World Applied Sciences Journal 25 (1): 106-112, 2013
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2013.25.01.7030

Some Ways of Solving the Problem of Control Process of Clinker's Firing in the Cement Kilns

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Submitted: Aug 18, 2013; **Accepted:** Sep 21, 2013; **Published:** Sep 24, 2013

Abstract: The methodology of application of fuzzy logic and fuzzy control theory to solve the problem of process control of firing of a clinker is described in the article. The methodology presented in the article consists of the model of human behavior in the management of complex engineering systems using fuzzy inference. The direction of building an advising system that provides a qualitative assessment of the cement kiln is based on the analysis of its thermodynamic parameters and is considered on the basis of this methodology. This article provides an example of calculating the quantitative value of the manipulated variable gas flow rate for the automated control system based on fuzzy logic equations. Fuzzy base of production rules for fuzzy control system is formed from the experimental data obtained in the course of implementation of data-processing system at a cement plant. The obtained results allow to appreciate the advantages of fuzzy systems compared with other control systems as well, using the obtained fuzzy logic equations and can be synthesized by fuzzy inference system for fuel control in a cement kiln.

Key words: Management of clinker · Methods of fuzzy logic · Advising system · Fuzzy inference system

INTRODUCTION

Automation of the process control of clinker in cement kilns is a difficult scientific and technical challenge. This is due to the fact that in the kiln, chemical, hydraulic heat-mass exchanging high temperature processes are flowing continuously. For example, cement clinker sintered at 1450°C and the flame temperature is maintained in the region of 1700 °C - 1900 °C. In this burnt material it is in constant motion and the residence time in the furnace is up to 3 hours. All processes run in a non-stationary and the heterogeneity of physico-chemical and hydrodynamic fields of distributed and concentrations inside the process vessel are called cement kiln [1-3].

In this context, for a control of the the cement kiln it is necessary to control a large number of operating parameters with a limited number of control actions. The authors have developed and tested the information analysis system (IAS) of the control and management of the clinker burning on 4 Balakleysky cement kiln in a cement plant in an operation advisor. In particular, to solve problems of control cement kilns in the developed information-analytical system and embedded in the clinker burning technology, more than 100 operating parameters are controlled, heat and material balances cement kiln and cooler burning fuel are optionally calculated. It allowed to analyze the state of furnaces, to determine the effectiveness of the process control and compare the technical and economic performance of the cement kilns. In addition, the calorific value of the fuel, the theoretical heat consumption for clinker burning, loss of heat through evaporation of moisture and heat loss from the exhaust gases were determined by the material of the heat balance [4-6].These parameters were used in the design of fuzzy inference system, coupled with the definition of the thermal state of the furnace. In the future, basic monitoring parameters for the development of a database of fuzzy production rules on the basis that control fuel consumption for clinker burning were selected from the database of IAS. All information is displayed on the monitor of a workstation operator. Based on this

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experience and analysis of the data presented in [1-4], the parameters to represent the chosen methods have been defined and on the basis of it some of the ways of solving the problem management process of clinker in cement kilns are represented in the article.

The aim of the research is the development of methods of analysis and process control clinker burning mode adviser and automated control based on fuzzy logic theory. As well as the formation of the fuzzy knowledge base of fuzzy inference on the basis of experimental data is obtained in the course of implementation of information-analytical system at a cement plant.

MATERIALS AND METHODS

Methods of research are to form a fuzzy knowledge base on the basis of experimental data, the definition of a quality assessment of the furnace and in the calculation of the manipulated by a system of fuzzy inference and fuzzy set theory.

Fuzzy inference system is central to the theory of fuzzy control, the central purpose of which is to obtain the fuzzy conclusions about the required control action on the object with the production model of knowledge representation based on the current state of the object [7].

The system implements a fuzzy inference algorithm for deciding whether to allow a fixed vector of input variables $X^* = \left(x_1^*, x_1^*, ..., x_n^*\right)$ associate a solution $y \in D$.

One of approaches is the formation of fuzzy inference system is the use of fuzzy logic equations. These equations are based on the production model of knowledge representation and allow you to calculate the values of the membership functions of various solutions for fixed values of the input variables of the object. The desired solution is chosen with the highest value of the membership function [8].

Let the membership function values of the input variable x_i fuzzy terms α_i^{jp} be as follows:

$$X_{ai} = \mu^{\alpha_i^{jp}}\left(x_i\right) : i = \overline{1,n} : j = \overline{1,m} : p = \overline{1,k_j} \tag{1}$$

in which n - the number of input variables, m - the number of output solutions, k_j - the number of fuzzy production rules corresponding to the solution d_j, then the membership function of fuzzy terms d_j of output variables as a function of the vector of input variables X = $(x_1, x_2, ... x_n)$ is as follows:

Table 1: The matrix of experimental data

11	12	…	$1k_1$	- number of combinations of input variables to solve the d_1
21	22	…	$2k_2$	- number of combinations of input variables to solve the d_2
…	…	…	…	
$j1$	$j2$	…	jk_j	- number of combinations of input variables to solve the d_j
…	…	…	…	
$m1$	$m2$	…	mk_m	- number of combinations of input variables to solve the d_m

$$Y_{dj} = \mu^{dj}\left(x_1, x_2, ..., x_n\right) \tag{2}$$

Communication between the functions (1) and (2) defined fuzzy knowledge base can be written as the following equations:

$$\mu^{dj}\left(x_1, x_2, ..., x_n\right) = \underset{p=1}{\overset{kj}{\vee}} \left[\underset{i=1}{\overset{n}{\wedge}} \mu^{\alpha_i^{jp}}\left(x_i\right) \right] mj = \overline{1,m} \tag{3}$$

The fuzzy knowledge base is designed for the formal presentation of empirical knowledge of experts in a particular subject area. It is based on production model of knowledge representation, i.e. it consists of rules of the form "If (condition) then (action)". Thus, the base of fuzzy production rules of fuzzy inference system reflects the expert knowledge about the methods of management of the object in a variety of situations.

The process of building a fuzzy knowledge base includes all of the key concepts of the theory of fuzzy sets: the language of production rules, linguistic variables, membership functions of fuzzy implication methods, etc. To form a fuzzy knowledge base necessary to take N experimental data linking inputs and output of the plant identification and distribute them as follows:

$$N = k_1 + k_2 + ... + k_m \tag{4}$$

in which k_j - number of experimental data corresponding to the output address d_j, $j = \overline{1,m}, m -$ the number of output solutions.

Enumerate N the following experimental data and present them in a matrix (Table 1).

Each row of the matrix represents some combination of input variables, referred to an expert one of the possible values of the output variable Y and the first k_1 rows correspond to the value of output variable $Y=d_1$, the 2nd k_2 rows - to the value $Y=d_2$ and the last k_m rows - to the value $Y=d_m$.

Consider the fuzzification step in the fuzzy inference, which is to find the values of the functions of fuzzy sets (terms) based on conventional (non-fuzzy) input data [9]. The purpose of this process is the establishment of correspondence between the numerical values of the input variables X_i and the values of membership functions for each of the terms of linguistic variables A_i. Fuzzification procedure reduces to determining the degree of truth of statements:

$$x_i \ is \ \alpha_i^p, \forall i = \overline{1,n}, \forall \alpha_i^p \in A_i \tag{5}$$

in which x_i - the numerical value of the input variable X_i.

Performing fuzzification matrix elements on the set of membership functions for each input and output variable, we obtain a basis of fuzzy production rules in which the element a_{ji} at the intersection of i-th column and j-th row corresponds to the linguistic evaluation parameter X_i in the j-th row of the fuzzy knowledge base. Linguistic evaluation a_{ji} is selected of term-set corresponding to the variable X_i, i.e. $a_{ji} \in A_i$.

The next stages of formation of fuzzy inference are aggregation, activation and accumulation. In this case, the procedure is aggregating in determining the degree of truth of the conditions of each element of the fuzzy knowledge base. Further, the procedure is to find the activation degree of truth of each of the elementary logic statements regarding the output linguistic variables. In addition, at the final stage of accumulation is the definition of membership functions for each of the output linguistic variables. The stages of aggregating, activation and accumulation are realized with the help of logical equation (3).

In real problems the administration requires that the result was presented clearly (numerical) value of the output parameter. In this case, you must complete the fuzzy logic algorithm defuzzification step.

We divide the interval of variation values of the output variable $\tilde{Y} = \left[\underline{y}, \overline{y}\right]$ into m parts:

$$\tilde{Y} = \left[\underline{y}, \overline{y}\right] = \bigcup_{j=1}^{m} d_j \tag{6}$$

where in $d_j = [y_{j-1}, y_j$ while $y_0 = \underline{y}, y_m = \overline{y}$.

Now the fuzzy knowledge base will represent the following relationships:

$$\bigcup_{p=1}^{k_j} \left[\bigcap_{i=1}^{n} \left(x_i = a_i^{jp} \right) \right] \rightarrow y \in d_j \ , \ j = \overline{1,m} \tag{7}$$

For the output variable Y is not specified the value of the linguistic variable and the number of the interval j, which has got the appropriate value from the table of experimental data. Changed line numbers in the fuzzy knowledge base. Now the room is formed by the following principle: the slot number - the number of rules.

Objective decision in this case is fixed to the vector input variables $X^* = \left(x_1^*, x_1^*, \ldots, x_n^* \right)$ associate a decision $\tilde{Y} = \left[\underline{y}, \overline{y}\right]$. The above algorithm for fuzzy logic allows us to calculate the output value y in the form of a fuzzy set:

$$\tilde{Y} = \left\{ \frac{\mu^{d_1}(y)}{\left[\underline{y}, y_1\right)}, \frac{\mu^{d_2}(y)}{\left[y_1, y_2\right)}, \ldots, \frac{\mu^{d_m}(y)}{\left[y_{m-1}, \overline{y}\right)} \right\} \tag{8}$$

Perform defuzzification operation, ie pass from the membership functions of output linguistic variable to its clear (numeric) value. To do this, we calculate the value of a fuzzy set (8) and obtain quantitative values for the output variable from the interval $\tilde{Y} = \left[\underline{y}, \overline{y}\right]$.

We define a clear number y^*, which corresponds to the set (8) is the desired control action for a fixed vector of input variables X^*, as follows:

$$y^* = \frac{\underline{y}\mu^{d_1}(y) + y_1\mu^{d_2}(y) + \ldots + y_{m-1 y_{m-1}}\mu^{d_m}(y)}{\mu^{d_1}(y) + \mu^{d_2}(y) + \ldots + \mu^{d_m}(y)} \tag{9}$$

If the interval $\tilde{Y} = \left[\underline{y}, \overline{y}\right]$ is divided into m equal parts, the formula (9) takes the following form [8]:

$$y^* = \frac{\sum_{j=1}^{m} \left[\underline{y} + (j+1).\Delta \right]. \mu^{d_j}(y)}{\sum_{j=1}^{m} \mu^{d_j}(y)} \tag{10}$$

where $[\text{delta}] = \frac{\overline{y} - y}{m-1}$.

The main part. The task of managing the process of clinker in the cement kiln is quite complicated. On the driver's responsibility oven function is to control the key parameters of the furnace and the adjustment of the control parameters of the process. From the quality of the machinist of its functions to a large extent on the performance of the furnace, fuel consumption and the quality of clinker production. In this connection it is necessary to warn the driver of the furnace exit from optimal. Development advising system parameters analysis and classification of the firing would largely solve the problem.

Clinker burning optimally provides the required thermal state of the sintering zone and leads to the formation of clinker granules of the desired size. The deviation from optimum results in sintering and cooling zones not appearance clinker leaving the kiln. In case of thermal decomposition occurs a phenomenon clinker granules and formation of clinker dust.

The input data for the work of the Expert Council of the system is information on the current values of the process parameters, as well as the background to change these values. The result of the classification is to assess the condition of the firing process, which is done according to the following scale:

- Normal (formed clinker granules which have a size of 5-15 mm);
- The oven is overheating (formed quarrels);
- Furnace cool (insufficient liquid phase to form a clinker granules appearance is not sintered material at the outlet of the oven);
- Heavy overheated oven (the appearance of the collapse of clinker granules, formation of fine clinker);
- Strong cooling oven (education dusting of raw mix, the appearance of unbaked material "mustard").

Mode of heating unit depends on many different factors and parameters and to estimate the scale of this mode with the quantitative measurement is difficult. This fact makes the reasonable application of the model of knowledge representation based on fuzzy logic.

The knowledge base is formed with the participation of experts. Expert estimates to operate the furnace according to the proposed timeline. The knowledge base contains a comparison of the measured values of process parameters and defect mode of the object. During the operational phase output mechanism performs the manipulation of knowledge, using the fuzzy inference rules and on the basis of input data calculates the result. Solution to the problem of classification will be the output value of the linguistic variable.

The criteria on which the assessment process is appropriate to choose the unit:

- K_1 - The calorific value of the fuel;
- K_2 - The theoretical heat consumption for clinker burning;
- K_3 - The cost of heat by evaporation of moisture from the raw materials;
- K_4 - The heat loss from the exhaust gases.

Thus, at the entrance there are the numerical values of K_i and the output is necessary to obtain the corresponding values of the linguistic variable. To solve this problem it is proposed to use fuzzy inference system without defuzzification stage, since in our advising system only requires the definition of evaluation of the firing process. The principle of this method is for example the problem management process cement clinker burning through the control of gas flow with a limited number of monitored parameters.

Numerous attempts to automate the management of cement kiln using the methods of classical control theory turn out to be ineffective because of the high nonlinearity of the problem, as well as the difficulties of accounting for various disturbances [2]. Watching the activities of the operator, you can see that it manages stove on the basis of some discussion. Since the rotary cement kiln is a complex nonlinear object, the operator selects 4...6 parameters without considering the other information about the behavior of the managed object.

Consider the algorithm for the formation of fuzzy logic equations and calculating the quantitative value of the manipulated variable.

We define the input linguistic variables and ranges of change for fuzzy inference system:

X_1 - Moisture of raw materials (41...44%);
X_2 - Temperature blowing chamber (210...250 °C);
X_3 - Temperature zone circuits (450...500 °C);
X_4 - Temperature heat exchanger zone (550...650 °C);
X_5 - Depression in the dusty chamber (140...165 Pa);
X_6 - Vacuum in the furnace head (2...10 Pa).

Output variable and the control action for the system under study will be:

Y - Gas consumption (12600...13500 m^3).

For each linguistic variable form the term-set of its values:

X_1 - Moisture raw material <very low, low, medium, high, very high>;
X_2 - The temperature in dusty chamber <low, medium, high>;
X_3 - The temperature for the chain <low, medium, high>;
X_4 - The temperature for the heat exchanger <low, medium, high>;
X_5 - Depression in the dusty chamber <low, below average, above average, high>;
X_6 - The negative pressure in the furnace head <low, below average, above average, high>;
Y - Gas flow rate <1, 2, 3,... 9>.

The most important task in the management of the cement rotary kiln by automated systems based on fuzzy logic is to obtain an adequate set of production rules that implement the strategy furnace control [10]. Traditionally, the rules for managing technical objects are drawn from a survey of operators working for them [11]. As part of the implementation of information- analytical system of process controls the clinker cement plant at Balakleysky the opportunity to automatically generate a database of parameter values clinker burning mode.

Based on the experimental data, a fragment of which is shown in Table 2, we construct the fuzzy knowledge base using the formula (4). For this feasible fuzzification data using the formula (5), with the value x_i is used as the argument of the membership function *μ(x)* the linguistic term α_i^p . The value $b=\left[\mathrm{mu}\right]^{\alpha_i^p}\left(x_i\right)$ will be the result of fuzzification conditions $\ll x_i \text{ is } \alpha_i^p \gg$.

Let us consider the procedure. Take the first line of the experimental data, in which the variable X_2 (the temperature in the dust chamber) has a numerical value of 235,6 °C. We define the degree of truth of the elementary fuzzy statements (Table 3) based on the membership function of the variable X_2 (Fig. 1).

As the value of the linguistic variable corresponding to the clear value of the input variable, let's select a term for which the maximum value of membership function. For values of *x*=235,6 variable α_2^2 *<normal>*.

Fuzzification performing the function for all the selected elements of the basis of experimental data, we obtain the fuzzy production rule base (Table 4), which can be determined using the gas flow to control the process of clinker.

Consider the principle of calculating the numerical value of the manipulated variable fuzzy inference system for fixed values of the input variables. Assume vector values of input variables are written as follows:

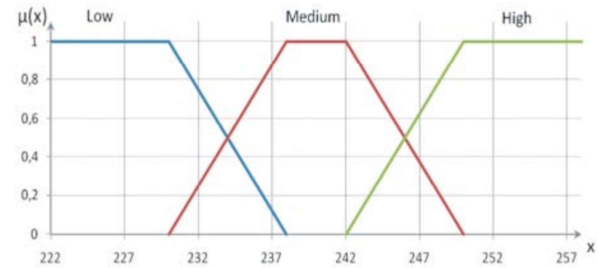

Fig. 1: The functions of fuzzy terms of the linguistic variable X_2

$$X = (43, 243, 457, 600, 150, 5,0) \tag{11}$$

Define the correspondence between the numerical values of the input variables (11) and the values of the membership functions of the corresponding terms of linguistic variables, ie fuzzification step feasible fuzzy inference system, the principle of performance which is given above. In this case, we agree that the membership functions are formed.

The values of the membership functions for a given input variable X_1 (moisture of raw material) are shown in Table 5.

For input variables, X_2, X_3, X_4, X_5, X_6 perform similar calculations and present the results in Table 6.

Implementing the steps of aggregation, activation and accumulation using a logical equation (3), we calculate the multidimensional membership function $\left[\mathrm{mu}\right]^{d_j}\left(x_1^*, x_1^*, ..., x_n^*\right)$ of vector *X* for all values d_j, $j=\overline{1,m}$, of the output variable *Y*.

In this case, the logical operation AND(/\) and OR(\/) membership functions are replaced by operations min and max:

$$\mu(a) \wedge \mu(b) = \min\left[\mu(a), \mu(b)\right]$$
$$\mu(a) \wedge \mu(b) = \mathrm{man}\left[\mu(a), \mu(b)\right]$$

As a result of the calculations we obtain:

$$\mu^{d_1}(43, 243, 457, 600, 150, 5{,}0) = 0{,}4$$
$$\mu^{d_2}(43, 243, 457, 600, 150, 5{,}0) = 0$$
$$\mu^{d_3}(43, 243, 457, 600, 150, 5{,}0) = 0$$

Next, you must perform a defuzzification step. Thus, we assume that the output variable *Y* (gas consumption), the changing interval $\tilde{Y}=\left[12600, 13500\right]$. Divide it into 9 parts:

Table 2: Detail of the base of the experimental data

Date	X_1	X_2	X_3	X_4	X_5	X_6	Y
24.06.2008 8:00	43	235,6	454,9	608,4	147,8	4,9	12812
24.06.2008 20:00	43	237,2	456,4	562,5	153,9	5,1	13137
26.06.2008 20:00	43	238,3	460,1	567,1	156,5	4,7	12923
27.06.2008 20:00	43	240,9	461,8	584,0	160,6	4,3	13198
28.06.2008 8:00	43	243,1	472,8	593,4	164,5	4,3	13241
29.06.2008 8:00	43	239,5	492,0	584,2	157,6	3,8	13114
30.06.2008 20:00	43	242,1	467,7	564,3	161,0	6,3	13003
01.07.2008 8:00	43	243,8	460,9	566,1	160,3	5,9	13156

Table 3: The result of fuzzification for the terms of the linguistic variable X_2

x	α_2^1 =<*lowest*>	α_2^2 =<*normal*>	α_2^3 =<*high*>
235,6	$\mu(x)=\frac{238-235{,}6}{8}=0{,}294$ 35,6	$\mu(x)=\frac{235{,}6-230}{8}=0{,}706$	$\mu(x)=0$

Table 4: Detail of the base of production rules of fuzzy inference system

Date	X_1	X_2	X_3	X_4	X_5	X_6	Y
24.06.2008 8:00	*normal*	*normal*	*low*	*ñðåäíÿÿ*	*low*	*normal*	2
24.06.2008 20:00	*normal*	*low*	*low*	*low*	*normal*	*normal*	*1*
26.06.2008 20:00	*normal*	*high*	*high*	*high*	*normal*	*high*	*2*
27.06.2008 20:00	*normal*	*normal*	*low*	*low*	*normal*	*normal*	*3*
28.06.2008 8:00	*normal*	*low*	*low*	*low*	*normal*	*normal*	*6*
29.06.2008 8:00	*normal*	*normal*	*low*	*normal*	*high*	*low*	*5*
30.06.2008 20:00	*normal*	*normal*	*normal*	*low*	*very high*	*very high*	*5*
01.07.2008 8:00	*normal*	*normal*	*low*	*low*	*high*	*high*	*6*

Table 5: Values of membership functions of the linguistic variable X_1

The input variable	*very low*	*low*	*normal*	*high*	*Very high*
X_1 moisture of raw material	0	0	1	0	0

Table 6: The values of the functions of linguistic variables X_2-X_6

	The parameters of membership functions		
Input variables	*low*	*normal*	*high*
X_2 The temperature in the dusty chamber	0	0,875	0,125
X_3 Low zone chains	0,85	0,15	0
X_4 Temperature in the zone heat exchanger	0	0,45	0,55
	reduced	*normal*	*increased*
X_5 The vacuum in the dusty chamber	0,4	0,6	0
X_6 The negative pressure in the furnace head	0	1	0

Table 7: Membership functions

Slot number j	1	2	3	4	5	6	7	8	9
The left boundary of the interval y_{j-1}	12600	12700	12800	12900	13000	13100	13200	13300	13400
Value μ^{d_j}	0	0	0,4	0	0	0	0	0	0

d_j = [12600 + (j + 1) 100,12600 + j . 100], j = 1,2,3,...(15)

Using fuzzy logic algorithm, we calculate the multidimensional membership function $[\mathrm{mu}]^{d_j}\left(x_1^*,x_1^*,...,x_n^*\right)$ of vector X^*=(43;243;457;600;150;5,0) for all intervals $d_j=\left[y_{j-1},y_j\right], j=\overline{1,m}$, into which the interval $\tilde{Y}=\left[\underline{y},\overline{y}\right]$ changes in the output variable Y (Table 7).

Applying the operation in fuzzy inference system (10), we obtain the desired value:

$$y^*=\frac{(12600+2.100)}{0,4}=12800\ M^2/\Upsilon \qquad (16)$$

Thus, using the method of fuzzy inference based on the use of fuzzy logic equations, we have obtained the desired solution (the value of the output variable Y) in the form of a clear number.

CONCLUSION

Approach to the problem of managing complex non-linear process objects from the perspective of fuzzy logic is not the only one. However, the use of the theory of fuzzy control cement kiln will provide an opportunity to model human behavior - the expert has no information about his mathematical model. The obtained results allow to appreciate the advantages of fuzzy systems compared with other control systems as well, using the obtained fuzzy logic equations can be synthesized by fuzzy inference system for fuel control in a cement kiln.

The proposed advising system will not allow to obtain accurate quantification of the thermal state of the sintering zone, however, its use will enable the engineer to timely provide an integrated assessment of the furnace mode of operation of the unit. The developed automated system for monitoring the flow of gas during the firing of cement clinker based on fuzzy inference system will reduce fuel consumption and improve the quality of clinker.

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