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Neuro Fuzzy Model For Equipment Health Management in Yellow Phosphorus Production Process

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Abstract: This study had solved the problem of reliability of production equipment with intelligent technical condition diagnostics system. The purpose of the study is to provide an adaptive model of operational system diagnostics and predicting of possible emergencies for electrothermal furnace based on the comprehensive change of its diagnostic parameters. To achieve this purpose, we used methods of artificial neural networks, fuzzy logic, expert evaluation and mathematical modeling. Based on the expert method and matrix planning of fractional factorial experiment, we formed the base of fuzzy production rules for setting up and training of adaptive diagnostic models of electric furnaces. It was found that ANFIS Model has the lowest value of the relative electric furnace state error recognition. The practical implementation of the proposed model is realized in the development of a production equipment diagnostics subsystem of the sintering floor at Novodzhambul sky phosphate plant.

Key words: Runtime diagnostics system, production equipment reliability, electrothermal furnace, sintering plant, yellow phosphorus, equipment health management

INTRODUCTION

Modern operation and maintenance strategy of complex technical facilities including Production Equipment (PE), requires the improvement of reliability estimate of the "actual state" under significant restrictions on the different types of resources (Suleimenov *et al*., 2014a, b; Ionov and Krasnyansky, 2012). The problem of ensuring a high level of reliability and reducing the cost of sintering production PE maintenance necessitates the development and implementation of run time technical condition diagnostic subsystems, allowing to search for an impurity spot or equipment malfunction in order to predict its reliability for a limited number of indicators within a certain time.

Reducing the time and cost for repairs and emergency recovery of yellow phosphorus production process units will increase the efficiency of sintering production through the creation and implementation of the system of operative diagnostic of the actual state of PE. The main aggregates for electrothermal acquiring of yellow phosphorus are different kinds of furnaces, the reliability of which is largely determined by the diagnostic software, representing a set of interrelated practices, rules, algorithms and tools needed to carry out diagnostics at all stages of the object's life cycle.

The diagnostics process of the electrothermal furnace state is an important part of the sintering production quality assurance system and is extremely demanding as it requires time and the use of sophisticated methods for determining individual diagnostic parameters. In this case, the classical methods of technical diagnostics, based on the use of physical means of non-destructive testing and statistical data processing algorithms, do not allow adapting to the changes of the diagnosed object parameters and obtaining the necessary information to control the electric furnace (Birger, 1978; Yousif Yahya and Yahya, 2016). In addition, the problem of obtaining reliable results, rapid diagnosis and evaluation of the PE's technical condition is complicated by the fact that the presence of malfunctions in the electric furnace is characterized by complex changes in a variety of diagnostic parameters. To solve such problems, at present, speialists widely use intelligent methods of diagnosis and predicting nonlinear characteristics of technical objects based on neural networks and fuzzy

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modeling (Subbotin and Oleynik, 2008; Nguyen *et al*., 2016). These methods are actually designed to build reliable and adequate models, differing in properties of adaptation to value changes of the diagnosed object parameters which leads to the possibility of early detection and prevention of PE malfunctions or emergencies.

Early detection of adverse technical state and maintenance of high reliability of PE malfunctions rate prediction evaluation for the next period of operation is the main technical challenge of diagnosis (Parkhomenko, 2009). Technical diagnostics is a scientific field, based on the methods of establishing effective recognition algorithms, decision rules and diagnostic models to obtain diagnostic information, automated monitoring and troubleshooting in technical objects and systems (Birger, 1978; Uvaysov *et al*., 2014).

At present, the rapid development of information technologies allows allocating a separate area of technical diagnostics-intellectual diagnosis, based on the use of neural networks and fuzzy systems of artificial intelligence (Subbotin and Oleynik, 2008; Konstantinov *et al*., 2016; Rutkovska *et al*., 2004; Bilski, 2014; Swedrowski *et al*., 2014; Huang, 2003; Boseniuk *et al*., 1990). The method of intelligent diagnostics generally includes the following stages: construction of a priori PE conceptual model, planning and conducting experiments, statistical processing of the experimental data, properties informativeness assessment and selection, math modeling, optimization of the resulting model (Subbotin and Oleynik, 2008). The choice of thistechnique is due to the expediency of getting both reliability ratings predictions and ratings for PE controllability for a reliable description of its technical condition and early detection of failures and malfunctions, provided limited information (for example, during operation or pilot testing).

The prediction of PE technical condition and reliability can be carried out on various stagesof the life cycle. At the same time, during the operational phase the initial data are the anticipated patterns of change in the technical parameters of the equipment while the purpose of predicting is a timely warning of failures and use of such operating conditions and modes of PE maintenance that best fit the given task of ensuring reliability. At this stage, the situations of sudden, unpredictable traditional methods of PE subsystems or parts failures are not excluded (Subbotin and Oleynik, 2008). This fact can be attributed to several factors: the object under study in the reporting period of operation is on the stage of "running-in", insufficient a priori information on changing specifications when starting object's operation, a rough description of specificity of subsystems and components functioning in the operational documentation. In emergency situations on the stage of operation or testing of technical objects, the choice of a control action it is usually based on the experience of skilled professionals of a narrow subject area.

However, due to the constant need for high-quality expertise and taking into account the requirements for the exact solution of a certain class of PE control tasks and pattern recognition, expert solutions are often ineffective. Thus, the obtaining and using the information about the a posteriori PE subsystem parameters and various test data can increase the accuracy of predictions and consequently, the quality of the control (Fedin and Trisch, 2006; Jaber *et al*., 2008).

In this regard, the study offers one of the solutions to the problem of diagnostics of technical condition of electrothermal furnaces based on expert knowledge using neural networks and fuzzy logic techniques. According to these methods of artificial intelligence, the diagnoses prediction process in contrast to the classical probabilistic or deterministic methods can be carried out more quickly and at a different algorithmic level (Miranda and Castro, 2005; Hao and Cai-Xin, 2007; Naresh *et al*., 2008).

It should be noted that the self-learning neural network and fuzzy models are the foundationof modern intelligent decision-making support systems on the actual state of PE in a noisy or inconsistent diagnostic information. The use of such models in the structure of theautomated Process Control System (PCS) can improve the effectiveness of operational diagnostics to (Suleimenov *et al*., 2014a, b).

Therefore, the topical task of improving the PCS efficiency of sintering production is the development and introduction of resource-saving technologies of intellectual information decision-making support to ensure the reliability of PE and the quality of yellow phosphorus production.

The purpose of the study is to provide an adaptive system model of runtime diagnostics of technical condition of PE and predicting emergency situations in the process of production of yellow phosphorus on the example of electrothermal furnace in a comprehensive change of its diagnostic parameters.

MATERIALS AND METHODS

The analysis of the conditions of sintering production and phosphorus electric melting modes allowed identifying the following features of its production process:

- The electric melting process lag due to the large volumes of the used ingredients
- Large volumes of silos and storage hoppers, resulting in significant delay in the corresponding control channels
- Wide range of the charge ingredients: phosphates, sinter and quartzite fines, dust, coke
- Composition heterogeneity of the mixture components in ore silos

Besides, the production of yellow phosphorus is characterized by a variety of potential PE problems and their solutions. In particular, one of the common problems is the "temperature rise under an electric furnace cover". This type of problem belongs to electric furnace failures or its defective conditions which occur due to the following main reasons: charge hang in the loading chutes, slag overexposure, short electrodes, coke excess in the charge, electrode break (Suleimenov *et al*., 2014a, b). This issue as well as a number of other PE malfunctions, may be caused by structural or operational reasons, may occur accidentally or gradually and is a prerequisite for an emergency, i.e., ascertains the occurrence of an emergency but one cannot predict it by the actual state of the electric furnace.

The change of temperature in the electric furnace is a "standard" situation which is explained by the uneven chemical composition and physical properties of the loaded blend. The temperature is controlled based on the so-called "fine adjustment" by lifting or deepening the electrodes or "rough adjustment" through switching transformer stages. However, a condition in which the temperature exceeds a certain level and is not reduced by the implemented management system algorithm, indicates occurrence of an emergency due to the above-stated reasons. Thus, it can be argued that if the change in temperature within the prescribed limits is compensated by the manipulated PCS influence, the technical condition of the electric furnace is considered normal. At the same time, a condition in which an electric furnace is not "subordinate" to the PCS, regulating the temperature in the range close to acceptable, suggests the possibility of an emergency and the appropriateness of subsystem intellectual diagnostics. Still, the indicator of current handling of electrothermal furnace can be used as a diagnostic parameter which will allow assessing the emergency risk at an early stage (Suleimenov *et al*., 2014a, b).

Electrothermal furnace diagnostics process which is a non-linear dynamic management object, can be described by a set of parameters $X = (X_1, X_2, ..., X_n)$ which are characterized as a rule by different informative and non-linear links with projected electric condition (diagnosis) $Y = (Y_1, Y_2, ..., Y_k)$. This does not allow constructing a linear model for the classification of diagnoses of the control object.

Therefore, as a mathematical device of an intellectual technical PE diagnostics system as a non-linear dynamic object, it is proposed to use the method of recognition and classification of diagnoses based on artificial neural networks. The choice of neural network modeling methodology in electric furnaces diagnostics is due to its advantages.

Firstly, neural networks represent the best of the existing methods of image classification, approximating and extrapolation of nonlinear functions.

Secondly, the presence of non-linear activation functions in the multilayer neural network provides an efficient implementation for sufficiently flexible control changes, identification and diagnosis of complex nonlinear technical objects.

Thirdly, the parallelism of neural networks is a prerequisite for the effective implementation of software and hardware support of neural network controller in the control loop during operation or testing (You *et al*., 2014; Pegat, 2009).

It should be noted that the model constructing process of runtime PE intelligent diagnosis is based on expert knowledge formalization that, despite its reliability, is characterized by thepresence of subjectivity in the expert estimates. Therefore, when creating intellectual systems of runtime diagnostics of PE technical condition along with neural network modeling is advisable to use the mathematical device of fuzzy logic (Kosko, 1991; Borisov *et al*., 2007; Jang, 1993). However, the classic system with fuzzy logic does not has the ability to auto-learn and the disadvantage of the subjective choice of a set of fuzzy rules, membership functions type and parameters, describing the input and output variables as well as the type of fuzzy system output algorithm (Konstantinov *et al*., 2016). Eliminating this disadvantage is possible basedon Adaptive Neuro Fuzzy Inference System (ANFIS) which is a multilayer neural networks, in which the layers serve as elements of a fuzzy inference system (Jang, 1993; Nauck *et al*., 1997).

RESULTS AND DISCUSSION

The objective of computational experiments is the development of self-learning intelligent diagnosis system model of electric furnace technical condition based on neural networks and fuzzy modeling. As a way, i.e., a teaching indicator of adaptive intelligent diagnosis model of electric furnace, we used the possible values of control estimates (diagnosis) Y to the problem of "raising temperature under the cover of an electric furnace" (Table 1) (Suleimenov *et al*., 2014a, b).

Table 1: Values of Y electric furnace control estimates

Y values	Electric furnace conditions	Possible solutions
0.00, ..., 0.25	Emergency situation	Acting on the orders of plant technician
0.26, ..., 0.50	Preemergency	Detect the charging chute with a frozen charge and "break" it according to the instructions
0.51, ..., 0.75	Emergency possible	Drain slag with a maximum removal of coke
0.76, ..., 1.00	Normal state	Let electrodes pass or "wash" with charge, depleted of coke, to analyze the possible reasons for control lowering: charge hang in loading chutes, slag overexposure, short electrodes, coke excess in the charge, electrode break, no influence

Table 2: Fragment of the training sample of neuro-fuzzy model

Experiment No.	X_1	X_2	X_3	X_4	Y
1	0.0	0.5	0.5	0.5	0.75
2	0.5	0.5	0.5	0.5	0.95
3	1.0	0.5	0.5	0.5	0.25

Table 3: Comparative analysis of the intelligent models reliability

	Model		
Criterion (%)	Fuzzy	Neural network	ANFIS
Prediction error	0.45	3.00	0.20

The data in Table 1 data allowed to define four fuzzy terms of Y control assessment, describing the state of the electric furnace, namely "low" -(0.00, ..., 0.25); "average" -(0.26, ..., 0.50); "rather high" -(0.51, ..., 0.75); "high" -(0.76, ..., 1.00). To determine the degree of current PE controllability, scientists use the evaluation criteria of static control channels and PE lag evaluation. As input models we used static values (X_1, X_2) and dynamic (X_3, X_4) diagnostic parameters: temperature under the electric furnace arch X_1, electrodes penetration value X_2, temperature rise rate X_3, electric power X_4. To specify the range of the input variables, identical to the range of the output variable, we performed their normalization as a result of which based on expert estimates, the values of 0.0, 0.5 and 1.0 are assigned a three fuzzy terms, describing diagnostic parameter values of "minimum", "medium" and "high". A fragment of the fuzzy model training sample-a knowledge base, prepared by analogy with the planning matrix of fractional factorial experiment to assess the degree of control electric is given in Table 2.

The knowledge base is the foundation of the fuzzy inference mechanism and is formed through the heuristic method as a set of fuzzy production rules:

$$\text{IF } \vec{X} \text{ is } A_r, \text{ THEN Y is } C_r \tag{1}$$

Where:

A_r and C_r = The fuzzy variables, determined by the correspondent n-dimentional membership functions

$\vec{X}$ = The dimension of the input vector

r = The number of a fuzzy production rule

Creating a comprehensive knowledge base for electric furnace system runtime diagnostics can be carried out based on the type of production rules of Mamdani output algorithm. IF X_1 is A_{r1} AND IF X_2 is A_{r2} AND ... IF X_n is A_{rn}, THEN Y is C_r or the type of Sugeno output algorithm:

$$\begin{aligned}&\text{IF} X_1 \text{ ec is } A_1 \text{ AND IF } X_2 \text{ is } A_2 \text{ ANA...IF}\\ &X_n \text{ is } A_m, \text{ THEN } Y = F_r\left(X_1, X_2, ..., X_n\right)\end{aligned} \tag{2}$$

where, $Y = F_r (X_1, X_2, ..., X_n)$ is a certain function, r is the rule number. Here, $A = A_1 \cap A_2 \cap ... \cap A_m$. Fragment of the training sample Table 2 is presented in the form of three production rules.

Rule 1: IF the temperature is "minimal" AND the electrodes depth is "medium" AND temperature increase is "medium" AND power is "medium" THEN the controllability is "rather high".

Rule 2: IF the temperature is "medium" AND the electrodes depth is "medium" AND temperature increase is "medium" AND power is "medium" THEN the controllability is "very high".

Rule 3: IF the temperature is "high" AND the electrodes depth is "medium" AND temperature increase is "medium" AND power is "medium" THEN the controllability is "low", etc. The implementation of computational experiments, aimed at restoring the multidimensional dependence $Y = F (X_1\text{-}X_4)$ was carried out using three model types of electric furnace intelligent diagnosis: fuzzy neural network and ANFIS in a mathematical modeling system (MATLAB). Still, ANFIS Model implements a fuzzy system, based on the Sugeno algorithm output in a 5 layer neural network of feedforward signal where the first layer is intended to define the terms of the input variables (X_1-X_4), the second specifies the antecedents (prerequisites) for fuzzy rules "X is A_r" (Eq. 1), the third normalizes the degrees of rules implementing, the fourth realizes the rule consequent (conclusion) "THEN Y is C_r" and the fifth performs the result aggregation of inference Y, obtained based on a set of various rules. Comparative reliability evaluation of the simulation results by the criterion of the relative error prediction (detection) diagnosis of electric furnace malfunction using the control sample showed that it is advisable to use an adaptive ANFIS Model (Table 3) for intellectual runtime diagnostics subsystem.

The learning result of ANFIS Model with the error value equal to 5.4003×10^{-7} and reached 50 training cycles (Fig. 1) is a corrected smooth membership function, implemented in the Sugeno fuzzy inference algorithm for

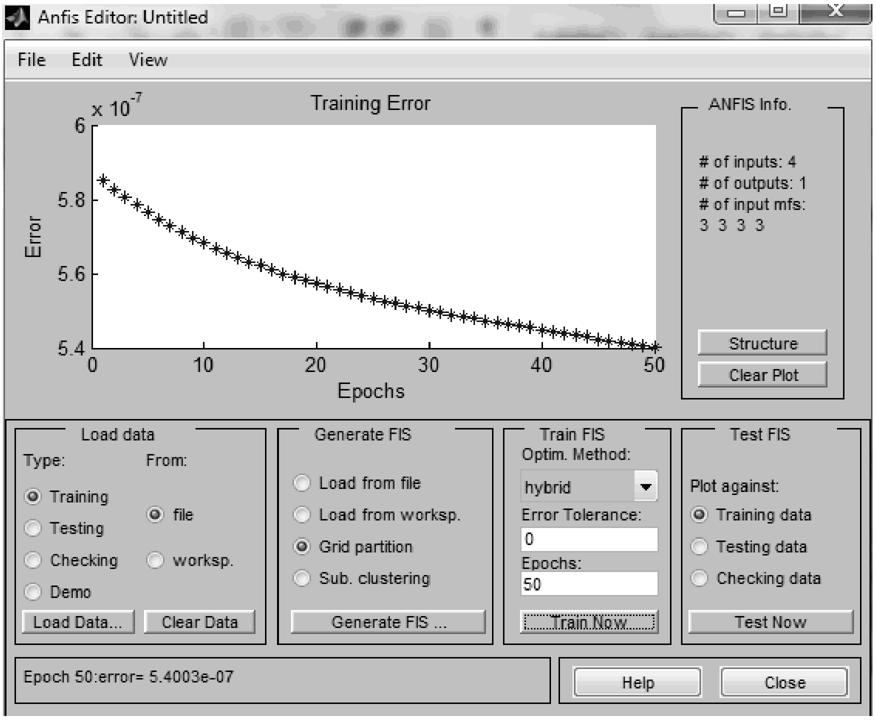

Fig. 1: Screenshot of the ANFIS Model learning process in a MATLAB system

the variable "degree of controllability". Using this algorithm allows to base the production rules (Eq. 2) and define the output Y for a given input vector $\bar{x}$

A distinctive feature of membership functions, obtained as a result of ANFIS Model learning is the ability to describe complex control principles of obtaining reliable results of electrothermal furnace technical condition diagnostics.

The results of the modeling assessment of controllability Y at different values of the input variables X_1-X_4 are presented as graphs in Fig. 2-5. To assess Y depending on the changes in any of the two input variables, the modeling was carried out under nominal conditions of the other two variables. For example, single-factor dependence of $Y = f(X_1)$ was obtained with the maximum value of $X_2 = 1.0$, average $X_2 = 0.5$ and minimum $X_2 = 0.0$ of electrode depth at nominal rate of temperature change modes $X_3 = 0.5$ and electric power $X_4 = 0.5$ (Fig. 2).

Analysis of the graphs shown in Fig. 2, shows that the degree of control reaches a maximum value of Y = 0.95 at medium temperature under the electric furnace arch of $X_1 = 0.5$ and at a nominal electrodes depth of $X_2 = 0.5$ which is explained by the electric furnace's state, whenall the input variables are equal to each other, i.e., $X_1 = X_2 = X_3 = X_4 = 0.5$.

However, at the same position of electrodes crosshead, the temperature in an electric furnace increases

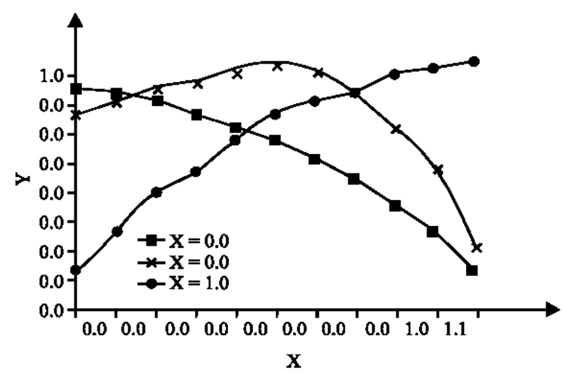

Fig. 2: The modeling results for estimation of Y depending on changes in an electric furnace at a temperature of $X_3 = 0.5$ and $X_4 = 0.5$

to a maximum $X_1 = 1.0$ when Y = 0.25 which is a prerequisite for an emergency (Table 1). If at $X_2 = 0.5$ temperature in the electric furnace takes a minimum value of $X_1 = 0.0$, then there is a possibility of an emergency, because in this case controllability Y = 0.75.

At the maximum immersion electrodes $X_2 = 1.0$ and a maximum temperature in an electric furnace $X_1 = 1.0$, controllability takes the maximum value of $X_1 = 0.95$ which characterizes the normal state. Similarly, we can interpret the results of controllability evaluation at the minimum electrode traverses immersion of $X_2 = 0.0$ (Fig. 2).

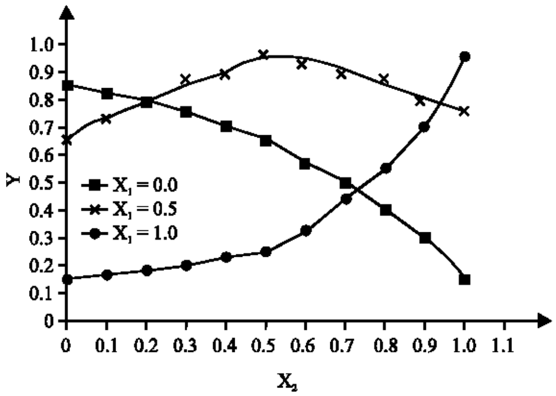

Fig. 3: The modeling results for evaluating Y depending on the electrode traverses position at X_3 = 0.5 and X_4 = 0.5

It should be noted that particularly interesting is the result, obtained as a function Y = f(X_2) as, for example, in case of electrode breakage furnace handling becomes more difficult which is shown at graphs (Fig. 3).

Since, the minimum temperature for the electric furnace arch is X_1 = 0.0 with the electrodes traverse immerse the controllability curve tends to decrease from Y = 0.85 when X_2 = 0.0 to Y = 0.65 when X_2 = 0.5 to a state of total unit uncontrollability of Y = 0.15 when X_2 = 1.0. The resulting pattern is reversed at the maximum temperature for the electric furnace arch of X_1 = 1.0 when Y = 0.95 at X_2 = 1.0 to Y = 0.25 at X_2 = 0.5 and Y = 0.15 when X_2 = 0.0. For electrodes position of X_2 = 0.0 the controllability Y = 0.65 does not drop below Y = 0.75 when X_2 = 1.0 considering X_1 = X_3 = X_4 = 0.5 while the highest unit controllability Y = 0.95 is observed for the nominal regimes X_1 = X_2 = X_3 = X_4 = 0.5 (Fig. 3).

To evaluate the dynamic component of the controllability, we determined the dependence of Y = f(X_3) under the condition of increasing temperature as at the temperature over 800°C there is an increase of exhaust gas volume and respectively the exhaust velocity that leads to the gas "slip" through the condensers and irreversible losses of part phosphorus in gas offtakes (Fig. 4).

Also at temperatures above 800°C the phosphorus atoms go over to tetravalence as a result of which such phosphorus compounds are poorly soluble in water, resulting in a loss of phosphorus on capacitors. Therefore, the curve at the minimum temperature under the electric furnace arch X_1 = 0.0 has a positive trend with an increase of temperature change rate. As at X_3 = 0.0 furnace controllability Y = 0.5, at X_3 = 0.5 controllability increases to Y = 0.75 and given X_3 = 1.0 it reaches the

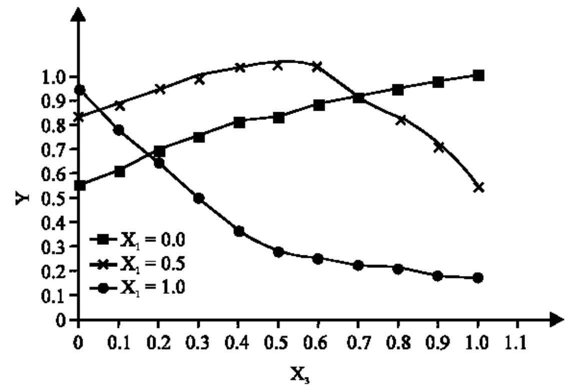

Fig. 4: The modeling results for Y estimates depending on the temperature change rate under an electric furnace arch at X_2 = 0.5 and X_4 = 0.5

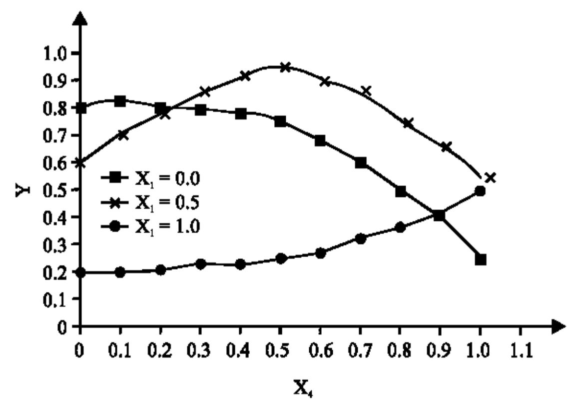

Fig. 5: The modeling results for evaluating Y depending on an electric furnace power when X_2 = 0.5 and X_3 = 0.5

value of Y = 0.9. However, the maximum temperature under the electric furnace arch X_1 = 1.0 the controllability decreases from Y = 0.85 when X_3 = 0.0 to Y = 0.15 when X_3 = 1.0. The dependence of electric furnace controllability Y = f(X_3) from power when X_2 = X_3 = 0.5 (Fig. 5) shows that for X_1 = 1.0 the Y value is changed from Y = 0.5 when X_4 = 1.0 to Y = 0.25 when X_4 = 0.5 and to Y = 0.2 when X_4 = 0.0, indicating an emergency or a pre-emergency condition (Table 1).

Thus, the practical use of the developed neuro-fuzzy model allows, based on current state of the electrothermal furnace, to carry out its runtime diagnosis and to obtain information to support decision making in the management process of yellow phosphorus production.

CONCLUSION

The study shows that the use of adaptive neuro-fuzzy models for runtime diagnostics is efficient in implementing the strategy of operation and maintenance of sintering production units based on reliable predictive estimates of their actual status in terms of restrictions on the use of material and information resources.

It develops an adaptive model of neuro-fuzzy expert system for technical diagnostics of production equipment of sintering production, the distinctive feature of which is the use of learning sample, obtained through fractional factorial experiment, using a production fuzzy rules database, created for situational modeling of possible failures and emergencies of electrothermal furnaces during their operation.

Practical use of ANFIS Model, developed in MATLAB-system of mathematical modeling, allowed to establish regularities between the electric furnace controllability and the main diagnostic parameters in the event of a "growing temperature under an electric furnace cover" problem which allows predicting and preventing this kind of accidents in electrothermal furnace operation.

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