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Application of Multilayer Perceptron for the Calculation of Pressure Losses in Water Supply Lines

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1. Introduction

Numerical methods have been used widely for many years in the design and operation of water supply systems. Specialised computer programmes offer ever more facilities, especially for data entry and viewing, but they still function on the basis of predetermined algorithms. At the same time, we are also dealing with the game-changing development of artificial intelligence techniques, which are increasingly paving the way for practical applications. To this end, traditional calculation programmes are supplemented with artificial intelligence methods. This trend can also be seen in issues related to the supply of water. The aim of this article is to present the method of artificial neural networks for the calculation of pressure losses in water supply lines.

2. Artificial Neural Networks (ANN)

Intelligence is attributed solely to man, but since the creation of the first computer, many attempts have been made to build a machine with such a feature. This led to the creation of a field of science known as artificial intelligence AI (Negnevitsky 2004). There are several trends, but expert systems, artificial neural networks and various types of metaheuristics have gained the greatest popularity.

Such methods are based on the observation of the processes occurring in the natural world or functioning of the nervous system. This group includes, among other things, artificial neural networks (ANN) that simulate the processing of information in the nervous systems of animals and humans. The most commonly used type of uni-directional artificial neural network is the multi-layer perceptron, which consists of neurons arranged in layers (Bishop 1966).

3. The Current State of the Application of Artificial Neural Networks in the Design of Water Distribution Systems

In the works (Lingireddy & Ormsbee 1998, Saldarriaga et al., 2004), artificial neural networks, aimed at streamlining the process of taring a numerical model in a water distribution system, was described. Hydraulic calculations using the Darcy-Weisbach formula require determination of the coefficient of linear resistance, most often by the application of an iteration method. In the articles (Besarati et al. 2015, Brkić & Ćojbašić 2016, Salmasi et al. 2012, Shayya & Sablani 1998), the methods for calculating this factor, using artificial neural networks, in order to reduce calculation times, were presented.

Calculation modules based on artificial neural networks were also introduced into the simulation methods used in the real-time control of water supply networks. The task of neural computing in this case is to simplify the computational model and accelerate calculations (Bargiela 1995, Xu et al. 1997).

The problem of controlling the adjustment of control valves using neural networks was discussed in articles (Haytham et al. 2005, Van den Boogaard & Kruisbrink 1996).

In the study (Dawidowicz 2015), it was assumed that the hydraulic calculations of water distribution systems are a multi-stage process requiring performance evaluation, appropriate data correction and subsequent calculations. Therefore, the methodology of process diagnostics was used to evaluate the results of the calculations. Diagnostic methods were introduced to detect computational abnormalities using artificial neural networks. In the article (Dawidowicz 2017), an artificial neural network for evaluation of a pressure lines and pressure zones, in the water distribution system, was discussed.

An effective control of the water distribution system requires accurate information about the current state of the network. For economic reasons, some parameters must be calculated on the basis of the information available. In the group of parameter estimation methods, estimators based on artificial neural networks appear (Gabrys & Bargiela 1996). A computerised system for controlling pumping systems using genetic algorithms and artificial neural networks is described in the article (Lingireddy & Ormsbee 1995).

4. Development of Artificial Neural Network for Calculation of Pressure Losses in Water Supply Lines

The type of unidirectional artificial neural network most commonly used is the multi-layer perceptron, which consists of neurons arranged in layers (Bishop 1966). There are three basic types of layers, viz. the input layer, the hidden layer, and the output layer. Neurons are interconnected between layers on a *peer-to-peer* basis, whereas in one layer there are no connections between neurons. Each connection is assigned a weighing factor. The combined weight factors of the neural network creates the weight vector, viz., $\mathbf{W}=[w_1,\ w_2,\ldots,w_i,\ldots,\ w_N]^T$.

A multi-layered perceptron is taught by means of a strategy with a teacher that has an iterative nature and consists of repeatedly presenting a network of learning examples $\{X_i,d_i\}$, where $X = [x_1,\ x_2...,x_i...,x_N]^T$ is a vector of the input variables and d is a valid or *real* response to the set of specified input data. The artificial neural network learning algorithm consists in choosing the weights so that the differences- δ_i - between the value calculated by the network- y_i - and the correct value- d_i - for all training examples $i = 1$, ...T was the smallest. An error function is used to evaluate the current quality of a neural network in the learning process, which is a measure of the compatibility of the prediction of a network with the value set. The error function is used to determine the magnitude of the neuronal weight corrections which are necessary at every stage of network learning. In this paper, the function of an error is the sum of the squares of differences:

$$E_{SOS} = \sum_{i=1}^{T} \left(y_i - d_i\right)^2 \tag{1}$$

where:
T – is the number of learning cases (input-output pairs),
y_i – is the network prediction (network output) for the i-th case of the training case,
d_i – is the correct (real) value of the i-th case.

In the neurons of the input layer, a linear activation function was applied, whereas in the hidden and output layer, a logistic function was applied:

$$y = \frac{1}{1+e^{-\beta S}} \qquad y \in (0 \ldots +1) \tag{2}$$

where:
y – is the initial value of the neuron,
β – is a numerical factor, usually with the value of 1,
S – is the value of the post-synaptic potential function *PSP*.

The use of artificial neural networks requires a set of training examples describing the object or process being modelled. Neural network calculations in this example rely on the generation of pressure losses on the computational sections of the water supply lines. Therefore, it is a regression problem and the output variable is numeric in character. Input variables may be numerical or nominal. In the training data set, the following parameters of the computational sections are stored:

- nominal flow q [l/s],
- nominal diameter DN [mm], supplied to the network as a nominal value,
- length of the section/segment L [m],
- coefficient of absolute roughness k [mm],
- calculated level of pressure losses on the computational section Δ/segment H [m].

The hydraulic calculations were performed with the following assumptions:

- pressure losses were calculated using the Darcy-Weisbach formula,
- internal diameters of the water pipes were assumed for the calculations,

- PE100 polyethylene pressure pipes of the SDR17 series (EN 12201-2: 2011) for diameters up to DN225 and ductile iron pipes (EN 545: 2010) for higher diameters were applied,
- minimum cable diameter DN90,
- maximum cable diameter DN500,
- range of lengths of computational pipelines L = 50-3000 [m],
- range of reliable flow in the relation q = 0.5-570 [l/s],
- range of roughness coefficients was assumed at k = 0.01-2.0 [mm].

Nominal diameters were adopted as follows:
- DN90, DN110, DN160, DN225 for PE100 polyethylene pipes of the SDR17 series (EN 12201-2:2011),
- DN250, DN300, DN350, DN400, DN450, DN500 for ductile iron pipes (EN 545: 2010).

As a result of hydraulic pipeline calculations for various input parameters, 16,260 training examples were obtained.

An artificial neural network was investigated to determine the structure of the neural network, in order to obtain the results of pressure losses in the water pipes with the smallest error. In the learning process, the training data set was divided into three subsets, viz., the training set (70%), the validation subset (15%) and the test subset (15%):
- the training set – is used to teach the network,
- the validation set – cases in this set are not used to modify network parameters in the training process, but are used independently, in parallel to the training process, in quality assessment and generalisation ability,
- the test set – is not used at all during the training process, but enables a final, quality assessment of the network's performance to be carried out after the training process has been completed.

The network was taught by the BFGS method. As a result of training various structures of the multi-layer perceptron, a neural network composed of the following elements was assumed for the calculation of pressure losses in the water supply lines:

- a layer with 15 neurons for input variables, 12 of which correspond to the nominal diameter DN,
- a hidden layer built of 85 neurons with a logistic activation function,
- an output layer with 1 neuron and a logistic, activation function.

A schematic diagram of the neural network, with a shortened inner layer, is shown in Figure 1. The input of the nominal variable, describing diameters according to the "one of N" principle, is worth mentioning.

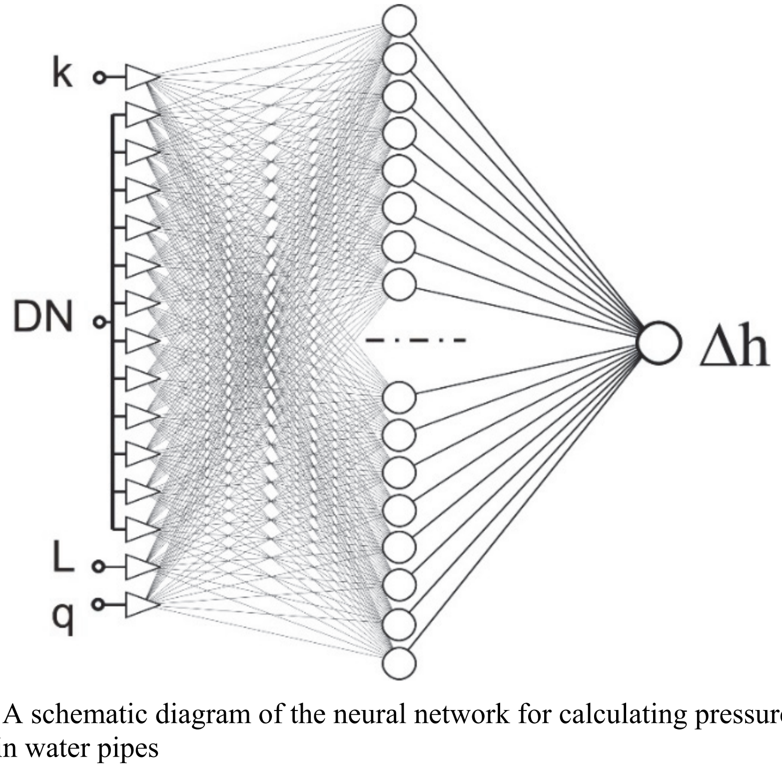

Fig. 1. A schematic diagram of the neural network for calculating pressure losses in water pipes
Rys. 1. Schemat sieci neuronowej do obliczeń strat ciśnienia w przewodach wodociągowych

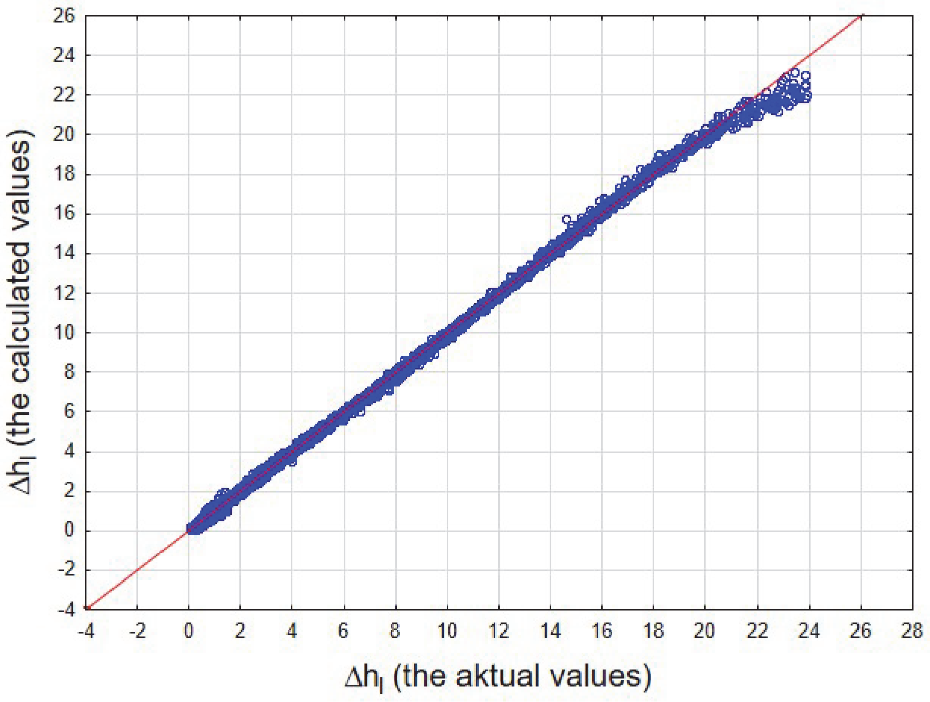

Fig. 2. The relationship between the actual values of pressure losses Δh_l and those calculated by the artificial neural network

Rys. 2. Zależność pomiędzy rzeczywistymi wartościami strat ciśnienia Δh_l a wyliczonymi przez sztuczną sieć neuronową

Table 1. Parameters of the multi-layer perceptron for calculating pressure losses in water supply lines

Tabela 1. Parametry perceptronu wielowarstwowego do obliczania strat ciśnienia w przewodach wodociągowych

Parameter	Training subset	Validation subset	Test subset
SOS error	0.007970	0.009528	0.009493
Correlation coefficient	0.999601	0.999486	0.999518

A very low SOS error value for the three subsets and a high value for the Pearson correlation coefficient r, between the actual values and the values calculated by the neural network, shows that it can be used to simplify the hydraulic calculation model. Artificial neural networks with parallel structures are characterised by very short data processing times and can be used in real-time control systems where calculation time is critical.

5. Summary and Conclusions

In the design of water distribution systems, hydraulic calculations are carried out together with calculations for the selection of the pumps, the reservoir sizes or optimisation of the components of the operating parameters of individual systems. Computational methods based on classical numerical algorithms have largely exhausted their development possibilities. Accelerating computing by using the latest generation of computers does not always deliver better results. Only the application of new calculation methods can significantly improve both the quality of the solutions obtained and the results of calculations. Increasingly, when dealing with a number of problems, artificial intelligence is referred to. It is used to solve problems that have not had classical computational algorithms, or significant amounts of required data, to date and where constraints have caused their use to be unfeasible.

This paper reviews the proposed use of artificial neural networks in the calculation of water distribution systems implemented by computer programmes. On the other hand, there are hardware-based software drives that use smart software, which greatly enhances the ability to use smart methods in practice. The wide range of solutions indicates that they pave the way for their implementation, in practice.

A computational example in the form of an artificial neural network calculating pressure losses in water supply pipes shows that artificial intelligence methods can play a significant role in the design, control, and management of water distribution systems in the future. A very high convergence was found between the results obtained from the EPANET calculation programme and the results generated by the multi-layer perceptron.

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Zastosowanie perceptronu wielowarstwowego do obliczeń strat ciśnienia w przewodach wodociągowych

Streszczenie

Metody numeryczne stosuje się powszechnie od wielu lat w projektowaniu i eksploatacji systemów zaopatrzenia w wodę. Specjalistyczne programy komputerowe oferują coraz więcej udogodnień, szczególnie w zakresie wprowadzania danych oraz przeglądania wyników, lecz nadal funkcjonują na podstawie z góry określonych algorytmów. Obecnie dąży się jednak do stworzenia programów obliczeniowych, które będzie charakteryzować pewien stopień kreatywności, co powinno ułatwić użytkownikom podejmowanie decyzji na różnych etapach realizacji zadania i poprawić jakość rozwiązań. Zwiększająca się moc obliczeniowa komputerów samoistnie nie rozwiąże złożonych problemów. Dopiero wprowadzanie odpowiednich metod obliczeniowych, pozwala uzyskać właściwe efekty. Wydaje się, że klasyczne algorytmy o sformalizowanym przebiegu, można obecnie uzupełnić znacznie bardziej zaawansowanymi technikami obliczeniowymi. W niniejszej pracy dokonano przeglądu literatury w zakresie zastosowania sztucznych sieci neuronowych w projektowaniu systemów dystrybucji wody. W drugiej części artykułu zamieszczono omówienie sztucznej sieci neuronowej do obliczeń strat ciśnienia w przewodach wodociągowych. W wyniku obliczeń hydraulicznych przewodów wodociągowych za pomocą programu EPANET dla różnych wartości parametrów wejściowych uzyskano zbiór 16260 przykładów uczących. Parametry wejściowe sieci neuronowej to długość przewodu, przepływ miarodajny, współczynnik chropowatości bezwzględnej oraz średnica nominalna. Uzyskano bardzo wysoką zgodność pomiędzy wynikami obliczeń strat ciśnienia z programu EPANET i perceptronu wielowarstwowego z jedną warstwą ukrytą.

Abstract

Numerical methods have been widely used for many years in the design and operation of water supply systems. Specialised computer programmes offer more and more facilities, especially for data entry and viewing, but they still function on the basis of predetermined algorithms. At present, however, we strive to create computational programmes with a certain degree of creativity, which should make it easier for users to make decisions at various stages of the task and improve the quality of their solutions. The increasing power of computers will not solve complex problems alone. Only by introducing appropriate calculation methods can we obtain the right results. It seems that classical algorithms with a formalised course can be supplemented, nowadays, with far more advanced computational techniques. This paper presents an literature review on the use of artificial neural networks in the design and operation of water distribution systems. Presented in the second part of the paper, is an overview of the artificial neural network, developed for the calculation of pressure losses in water supply lines. The calculation of hydraulic piping with the EPANET programme for various input parameters resulted in a collection of 16,260 training examples. Input parameters of the neural network include pipe length, measurable flow, absolute roughness coefficient and the nominal diameter. Very high compatibility was obtained between the calculation results for those pressure losses obtained from the EPANET programme and those obtained from the multi-layered perceptron with one hidden layer.

Keywords:
water distribution systems, artificial intelligence, expert systems,
artificial neuronal networks, heuristic methods, calculation of pressure losses

Słowa kluczowe:
systemy dystrybucji wody, sztuczna inteligencja, systemy ekspertowe,
sztuczne sieci neuronowe, metody heurystyczne, obliczenia strat ciśnienia