MANAGEMENT OF THE WATER SUPPLY SYSTEM OVERHAULS USING NEURAL NETWORKS

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ABSTRACT

The operation of the water supply system requires not only maintain its operation and its proper management, but also to restore its technical capacity and performance. Operational strategy technical renewal of water pipes should be established and recognized in plans and documents. To perform reliable analyses and assessments of necessary overhauls regarding failure modes and effects in water-pipe networks, also it is necessary to have access to a comprehensive database. A major problem in such determination of overhauls plan is the analysis which deal with uncertainty of the operating data required both for statistical analysis and cause-and-effect assessment. The paper concerns a model for the analysis of failure and overhauls in a water supply system using neural networks. The method proposed in this paper may constitute a procedure of practical use to the operator of a water distribution system.

Keywords: water supply system, neural network, water network overhaul

1. Introduction

Water supply systems (WSS) are being operated in a continuous manner for a long time. Therefore the elements building them are also subject to intensive exploitation. Damage of the object or device usually entails the necessity of exclusion it from the operation in order to remove a failure. It causes economic consequences for the water supply company, resulting from the reduction or interruption of water supply. For this reason, to make appropriate service (repair, renewal, replacement) only after the damage of the element can be irrational. Human interference detects and removes defects that are a potential source of failure (Tabesh *et al.*, 2010).

After several decades, the trend of the increase in the intensity of damages of water pipes associated with ageing is observed. In such cases, we face the alternative to repair the increased number of failures or to carry out technical renewal of pipelines through major overhauls (Herz, 1998).

A commonly used solution becomes the prophylactic renewals aimed at reducing the rate of loss of usability of the element. The prophylactic renewals do not eliminate the possibility of damage, but they can reduce the likelihood of the emergency renewals. Strategy of the prophylactic renewals means to perform them in proper time, in order to achieve maximum profitability of the project or the required level of reliability, using, for example, periodic strategies involving the prophylactic renewals after a predetermined operating time of each element and the emergency renewals as soon as the element is damaged (Valis *et al.*, 2012). The database on failures will allow using it effectively for the analysis and preparation of statistical summaries for one specific year or for any years. It should be legally obliged to register data relating to water supply failures, as was stated in (Rak, 2009).

The aim of the paper is to achieve the failure analysis with neural network implementation in order to understand and predict failure occurrence in water supply infrastructure and will be used in developing a strategy for activities in the face of a pipe renovation.

2. Material and method

Data on failures are divided into following groups:

- general information about the objects (addresses, dates, etc.),
- technical data about the objects (types of objects considering their functionality, construction, technology, etc.),
- data on failure (type of event, cause, etc.),
- data on the effects and consequences of failure (type, scope of damage, causes, etc.),
- additional information.

Artificial neural networks are defined as a type of learning systems and their effects are based on the principles of the functioning of biological neurons. A neural network is a system of complex computational elements operating in parallel mode, having the ability to learn from examples and application such abstracted knowledge to future unknown situations. Knowledge is stored in the synaptic connection weights values (Kamruzzaman *et al.*, 2006). Currently several different types of neural networks have a very broad employs, among others, in the diagnosis, prognosis and optimization processes of various phenomena. Fuzzy systems are mainly used in models where there is imperfect (uncertain) database, while neural networks are capable of learning and the creation of new rules of inference based on the gained knowledge.

The Neural Network Perceptron is an algorithm, which sums up the weighted input signals and compares this sum with a threshold activation, depending on the result of Perceptron can be either triggered (score of 1) or not (score 0), the method introduced by Frank Rosenblatt in 1957 and presented in work (Rosenblatt, 1958).

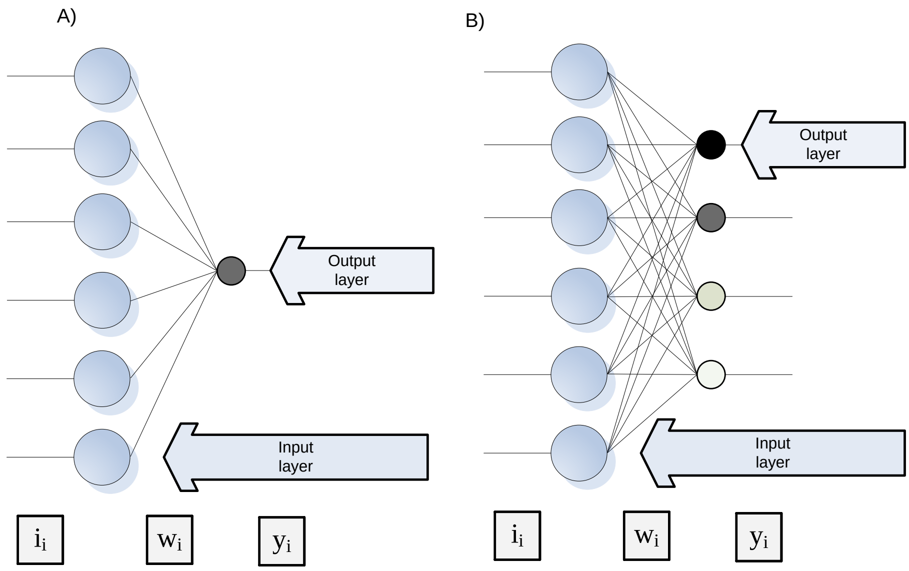

Figure 1: The structure of the perceptron: A) network, B) single; where: i_i is the value of the i-th input, w_i is the weight of i-th uplink element.

Mathematical model describing the artificial neuron forming part of perceptron has the form (in case of the unipolar activation):

$$f(x)=\begin{cases}1, \text{ when } x>0,\\ 0, \text{ when } x\leq 0.\end{cases} \quad (1)$$

and for polar function:

$$f(x)=\begin{cases}1, \text{ when } x>0,\\ -1, \text{ when } x\leq 0.\end{cases} \quad (2)$$

then

$$x = \sum_{i=1}^{m} w_i \cdot i_i - \Theta \quad (3)$$

where θ is a threshold of the activation function.

Perceptron has the following characteristics: it does not include connections between components belonging to the same layer, the connections between layers are asymmetric and there is no reciprocal connection. In detail, learning process of element perceptron and the weighting factors determining in the learning process of perceptron element is presented in works (Osowski, 2000; Raudys, 2001). For the classification estimation Networks Naural Statistica v. 10.0 simulator was used, regarding the relationship between the input and output from the network.

Based on the failure analysis and assessment of water pipe, on the basis of operational data, water pipes were classified into groups: 1st failure occurred on the pipe and require technical strategy renewal and 2nd failure-free. The following variables were distinguished: year of pipe build, material (cast iron, cast iron spheroid, steel, PVC, PE, AC), ground conditions (wetland ground, rocky ground, unstable ground, normal ground; location of water pipe: in the lanes of heavy traffic; in the lanes; off the main road in the pavement, parking lot; off the main road in green areas, on the side of the road and the asphalt, concrete, flagstone, cobblestone and other pavement), thee failure rate index - estimator was determined according to the formula:

$$\lambda_i = \frac{k_i}{l_i \cdot \Delta t} \quad (4)$$

where λ_i is the failure rate index estimator per year for particular type of water pipes per one year, [$km^{-1}a^{-1}$]; k_i is the number of failures in one year for particular type of water pipes; l_i is the lenght of particular type of water pipes, on which failures appeared per one year, [km]; i is a type of water pipes; Δt is the length of time that equals 1 year, [1 year].

For the effectiveness of neural network, the degree which describes and predicts unused data in the learning process has the great influence. For this purpose the division into a learning and sample test, that was applied to learning and tests the efficiency of the network.

3. Results

As a result of the designed network multi-layer perceptron was obtained with four input neurons, four neurons in the hidden layer and two output neurons. The quality of the training set was 94% and for the test set - 96%, in the learning process BFGS algorithm was used, which allowed to obtain the best result in the seventh learning cycle (Table 1).

Table 1: Summary of learning outcomes.

Network Id	Learning algorithm	Quality (learning)	Learning algorithm	Error function	Activation (hidden)	Activation (output)
1	94%	96%	BFGS7	Entropy	Tanh	Softmax

The result of the classification and errors matrix confirmed information about the effectiveness of the neural network classifier, only five percent of cases were misclassified in the case of a group of failure occurrence on the water pipe (Table 2). Trained network can be used for future applications, or implement to normal operation.

Monitoring of water pipes exploitation connected with identifying unacceptable conditions associated with the failure occurrence, will significantly improve the operational planning of technical strategy renewal. Applied application for water pipes database, can be used for automatic recognition of providing water pipes overhaul.

Table 2: Summary of classification.

The expected class	Failure occurred on the pipe and require technical strategy renewal	Failure-free
Correct	95%	100%
Incorrect	5%	0%

4. Conclusion and perspectives

Decision-making scenarios taking into account the incurred costs and obtaining relative or large profits offer a choice of strategies of conduct. Selection for particular groups of undesirable events associated with the operation of WSS should be preceded by a detailed failure analysis and assessment.

One should take into account that the real technical durability of pipes can significantly exceed the amortization period, but it can also be much shorter. In this respect, dependences are multicausal and only monitoring of failures of network allows drawing correct conclusions.

Limited period of operation of the water supply system should be planned on the basis of literature and operating data, according to the criterion of increasing failure rate and loss of functionality, reduction in capacity due to incrustation and corrosive wear of the pipe.

The development of appropriate methods to assess the management of water pipes contributes to the reduction of the potential consequences of failures, helps in making by engineers, designers or government official's right decisions as to the choice of the optimal solution, as well as methods of protecting the users and the surrounding environment from the negative consequences.

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