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

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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:

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

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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 $\boldsymbol{x}$.

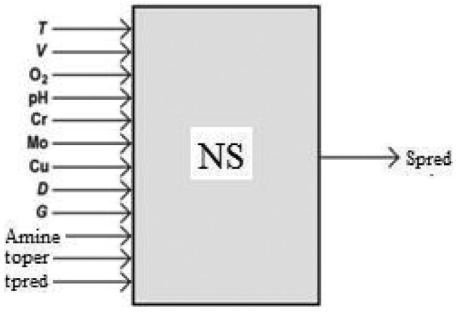

Fig. 1. A model of an artificial neural network for the prediction problem solution.