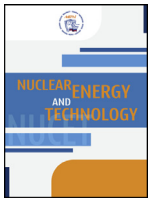
Available online at www.sciencedirect.com
ScienceDirect
Nuclear Energy and Technology 2 (2016) 54–59



www.elsevier.com/locate/nucet

Application of a neural network to predict the FAC rate of NPP equipment

A.D. Vishnyakova, O.M. Gulina*, N.L. Salnikov

Obninsk Institute for Nuclear Power Engineering, National Research Nuclear University MEPhI, 1 Studgorodok, Obninsk, Kaluga Region 249040, Russia

Available online 6 May 2016

Abstract

The intensity of the flow accelerated corrosion (FAC) process depends on a great number of parameters with a complicated effect on each other. The use of an intellectual neural network (INN) to solve the FAC prediction problem makes it possible to estimate the mutual effects from all the factors involved, to identify the essential properties of the information obtained, and, ultimately, to improve the accuracy of prediction without determining the whole range of dependences among a great deal of factors on which the FAC process depends. An approach is proposed to the creation and training of an optimal neural network for the NPP piping FAC rate prediction problem. *Matlab* software was used to develop an intellectual neural network to address the problem of the wall thinning prediction for a straight pipe with the VVER NPP single-phase secondary fluid. The network has been trained using an elastic back propagation algorithm, a number of the NS configurations have been studied, and the findings have been analyzed.

A conceptual framework has been built for the intellectual system in the form of three NS types: a replicative NS, a Kohonen self-organizing NS, and a back-propagation NS.

Keywords: Neural network; Learning algorithm; Flow accelerated corrosion; NPP piping.

Introduction

Practically all components of the nuclear power plant (NPP) steam-water line's pipelines and equipment, manufactured from perlite and low-alloy steels, are prone to flow accelerated corrosion (FAC). FAC processes occur under the action of hydrodynamic factors (the erosive component of damage) and electrochemical oxidation of the surface (corrosive component). The FAC effects manifest themselves in the form of thinning and, ultimately, "before-leak" failures of the power equipment components. A great diversity of the equipment metal damage zones and forms is explained by differences in the geometry, phase states, thermal- and hydrodynamic performance, and fluid water-chemistry.

Therefore, a vital task is to predict the FAC rate to optimize the NPP equipment monitoring scope and to avoid critical situations [1,2].

Globally, the most common FAC prediction technique is based on empirical data. Empirical models lack any physical sense but provide for a satisfactory description of experimental data that characterize the properties of real objects. Generalization and analysis of long-term operating experience and statistical data on the NPP damage rate, as well as investigation of the FAC processes and regularities in metals have led to the development of dedicated codes in the USA (*CHECWORKS*), Germany (*WATHEK*), France (*COMSY*) and Russia (*EKI-02*, *EKI-03*). The most well-known empirical model is the *Chexal–Horowitz* model [2] used in the CHECWORKS code. It employs an extensive array of experimental and laboratory research data for the quantitative estimation of the FAC influencing factors:

$$\text{FAC rate} = F_1(T) \cdot F_2(\text{AC}) \cdot F_3(\text{MT}) \cdot F_4(\text{O}_2) \cdot F_5(\text{pH}) \cdot F_6(G) \cdot F_7(\alpha) \cdot F_8(H),$$

* Corresponding author.
E-mail addresses: anvish@iate.obninsk.ru (A.D. Vishnyakova), olga@iate.obninsk.ru (O.M. Gulina), salnikov@iate.obninsk.ru (N.L. Salnikov).

Peer-review under responsibility of National Research Nuclear University MEPhI (Moscow Engineering Physics Institute).

Russian text published: Izvestia Visshikh Uchebnikh Zavedeniy. Yadernaya Energetika (ISSN 0204-3327), 2015, n.4, pp. 61-71.

http://dx.doi.org/10.1016/j.nucet.2016.03.011

where T is the temperature; AC is the alloy composition; MT is the mass transfer; O_2 is the oxygen effect; pH is the pH effect at a given temperature; G is the geometry; α is the steam quality; and H is the hydrazine effect.

However, no prediction based on empirical models provides for acceptable results. For instance, in the semi-empirical *Chexal–Horowitz* model built with regard for the dependence among the factors defined implicitly with the use of empirical tables [2], the major uncertainty sources are the initial thickness of the component wall, the alloy components not used in the model, the actual steam quality in the two-phase flow, uncertainties of the water chemistry, and others.

The only objective source of information on the state of a pipe component is monitoring data. Therefore, it is suggested that a FAC process model based on neural networks should be used for prediction. Neural networks have proved themselves to perform well in simulation of systems and processes the internal constraints in which have been either understudied or interact in a complicated way [3–5].

A great number of parameters that define the FAC rate have a complex effect on each other. The use of neural networks to address the FAC prediction problem makes it possible to assess the mutual effects of all the factors involved, to identify the essential properties of the information obtained, and, ultimately, to improve the accuracy of prediction. The generalization and abstraction capability of an artificial neural network helps predict correctly the FAC rate without determining the whole range of dependences among a great deal of factors on which the FAC process depends. But the real model is complex and involves many input variables.

The paper suggests an approach to the creation and training of the optimal artificial neural network for solving the problem of the NPP piping FAC rate prediction.

Application of neural networks for the FAC process prediction

A network is the model of a process. Its major attributes are structure, number of layers, neuron type, input and output values, and learning algorithms. The selection of the neural network attributes depends on the amount and quality of experimental data available for the network training. The training framework includes ultrasonic thickness measurement results, the metal's chemical composition, the coolant water chemistry, flow temperature and velocity, etc. (e.g., *CHECWORKS* model [2]). And no prior data processing and determination of respective dependences for the particular factor is required. However, an increase in the prediction accuracy requires data to be filtered based only on thinning data, since the FAC process causes wall thinning, while thickening is caused by another process (transport of corrosion products), which is not expected to add more noise to the predicted process.

For the FAC prediction, there is no sense in building a versatile network that takes into account the effects from all potential input factors. Such approach requires the development of an intricately structured network with a great number of layers and neurons and a greater volume of learning sampling to obtain the satisfactory result. For each geometrical type of the piping components (straight pipe, bend, tap and so on), it however makes sense to build a separate network to obtain a simpler structure of the neural network and to improve the model accuracy.

NS model for the FAC rate prediction

The training of a neural network for the FAC rate prediction requires data influencing the predicted value to be supplied to the network input. The output value, as defined for the problem, will be a characteristic of the FAC rate. The amount of the piping wall thickness deviation from the rated value has been chosen as such characteristic (S).

The inputs to be used will be the factors that influence the FAC process [1,2]: fluid temperature T; coolant flow velocity V; oxygen content in the coolant O_2; fluid's pH; mass content of chromium in material Cr; mass content of molybdenum in material Mo; mass content of copper in material Cu; inner diameter of the piping D; geometry of the piping component G; content of the amine (ammonia, ethanolamine, morpholine) used; piping operating time in years t_{oper}.

The larger is the input vector, the more complex shall be the NS architecture that handles this set. The more complex is the network configuration, the more time is needed to train the network and the more likely difficulties to occur in the training process.

An indispensable parameter of prediction problems is the time span for which the prediction is performed, t_{pred}. Therefore, the NS model we will get has the form of a "black box" (Fig. 1).

A sigmoidal (or logical) function of the form $F(x) = 1 / (1 + \exp(-x))$ (see Fig. 2) was used as the activation function.

A back propagation algorithm has been selected for training. This is a systematic approach to the training of multilayer artificial neural networks that enables a spatial construction of "approximation" weights for the path calculated by steepest descent method. The computational power of the algorithm consists of the efficiency of the calculation of the network function's partial derivatives $F(\boldsymbol{w}, \boldsymbol{x})$ for all components of the adjusted vector of weights $\boldsymbol{w}$ for the given input vector $\boldsymbol{x}$.

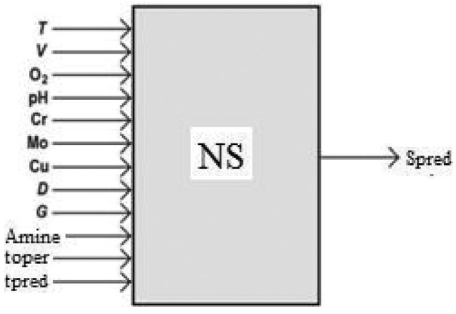


Fig. 1. A model of an artificial neural network for the prediction problem solution.

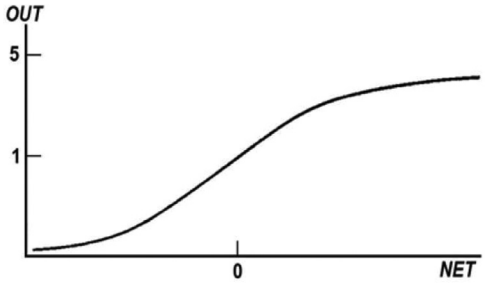


Fig. 2. Sigmoidal function. *OUT*—neuron output; *NET*—input.

The back propagation algorithm suggests the following sequence of actions:

(1) Selection of the next learning pair from the learning set and supply of the input vector to the network.
(2) Calculation of the network output.
(3) Calculation of the difference between the network output and the required output (the target vector of the learning pair).
(4) Correction of the network's weights such that to minimize the error.
(5) Repeated performance of steps 1 through 4 for each vector of the learning set until the error for the whole of the set reaches the acceptable level.

The weights are corrected using the formula

$$\Delta w_{pq,k} = \eta \delta_{q,k} \cdot \mathrm{OUT},$$

where $\Delta w_{pq,k}$ is the value of the weight correction from the vector p to the vector q; η is the learning rate; and *OUT* is the neuron output.

The value δ for the output layer neurons is found by the expression

$$\delta = \mathrm{OUT} \cdot (1 - \mathrm{OUT}) \cdot (\mathrm{T\,arget} - \mathrm{OUT})$$

where OUT (1 – OUT) is the derivative from the sigmoidal activation function; and Target is the target value.

The value $\delta_{q,k-1}$ required for the hidden layer neuron is obtained by totaling the products of the value $\delta_{q,k}$ for the neuron to which it is attached in the output layer and the respective weight and by multiplying by the derivative contractive function:

$$\delta_{q,k-1} = \mathrm{OUT}_{p,k} \cdot \left(1 - \mathrm{OUT}_{p,k}\right) \cdot \left[\sum_{q} \delta_{q,k}\, w_{pq,k}\right].$$

To solve the FAC rate prediction problem, a simplified neural network model was realized (Fig. 3), containing a reduced number of input parameters.

Implementation of a neural network

The construction of a neural network is an experimental process. The major difficulty involved in the network construction consists of the selection of the optimal complexity level.

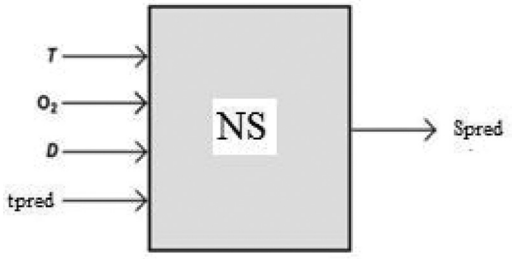


Fig. 3. A simplified neural network model for the FAC prediction problem solution.

Data processing

Input signals of the simplified neural network model have been selected with regard for their relative importance: fluid temperature, inner diameter of the piping, oxygen content in the fluid, and time for which the prediction is performed. Therefore, the learning set is composed of vectors containing four elements each. The intervals of possible values have been preset for each of the parameters. And the factors, not used in the model under implementation, have been assumed to be constant: pH = 7; Keller coefficient: 0.04; chromium content: 0.03%; copper content: 0.03%; molybdenum content: 0.03%; amine type—ammonia; flow velocity $V = 6.1$ m/s.

To provide for an equal effect from each of the variables on the weight variation in the training process, data has been normalized for the interval (0.1)—the range of the sigmoidal function's output values. This was done by linear scaling. Linear scaling of the variable v to the variable s, distributed in a range from zero to unity, was based on the formula

$$s = [v - \min(\mathrm{v}_{1\ldots n})]/[\max(\mathrm{v}_{1\ldots n}) - \min(\mathrm{v}_{1\ldots n})].$$

Back propagation from s to v is based on the formula

$$v = \min(\mathrm{v}_{1\ldots n}) + s[\max(\mathrm{v}_{1\ldots n}) - \min(\mathrm{v}_{1\ldots n})].$$

Network structure selection

A decision was made in the design of the neural network for the FAC prediction problem solution that a narrowing network shall be constructed, since, in this case, it has its generalization capability increased.

To calculate the upper boundary h for the number of hidden elements, Kolmogorov's theorem may be used according to which any function of n variables may be presented as the superposition $2n + 1$ of univariate functions: $h \leq 2i + 1$.

The analysis of published results shows that one or, sometimes, two hidden layers are enough to solve most practical problems [4,5].

The number of neurons in hidden layers depends greatly on the available learning set. The number of learning examples should be approximately equal to the number of the network weights ω multiplied by the inverse error value ε:

$$n \geq = \omega/\varepsilon.$$

Table 1
Target and resultant values.

Target values	0.128	0.423	0.109	1.352	0.707	4.65	0.265	0.628	1.81	0.155
Resultant values	0.128	0.170	0.127	1.046	0.570	4.412	0.198	0.654	1.475	0.121

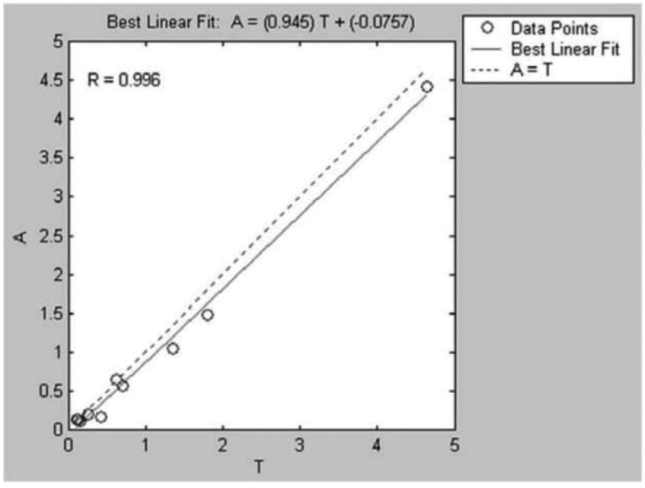


Fig. 4. A data display fragment. A diagram of the linear regression between the network output and the standard.

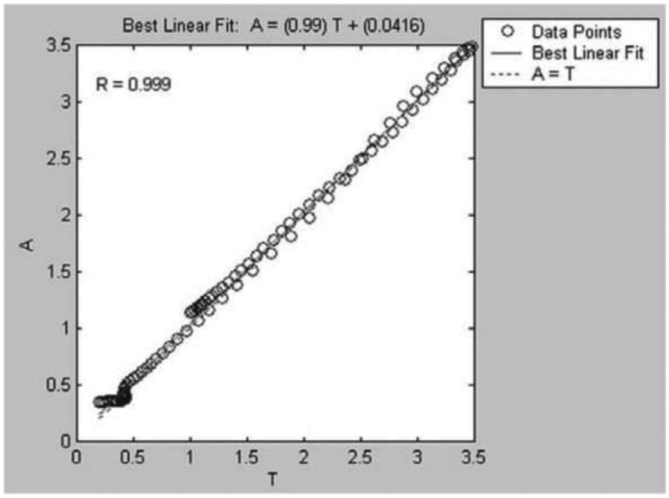


Fig. 5. A data display fragment. A diagram of the linear regression between the optimal network output and the standard versus temperature.

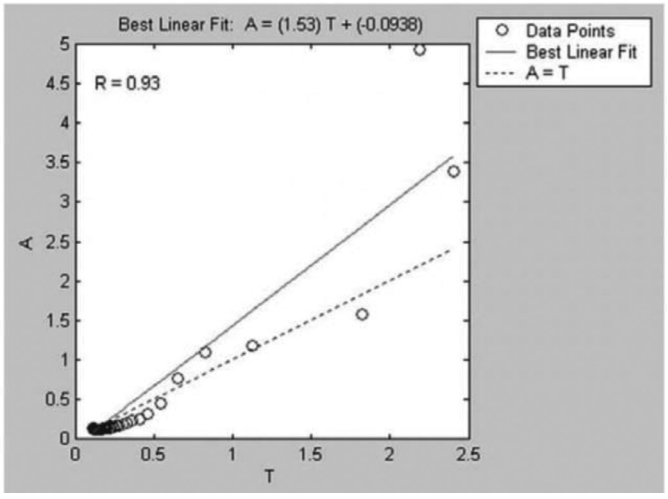


Fig. 6. A data display fragment. A diagram of the linear regression between the optimal network output and the standard versus oxygen content.

Neuron network training

The construction of a neural network for any problem requires several neural networks of different complexity to be built from which the optimal one will be selected.

The prediction of the piping wall thinning under the action of the FAC process, based on different neural networks trained using the back propagation algorithm, either led to the network paralysis or was too time-consuming.

It was decided to use a faster learning algorithm, namely, the elastic back propagation algorithm which, in contrast to the standard back propagation algorithm, uses only signs of partial derivatives for the weight coefficient readjustment. A dedicated procedure has been developed to cover uniformly the field of input values.

As a result, a neural network composed of a four-element input layer, two hidden layers of four neurons each, and a single-element output layer was built in the *MatLab* environment and trained using the elastic back propagation algorithm. The average root-mean-square error of the prediction based on the implemented network is equal to 0.035 (Fig. 4).

Table 1 presents target values of the network output and the values generated by the network.

Model investigation

To judge on the adequacy of the optimal neural network built, it needs to be found out in which domain of the input parameter determination the neural network behaves correctly. Figs. 5–8 present dependences between the network outputs and the standard for the parameters used.

It was found as the result of the investigation that the obtained neural network predicts correctly in a range of the piping inner diameter variation to 600 mm at the oxygen concentrations of up to 45 μg/kg and in the time range of 1–4 years.

Learning algorithms and neural network models

First of all, neural networks are classified based on if supervised or unsupervised learning is used. Supervised learning suggests that the target vector representing the required output exists for each input vector. Jointly, these are referred to as

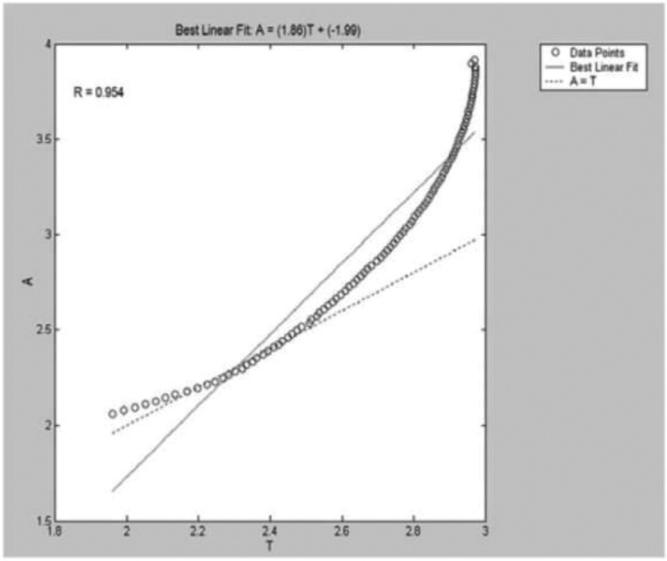


Fig. 7. A data display fragment. A diagram of the linear regression between the optimal network output and the standard versus inner piping diameter.

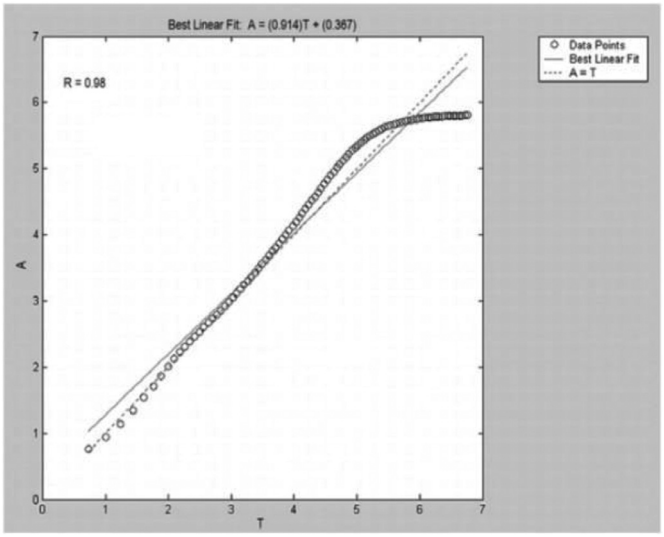


Fig. 8. A data display fragment. A diagram of the linear regression between the optimal network output and the standard versus operating time.

learning pair. Normally, the network is trained using a certain number of such pairs until the error for the entire learning array reaches an acceptably low level.

Unsupervised learning does not require the target vector for outputs, so no comparison against the predefined ideal answers is required. The learning set comprises only output vectors. The learning algorithm readjusts the network weights such that to obtain consistent output vectors, that is, that the production of sufficiently close input vectors led to similar outputs.

The training process therefore identifies the statistical properties of the learning set and combines similar vectors into classes. The supply of the vector in a given class to the network will yield a particular output vector, but it cannot be predicted prior to the training which output will be produced by the given class of input vectors. Therefore, the outputs of such a network shall be transformed into a certain conceivable form defined by the training process.

It is proposed that the considered models of neural networks to be combined such that to optimize the FAC rate prediction problem solution using an NS to improve the desired prediction quality.

A detailed study into the NS learning algorithms has shown that the problem under consideration cannot be solved only through the unsupervised NS learning, that is, the major problem of these networks address is classification and separation of features from data. However, combined with supervised NS learning algorithms (for instance, with the error back propagation algorithm), such methods are capable to improve and facilitate the FAC rate prediction problem solution.

A *replicative neural network* can be used to reduce the input vector dimensionality [4,5]. The training of such an NS aims to make the vector reproduced by the output layer fit the vector supplied to the input layer. It can be said that training is unsupervised since input data as such is used as the standard. Prior handling of input data based on a replicative network reflecting the m-dimensional input space to an n-dimensional one ($n < m$) by "identifying" the attributes of the input set makes it possible to facilitate further training of the base NS solving the prediction problem.

Kohonen's self-organizing maps are useful for increasing the accuracy of the FAC prediction. In these maps, neurons are contained in the nodes of the lattice, normally one- or two-dimensional. In the competitive process, neurons are selectively adjusted to different input images or classes of input images. In the course of the adjustment, the positions of neurons are arranged with respect to each other such that a notional system of coordinates is generated on the lattice. The network representing Kohonen's self-organizing maps is trained using the following algorithm.

1. The input set vector $\boldsymbol{x}$ is supplied to the network input.
2. The distances D_j are determined between $\boldsymbol{x}$ and the weight vectors $\boldsymbol{w}_j$ of each neuron using the formula

$$D_j = \sqrt{\sum_i (x_i - w_i)_j^2},$$

   where x_i is the ith element of the input vector $\boldsymbol{x}$, and $\boldsymbol{w}_{ij}$ is the weight of the neuron j's input i.
3. Neuron the weight vector of which is the nearest one to $\boldsymbol{x}$ is declared the winner. This weight vector, called $\boldsymbol{w}_c$, becomes the base one in the group of the weight vectors lying in the limits of the distance D from $\boldsymbol{w}_c$.
4. The group of weight vectors is adjusted in accordance with the condition

$$\boldsymbol{w}_j(t+1) = \boldsymbol{w}_j(t) + \alpha\left[\boldsymbol{x} - \boldsymbol{w}_j(t)\right]$$

   for all of the weight vectors in the limits of the distance D from $\boldsymbol{w}_c$.
5. Steps 1 through 4 are repeated for each input vector.

The learning vector adjusts the weight vectors in the vicinity of the excited neuron such that they looked like an input vector. In the process of the training, the group of neighboring weight points moves closer to the input vector point. Input points are combined into classes according to the positions thereof in the vector space. A particular class is associated with a particular neuron by moving its weight vector towards the class center and by contributing to its excitation when any vector of the given class appears at the input.

After the dimensionality of the input vector is reduced using a replicator and a coded input signal is received, it needs to be found which class of the input space the signal in question belongs to. Finally, an NS *trained using a back propagation algorithm* should be built for each class of the input set, and it is this NS that will compute the desired prediction for the piping wall thinning versus the rated value over the predicted time period.

Therefore, the intellectual system implemented as a set of neural networks for the FAC rate prediction problem solution comprises three NS types:

- A replicative neural network reducing the input set dimensionality.
- A Kohonen self-organizing map classifying the input signal.
- Neural networks trained using a back propagation algorithm for calculating the predicted value for each class of input signals.

The proposed intellectual system makes it possible to optimize the learning set volume for a random quantity of the model parameters.

Conclusion

A neural-network approach has been implemented, making it possible to estimate the mutual effects from the factors defining the FAC process intensity in the NPP equipment, to identify the essential properties of the information obtained, and, ultimately, to improve the accuracy of prediction.

An artificial neural network has been developed using *Matlab* software to address the problem of the wall thinning prediction for a straight pipe with the VVER NPP single-phase secondary fluid. The network has been trained using an elastic back propagation algorithm, a number of the NS configurations have been studied, and the obtained results have been analyzed.

Consequently, a conceptual framework has been built for the intellectual system implemented in the form of a set of three NS types: a replicative NS, a Kohonen self-organizing map, and an NS trained using a back propagation algorithm.

References

[1] V.I. Baranenko, Ya.A. Yanchenko, O.M. Gulina, D.A. Dokukin, Izvestiya vuzov. Yadernaya Energetika (2) (2010) 55–63.
[2] Chexal V.K. (Bind), Horowitz J.S. 1995, pp. 231–243.
[3] O.M. Gulina, V.I. Baranenko, D.A. Dokukin, Izvestiya vuzov. Yadernaya Energetika (1) (2008) 3–8.
[4] Wassermann F. 1992. Available at: http://www.codenet.ru/progr/alg/nks/ (in Russian).
[5] Swingler K. Available at: http://matlab.exponenta.ru/neuralnetwork/book4/3_3.php/ (in Russian).