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Neural network approach for failure rate prediction

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ABSTRACT

The aim of this paper was to present the possibility of artificial neural networks application to the failure rate modeling. Operating data from one Polish water utility were used to forecast output value of failure frequency. The prediction results indicate that artificial networks may be used to model the damages frequency in the water supply systems. It was found that the artificial neural network (multilayer perceptron) trained by quasi-Newton approach gave acceptable, from engineering point of view, convergence. The network was learnt using 173 and 147 data (house connections and distribution pipes, respectively). 50% of all data was chosen for training, 25% for testing and 25% for validation. In prognosis phase, the best created network used 100% of 133 and 114 values for testing. The correlation between experimental and predicted data (relating to house connections and distribution pipes, respectively) was characterized by indicator $R^2 = 0.9510$ and $R^2 = 0.9268$ (learning phase). Worse results were obtained in prognosis phase. In this step of modeling once created network predicted failure rate using not known input signals. The coefficient R^2 was equal to 0.4142 for house connections. For the distribution pipes the significant relation between experimental and modeled data was not found. The created model could be used by water utility in the future to establish the level of failure frequency and to plan the renovation of the most deteriorated pipes.

1. Introduction

The water supply system is a vital component of all buried infrastructure. Water should be delivered to the consumers under required pressure, with required amount and with proper quality. The technical condition of water-pipe network should be observed and improved continuously. The studies concerning reliability and failure analysis relating to water-pipe networks are quite advanced in Poland and abroad [1–6]. Suitable maintenance and operation is necessary to decrease unreliability of water supply systems. Mathematical modeling of the reliability indicators is a promising tool which seems to be used more often nowadays. Relatively high costs of pipes renovation or replacement require to optimize the reliability and safety level. There are a lot of mathematical models which are used to forecast the technical condition, number of failures and reliability of water-pipe networks. The detailed description and some critique of existed statistical and physically based models was carried out by Kleiner and Rajani [7,8]. The results of number of failure prediction using statistical models seem to be convergent with experimental data from Switzerland [9]. Moreover, promising results were obtained by authors who used genetic approach or fuzzy logic to model: e.g. pipe replacement scenarios, pipe damages, risk of failure [10–14]. Nowadays, the artificial neural networks (ANN) are widely used as new mathematical tool offering an alternative way to deal

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with the complex problems. ANNs are used to predict water network deterioration as well as the number and time of failure, or to classify damages and make a prognosis of costs of buried infrastructure [15–22].

This paper presents the results of failure rate (fail./(km a)) prediction using artificial neural networks (ANN). Failure rates of distribution pipes and house connections in one selected Polish city were predicted using typical network structure – multilayer perceptron (MLP). The results of modeling were compared with experimental data. Till now in Poland there is lack of such modeling. ANN seems to be a promising tool for quick prediction of failure rate indicator. The created model could be used by water utility in the future to establish the level of failure frequency and to plan the renovation of the most deteriorated pipe. Moreover, other researchers (from other parts of the world) may compare their results of failure rate prediction with the results of modeling described in this paper.

Nowadays, each water utility should collect the basic information about the water-pipe network, e.g. length, material, diameter, age. The aim of the presented paper was to create quite simple model which will be used by water utility without necessity of collecting more complicated data. To predict failure rate of chosen type of water pipes (house connections or distribution pipes) it is enough to have the main information about the conduit (material, length, diameter, year of installation). Implementation of the model is very simple and from engineering point of view it is the main advantage of such modeling.

2. Methodology and range of studies

2.1. Basic information about artificial neural networks

The prototype of artificial neural networks is the brain and the entire nervous system in the human body. In artificial neural networks the method of information transferring is imitating the way of human nervous system performance. Natural neurons, the main elements of nervous system, are responsible for transferring information. ANN consists of neurons which are data processors. Each neuron is responsible for summarizing input signals. The first model of artificial neuron was created by McCulloch–Pitts in 1943 [23]. The principle of this model is based on the summarizing input signals with proper weight. Next, the sum is activated by the function. The signals are transferring from the node j to node i. Output signal is described by the relation:

$$y_i = f\left(\sum_{j=1}^{N} w_{ij} \cdot x_j + b_i\right), \quad i,\ j = 1, 2, \ldots, N \tag{1}$$

where

x_j – input signals,
W_{ij} – synaptic weights,
f – activation function.

The function f, as shown in the Eq. (1), is called activation function that stimulates the information transmission. Above mentioned model is quite simple and since 1943 ANN has been developed and improved to be sufficient for modeling a lot of dynamic processes.

Artificial neural networks are used to predict, classify, recognize, associate and analyze data, to filter signals and for optimization purposes. Neural networks enable to model non-linear and complex problems. The information between neurons laid in layers (input, hidden and output) is transferred in one direction and neurons calculate the weighted sum of signals. The weight values are obtained during the learning process. Depending on their structure and way of transmitting signals between neurons, the following types of artificial neural networks are distinguished: linear networks, networks with radial base functions, recursive networks and multilayer perceptron networks (MLP). Today the most popular and best theoretically described are MLP networks [24]. This type of the network has one input layer, one or more hidden layers and one output layer. Generally, it should be remembered that ANN modeling is like "black box" approach and that is why it is impossible to penetrate deeply inside the way of forming the network structure.

The main and the most popular learning methods are [25]: back propagation algorithm, Levenberg–Marquardt algorithm, conjugated gradient algorithm and quasi-Newton approach. Nowadays, it is told that network training based on quasi-Newton algorithm is the most effective. Even completely different tasks (e.g. short-range forecast in membrane processes) were successfully solved using this approach [26].

Quasi-Newton algorithm requires a small number of iterations to train a neural network given their fast convergence rate and more intelligent search criterion. It is recommended technique for most networks with a small number of weights (less than a couple of hundred). The aim of using this method is to point out the direction which allows us to determine the function minimum. It is necessary to calculate the value of gradient parameters and Hessian matrix in the point of last known solution. The determination of Hessian matrix is quite complicated and inverse matrix of approximate Hessian is calculated as follows $\mathbf{V}_k = [\mathbf{G}(\mathbf{w}_k)]^{-1}$. The most effective formula of recurrent determination of matrix $\mathbf{V}$ was described by Broyden–Fletcher–Goldfarb–Shanno (BFGS) [27]. This formula is defined as follows: