

**The example of application of the developed method of Neuro-Fuzzy rationing of power consumption at JSC "YuGOK" mining enrichment plants**



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**Abstract**

The results of developing of a method of rationing of power consumption at mining enrichment plants on the base of usage of neuro fuzzy process model of a power consumption by these units are presented. The results of industrial tests confirm the effectiveness of the proposed method application, which allows systematically implement energy efficiency measures at mining enrichment plant enterprises.

Keywords: ENERGY CONSUMPTION, RATIONING, MINING ENRICHMENT PLANT, ADAPTIVE NEURAL NETWORK

# Automatization

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## 1. Introduction

A considerable part of the basic equipment of the Ukrainian mining enrichment plants has fulfilled operating term, which is fixed in standards: 80% of equipment exceeded their design life, 52% - exceeded the limit one. This resulted in increased specific energy production, which is 18% of the total cost, at the same time the quality of domestic mining enrichment plant production is on average 1-3% lower than of foreign competitors. In present-day manufacturing replacement of about 50% of new equipment in a short time is impossible, yet the replacement of equipment of mining enrichment plants in wide scales is not always economically and practically expedient.

According to the abovementioned, the most important issue of modern mining and enriching production in the next 15-20 years is to continue the reliable and efficient operation of main process equipment more than terms defined standards and other regulatory documents. Accordingly the scientific work related to the study of power consumption norms of basic process equipment of manufacturing complex in order to implement appropriate systemic measures aimed at energy conservation are strategic and relevant for the mining and metallurgical industry of Ukraine.

## 2. The analysis of literature data and formulation of the problem

The results of the second stage of research work, which is funded by PJSC "YuGOK" (Kryvyi Rih) according to the contract №1392 of 01.09.2012 with the State University "Kryvyi Rih National University", are presented. The purpose of work is to develop a method of rationing of power consumption by mining enrichment plant in order to implement energy efficiency measures systematically.

The expected results: while implementing the proposed method in the conditions of power consumption rationing ore production there will be a reduction of the costs for planned and preventive maintenance works up to 40% and reduction of energy consumption by structural units of mining enrichment plants up to 2%.

The economic effect is achieved due to: improving the reliability of a power consumption rationing by the objects during application of neuron fuzzy prediction methods; identifying the objects and units, which consume electricity irrationally and have the greatest potential of energy saving.

To the problems of statistical analysis of a power consumption and building elements of

techno-cenoses of empirical process models of a power consumption there devoted significant amount of scientific papers of B.I. Kudrin, V.V. Fufayeva, V.I. Gnatiuk [1-2] and others. In the abovementioned studies there proposed methods of normalization of a power consumption and developed methodology for determining the schedule of planned and preventive maintenance works at techno cenoses objects. Among the main features of the proposed techniques are: alternation and frequency of repairs determined by the purpose equipment repair and its design features and by the operating conditions; scheduled and preventive maintenance of performing equipment involves: overhaul services; periodic review; periodic scheduled maintenance - small, medium and capital; planned and preventive maintenance are carried out according to the scoreboard, which is based on standards of planned and preventive maintenance duration of the repair, overhaul cycles; categories repair complexity; labor and material consumption repairs.

The closest solution chosen as a prototype, is a method of optimal power management at the system level [2]. The method includes the use of average binding for one-dimensional data, where at each step there is estimation of distances between applied statistics, determination of the next couple of data and replacing them with a mean value, obtaining a single association (cluster), creation of a multi-hierarchy, grouping of objects of normalization power consumption in each group and determination of the queue for energy facilities.

This method of statistical planning energy audits [2] has several disadvantages: synthesis of empirical process model of a power consumption is based on the classical theory of statistical data, which includes interval estimation and rank and cluster analysis, methods error is 15%; power consumption prognosing by individual objects and infrastructure in general shall be conducted using rank analysis, herein prognosing accuracy may be improved by using of well-known paradigms of neural networks; cluster analysis allows to divide objects into groups according to certain characteristics, but the number of clusters is given a priori, which significantly reduces normalization accuracy of power consumption by the objects in each group; statistical analysis is performed using only data of active power.

## 3. The purpose and tasks of the research

The basis of electricity preservation for energy-intensive industries is planned

implementation of complex technical and technological measures aimed at reducing of a power consumption infrastructure. At the first stage of electricity method application, optimization of a power consumption of technological complex infrastructure at the system level should be fulfilled.

Its purpose is to create scientifically based prerequisites for targeted energy audits, followed by the implementation of technical and technological measures focused on energy efficiency in the conditions of energy-intensive industries. Work objective is to improve the basic techniques [2] by using developed method of neural prediction departments of a power consumption, which allows reducing prognosis error taking into account the combined effect of factors.

Consistent implementation of the developed method of optimal control of power consumption of functional groups of technocenoses neural prognosis, allows affect purposefully the objects, which need maintenance. At the same time funds aimed at conducting energy audit will be spent most effectively, and total power consumption of infra-structure will be reduced by 1-2% which is confirmed by production testing of neuro-fuzzy model in the short-term prediction of power consumption by JSC "SevGOK" units. [3, 5].

#### 4. The method of normalization of power consumption of Ore Beneficiation Factory

As noted above, the valuation of power consumption of mining targets and processing enterprise planning is based on the use of efficient neural prediction of power consumption. One of the important factors of effective prognosing based on neural structures is record of prognosing depends on the values of the load in previous months. As additional elements of the input array neuron fuzzy network it is proposed to use live power quality, the main technological parameters of the unit and meteorological factors.

An example of tabulated values of input and output components of the vector for training of neuron fuzzy prediction system of power consumption units of JSC "YUGOK" (Ore Beneficiation Factory 1, 2): actual power consumption (ths. kV h): Ore Beneficiation Factory-1 / total; concentrate; composition; light of industrial purposes; lighting of admin. facilities /; Ore Beneficiation Factory-2: / whole; concentrate; composition; light of industrial premises; lighting of admin. facilities /; ore (m<sup>3</sup>); ore (thous. tons); total Fe content (%); magnetic

Fe content (%); ore humidity (%); 2-3 flow (thous. tons); Class 20 mm (%) <sup>3</sup>/<sub>4</sub> stage (thous. Tons); Class 20 mm (%) concentrate production (thous. tons); outside temperature (° C); pressure (mm. Hg. century); outdoor humidity (%).

Taking into account previously provided statistical data, as components of the input vector it is proposed to use indicators of maximum correlation coefficient (R) to the predicted value (electricity consumption Ore Beneficiation Factory-1): actual power consumption (FVE) Ore Beneficiation Factory-1 for previous periods (total); FVE concentrate on (R = 1); FVE in composition (R = 0,6); FVE for the light industrial premises (R = 0,9); FVE Ore Beneficiation Factory-2 total (R = 0,9); FVE Ore Beneficiation Factory-2 K3 condition. Concentrate (R = 0,9); FVE Ore Beneficiation Factory-2 K3V concentrate with wit. Content of Fe (R = 0,9); ore (m<sup>3</sup>) (R = 0,6); concentrate production (R = 0,8); outside temperature (R = 0,8 in syllables FVE).

As the extrapolator we selected hybrid technology of adaptive neuro-fuzzy system of findings, characterized by high speed and ease of learning of algorithm This allows to improve the accuracy of prediction of the application developed algorithm of adaptation membership functions.

Neural network architecture of Mamdani –Zade and TSK conclusion allow describing the output dataset of multidimensional object as a nonlinear function of the input variables  $x_i (i = 1, 2, \dots, N)$  and parameters of fuzzy system

$$y = \sum_{i=1}^M \frac{w_i}{\sum_{j=1}^M w_j} \left( P_{i0} + \sum_{j=1}^N P_{ij} x_j \right) \quad (1)$$

where  $p$  - digital weight of neurons, which are selected during adaptation;  $w_i$  - weight of neurons, which corresponds the normalization condition:

$$\sum_{i=1}^M w_i / \sum_{j=1}^M w_j = 1$$

The characteristic feature of fuzzy neural networks is the use of fuzzy rules for calculating the conclusion initial value. Unlike classical fuzzy systems in these architectures instead of directly calculating of the level of activation of specific rules, adaptive selections of phasing parameters are implemented.

To consider general trend of graphics of power consumption section, conditioned by technical and technological changes of



Let us write phasing formula based on generalized Gaussian function

$$\mu(x) = \alpha_i = \exp\left(-\left(\frac{x-c}{\sigma}\right)^{2b}\right) \quad (7)$$

where  $c, \sigma, b$  center parameters, width and component form of input vector for fuzzy rule conclusion.

Applying (8) to defuzzification we have modification of fuzzy conclusion:

$$y_0 = f(x) = \frac{\sum_{i=1}^M w_i \left[ \prod_{j=1}^N \exp\left[-\left(\frac{x_j - c_j^{(i)}}{\sigma_j^i}\right)^{2b_j^i}\right] \right]}{\sum_{i=1}^M \left[ \prod_{j=1}^N \exp\left[-\left(\frac{x_j - c_j^{(i)}}{\sigma_j^i}\right)^{2b_j^i}\right] \right]} \quad (8)$$

The last formula of Mamdani-Zadeh model output defines continuous function of defuzzification of input vector based on the use of fuzzy neural network. The first layer of this structure makes four-phasing of the input vector, the second one - aggregating of values of activation condition, the third one - M aggregation of inference rules and normalized signal generation, the last layer forms the output signal. The first and third layers have parametric properties. The first layer sets function of phasing parameters  $(c_j^k, \sigma_j^k, b_j^k)$ , the weights are activated in the third layer  $V_M$ , which are interpreted as the center of function that belongs to fuzzy rules result.

The modified algorithm of self-organizing of fuzzy prognosis of power consumption:

At the start from the first pair of data  $\langle x_1, y_1 \rangle$  there created the first cluster with center  $c_1 = x_1$ . We accept that  $w_1 = y_1$ , and  $L_1 = 1$  is the power of multiplicity.

Let us denote the limit of the Euclidean distance between the vector  $x$  and the center  $c_i$ , at which the data will be interpreted as referring to the created cluster, symbol  $r$ .

After reading of  $k$ -th learning pairs  $\langle x_k, y_k \rangle$ , distances between the vector  $x_k$  and all existing centers  $\|x_k - c_l\|$  for  $l = 1, 2, \dots, M$  are calculated.

If  $\|x_k - c_{l_k}\| > r$ , then a new cluster is created.

$$c_{M+1}(k) = x_k, \quad (9)$$

$$w_{M+1}(k) = d_k, \quad (10)$$

$$L_{M+1}(k) = 1. \quad (11)$$

The parameters created for this cluster do not change:  $w_l(k) = w_l(k-1)$ ,  $L_l(k) = L_l(k-1)$  for  $l = 1, 2, \dots, M$ . The number of clusters  $M$  increases by one.

If  $\|x_k - c_{l_k}\| \leq r$ , then the data is included in the  $l_k$ -th cluster, parameters of which should be specified in accordance with the following expressions:

$$\begin{aligned} w_{l_k}(k) &= \frac{[w_{l_k}(k-1) + d_k]}{2} \\ L_{l_k}(k) &= L_{l_k}(k-1) + 1 \\ c_{l_k}(k) &= \frac{c_{l_k}(k-1) + x_k}{2} \end{aligned} \quad (12)$$

The resulting function, which approximates the original system has the form:

$$\hat{f}(x) = y = \frac{\sum_{l=1}^M w_l(k) \exp\left(-\frac{\|x - c_l(k)\|^2}{\sigma^2}\right)}{\sum_{l=1}^M L_l(k) \exp\left(-\frac{\|x - c_l(k)\|^2}{\sigma^2}\right)} \quad (13)$$

*Simulation testing of developed structure of short-term neuro-fuzzy forecast of electricity consumption.* In order to test the efficiency of developed system of neuro fuzzy prognosis of electricity consumption by Mining Processing Plant units, there used input data, which is given in Table 1. As the initial value there taken actual consumption of electric energy by Ore Beneficiation plant No. 1 (thousand kWh).

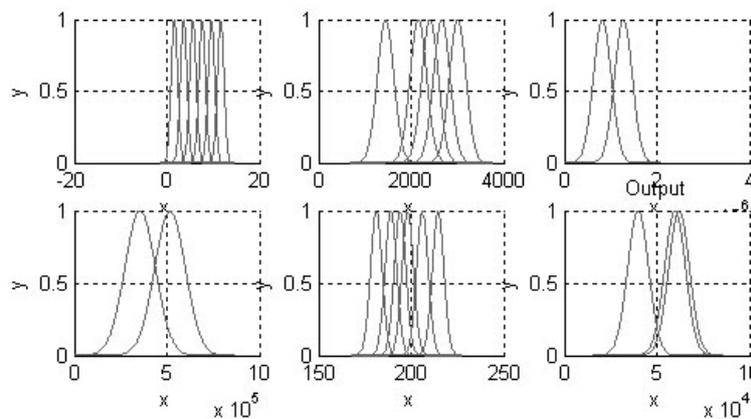
Training is fulfilled by iterative method by successive presentation of input vectors (table No 1) with simultaneous adaptation of the weights. During training, the weights of the network gradually become such that each input vector produces the initial prognosis value for the next interval.

In accordance with the obtained values, cluster-assessments in the Fig.1 show corresponding membership functions of five input and one output variable after learning of neuro-fuzzy system.

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**Table1.** Example of learning tuples for testing of efficiency of neuro-fuzzy forecasting system works

The cost of electrical energy			Period		
			I.2011	II.2011	...
OBP-1	Actual consumption electricity (thousand KW*h)	Total	21073	18656	...
		Concentrate	20800	18410	...
		Storage area	93	84	...
		Lighting	160	145	...
OBP-2	Actual consumption electricity (thousand KW*h)	Total	40964	34410.64	...
		K3	23660	19700	...
		K3B	16272	13796.64	...
Ore mining		thousand m <sup>3</sup>	491.3	481.4	...
Production. (thousand tons)			311.8	290	...
Outside air temperature (°C)			-4.4	-6.1	...



**Figure 1.** Membership functions of five inputs and one output variable after learning of neuro-fuzzy system.

Forecasted and actual energy consumption of Ore Beneficiation Plant No 1 of Mining and Processing Plant is shown in Fig.2. A separate graph shows the relative change of prognosis error. The average value of MAPE-error was 2.54%.

Accuracy of the prognosis must be found satisfactory (100% of error does not exceed 5%). Analysis of energy consumption prognosis developed by fuzzy neural network structure allows to suggest efficiency increase of data extrapolation by 15% as compared with the known analogues, thus there proved the possibility of using of developed structures as neuro fuzzy models of energy-intensive objects when using analytical procedure of interval estimation, which allows to define the list of objects of technological complex of enrichment (Ore Beneficiation Plant No 1, Ore Beneficiation Plant No 2), which consume electricity irrational. According to the results of determination of spatial position of predicted value of power

consumption of the unit at the rank distribution there is a possibility to estimate the coefficient of rational use of electricity during technological processes of enrichment. Thus, according to the proposed methodology [2], in the framework of the Gaussian distribution of the parameters, they say that the object consumes power normally in case when predicted values are within the confidence interval. Offset of the predicted value for the lower boundary of the confidence interval indicates the disruption of the normal process and accordingly the power consumption at this facility, while the offset for the upper limit indicates the irrational use of energy and inefficient implementation of energy conservation measures.

*The algorithm for determining the confidence interval.* As an example let us consider the definition of statistical confidence interval for a sample of actual electrical consumption of Ore Beneficiation Plant No 1 period 2009-2011.

1. Let us set the sampling values of power consumption by the facility for a specified period. As an example we use a statistical sample of the total actual power consumption of Ore Beneficiation Plant No 1 (kWh) for April 2009, 2010, 2011:  $X_0=6361.0$ ;  $X_1=20598.0$ ;  $X_2=14883.0$  (kWh)

2. Let us determine the sample size, and set the level of significance:  $N=3$ ;  $\alpha=0.05$ .

3. The degree of confidence is determined by the formula

$$1 - \alpha = 0,95. \quad (14)$$

4. Average value of the sample ( $X_{\alpha\nu}$ ) is calculated.

5. Medium square deviation ( $S_X$ ) is calculated.

6. The procedure of determination of the confidence interval.

6.1. Let us set the Student's coefficient for a given sample volume and confidence. At this stage it is proposed [2] to use the standard t-distribution function of Student. As arguments let us take the number of degrees of freedom  $d$  ( $d > 0$ ) and  $0 < p < 1$ , but the probability density of  $t$ -distribution of Student is calculated according to the formula

$$t(\alpha, N) = \frac{\Gamma((d+1)/2)}{\Gamma(d/2)\sqrt{\pi d}} \left(1 + \frac{x^2}{d}\right)^{-0,5(d+1)}. \quad (15)$$

6.2 Absolute random error is calculated

$$\Delta X_{sl} = t(\alpha, N) \cdot \frac{S_X}{\sqrt{N}}. \quad (16)$$

6.3. MARE-error of the prognosis for the previous period (2) is defined;

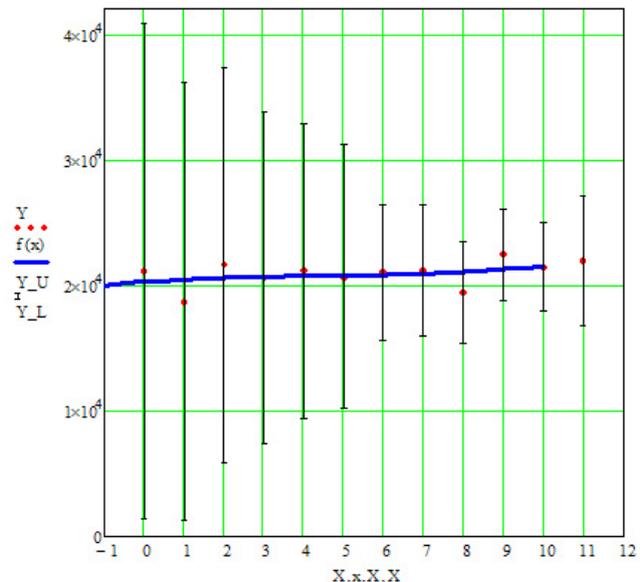
6.4. Absolute error with MARE-based prognosis error is specified

$$\Delta X = \sqrt{(\Delta X_{sl})^2 + (\Delta X_{mape})^2} \quad (17)$$

6.5. The upper and the lower limit of the confidence interval is calculated

$$X_L^U = X_{\alpha\nu} \pm \Delta X. \quad (18)$$

The results of the calculation algorithm of the confidence interval at rationing of electrical consumption of Ore Beneficiation Factory 1 in 2012, based on statistical sampling of 2009-2011 and neuro fuzzy prognosis for 2012 are shown in Fig. 2.



**Figure 2.** Confidence intervals of electrical consumption of Ore Beneficiation Factory 1 in 2012.

## 5. Conclusions

The results of developing of a method of neuro fuzzy rationing of electrical consumption of Ore Beneficiation Factory, Mining and industrial tests conducted according to the contract No 1392 of 01.09.2012 with the State University "Kryvyi Rih National University" confirm the efficacy of method in the information system of rationing of electrical consumption, which will allow to implement systematically energy efficiency measures at ore mining enterprises and reduce electrical consumption by structural units of mining and processing enterprises up to 2%.

## References

1. Kudrin B. I. *Problemy sozdaniya i upravleniya cenozami iskusstvennogo proishozhdeniya. Kiberneticheskie sistemy cenozov: Sintez i upravlenie.* [Problems of creating and managing the price of artificial origin. Cybernetic system communities: Synthesis and management.]
2. Gnatjuk V.I. *Zakon optimalnogo postroenija tehnocenzov. Cenologicheskie issledovaniya.* [The law optimal build technocenosis. Dependent studies.]. Issue 29. Moscow, Publishing house of Tomsk state University. Center for system studies, 2005.
3. Analiz energetichnih rezhimiv roboti osnovnih cehiv VAT «PivnGZK»: Zvit z NDR/ Krivorizkij tehn. universitet. [The analysis of the energy modes of the major

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- departments of JSC "SevGOK". Report on the research, technical University of Krivoy Rog]. No 1238, 2003, 150 p.
4. Osowski S. Sieci neuronowe do przetwarzania informacji. Oficyna wydawnicza politechniki warszawskiej, Warszawa, 2000, p.p. 124-128.
  5. Shchokin V. , TkachukV. (2014). Automatization of agglomerative production on the base of application of Neuro - Fuzzy controlling systems of the bottom level. *Metallurgical and Mining Industry*. No 6, p.p. 32–39.