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Intelligent Systems for Equipment Health Management and Optimum Control in Phosphate Production

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Abstract: The aim of this research is the development and testing of intelligent system for equipment health management in the technological process of yellow phosphorus production. In the course of research, the methods of mathematical modeling, experimental design methods, methods of fuzzy modeling, methods for creating and training neural networks and neural network algorithms were used. The peculiarities of the technological process of phosphorus electric smelting are discussed. The three-step procedure of developing intelligent or hybrid models for the management process is proposed to increase the effectiveness of this process on the example of ore-thermal smelting of phosphate ore. A subsystem for calculating the power on the mean level of the automated management system of technological process parameters with the calculations readability once in 10 min is developed which allows stabilizing the temperature under the furnace roof arch which in turn leads to the reduction of phosphorus loss with the exhaust gases out of the condenser. It is indicated that the mean level subsystem determines the optimal values of power depending on the voltage level, linear current, the arrangement of the electrodes on the crossbar and the average temperature under the furnace roof arch.

Key words: Intelligent management systems, phosphorus electric smelting, equipment health management, fuzzy models, neural networks models, linear current

INTRODUCTION

Intensive progressive stage in the development of optimum control systems for various parameters of technological processes started a long time ago (Suleimenov and Hammetov, 2011), however, still the significant optimum control system was not implemented. The threshold, after which the automatic control of the technological process will be recognized as completely successful is the complete exclusion of the human control of the process. At the moment, it has not yet, crossed this boundary, human experience and human competence is still needed in the management of production processes. This is due to the extreme complexity of technological processes in ferrous and nonferrous metallurgy, chemical and other economy branches. Currently, there is an urgent need for the development of optimum control systems for parameters of technological processes in industry which enables to use mineral resources, save thermal and electrical energy, reduce environmental problems, increase economic returns from production, etc. (Hodge *et al*., 2016; Saxena *et al*., 2015). Artificial intelligence and neural networks become a relevant issue in various fields of human activity. The development of information technologies allowed us to store large amounts of information (Zaychenko, 2008), thanks to their associative memory they are most often used in the chemical industry for pattern recognition in analytical purposes and for predicting the possibility of a specific compound synthesis and its properties (Vijayaraghavan *et al*., 2014). Manufacturers are trying to cope with the problem of a constantly evolving range of products in order to meet customer requirements. Using an artificial neural network, we can process large amounts of data to understand market trends and to be able to produce products with the evolutionary characteristics (Uraikul *et al*., 2007). Application of artificial neural networks has also extended into the planning process for critically important objects of infrastructure (Suleimenov *et al*., 2012) and control of nonlinear systems (Rutkovskiy, 2010). In modern industry,

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the actual application of the neural networks theory, fuzzy logic and fuzzy sets, artificial intelligence and modeling systems, the study of the principles of mechanism and algorithms of intelligent management, pattern recognition and image understanding becomes relevant (Kalman *et al*., 1969).

The above directions found wide application in metallurgy both in stand-alone and combined use cases. The areas in which they are effectively used are various: assessment and forecast of technological parameters, control and diagnostics of technological processes, optimization and planning of results, process modeling and interactive modeling in dialogue modes. They allow creating intellectual models of automation objects and applied neuro-systems which help to facilitate technical condition control of industrial facilities (Aitbayevich *et al*., 2015).

Today, in the field of the theory and practice of artificial intelligence, effective artificial intelligence technologies are created and used in various practical applications including management. It should be noted that the majority of these studies focus on the development and implementation of systems for local control, designed to solve problems of stabilization of some output variables of the technological process using intelligent controller (Suleimenov, 2009; Kalogirou, 2003).

However, in our view, the most effective use of intelligent technologies is together with classical methods of technological process management (Mayrhauser *et al*., 2000; Mukhanov *et al*., 2012; Abas, 2013; Suleimenov *et al*., 2014). Thus, it is possible to combine the advantages of traditional methods, techniques and algorithms with the mathematical apparatus of the artificial intelligence theory. Let us call such systems hybrid management systems (Szandala, 2015; Wang *et al*., 2015; Khatibi *et al*., 2011).

Especially important is the establishment of effective management systems for the complex and large-tonnage technologies that manufacture high-value products. This class includes the production technologies of non-ferrous and rare metals, production of chemical and petrochemical industry, pharmaceutical engineering, etc. It says that the expansion of neural networks sphere is caused by the means of mathematical modeling of complex processes and systems, in which there is a need for processing large amounts of data (Yang *et al*., 2013; Leonenkov, 2003; Zadeh, 1975; Wojcik *et al*., 2014).

In this study, the researcher propose to test the developed methods and tools for the creation of smart technology to control parameters of a complex technological process at the mean level of the automated management system-production of yellow phosphorus. Even a slight improvement of this process can lead to significant economic and environmental effects. The industry constantly needs the modernization and automation of equipment to control its state because the equipment becomes obsolete in terms of technology and out of order in connection with the expiration of production time and in some cases reaches a critical state which entails production accidents and the danger to life and health of employees. The main trend of industrial development is the presentation of more stringent requirements for security and reliability of technological processes. Integration of systems and creation of a unified database help to automate industrial processes. Along with the requirements of high economic efficiency, the attention is focused on the products quality that is impossible to implement without the use of control methods based on modern intelligent technologies.

Thus, the aim of this research is to develop and test intelligent system for optimum control of complex objects, in particular the parameters of the technological process of yellow phosphorus production in the chemical industry, to improve the efficiency of this process. The main objective of this research is to create management methods of complex technological process which (unlike existing) combines various models at different levels of the automated system and includes a model based on full-factor experiment that provides a basis for justifying decisions on the basis of expert knowledge.

MATERIALS AND METHODS

The researcher of this study proposed a three-step procedure of creating optimum control systems for technological processe's parameters by Szandala (2015), Wang *et al*. (2015), Khatibi *et al*. (2011) and Zadeh (1975).

The first stage: The transcendent studies of the technological characteristics of the management object are carried out according to the literary sources, publications in periodical editions and the manufacturer's technical documentation. As a rule, existing processes had to go through a long phase of research, experimental-industrial and industrial testing before they were put into production. The case studies and attempts to develop mathematical models remain. A careful analysis of all this information is needed in order to use it in the development of intelligent management systems. This is especially important in the possible creation of Hybrid Management Systems (HMS).

At this stage, it is necessary to analyze the performed process as a management object identifying input and output, controlled and uncontrolled, ruled and unruled variables. It is necessary to estimate the object delayed action according to different channels, the object's class (continuous or discrete), the degree of information completeness considering object variables, the operating range of object variable changes, etc.

After careful analysis of the available information, it is necessary to develop the structure of the future control system that will greatly facilitate further work.

The second stage: A process control model is developed. With the help of sophisticated experts (operators technologists or engineering personnel at a production department or plant) the main purpose of the control is determined (an analogue of the objective function in optimization issues) which is generally known and which experienced operators usually aim to achieve. Then with the help of ranking method, the variables which in the opinion of experts are basic to the object (process) are determined from the total list of all types of variables.

The main objective of the second stage is the development of the planning matrix for the Full Factorial Experiment (FFE). Using the FFE on matrix, a model of the control object (process) is created. Thus, for a three-level factors, the total number of possible factors combinations with two input variables is $N = 3^2 = 9$ with three variables is $3^3 = 27$, etc.

For example, when there are two input variables, the FFE planning matrix is created as shown in Table 1 and 2 are the basis for the development of intelligent systems, since, they focus years of experience, knowledge and intuition of experts in a particular subject area. The efficiency of the entire control system will depend on the quality of the FFE matrix.

Values: 0.0; 0.5; 1.0 mean minimum, average and maximum values of the input variables X_1 and X_2. The expert only assigns values of the output variable Y^{ex} (control action) in the range from 0.0-1.0 considering his/her experience, knowledge and intuition. Normalization of input and output variables in the range from 0-1 is based on a Eq. 1:

$$\bar{X} = \frac{X-X_{min}}{X_{max}-X_{min}} \quad (1)$$

Where:

$\bar{x}$ = Normalized (from 0-1) value of input or output variable

X = The current value of the variable

X_{min}, X_{max} = Minimum and maximum values

The matrix design for experiments is more convenient for experts than recommended in all textbooks and publications (Saxena *et al*., 2015; Mukhanov *et al*., 2012; Abas, 2013; Suleimenov *et al*., 2014) composition of the fuzzy productions rules. In this case, it is not necessary for the expert to invent endless terms ("a lot", "very little", "quite normal", etc.,) he just puts the value of the output (control) variable to the range from 0.0-1.0. The FFE planning matrix can be used for four different methods of creating management models: experiment planning, expert systems, neural networks and neuro-fuzzy algorithms.

Table 1: FFE planning matrix

Experiment No.	X_1	X_2	Y^{ex} expert evaluation
1	0.0	0.0	1.0
2	0.0	0.5	0.8
3	0.0	1.0	0.7
4	0.5	0.0	0.8
5	0.5	0.5	1.0
6	0.5	1.0	0.9
7	1.0	0.0	0.7
8	1.0	0.5	0.8
9	1.0	1.0	1.0

Table 2: Comparison matrix of calculated and experimental values of the output variable

Experiment No.	X_1	X_2	Y^p model evaluation	Y^a expert evaluation
1	0.0	0.0	1.0	0.95
2	0.0	0.5	0.8	0.85
3	0.0	1.0	0.7	0.65
4	0.5	0.0	0.8	0.80
5	0.5	0.5	1.0	1.00
6	0.5	1.0	0.9	0.85
7	1.0	0.0	0.7	0.80
8	1.0	0.5	0.8	0.75
9	1.0	1.0	1.0	1.00

In contrast to the well-known classical methods of the experiment planning, FFE planning matrix with the help of experts significantly accelerates and reduces the cost of the procedure. Experts carry out the so called "thought experiments" instead of a costly, actually carrying out active experiments. In addition, we need to consider that the conduct of active experiments in the conditions of production are unrealistic because of the possible emergency situations during the change of variables from their minimum values to maximum values and vice versa. Moreover, many enterprises simply cannot change the variables, according to the FFE planning matrix.

It should be emphasized that the output values Y_i are actually controlling variables that is why the planning matrix displays the process management model for all scheduled combinations of input variables. To calculate values at intermediate combinations of input variables (e.g., when $X_1 = 0.21$ and $X_2 = 0.74$), it is necessary to synthesize the process control model which is the main objective of the second phase.

It is also important that the FFE planning matrix can be used to create a management model in five different ways: experiment planning, fuzzy algorithms, neural networks, neuro-fuzzy networks, hybrid models.

It should be noted that the use of known mathematical relationships identified in the first phase of the research is the most effective together with intelligent models. In this case, you should be sure that such dependencies adequately reflect the various physic chemical regularities of a specific process.

The third stage: The obtained models are subjected to rigorous study and analysis of their sensitivity, stability and uniqueness. For this, the management process modeling is carried out at different variations of input variables, the curves of the output variables change are constructed at the input variables change and their analysis is performed together with experts. After the study completion of models, obtained by different methods, they are compared for their adequacy. For this reason with the help of models, output variables are calculated at values of input variables taken from the planning matrix FFE and are compared with the estimates given by the expert. After that, a matrix of comparisons is created (Table 2) which allows calculating the amount of modeling error in various ways. For example, the absolute percentage error is calculated according to Eq. 2:

$$\delta = 100\frac{1}{N}\sum_{i=1}^{N}|Y^{ex} - Y^{cal}| \tag{2}$$

where Y^{ex} and Y^{cal}, respectively the experimental and calculated values of output variables. The absolute error is calculated for the models obtained in four different ways and then their comparative analysis takes place. The model with the smallest absolute error is considered the most effective. In addition, it should undergo modeling tests in the conditions of existing industry. Thus, the valid input variables are served to the input of the model taken from the measuring equipment of the industrial unit the modeling results (output control variable) are compared with the control value which is actually carried out by an experienced operator-technologist. In the case of a satisfactory modeling result, the model is integrated into an industrial controller. Otherwise, everything starts from the beginning a return to the first stage and updating all of the model parameters.

RESULTS AND DISCUSSION

Let us consider the application of the proposed method on the example of the creation of an intellectual control system for parameters management of electric smelting in the production of yellow phosphorus.

The technology of phosphorus electric smelting is described in detail by Biswas and Breuel. Taking into account this information, we can identify its following characteristics as the control object:

- Considerable delayed action of the electric smelting process due to large amounts of ingredients
- Large volumes of silos and bunkers, leading to significant delays on the respective control channels
- Wide range of components of the furnace burden phosphates, sinter fines, quartzite fines, dust, coke
- Heterogeneous composition of the furnace burden components in the ore silo

On the one hand, the process of electric smelting, in terms of furnace burdening is not difficult. Its optimal composition is known from a predetermined calculation of the furnace burden based on the balance equations. The furnace burden enters the furnace with its penetration. The versatility of the electro-thermal method lies in a clear separation of the recovery reaction products: gases containing phosphorus, slag consisting of calcium and magnesium silicates and ferrophosphorus. We condense the phosphorus from gases and get it in pure form (99.5%).

The main difficulty in the preparation of the furnace burden is a disturbance action of variable (but controlled) amounts of loaded components: sinter fines, coke and siliceous raw materials. Largest perturbations in the electric smelting process are made by the acidity index and the content of sinter fines which does not allow withstanding a given amount of fuel in the furnace burden. This is due to the fact that the furnace burden fuel does not fade completely during agglomeration of phosphorites. There is a certain optimum in the acidity index. If this optimum is exceeded, the quantity of the finished product decreases and the furnace efficiency reduces and when the value ranks below the optimum not all reactions proceed to the end. However, there is no exact dependence of the furnace power on the acidity index.

To accomplish the above goal, we proposed a three-step structure of a control system for process parameters of ore-thermal smelting of phosphate ore which is shown in Fig. 1.

At the top level of management, an optimal calculation of the furnace burden and furnace mean power is performed depending on the physic-chemical composition of the starting components and a necessary amount of the yellow phosphorus. The calculation increment 1 time per shift.

On the lower level of the Automated Control System for Technological Process (ACSTP) there is a subsystem of furnace capacity stabilization which works in a mode of Direct Digital Control (DDC), i.e., constantly. However, as experience has shown, for various reasons, the furnace temperature changes continuously during melting, mainly

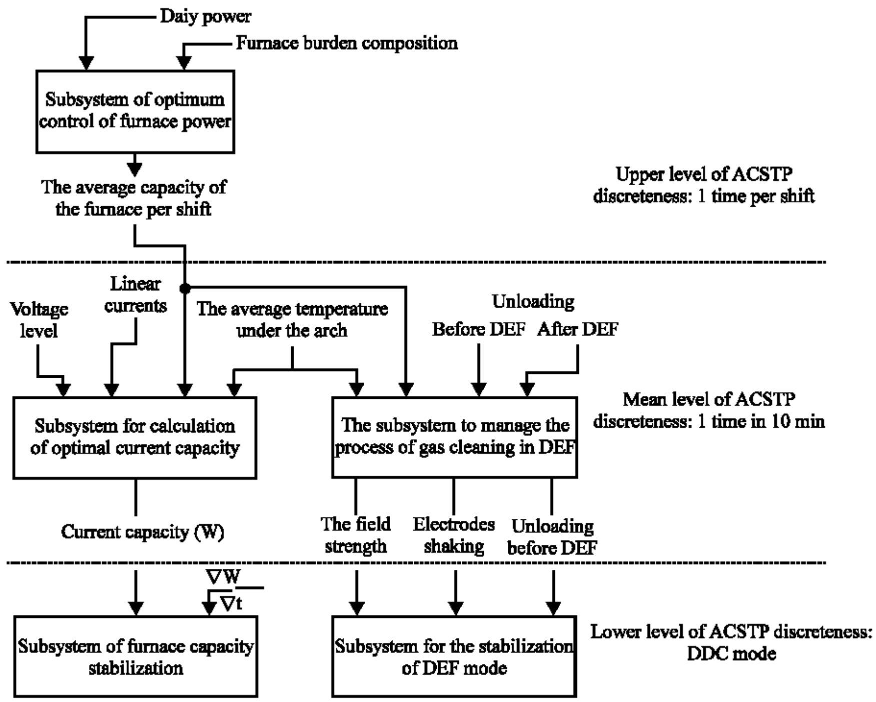

Fig. 1: A three-level hierarchical structure of the optimum control system for process parameters of yellow phosphorus production

due to uneven composition of the furnace burden over the height of the furnace. The furnace temperature is estimated indirectly from the mean temperature measured by the sensors under the furnace roof arch and is a very important indicator of the furnace operation.

The phosphorus removal in the condenser depends ultimately on the temperature in the furnace. At high temperature (above 800 N), an increase in the volume of exhaust gases takes place and therefore the speed of their expiration which leads to "skips" of gases parts through the condensers and irreversible loss of part of the phosphorus. Additionally, at temperatures above 800°C, part of the atoms of phosphorus passes into the 4-valent state, resulting in poor solubility of such compounds in water which also leads to its losses in the capacitors (Mukhanov *et al*., 2012).

In these circumstances, the researchers of this study suggest to develop another level subsystem calculate power of the mean level of ACSTP with a readability calculations 1 every 10 min. Synthesis of one-level process control system will change the capacity of the furnace during the shift increments once per 10 min. This discreteness allows often enough to adjust the temperature and at the same time it corresponds to the delayed action of the furnace temperature. At high temperature under the furnace roof arch, system will recommend to reduce the capacity of the furnace and with the low temperature-to increase. The average capacity of the furnace per shift must be approximately equal to the value calculated for the ACSTP.

In regard with this problem, a three-level hierarchical structure of the system of optimum control of process of production of yellow phosphorus will be of the form shown in Fig. 1. On the upper level of ACSTP on the basis of information on capacity of the furnace in the current days, coming from the management of the plant and taking into account the physic-chemical properties of the components of the furnace burden produces the calculation of the optimal composition of furnace burden and power the furnace on the current shift. Mean level of ACSTP has two subsystems: the subsystem of calculating the optimum current capacity of the furnace and the control subsystem purification of exhaust furnace gases in dry electrostatic precipitators (GAP). Taking into account the current values of voltage level, line current and average temperature under the furnace roof arch. Taking into account the designed at the ACSTP upper level capacity of the furnace for the shift, the first subsystem calculates the current power based on the temperature under the furnace roof arch: at low temperatures it increases and at high values reduces the current capacity of the furnace. The second subsystem is

Table 3: The FFE planning matrix for the subsystem of mean-level management

Income variable					Outcome variable
Experiment No.	Voltage level (X_1)	Linear current (X_2)	Crossbar height (X_3)	The temperature under the arch (X_4)	The current voltage (Y)
1	0.0	0.5	0.0	0.5	0.76
2	0.5	0.5	0.0	0.5	0.53
3	1.0	0.5	0.0	0.5	0.00
...	...	...	...	...	...
79	0.0	1.0	1.0	1.0	0.78
80	0.5	1.0	1.0	1.0	0.63
81	1.0	1.0	1.0	1.0	0.07

based on the average temperature under the furnace roof arch, the furnace on and off before and after the ESP calculates the current values of the field strength, length of time between electrodes on and off in front of set. On the lower level, subsystem of the process control system to stabilize the power of the furnace produces the stabilization by immersion or lifting of the electrodes, this subsystem performs the stabilization of the calculated mean parameters of furnace operation.

Thus, adding to system an additional mean-level ACSPT allows stabilizing the temperature under the furnace roof arch which leads to the reduction of phosphorus in the exhaust gases after the condenser. Due to the fact that the task of calculating the optimum furnace burden composition and average capacity per shift is purely a technological problem that is well studied and widely used in practice, we will not consider it in this article.

The issue of the purification process management of waste furnace gases is rather complicated and requires separate consideration; therefore, it is not considered in this article. The problem of stabilization of power is well known and currently used in the production, we will not consider it.

Thus, we consider the problem of creating an intelligent subsystem control parameters of the process of electric smelting of phosphorus at the mean level of ACSTP, i.e., the problem of stabilization of the temperature in the furnace. The survey of operators technologists phosphoric factory is the optimal value of power depends on the level of voltage, linear current, the arrangement of the electrodes on the crossbar and the average temperature under the furnace roof arch.

The main challenge in developing the model of management is the preparation of the planning matrix of the Full Factorial Experiment (FFE). The quality of the FFE matrix will depend on the efficiency of the entire control system. The planning matrix FFE should reflect the experience, knowledge and intuition of the technicians, operators, long time working on phosphoric ore-smelting furnaces. As noted above, the task subsystem intermediate level is to determine the optimal values of power (Y) depending on the level of voltage (X_1), line currents (X_2), the arrangement of the electrodes on the crossbar (X_3) and average temperature under the furnace roof arch (X_4). As a rule such calculations should be performed continuously (about once every 5-7 min), depending on the situation. A survey of technology workshops has allowed us to compile a FFE planning matrix for 81 experiment with a three-level assessment (0, 0; 0, 5 and 1, 0), four input variables: N = 34 = 81. Table 3 and 4 shows a fragment of the FFE planning matrix for four input and one output variable.

Table 4: Comparative analysis of calculated and experimental values of the output variable by the method of experiment planning

					Y	
No.	X_1	X_2	X_3	X_4	$Y^{cal.}$	Y^{ex}
1	-1.0	-1.0	-1.0	-1	0.79	0.800
2	1.0	-1.0	-1.0	-1	0.02	0.046
3	-1.0	1.0	-1.0	-1	0.90	0.870
4	1.0	1.0	-1.0	-1	0.10	0.090
5	-1.0	-1.0	1.0	-1	0.84	0.800
6	1.0	-1.0	1.0	-1	0.07	0.070
	...	...	...	...	...	...
75	0.5	1.0	0.5	1	0.24	0.580
76	1.0	0.5	0.5	1	0.05	0.800
77	-1.0	0.5	1.0	1	0.79	0.760
78	0.5	0.5	1.0	1	0.24	0.560
79	1.0	0.5	1.0	1	0.06	0.000
80	0.5	-1.0	1.0	1	0.20	0.600
81	0.5	1.0	1.0	1	0.26	0.630

Absolute error (%) = 14.41%

Normalization in the range from 0-1 input and output variables was carried out according to Eq. 1. In Table 3, all the variables are in a normalized form between 0.0 and 1.0. Thus, the seventh step in the voltage corresponds to the value 0 and the forty third to the value of 1; the maximum value of line current is 70 kA which corresponds to 1 in Table 3 and minimum 0 kA; the maximum value of the stroke of the electrodes or the height of the crossbar 100 cm, minimum 20 cm; the maximum furnace power is 70 MW and the minimum was 0 MW.

The FFE planning matrix is composed of experienced technologists using the “intellectual” experiment. That is why it is much easier to make such a matrix, than according to active experiment. In Table 3, the years of technologists experience with the furnace are focused. In the FFE planning matrix, the expert knowledge for the management of current capacity is founded depending on the temperature under the furnace roof arch, the steps of the voltage values of linear currents and height of the electrodes crossbar. The FFE planning matrix can be used to develop management models in four ways: by the design of the experiment, the fuzzy modeling method is neural networks and neuro-fuzzy methods.

Due to the fact that the method of experiment planning often includes a two-stage estimation variables (from -1 to +1), the experiments only with such levels of assessment variables were selected from Table 3. Thus, the rating of 0.0 of Table 3 corresponds to the rating of -1.0 and assessment 1.0 to assessment of +1.0. Using this simple technique, a FFE matrix was prepared for the two-level assessment.

For two-level factors, the total number of possible combinations of the number of factors is $N = 2^4 = 16$. In this regard, the plan is developed in which the number of columns of the factors and their combinations equals the number of terms in Eq. 3:

$$Y = b_0+b_1x_1+b_2x_2+b_3x_3+b_4x_4+b_{12}x_1x_2+ b_{13}x_1x_3+b_{14}x_1x_4+b_{23}x_2x_3+b_{24}x_2x_4+b_{34}x_3x_4 \quad (3)$$

It now remains to find the appropriate coefficients of Eq. 3 by the equations:

$$b_0 = \frac{\sum_{u=1}^{n} y_u}{n},\ b_i = \frac{\sum_{u=1}^{n} x_i y_u}{n},\ b_{ij} = \frac{\sum_{u=1}^{n} x_i x_j y_u}{n} \quad (4)$$

Using Eq. 4, we calculated the coefficients of regression equations which after substitution in Eq. 4, gave the following relation to calculate Y:

$$Y = 0.436-0.3678X_1+0.039X_2+0.0278X_3-0.0485X_4- 0.0098X_1X_2-0.001X_1X_3+0.0153X_1X_4+ 0.0098X_2X_3-0.0165X_2X_4-0.0052X_3X_4 \quad (5)$$

Using the regression Eq. 5, the output (control) variables were modeled for all 81 experimental points. A comparative table of the modeling results and the experimental values was developed with the help of which using Eq. 2, we calculated the error. Table 4 shows fragments of calculations by Eq. 5 $-Y_p$ and the experimental value of the output variable $-Y_Э$.

Analysis of publications (Hodge *et al*., 2016; Saxena *et al*., 2015; Zaychenko, 2008) have shown that intellectual technologies can be used directly in the development of process optimum control models not a model of the process itself. That is considered technologies allow you to develop control algorithms in contrast to the traditional chain: development of process model structure→experimental research on the object→model identification→formulation of optimization problem→selection of optimization method→development of optimum control algorithm.

The use of intellectual technologies allows solving a similar problem immediately and as shown by the experience of the researchers of this study (Suleimenov, 2009; Mukhanov *et al*., 2012; Suleimenov *et al*., 2014) successfully. The methods of artificial intelligence involve the use of knowledge, experience and intuition of human experts who are familiar with the subject area. That is, the so-called effect of "ready knowledge" is used here. In contrast, the development of a mathematical model (main system component) is the process of creating "new knowledge" and therefore requires a fairly long time to conduct theoretical research as well as high material and labor costs for conducting the experimental studies and model identification.

Moreover, experienced operators-technologists during their long work learned to make the technological process in optimal modes at different initial situations (and they often succeed) (Abas, 2013; Suleimenov *et al*., 2014; Szandala, 2015; Wang *et al*., 2015; Khatibi *et al*., 2011; Yang *et al*., 2013; Leonenkov, 2003). The "ready knowledge" transferred from experts to the knowledge base of intelligent system greatly simplifies the creation of intelligent systems. Their operation allows excluding the human factor in the process management (these are such properties of the human body as fatigue not fast enough reaction not enough psychological stability, sleepiness during monotonous work, slight experience of young operators and others) (Zadeh, 1975, 2008; Wojcik *et al*., 2014; Fazilat *et al*., 2012; Swedrowski *et al*., 2014; Bobillo and Straccia, 2008).

The development of intelligent models (algorithms) for process parameters control in yellow phosphorus production at the average level of ACSTP is performed by three methods: fuzzy modeling, neural network method and neuro-fuzzy method.

Fuzzy modeling: Developing a fuzzy model (Leonenkov, 2003) is performed using the graphical tools of Matlab system. Then we define membership functions for the four input and one output variable for this reason we will use the editor of membership functions in the MATLAB system. The graphical interface editor of membership functions is shown in Fig. 2 which shows the membership functions for the four input variables: level of stress (X_1), linear currents (X_2), the height of lifting (lowering) of crossbar with electrodes (X_3) and average temperature under the furnace roof arch (X_4) and one output variable current furnace capacity (Y). Then, the fuzzy products rules are formed, i.e., each experiment from Table 3, corresponds to a product rule, for example.

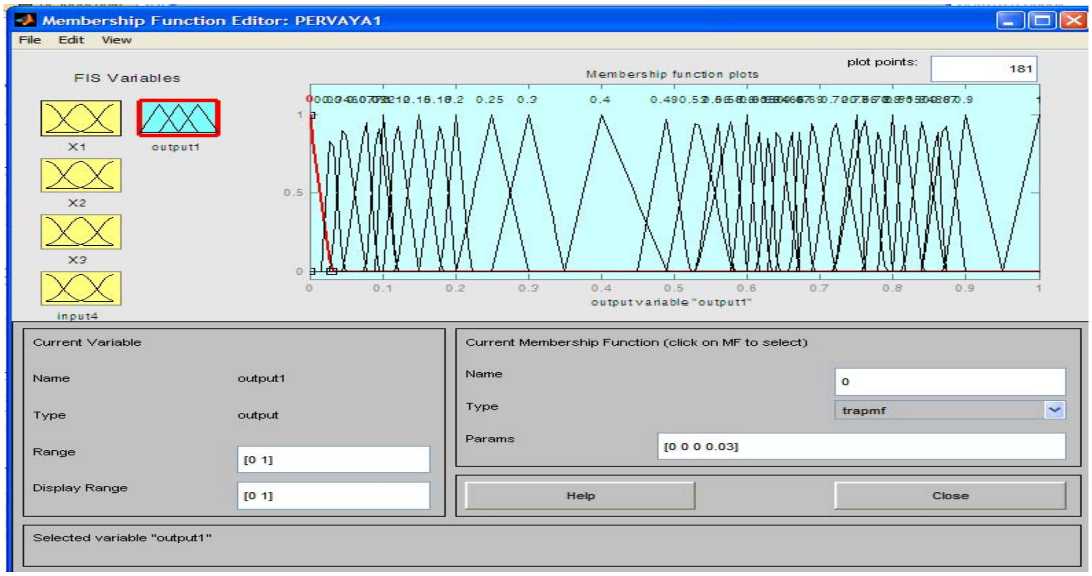

Fig. 2: The graphical user interface of membership functions editor after defining the first input variable

Rule 1: "IF X_1 is EQUAL to 0" AND "X_2 is EQUAL to 0.5" AND "X_3 IS EQUAL to 0" AND "X_4 is EQUAL to 0.5" THEN "Y is EQUAL to 0.76".

Rule 2: "IF X_1 is EQUAL to 0.5" AND "X_2 is EQUAL to 0.5" AND "X_3 is EQUAL to 0" AND "X_4 is EQUAL to 0.5" THEN "Y is EQUAL to 0.53".

Rule 3: "IF X_1 is EQUAL to 1" AND "X_2 is EQUAL to 0.5" AND "X_3 is EQUAL to 0" AND "X_4 is EQUAL to 0.5" THEN "Y is EQUAL to 0".

Rule 4: "IF X_1 is EQUAL to 0" AND "X_2 is EQUAL to 0" AND "X_3 is EQUAL to 0" AND "X_4 is EQUAL to 0.5" THEN "Y is EQUAL to 0.72".

Using the similar technique, we have drawn up the products rules for all 81 experiments from Table 3. After MATLAB generates all the necessary procedures in accordance with the selected algorithm of fuzzy inference (for example, Mamdani algorithm), a fuzzy optimum control model for the melting phosphorus process at the mean level of the hierarchy (Fig. 3) will be presented in the interface of rules view.

Thus, the interface shown in Fig. 3 is an optimum control model (algorithm), using which you can simulate different modes at all possible combinations of values of input variables.

Modeling using neural networks: For process control modeling can also be used in the neural network, instead of fuzzy models. For training the neural network, it is necessary to introduce the results of the 81 experiments of FFE planning matrix. The program MATLAB 2006 has a graphical interface that allows you to introduce the necessary data for the network architecture choice and its training method.

To train the neural network, we input source data from the FFE rapid planning matrix (Table 3). Output variables (control actions) are using the window "Datatarget". Next, we create a neural network (Fig. 4).

In the margin "input data", we specify a previously created data, set the type of neural network; we choose the perceptron (Feed-ForwardBackPropagation) with 10 sigmoid (TANSIG) neurons of the hidden layer and one linear (PURELIN) neuron of the output layer. Training will be done using the Levenberg-Marquardt algorithm (Levenberg-Marquardt) which implements the function of TRAINLM. The error function is MSE. The program will show progress and learning outcomes.

Modeling using neuro-fuzzy algorithms: Instead of fuzzy models and neural networks it is possible to apply hybrid models such as neuro-fuzzy network which is supposed to combine all the advantages of the two above mentioned methods (Fazilat *et al*., 2012; Swedrowski *et al*., 2014; Zadeh, 2008; Bobillo and Straccia, 2008). The capabilities of MATLAB allow you to carry out these studies. To do this, in MATLAB there is the ANFIS editor that allows you to create or download a specific model of an adaptive system of neuro-fuzzy inference, to complete her training, to visualize its structure, change and

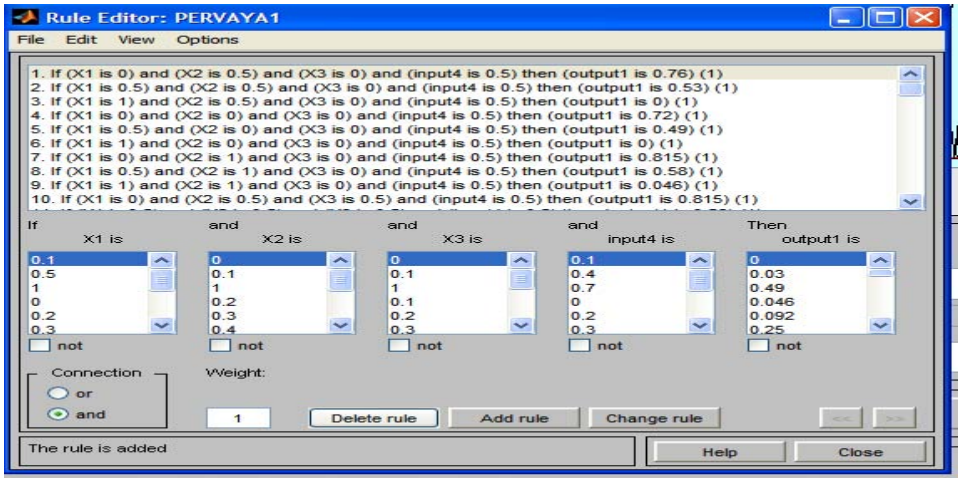

Fig. 3: Fuzzy model of process management at the mean level of ACSTP

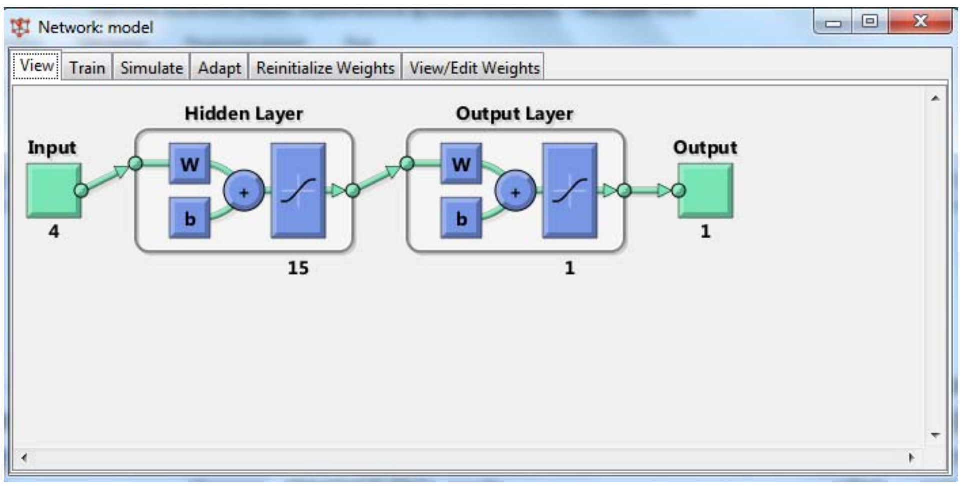

Fig. 4: Neural network control model at the mean level of ACSTP

configure its settings and customize the network to obtain results of fuzzy inference. Entered in the main command window of MATLAB anfisedit and press enter screen appears. It should be noted that in MATLAB 2008 and above there is no need to do this because this editor is launched as with all programs via the Start button-opens the editor ANFISA.

Each row corresponds to an individual data point on the graph that for the training data depicted with a circle. On the horizontal axis, you specify the ordinal (index) of the individual rows of data and the vertical axis indicates the values of the output variable. The next step in the development of hybrid network is to generate the structure of the fuzzy inference system. At this stage, you can view the network architecture (Fig. 5).

Now it is necessary to choose a teaching method for a hybrid network such as the optimization method, the number of learning epochs and permissible error. The network shown in Fig. 5 is the governance model at the mean level of the hierarchy using neuro-fuzzy algorithms. In the future, this model can be used for the calculation of output variables for any changes in the input. After training the network, it is possible to test, upload the test data to view or to ask any valid value in FIS editor rule viewer as well as fuzzy logic (Fig. 6) which is a neuro-fuzzy control model for the mean level of ACSTP. The studie's results of intellectual control models at the mean level of ACSTP are summarized in Table 5. The magnitude of the absolute error was calculated by Eq. 2, analysis of Table 4 showed that the use of the method of experiment planning is impossible due to unacceptably high values of absolute errors. Intellectual models (Table 5) showed their advantage: from 0.2-2.9% while the best proved method is the method of neuro

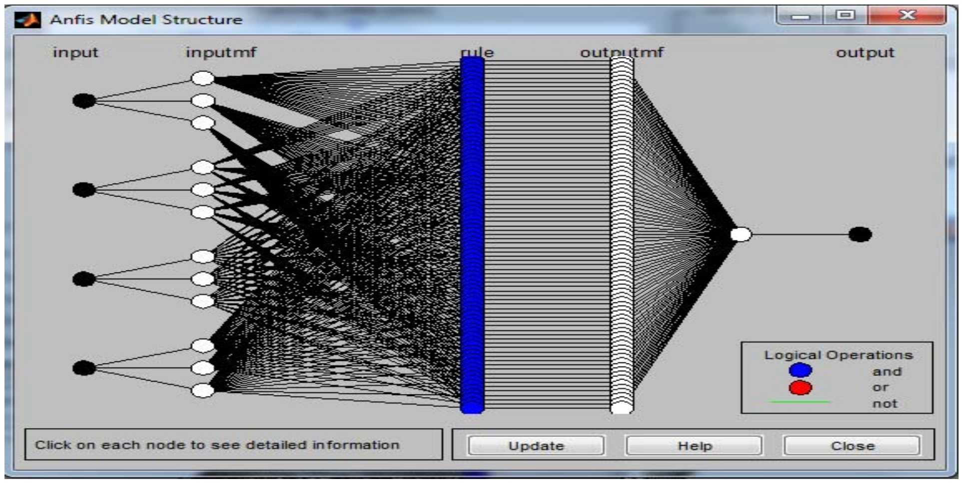

Fig. 5: Structure of the hybrid network

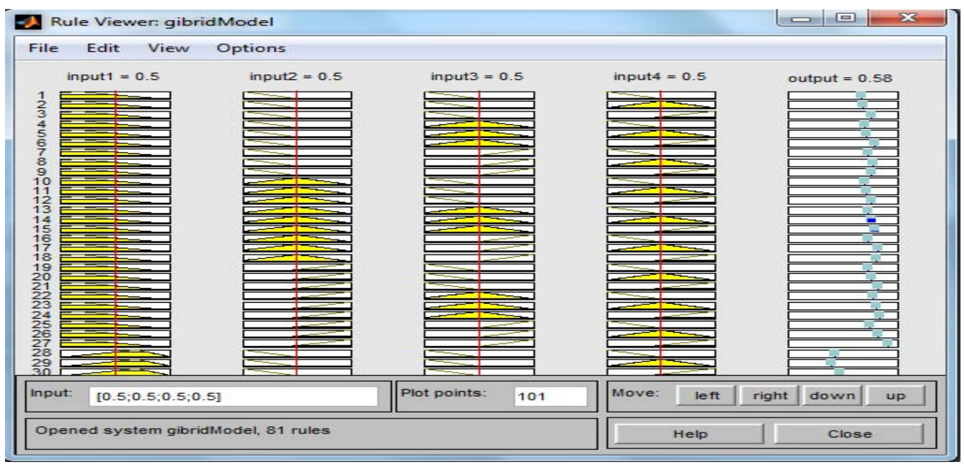

Fig. 6: Neuro-fuzzy control model

Table 5: The results of intellectual models modeling

Experiment No.	Fuzzy logic	Neural network	Neuro-fuzzy network	Right answer Y
1	2.000	3	4	5.00
1	0.760	0.76357	0.76	0.76
2	0.530	0.53443	0.53	0.53
3	0.006	0.033213	0.0000002	0.00
...	...	...	...	...
77	0.600	0.52031	0.6	0.60
78	0.050	0.021506	0.04	0.04
79	0.780	0.75978	0.78	0.78
80	0.630	0.57944	0.63	0.63
81	0.070	0.064694	0.07	0.07
Error (%)	0.300	2.9	0.2	-

fuzzy networks (0.2%). As the analysis of works in the field of the theory and practice of artificial intelligence shown, currently there are created effective artificial intelligence technologies. However, most authors use these technologies for design, research and implementation of only local control systems which are mainly designed to solve stabilization problems of some variables of the technological process. The mentioned studies have shown high efficiency of the control algorithms, obtained by using the artificial intelligence methods. Compared to classic methods of building analytical and statistical models, methods based on knowledge, experience, intuition of human experts allow you to create a system of optimum control for complex processes much easier, faster and more efficient. Assessment of the intellectual models adequacy is much higher than in traditional modeling.

CONCLUSION

As a result of the conducted analysis of the synthesis methods and investigation of intelligent and hybrid models, it can be seen that most authors use intelligent technologies for development, research and implementation of local management systems. Information technology can be used directly in the development of an optimum control model for the process parameters, not the model of the process itself.

In this research, we specified the features of the technological process of electric smelting of phosphorus and described the technique of development of intelligent control technology which combines various models at different levels of the automated system and improves the efficiency of such process.

We have proposed the concept of a three-step process for creating control systems for the process parameters of ore-smelting smelting of phosphate ore, based on the preparation of the FFE planning matrix, instead of recommended in the literature products rules which include years of experience, knowledge and intuition of human experts.

The FFE matrix are formed as a result of “intellectual” experimentation of experts and technologists, who worked hard on the project. It is much easier than costly, dangerous and long “real” experiments at existing facilities.

The structure is developed subsystem calculate power of the mean level of ACSTP with the discreteness of the calculations: 1 every 10 min. This discreteness allows adjusting the temperature and at the same time, it corresponds to the delayed action of the furnace temperature. Thus, adding to system mid-level process control system allows to stabilize the temperature under the furnace roof arch which leads to the reduction of phosphorus in the exhaust gases after the condenser. Four management models were synthesized at the mean level of ACSTP: neural network, fuzzy, neuro-fuzzy and obtained by using the method of experiment planning.

The study of all four models of effectiveness revealed that the use of the method of experiment planning is impossible due to unacceptably high values (14.41%) of absolute error. In addition, the neuro-fuzzy model most accurately describes the management process (absolute error of 0.2%).

Studies performed in this research, have shown high efficiency of the control algorithms, obtained by using the artificial intelligence methods. Methods based on knowledge, experience, intuition of human experts allow creating systems of optimum control parameters of complex processes much easier, faster and more efficient. Assessment of the adequacy of the intellectual models is much higher than traditional modeling.

The proposed methods allow developing ACSTP instead of the development of a model of the process which can be used in industry to assess and forecast technological parameters, control and diagnostics of technological processes, optimization and planning results, etc.

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