines probability vector coding of program instructions, population-based incremental learning (PBIL), and tree-coded programs. The algorithm mostly includes creation of population, population evaluation, learning from population and probabilistic prototype tree (PPT). According the algorithm process, the paper describes the generation process of simulation model particularly.

B. Generating the model

Before generating population, information set for creating FNT should be identified firstly. The used function set F and terminal instruction set T are described as follows:

$$S = F \cup T = \{+_2, +_3, \ldots, +_N\} \cup \{x_1, \ldots, x_n\} \qquad (1)$$

Where $+_i$ ($i = (2,3,\ldots,N)$ denotes non-leaf nodes' instructions and taking i arguments; x_1, x_2 …, x_n are leaf nodes' instructions and taking no other arguments.

According to the definition of FNT information set, we can identify the model's terminal set and function set for s cement production process. There are many parameters relating with cement production process. The data coming from one Shan dong Cement Plant mainly relates with decomposing furnace, rotary calciner and grate cooler includes: amount of raw meal, fan frequency current, feeding of coal of decomposing furnace, back-end high-temperature fan current, back-end high-temperature fan motor speed, rotary calciner speed, feeding of coal of rotary calciner, one-length speed of grate cooler and *f-CaO* content (presentation of parameters in table1, their values in table 2). We take *f-CaO* content as output of the model, and other parameters are seen inputs of the model. Function set is defined as this $F = \{+_2, +_3, +_4, +_5, +_6, +_7\}$, so the information set for creating the model is $S = F \cup T = \{+_2, +_3, +_4, +_5, +_6, +_7\} \cup \{x_1, \ldots, x_8\}$.

Population generates from PPT. The PPT is generally a complete m-ary tree with infinitely many nodes, where m is the maximal number of function arguments (m=6 in this paper). Each node N_j in PPT, with j>=0 contains a variable probability vector $\overrightarrow{p_j}$. Each $\overrightarrow{p_j}$ has n components, where n is the number of instructions in instruction set S (in the paper, n=14). Each component $p_j(\mathrm{I})$ of $\overrightarrow{p_j}$ denotes the probability of choosing instruction $I \in S$ at node N_j .For example, $p_1(I)$ denotes the selection probability of amount of raw meal in the first node of population in the paper.

According to the distribution of probabilistic vectors contained in the PPT, every generation generates the same scale of individual (in this paper, generation=50, population size=20).The process for selecting node information of individual is: the individual nodes correspond to PPT nodes. For example, the first node of individual generates from the first node of PPT. when select information, firstly a random number r1 is generated, and then it will be compared with the first probability of the first probabilistic vector stored in the PPT. If r1> $p_1(I)$, r1 will be reduced according to the formula: $r_1 = r_1 - p_1(I)$, and then turn to the next probability until $r_1 <= p_j(I)$. At the time, if j<=n, then the *j*th information will be selected; otherwise, the last information will be selected. Others' information selection is the same with above process. When all the children nodes are leaf node or the maximum depth is achieved, the process will end (in this paper, the maximum depth is 4).

TABLE I: THE PRESENTATION OF PARAMETERS

Parameters	Presentation
amount of raw meal	x_1
fan frequency current	x_2
feeding of coal of decomposing furnace	x_3
back-end high-temperature fan current	x_4
back-end high-temperature fan motor speed	x_5
rotary calciner speed	x_6
feeding of coal of rotary calciner	x_7
one-length speed of grate cooler	x_8
f-CaO content	x_0

TABLE II: VALUE OF PARAMETERS

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_0
181.9	61.9	7.06	496.6	907.6	3.34	5.34	3.61	0.0154
177.4	61.8	6.92	495.2	907.2	3.34	5.27	4.32	0.0138
178.5	62.1	7.01	508.3	907.2	3.33	5.34	4.21	0.0140
176.2	61.9	7.18	498.9	907.2	3.35	5.28	4.37	0.0130
……	……	……	……	……	……	……	……	……

C. Evaluating the model performance

After generating one generation individual, the performance of each individual will be tested. An evaluation criterion is based on the size of individual fitness. The selected fitness formula in this paper is:

$$Fit(i) = \frac{1}{p}\sum_{j=1}^{p}(y_1^j - y_2^j)^2 \qquad (2)$$

International Journal of Computer Theory and Engineering, Vol. 1, No. 1, April 2009
1793-8201

Where p is the total number of samples, ${y_1}^j$ and ${y_2}^j$ are the actual sample value and the FNT model output of *j*th sample, $Fit(i)$ denotes the fitness value of *i*th individual.

The minimum unit of individual computation is the flexible neuron; the method of computation is from left to right by depth-first. The output of a flexible neuron +n can be calculated as follows. The total excitation of +n is:

$$net_n = \sum_{j=1}^{n} w_j * x_j \tag{3}$$

The output of the node +n is then calculated by

$$out_n = f(a_n, b_n, net_n) = e^{-\left(\frac{net_n - a_n}{b_n}\right)^2} \tag{4}$$

w_j denotes the connection strength between $+_i$ node and its children; a_n, b_n are activation function parameters of the correspondent node. After calculating all individual's fitness, the individual with the minimum value will be preserved as the basis for individual study.

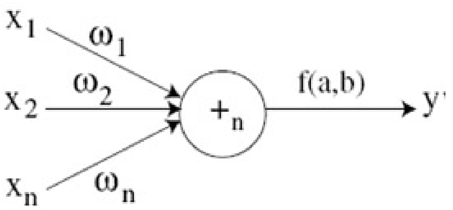

Fig. 2 flexible neuron

In this paper, the record of sample data set p1 is 200, and the count of test data set p2 is 200. ${y_1}^j$ denotes the actual *f-CaO* content of *j*th sample, ${y_2}^j$ denotes the output value of the model of *j* th sample. The smaller fitness means that the output *f-CaO* content is closer to the actual temperature. w_j, a_n and b_n are generated randomly, and their value range are [-1, 1] and [0, 1] respectively.

D. Evolving the model

Initially, when individual is generated, the information has the same probabilistic to be selected. Each probabilistic vector $\overrightarrow{p_j}$ is initialized as follows:

$$p_j(I) = \frac{p_T}{l} \forall I : \in T \tag{5}$$

$$p_j(I) = \frac{1-p_T}{k} \forall I : I \in F \tag{6}$$

p_T is a pre-defined constant, usually 0.5.

The evolution of the model depends on learning from individual and mutation of PPT. the goal of learning from individual and mutation of PPT is to increase the probability of node information of the current best individual and to make them have more opportunity to be selected in the next generation.

Individual study method is based on the information of the preserved individual of the current generation to modify the probability of the correspondent probabilistic vector in the PPT. The process is: firstly, computing P_{ROG_b} and P_{TARGET} according to formula (7) and (8);

$$P(P_{ROG_b}) = \prod_{j:N_j} P_j(I_j(P_{ROG_b})) \tag{7}$$

$$P_{TARGET} = P(P_{ROG_b}) + (1 - P(P_{ROG_b})) \cdot lr \cdot \frac{e + FIT(P^{el}_{ROG})}{e + FIT(P_{ROG_B})} \tag{8}$$

And then comparing the size of P_{ROG_b} and P_{TARGET}, if $P_{ROG_b} < P_{TARGET}$, then modifying the correspondent node information:

$$P_j(I_j(P_{ROG_b})) = P_j(I_j(P_{ROG_b})) + c^{lr} \cdot lr \cdot (1 - P_j(I_j(P_{ROG_b}))) \tag{9}$$

Until $P_{ROG_b} >= P_{TARGET}$ .the process described above will make the information increase, therefore, the information has more opportunity to be selected in the next generation.

Where $I_j(P_{ROG_b})$ denotes the instruction of program P_{ROG_b} at node position j. Here 'lr' is a constant learning rate, e is a positive user-defined constant, and c^{lr} is a constant influencing the number of iterations. Setting lr =0.01, e =0.000001, c^{lr} =0.1 in this paper.

If the best individual in one generation includes the nodes: +4, x_1, x_3 and so on , then it can show that amount of raw meal and feeding of coal of decomposing furnace have important impact on *f-CaO* content, their probabilities will be increased and they have more opportunity to be selected in the next generation.

Mutation of PPT is that the information probability of the current best individual mutates with the P_{M_p} :

$$P_{M_p} = \frac{P_M}{n * \sqrt{|P_{ROG_b}|}} \tag{10}$$

The process is: executing from the first node, generating one random number r1 firstly and then comparing it with P_{M_p}. If P_{M_p} >r1, then the probability of the first node information mutates as follows:

$$P_j(I) = P_j(I) + mr \cdot (1 - P_j(I)) \tag{11}$$

Otherwise, the probability doesn't change. The process will go on until all nodes are traversed.

From the process of evolution of the model, we can see that information selection is executed automatically.

E. Optimizing the model structure parameter

After generating fifty generations, the best individual of the fiftieth generation can be seen as the optimal individual. To acquire better fitness, that is, reducing the error between the actual value and the output value, we use SA algorithm [5-7] to achieve parameters (including connection strength and activation function parameters) optimization under fixed structure.

SA is one of the most widely studied heuristics local search algorithms. The basic ideas of the simulated annealing search are that it accepts worse solution with a probability

$$p = e^{-\frac{d}{T}} \tag{12}$$

$$d = f(s^{*}) - f(s) \tag{13}$$

the s and s* are the old and new solution vectors, $f(s)$ denotes the cost function, the parameter T denotes the temperature in the process of annealing. Originally it is suggested to start the search from a high temperature and reduce it to the end of the process by a formula:

$$T_{i+1}=T_i-T_i*b \tag{14}$$

Under each temperature value, L new solutions are generated. In this paper, we set T_max=100, L=20, T_min=0.1, b =0.95.

Solution vector is a combination of connection strength and activation parameter $s=(w_1,w_2,...w_n,a_i,b_i)$ .New solution vector are generated randomly, that is $s^{*}=(w_1^{'},w_2^{'},...w_n^{'},a_i^{'},b_i^{'})$. Computing the error d between $f(s)$ and $f(s^{*})$, if d <0, the new fitness $f(s^{*})$ will be accepted, otherwise, it is accepted by the probability.

F. Experimental results

The model of cement production process is gotten by PIPE and SA until now (see figure 3). The performance of the model has been tested by test data. The train result and test result are displayed in figure 4 and figure 5.

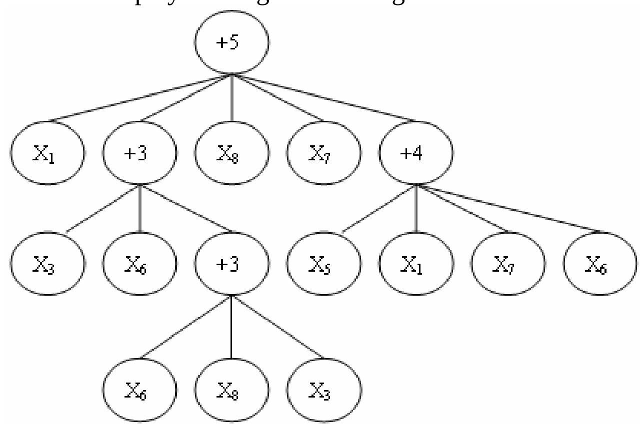

Fig. 3 The model of cement production process

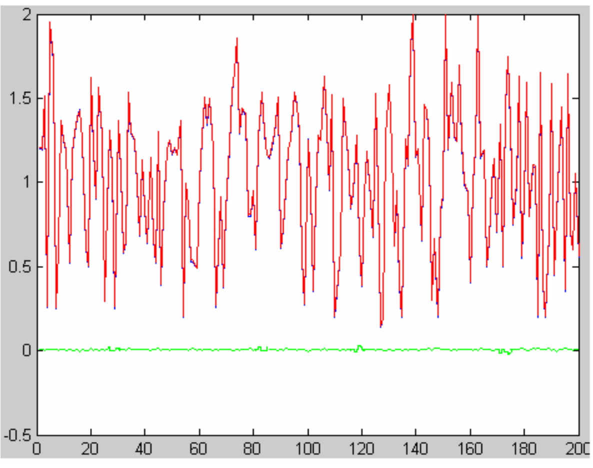

Fig. 4 train result

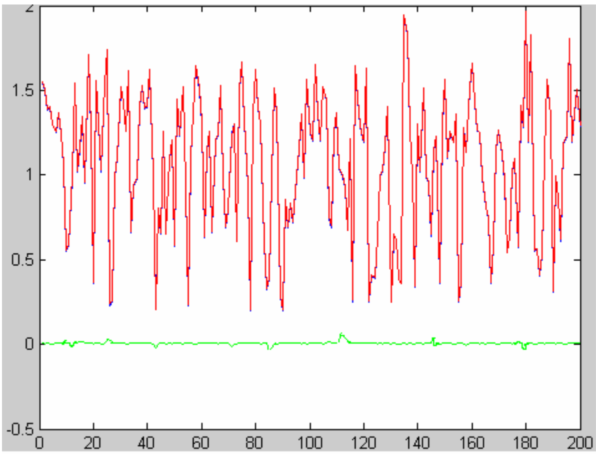

Fig. 5test result

III. Analyzing Result

From the final model(Figure 3), we can get such a conclusion: the parameters have great influence on f-CaO content are amount of raw material, feeding of coal of decomposing furnace, rotary calciner speed, feeding of coal of rotary calciner and one-length speed of grate cooler. For example, the *f-CaO* content will increase when the feeding of coal and amount of raw material is improper in ratio or one-length speed of grate cooler is too slow. From the results of the training model (Figure 4) and the test results (Figure 5), we can see the effectiveness and feasibility of the model.

According to the model, we can simulate the cement production process. Changing one variable value or several variables value to observe the change of *f-CaO* content, If the *f-CaO* content to the extent permitted by the changes, then you can get a better portfolio optimization program. For example, to a certain scope to reduce the amount of coal, if the *f-CaO* content is still normal, then we can reduce energy consumption and save costs. In addition, when the *f-CaO* content is higher, this model can help us analyze each production process to find the reasons, rather than blindly guessing which one is failure.

Compared with modeling for single process, modeling as a whole has some advantages; on one hand, it overcomes the defects of single modeling: A good control of one production process can not guarantee that the entire production line is the steady, but also ignores the inter-relationship of the processes, so it is not conducive to optimize the overall production line[1], [12]-[15]; on the other hand, it makes easier for operators to control the whole production process, and lay a good foundation in order to achieve the overall optimization of production lines.

IV. Conclusions

In this paper, cement production process modeling as a whole is realized by applying FNT model, and at the same time it overcomes some defects of the single-process modeling. The successful application of the method not only has injected new vitality for cement production process research, but also opened a new direction for fluid industrial production process.

ACKNOWLEDGMENT

It is a project supported by National Nature Science Fund (60573065) and State "863" Plan funded Project (2002AA4Z3240).

REFERENCES

[1] Liu-Xiao Lin."Neural Network Controller of Temperature of Cement Decomposing Furnace". School of Electrical Engineering, Yanshan University, Qing huangdao, 2003.
[2] Wang-Fu Sheng. Basic Knowledge of Modern Cement Production [M].China Building Materials Industry Press, Bei Jing, 2004.
[3] Chen-Yue Hui, Yang Bo, Dong-Ji Wen. "Time-series Forecasting Using Flexible Neural Tree Model ".Information Science. 2005, Vol.174, pp. 219-235.
[4] R.P. Salustowicz, J.Schmidhuber. "Probabilistic Incremental Program Evolution".Evol. Comput. 1997, Vol.2, NO.5, pp.123–141.
[5] Gao Juan. "Artifical Neural Network Theory and Simulation"..Machinery Industry Press, Bei Jing, 2003.
[6] Wang Bin, Wang-Sun An, Du-Hai Feng. "Parameters Optimization of Industry Process Control based on Fuzzy Genetic Algorithm". Xi'an Jiaotong University Journa l, 2004 .Vol.38, NO.4, pp.56-59.
[7] Wu-Jin Bo. "Study of the Immune Algorithm and Simulated Annealing Algorithm for TSP Problem". College of Computer Science and Technology, University of Wuhan Technology, Wuhan, 2007.
[8] Yu-Long Hua."Fuzzy Control of Cement Rotary Kiln Temperature". Jiangxi Building Materials.2001, NO.Z1, pp.29-31.
[9] Xu De, Zhu Jing. "On Calciner Temperature Control Algorithm and Realization for Cement Work with Wet_Griding and Dry Burning". Journal of the Chinese Ceramic Society. 2001, Vol.29, NO.02, pp.119-122.
[10] Duan-Guo Ping."Computer Simulation Application in Decomposing Furnace". Materials Institute, Kunming University of Science and Technology, Kunming, 2006.
[11] Yang-Li Yuan."Computer Simulation for Calcinations Process of Precalciner". Materials Institute, University of Wuhan Technology, Wuhan, 2004.
[12] Yao Wei."Application of Fuzzy Control for the Decomposing Furnace Temperature of Rotary Cement Kiln ". Measurement & Control Technology. 2000, Vol.19, NO.9, pp.36-40.
[13] Zou Jian. "Research on Intelligent Predictive Control and Its Applications". College of Electrical Engineering, Zhejiang University, Yuquan Campus Hangzhou, 2002.
[14] Zhang-Jian Min, Chen-Hong Li, Wei-Xiu Lan. "Application of dynamic BP neural net in temperature control of cement rotary kiln". Journal of Jilin Institute of Chemical Technology. 2001, Vol.18, NO.3, pp. 28-30.
[15] Chen-Ya Ming."Study on Calcinations in Precalcing Kiln Based on Artificial Neural Network". Materials Institute, University of Wuhan Technology, Wuhan, 2003.
[16] Huang Heqing, "Yu Jinshou. MES Process-Oriented Industry and key Technology"[J]. Process Automation Instrumentation, 2004, Vol25, NO1, pp:10-15.
[17] Zeng Xuemin. Calculation: "11th Five -Year" Cement Energy-Saving and Emission Reduction" [J]. China Cement, 2007, NO1, pp:9-13.