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NEURO-FUZZY FORECASTING OF NON-LINEAR PROCESSES OF BLAST FURNACE PRODUCTION

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ABSTRACT

Context. Neuro-fuzzy forecasting of the chemical composition of cast iron at the blast furnace output to improve the quality of blast furnace production control is considered.

Objective. The aim of the work is to reduce the errors of forecasting non-linear processes of blast-furnace production.

Method. It was proposed to use neural-fuzzy adaptive filter-approximators for forecasting non-linear processes of blast-furnace production (in the form of: Adaptive neuro-fuzzy inference system, fuzzy algorithm of subtractive clustering and fuzzy C-means clustering algorithm), which realize sequential and step-by-n step integration of current information. To optimize these filters for real processes, their parameters are identified by the accuracy criterion on the training and verification sequences.

Results. As a result of the simulation of neural-fuzzy forecasting of the content of the chemical composition of cast iron at the blast furnace output, it was found that the best accuracy is provided by a fuzzy filter with subtractive clustering with sequential integration of the current data. At the same time, the forecast error is 4.2%, and the time for finding the optimal solutions does not introduce time restrictions on the application of this approach in blast-furnace production. The adequacy of the data was confirmed.

Conclusions. Neural-fuzzy filters allow to increase the accuracy of the forecast of non-linear processes of blast furnace smelting and, due to this, to improve the quality of management of the production of cast iron. Further research should be directed to the development of automatic control systems for non-linear processes of blast-furnace production.

KEYWORDS: forecast, non-linear processes, integration, adaptive filter-approximator, chemical composition of cast iron, blast furnace production.

ABBREVIATIONS

AFA is adaptive filter-approximator;

Anfis is Adaptive neuro-fuzzy inference system;

CP is controlled process;

CS is control system;

Genfis2 is subtractive clustering;

Genfis3 is C-means clustering algorithm;

LF is level of fusion;

NN is neural network;

SI is sequential integration;

SnI is step-by-n step integration.

NOMENCLATURE

A, B, g, h are points;

a_U, a_L is settings for Anfis AFA;

α is positive coefficient;

α_k is value of the intermediate output;

C is relative mean square error;

C_{pr} is forecast error;

D is distance between the potential of the cluster center and the clustering object;

$E(x_k)$ is potential of each point x_k;

ε is stop parameter;

F is matrix of fuzzy partitions;

f_1 is harmonic trend;

f_2 is difference equation;

FD is function of iterative calculation belonging function;

FF_j is function of fuzzy rules synthesizing of the j-th ($j = \overline{1,3}$: singletons, Mamdani or Sugeno) connection type of the input signal to the output signal;

FV is function of iterative selection of cluster centers;

it is iteration number;

K is number of points in the training sequence;

k is intermediate input/output of the network;

k_c is number of clusters;

$L_{l,k}$ is belonging function of the fuzzy rule l of the input k with parameters a_L;

l is fuzzy rule;

M_D is matrix of fuzzy partitioning;

M_D^* is matrix of fuzzy partitioning at the previous iteration of the algorithm;

m is time tact;

$\mu_{\theta i}$ is degree of belonging of the object θ to the cluster i;

n is depth of forecast;

P is depth of memory;

PV is potential function;

Q is set of inputs of neurons/clusters;

q_0, q_{-1}, q_{-2} are output values;

q_{+1} is approximate forecast;

Ω_i is cluster centers;

Θ is number of elements;

R_c is radius of the cluster center;

r is constant that determines the range of influence of one cluster;

T_{norm} is arbitrary t-norm of modeling the logic operation "I";

U_k^{-1} is function inverse to the belonging function of the intermediate output k of the network with parameters a_U;

$\upsilon_0, \upsilon_{-1}, \upsilon_{-2}$ are correlated auxiliary variables given in a certain rectangle lying in the coordinate plane time-spatial axis ($t - x$);

ϖ is exponential weight, determining fuzziness, smearing of clusters;

$\widehat{Y}[m + n]$ is output AFA;

y_k is value of the input signal at the k input of the network;

z_h is cluster center;

Φ is structural function.

INTRODUCTION

Complex non-linear systems (processes) have nonstationary parameters, non-linear dependencies and stochastic variables, which determines the presence of various dynamic modes of functioning in them. Such complex systems include, for example, moving objects, telecommunication systems and networks, blast-furnace production, etc. The costs of blast furnace production are a significant part of the cost of mining and metallurgical production, so it is urgent to solve the problems of increasing the accuracy of forecasting these processes, ensuring a given quality of control [1].

One of the main indicators of blast furnace production is the chemical composition of cast iron at the blast furnace output, which makes it necessary to evaluate and forecast it for the purpose of optimal control of the blast furnace smelting process.

The object of study is the process of control dynamic objects with non-stationary parameters, nonlinear dependencies, and stochastic variables.

The subject of study is the forecasting of the characteristics of nonstationary stochastic processes.

The aim of the work is the improving the accuracy of forecasting the characteristics of nonlinear stochastic processes to ensure a given quality of control.

1 PROBLEM STATEMENT

Let the predictive model of the process look like:

$$\widehat{Y}[m + n] = \Phi\{y[m], a[m], m\}, \qquad (1)$$

where the forecast of the output coordinates serves to compensate for pure delay and time for synthesis and implementation of the control.

At the same time, the formation of vector $I = \{\Phi, a\}$ estimation of structure Φ (structural identification) and parameters a (parametrical identification) of the process model (1) is carried out based on vectors of signals of observation $y[m]$ by minimization of identification criterion:

$$\min_{I \in L_{ident}} J_{ident} \to I_{opt} = \{\Phi_{opt}, a_{opt}\}, \qquad (2)$$

subject to the limitations L_{ident}.

2 REVIEW OF THE LITERATURE

One of the leading concepts of the modern control theory consists in achievement of the main ultimate goal at each stage of system functioning. It supposes use of CP models and it is provided by its optimization in real time [2].

The synthesized model, which correctly transfers the dynamics of one mode of CP functioning, may be inadequate to the description of other mode. Therefore, it is needed the realization of adaptive structural-parametrical identification of CP in the course of CS functioning.

The process of structural-parametrical identification includes operations of structure determination, assessment, and optimization of parameters of the CP model [3, 4].

At that, the urgent problems are the choice of basis functions, in terms of which it is carried out the identification, the choice of way of generation and selection of structures of different complexity (the method of structural optimization), as well as the choice of method of parametrical optimization and effective criteria of selection and optimization.

Traditionally the polynomials of Legendre, Kolmogorov-Gabor, etc. are used for approximation of basis functions [5, 6]. The coefficients of these polynomials form the unknown parameters, the values of which are chosen to answer to observed temporary realization in the best way. The more productive is the use of NN and hybrid NN with fuzzy logic, which are universal and effective approximators [6, 7].

In [8, 9] it was proposed to use neuro-fuzzy AFA for forecasting the processes of mining and metallurgical production. At the same time, in these works there is no comparative analysis of different approaches to forecasting from the point of view of optimizing the parameters of AFA by the criterion of the minimum of the prediction error.

3 MATERIALS AND METHODS

The solution of the prediction problem is to interpolate the time series (using approximating functions) and extrapolate the values of the series to the future from its previous values (for a stationary process, extrapolation should take into account the constancy of the statistical moments of the time series, and for nonstationary – the evolution of its trend in time) in order to ensure the selected quality criterion [3].

The approximate forecast q_{+1} is carried out by means of preliminary selection of the optimal complexity polynomial or harmonic trend f_1 according to chosen algorithm $q_{+1} = f_1(t)$. In this case, the trend may be simply the average value of the predicted variable. For an accurate prediction, an additive (the second term) is used in the form of a solution of the difference equation f_2 [3]:

$$q_{+1} = f_2(q_0 q_{-1} q_{-2}...\upsilon_0 \upsilon_{-1} \upsilon_{-2}...) . \qquad (3)$$

In general, the forecast is obtained as the sum of the trend and the solution of the difference equation:

$$q_{+1} = f_1(t_0 x_0) + f_2(q_0 q_{-1} q_{-2}...\upsilon_0 \upsilon_{-1} \upsilon_{-2}...) ;$$
$$\{f_1, f_2\} \subset \Phi . \qquad (4)$$

The advantage of using difference equations for forecasting is that they are the most appropriate to the physics of the process and can be concretelyestimated by special criteria of the accuracy of step integration $i^2(N) \to \min$, which does not require dividing the experimental data into parts.

Thus, integration is a solution of the finite-difference equation (4), which can be realized by one of the following approaches:

– sequential integration, when the estimate obtained in the previous step is used to predict the next step;

– step-by-n step integration, when the estimate is calculated immediately on n steps forward.

In AFA, the adaptation process consists in estimating the required output of the filter and correcting its parameters, depending on the values of the current error [9].

AFA with fuzzy logic is based on the statement that the belongings function of an element to a set can take values in the interval [0, 1]. Than this value is closer to 1, the more the accordance: of an element of the universal set to the properties of fuzzy. The advantages of such AFA are the transparency of the derivation process, based on a verbal description of the ex-pert knowledge about the process and resistance to noise. Disadvantages – the absence of automatic knowledge acquisition, a limited number of input variables [4, 10].

Adaptive neural system of fuzzy inference realizes the system of fuzzy derivation of Sugeno in the form of a five-layer NN of direct signal propagation [10].

The AFA equation Anfis is represented as a convolution equation [9]:

$$\widehat{Y}[m+n] = \sum_{\tau \in P} \sum_{k \in Q} \beta_k[\tau] \cdot \alpha_k[m-\tau], \qquad (5)$$

where $\beta_k[\tau] = U_k^{-1}(\alpha_k[\tau]/\sum_k \alpha_k[\tau])$; $U = U(a_U)$;

$\alpha_k[m-\tau] = T_{norm} \{L_{l,k}(y_k[m-\tau])\}$; $L = L(a_L)$.
$\quad l,k \in Q$

The settings for this AFA are $\{a_U, a_L\} \subset a$.

Fuzzy AFA using subtractive clustering generates a fuzzy logic system such type as Sugeno from the input data. Extraction of rules from the data occurs in two stages. First, the number of rules and powers of term-sets of output variables is determined. Then, using the least squares method, the "then-" part of each rule is determined. As a result, a system of fuzzy logical deduction with a base of rules covering the entire subject area is obtained [5, 6].

The Genfis2 algorithm is as follows:

1. Calculation of the potential of each point x_k (measures of spatial proximity between it and others):

$$\mathrm{E}(x_k) = \frac{1}{K} \sum_{i=1}^{K} e^{-\frac{\|x_k - x_i\|}{(R_c/2)^2}} . \qquad (6)$$

2. Set the number of clusters k_c to 0.

3. Identification of the point with the highest potential $\mathrm{E}(x_p)$, x_p:

$$p = \arg\max_{i=1}^{K} \mathrm{E}(x_i) . \qquad (7)$$

4. Installation of j-th cluster center:

$$k_{c_j} = x_p . \qquad (8)$$

5. Reduction of the potential of all points:

$$\mathrm{E}(x_i) = \mathrm{E}(x_i) - \mathrm{E}(k_{c_j}) e^{-\frac{\|k_{c_j} - x_i\|}{(r/2)^2}} , \qquad (9)$$

where $r = [1, 1.5] R_c$.

6. Checking the value of the potential of points relative to the established threshold thr:

$$\max_{i=1}^{K} \mathrm{E}(x_i) < thr . \qquad (10)$$

If condition (8) is satisfied, then the end, otherwise must be a transition to item 3.

Thus, equation AFA Genfis2 can be represented in the form:

$$\widehat{Y}[m+n] = FF_j(FV(a_{FV}, \sum_{\tau \in P} \sum_{h=1}^{k_c} PV_h(D_{kh}))) , \qquad (11)$$

where $D_{kh} = \|z_h - y_k[m-\tau]\|$; $PV_h = \sum_{k=1}^{K} \exp(-\alpha \cdot D_{kh})$;

$j = \overline{1,3}$; $k_c = \overline{1,n}$.

The settings for this AFA are $\{\alpha, R_c\} \subset a_{FV}$.

The basis of the C-means clustering algorithm is the method of uncertain Lagrange multipliers, which allows the problem of finding the conditional extremum of the objective function on the set of admissible values to transform to the problem of unconditional optimization of the function.

The Genfis3 algorithm is an iterative procedure in which the following steps are performed [6, 7]:

1. Setting fuzzy clusters to a partition matrix

$$M_D = [\mu_{\theta i}]; \mu_{\theta i} \in [0,1], \ \theta = \overline{1,\Theta}, \ i = \overline{1,k_c} \ ; \quad (12)$$

wherein

$$\sum_{i=1}^{k_c} \mu_{\theta i} = 1, \ 0 < \sum_{\theta=1}^{\Theta} \mu_{\theta i} < \Theta . \quad (13)$$

2. Setting the initial values of the parameters: the number of clusters k_c; exponential weight, determining their fuzziness, smearing $\varpi \in [1, \infty]$; the stop parameter of the algorithm ε.

3. Generate randomly the matrix of a fuzzy partition taking into account the conditions (13).

4. Calculation of cluster centers Ω_i:

$$\Omega_i = \frac{\sum_{\theta=1}^{\Theta} \mu_{\theta i}^{\varpi} * |X_{\theta}|}{\sum_{\theta=1}^{\Theta} \mu_{\theta i}^{\varpi}}, \ i = \overline{1,k_c} . \quad (14)$$

5. Calculation of the distance between objects from the observation matrix X and the cluster centers:

$$D_{\theta i} = \sqrt{\|X_{\theta} - \Omega_i\|^2} . \quad (15)$$

6. Recalculation of partition matrix elements. If $D_{\theta i} > 0$

$$\mu_{\theta i} = 1 / \left(D_{j\theta}^2 * \sum_{j=1}^{k_c} \frac{1}{D_{j\theta}^2} \right)^{1/(\varpi - 1)}, \quad (16)$$

if $D_{\theta i} = 0$

$$\mu_{\theta i} = \begin{cases} 1, j = i \\ 0, j \neq i \end{cases}, \ j = \overline{1,k_c} . \quad (17)$$

7. Check the condition (if "not", go to step 4, if "yes", then end):

$$\left\| M_D - M_D{}^* \right\| < \varepsilon . \quad (18)$$

Then AFA equation Genfis3 can be represented as a convolution equation:

$$\widehat{Y}[m+n] = FF_j(FD(a_{FV}, \sum_{\tau \in P} \sum_{h=1}^{Q} V_h(D_{kh}(z_n, y_k[m-\tau])))), \quad (19)$$

where $\qquad\qquad D_{kh} = \|V_h - y_k[m - \tau]\|$;

$$V_h = \frac{\sum_{k=1}^{K} (\mu_{kh})^{\alpha} \cdot y_k[m-\tau]}{\sum_{k=1}^{K} (\mu_{kh})^{\alpha}}; \qquad h = \overline{1,Q}; \qquad k = \overline{1,K};$$

$$F = \{\mu_{kh}\}; \ \mu_{kh} \in [0,1]; \ \sum_{h=1}^{Q} \mu_{kh} = 1; \ 0 < \sum_{k=1}^{K} \mu_{kh} < K .$$

The settings for this AFA are $\{Q, K, L, \varepsilon\} \subset a_{FV}$.

In the general case, when predicting the processes of blast furnace production in order to improve the accuracy of the forecast and reduce the computation time at the beginning of the stage, it is expedient to determine the structure and parameters of the AFA using the methods of global optimization, and in the online mode – to adjust the parameters of the AFA, using parametric optimization methods (simplex method, golden section method, Fibonacci numbers method, etc. [11]).

The golden section method has a stable linear rate of convergence that does not depend on the relief of the function. This method is used to seek the minimum of a function of one variable on an interval, and uses the following property of continuous functions: if the points g and h ($g<h$) are located on (a, b) and, $f(g) \leq f(h)$, then on the interval $[a, h]$ there is at least one minimum of the function. Similarly, if $f(g) \geq f(h)$, then the minimum should be sought on the segment $[g, b]$.

The golden section method selects on the segment two symmetric points: $g = A + \dfrac{3-\sqrt{5}}{2}(B-A)$ and $h = A + \dfrac{\sqrt{5}-1}{2}(B-A)$. The above procedure is applied, leading to a segment $[A, h]$ or $[g, B]$. If you repeat the above procedure, you can again reduce the segment. An important property of the algorithm is that at each step one value of the function from the previous step can be used, since for a new partition of the interval $[A, h]$ by the points h' and g' such that $h'=g$.

The scheme for predicting the processes of blast-furnace production with the use of neural-fuzzy AFA, whose parameters are tuned by the parametric optimization method is presented in Fig. 1.
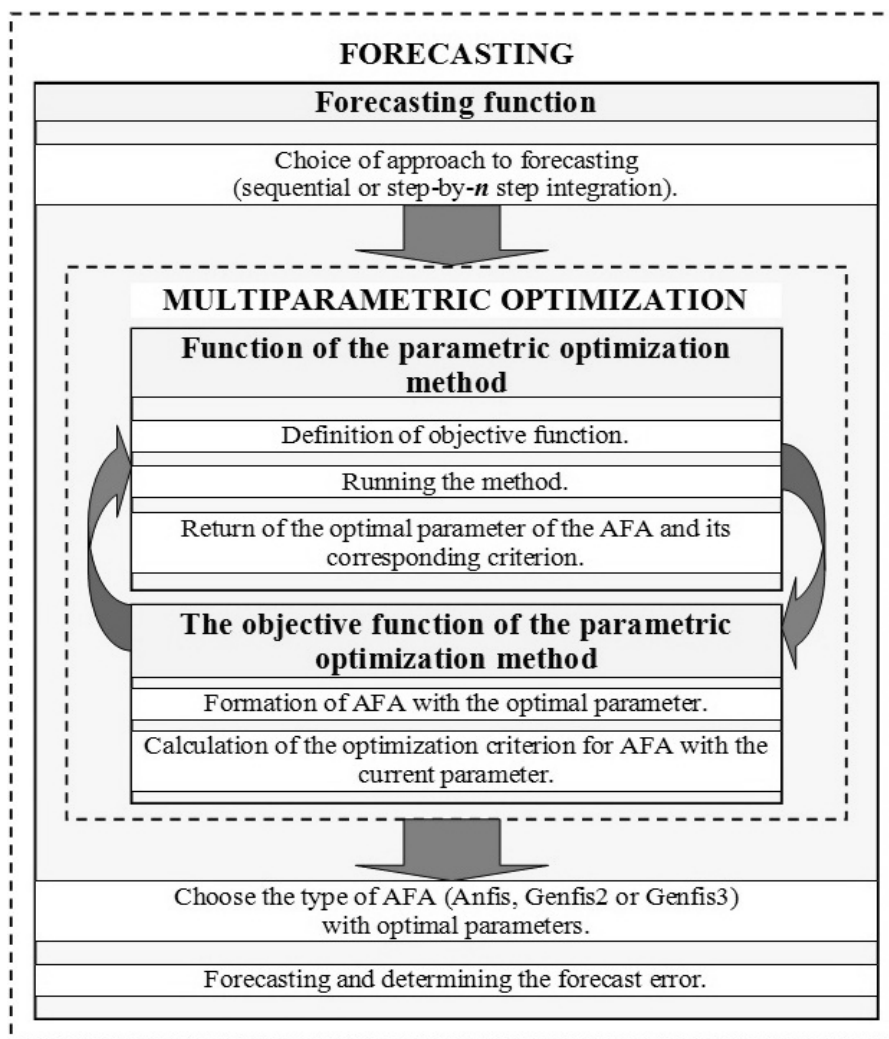
Figure 1 – Process forecasting scheme

4 EXPERIMENTS

The forecasting of the percentage content of the chemical composition of cast iron at the output (which is one of the main indicators of blast furnace smelting) can significantly improve the quality of control of the blast furnace process. To ensure the efficiency and continuity of control, LF was used in the blast furnace, which has a close correlation with the chemical composition of the cast iron at the outlet [9]. Studies on the effectiveness of the proposed methods of forecasting were carried out with an example of the percentage content of silicon in cast iron (data obtained in the Blast Furnace No. 3 of the Mariupol Metallurgical Plant named after Ilyich).

As an AFA, we used Anfis, Genfis2, Genfis3. As a method of parametric optimization, the golden section method was used, which varied the following parameters of AFA (Fig. 1):

– for Anfis it is the belonging function of the hidden layer;

– for Genfis2 it is the range of the cluster center influence R_c ;

– for Genfis3 it is the number of clusters k_c .

The initial sequence was divided into training and test samples equally, and as an optimization criterion, the relative mean square error between the real (Y^*) and predicted ($\widehat{Y}$) values, calculated on the test sample (B), was used [12]:

$$C = \frac{\left\| Y_B^*[m+n] - \widehat{Y}_B[m+n] \right\|}{\left\| Y_B^*[m+n] \right\|} . \qquad (20)$$

The remaining parameters of the AFA (the training function for Anfis, the fuzzy logic algorithm for Genfis3) varied with a simple search.

The depth of the forecast was taken 5 cycles, and the depth of memory was taken 4cycles.

As approaches to forecasting, SnI and SI were used, and the forecast error was calculated as a relative error at each step:

$$C_{pr} = \frac{(Y[m] - \widehat{Y}[m])}{Y[m]} . \qquad (21)$$

The result of predicting the silicon content in cast iron at the outlet using SI and SnI is shown in Table 1 and in Fig. 2, 3.

In Fig. 2, 3 is denoted: TREND is a time signal LF, which is closely correlated with the chemical composition of cast iron at the outlet, PREDICT is its forecast, URR is a forecast mode indicator.

Table 1 – Forecast errors

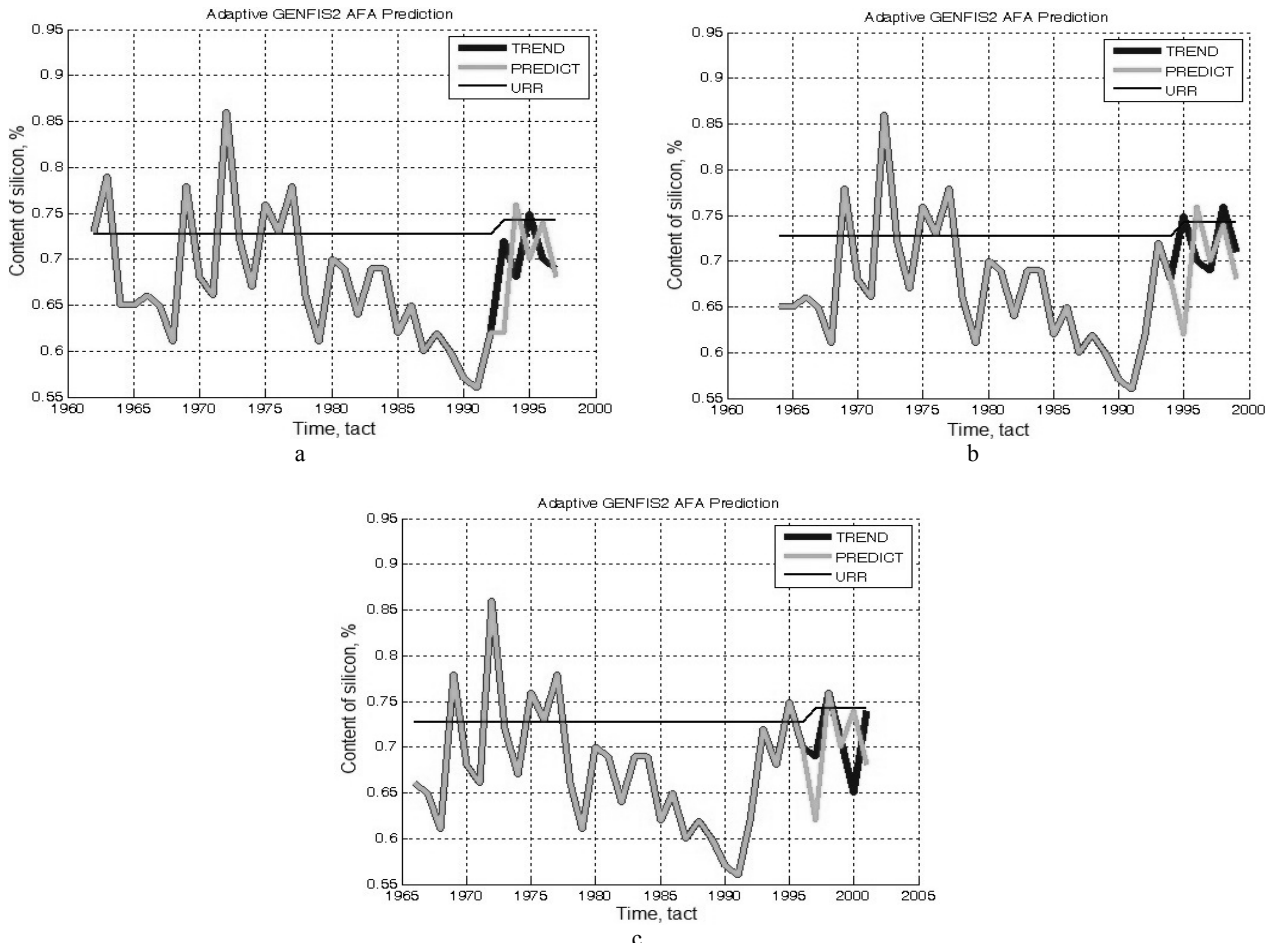| Approach to forecasting LF	Type AFA		
	Anfis	Genfis2	Genfis3
SnI, %	8,72	7,79	8,36
SI, %	6,53	5,63	6,25

Figure 2 – Forecast of the silicon content for 1 (a), 3 (b), 5 (c) cycles ahead using SI

5 RESULTS

As can be seen from the table 1, on the whole, the error in SI forecasting is 25–27% less than the SnI error. It is established that for both approaches to predicting AFA Genfis2 gives the best results: here, for the SI, the minimum of criterion (20) corresponds to the Genfis2 AFA with the cluster center effect range equal to 0.4, and for SnI it is equal to 0.6.

As a result of forecasting the silicon content using the Genfis2 AFA shown in Fig. 2, 3 it was established that the forecast errors (21) for the SnI was 5.62%, and for the SI – 4.16%.

Statistical check by the criterion of signs [13] showed the significance of the findings.

Time to find optimal solutions for optimizing the parameters of AFA on a computer with a Pentium IV processor was 12...18 minutes, and the forecasting time for silicon content in cast iron was 7...8 millisecond for the forecast cycle, which allows using this approach

online and does not introduce time limits on application of this approach in blast-furnace production.

In general, control errors are determined by prediction errors. Advancement of the AFA improves the convergence of the adaptation algorithms and, accordingly, provides a reduction in the control error.

6 DISCUSSION

As a result of the simulation of neural-fuzzy forecasting of the content of the chemical composition of cast iron at the blast furnace output, it was found that the best accuracy is provided by a fuzzy filter with subtractive clustering with sequential integration of the current data. At the same time, the forecast error is 4.2%, that is much less error when using linear or NN AFA [9]. The time for finding the optimal solutions does not introduce time restrictions on the application of this approach in blast-furnace production. The adequacy of the data was confirmed.
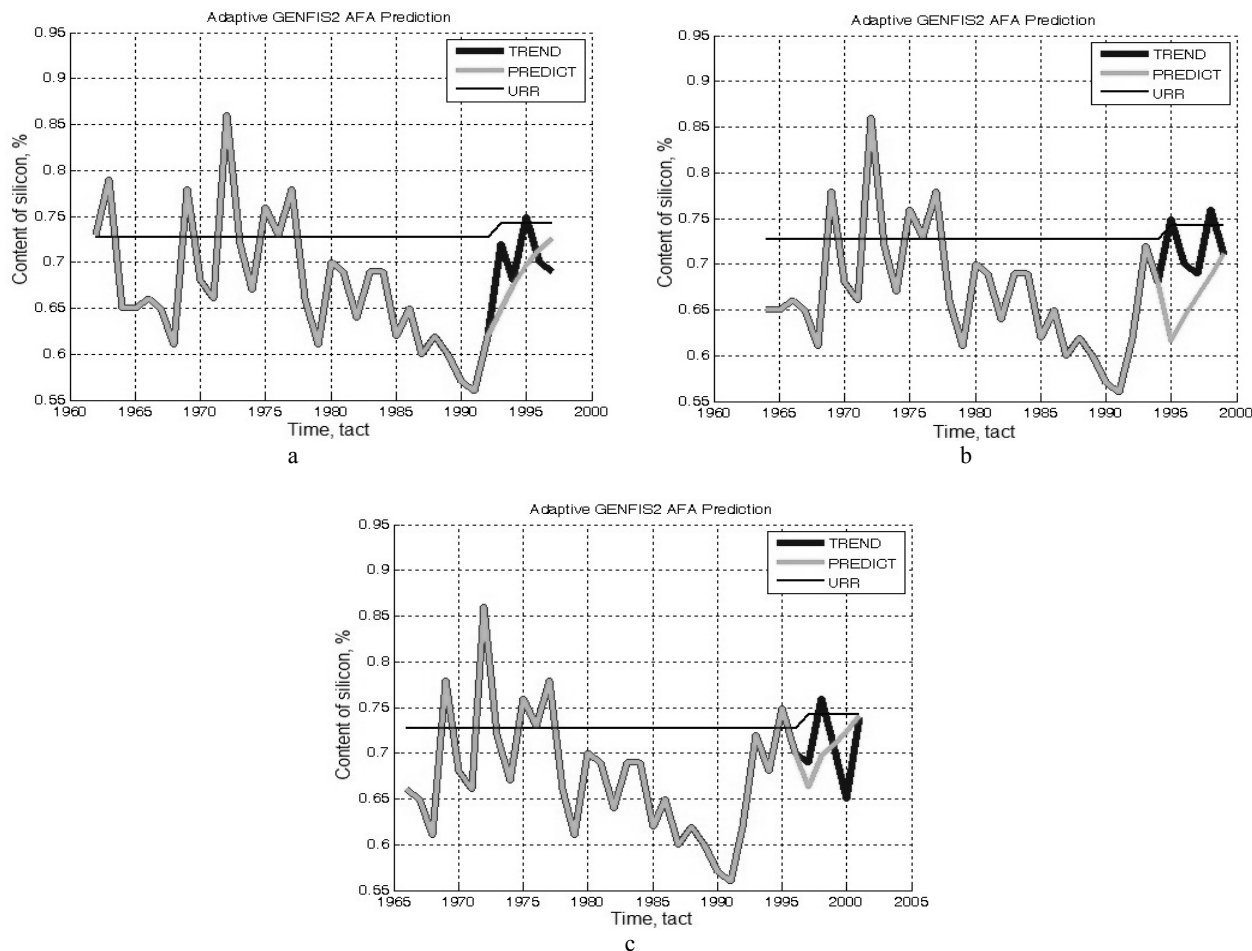
Figure 3 – Forecast of the silicon content by 1 (a), 3 (b), 5 (c) cycles ahead using SnI

Statistical check by the criterion of signs showed the significance of the findings.

Further research should be aimed at developing automatic control systems for nonlinear random processes.

CONCLUSIONS

The solution of the problem of forecasting nonlinear random processes based on the example of blast-furnace production is substantiated.

The scientific novelty of the obtained results consists in substantiating the use of neural-fuzzy adaptive filter-approximators for forecasting non-linear processes of blast-furnace production (in the form of: Adaptive neuro-fuzzy inference system, fuzzy algorithm of subtractive clustering and fuzzy C-means clustering algorithm), which realize sequential and step-by-n step integration of current information. To optimize these filters for real processes, their parameters are identified by the accuracy criterion on the training and verification sequences.

Neural-fuzzy filters allow to increase the accuracy of the forecast of non-linear processes of blast furnace smelting and, due to this, to improve the quality of management of the production of cast iron. Further research should be directed to the development of automatic control systems for non-linear processes of blast-furnace production.

The practical significance is that the obtained results allows to reduce prediction errors and improve the quality of data control by blast-furnace processes.

Prospects for further research should be directed to the development of automatic control systems for nonlinear random processes.

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НЕЙРО-НЕЧІТКЕ ПРОГНОЗУВАННЯ НЕЛІНІЙНИХ ПРОЦЕСІВ ДОМЕННОГО ВИРОБНИЦТВА

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АНОТАЦІЯ

Актуальність. Розглянуто нейро-нечітке прогнозування хімічного складу чавуну на випуску доменної печі для підвищення якості керування доменним виробництвом.

Метою роботи є зниження похибок прогнозування нелінійних процесів доменного виробництва.

Метод. Запропоновано для прогнозування нелінійних процесів доменного виробництва використовувати нейро-нечіткі адаптивні фільтри-апроксиматори (у вигляді: адаптивної нейронечіткої системи висновку, нечіткого алгоритму віднімаючої кластеризації і нечіткого алгоритму кластеризації С-середніх), які реалізують послідовне і покрокове інтегрування поточної інформації. Для оптимізації цих фільтрів під реальні процеси виконана ідентифікація їх параметрів за критерієм точності на навчальній і перевірочній послідовностях.

Результати. В результаті моделювання нейро-нечіткого прогнозування змісту хімічного складу чавуну на випуску доменної печі було встановлено, що найкращу точність забезпечує нечіткий фільтр з віднімаючою кластеризацією при послідовному інтегруванні поточних даних. При цьому похибка прогнозу становить 4,2%, а час пошуку оптимальних рішень не вносить часових обмежень на застосування цього підходу в доменному виробництві. Підтверджено адекватність отриманих результатів.

Висновки. Нейро-нечіткі фільтри дозволяють підвищити точність прогнозу нелінійних процесів доменної плавки й, за рахунок цього, поліпшити якість керування виробництвом чавуну. Подальші дослідження повинні бути спрямовані на розробку автоматичних систем керування нелінійними процесами доменного виробництва.

КЛЮЧОВІ СЛОВА: прогноз, нелінійні процеси, інтегрування, адаптивний фільтр апроксиматор, хімічний склад чавуну, доменне виробництво.

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НЕЙРО-НЕЧЕТКОЕ ПРОГНОЗИРОВАНИЕ НЕЛИНЕЙНЫХ ПРОЦЕССОВ ДОМЕННОГО ПРОИЗВОДСТВА

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АННОТАЦИЯ

Актуальность. Рассмотрено нейро-нечеткое прогнозирование химического состава чугуна на выпуске доменной печи для повышения качества управления доменным производством.

Целью работы является снижение ошибок прогнозирования нелинейных процессов доменного производства.

Метод. Предложено для прогнозирования нелинейных процессов доменного производства использовать нейро-нечеткие адаптивные фильтры-аппроксиматоры (в виде: адаптивной нейронечеткой системы вывода, нечеткого алгоритма вычитающей кластеризации и нечеткого алгоритма кластеризации C-средних), реализующие последовательное и пошаговое интегрирование текущей информации. Для оптимизации этих фильтров под реальные процессы выполнена идентификация их параметров по критерию точности на обучающей и проверочной последовательностях.

Результаты. В результате моделирования нейро-нечеткого прогнозирования содержания химического состава чугуна на выпуске доменной печи было установлено, что наилучшую точность обеспечивает нечеткий фильтр с вычитающей кластеризацией при последовательном интегрировании текущих данных. При этом ошибка прогноза составляет 4,2%, а время поиска оптимальных решений не вносит временных ограничений на применение этого подхода в доменном производстве. Подтверждена адекватность полученных результатов.

Выводы. Нейро-нечеткие фильтры позволяют повысить точность прогноза нелинейных процессов доменной плавки и за счет этого улучшить качество управления производством чугуна. Дальнейшие исследования должны быть направлены на разработку автоматических систем управления нелинейными процессами доменного производства.

КЛЮЧЕВЫЕ СЛОВА: прогноз, нелинейные процессы, интегрирование, адаптивный фильтр аппроксиматор, химический состав чугуна, доменное производство.

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