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# The Application of Artificial Neural Networks in the Assessment of Pressure Losses in Water Pipes in the Design of Water Distribution Systems

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## 1. Introduction

The water distribution system is a complex, technical object, extremely expensive and difficult to modernise. Pipelines should fulfil their role for many years. In connection with the above, one very important task is the correct design and execution of hydraulic calculations. During the implementation of calculations, it is often necessary to correct data, in order to obtain a correct solution. Numerous parameters are evaluated in the calculation process, including flow velocity through water supply pipelines, flow rate, pressure loss and pressure in individual network nodes. An important parameter, often underestimated, is the level of pressure loss in the calculation of sections of water pipes. This paper proposes a method for the assessment of pressure loss and for the use of artificial neural networks. For this purpose, one class DH1, describing the correct conditions and four classes DH2-DH5, describing problems related to the amount of pressure losses in the water pipes, have been defined. Based on the parameters characterising the operation of the water pipe, the artificial neural network selects one of the classes and thus indicates the occurrence of a specific problem -or gives the 'all clear'.

## 2. Literature review of the use of artificial intelligence in the calculation of water distribution systems

Artificial neural networks are increasingly being used in relation to water supply issues. A review of artificial intelligence methods, including artificial neural networks in the design and operation of water distribution systems, is provided in article (Czapczuk et al. 2015).

In works (Piasecki et al. 2016, Cieżak 2005), artificial neural networks were used to predict water demand. In the calculation of hydraulic water distribution systems, artificial neural networks are used to support the taring of simulation models (Lingireddy et al. 1998, Saldarriaga et al. 2004). This article (Xu et al. 1997) proposes recursive neural networks for calculating flows and looped systems in water supply networks.

Linear pressure losses are calculated by, among other methods, the use of the Darcy-Weisbach Formula which requires calculations of the linear friction factor, using, in the main, the iterative method. There are many works in which artificial neural networks are proposed for calculating the linear friction factor (Brkić & Ćojbašić 2016, Offor & Alabi 2016, Besarati et al. 2015, Shayya & Sablani 1998) which allows the calculation of time to be reduced. Proposals for a neural network in the calculation of direct linear pressure losses are provided in the article (Czapczuk et al. 2017).

Calculation modules, based on artificial neural networks, have also been introduced into the simulation methods used in the real-time control of water supply networks. The task of neural calculations is, in this case, to simplify the calculation model and speed up calculations (Damas et al. 2000, Yongchao & Wending 2003).

In the article (Kamiński et al. 2017), artificial neural networks were used to assess the technical condition of the water supply system.

The verification method for the results of hydraulic calculations, with the use of process diagnostics and artificial neural networks, is presented in the paper (Dawidowicz 2015). The method for estimating pressure levels and the pattern of pressure zones, using artificial neural networks, is described in the article (Dawidowicz 2017) and using the induction method of the decision tree at work (Dawidowicz 2012). The problem of the assessment of pressure loss, is discussed in papers (Biedugnis & Czapczuk 2018, Czapczuk 2013), in which different methods of artificial intelligence have been used, including expert systems and the method of k-nearest neighbours. In this work, artificial neural networks of the perceptron type have been used for the above purpose. The application of RBF neural networks for the assessment of the water flow rate in the pipework is presented in the paper (Czapczuk & Dawidowicz 2018). A method for estimating the diameter of water pipes using artificial neural networks of the multilayer perceptron type is presented in the paper (Dawidowicz 2018).

## 3. An introduction to artificial neural networks

In a multilayer perceptron, the number of neurons in the first layer, corresponds to the number of input variables. In the case of multi-criteria classifications, in the output layer, the number of neurons is equal to the number of classes. The number of K neurons in the hidden layer, should be determined in neural network training. Initially, the number of neurons based on Kolmogorov's Theory can be assumed (Bishop 1996, Konar 2005):

$$\mathbf{K} = 2 \cdot \mathrm{N} + 1 \tag{1}$$

where:
K – the initial number of neurons in the hidden layer,
N – number of variables in the input vector $X = [x_1, \ldots, x_n]^T$.

Nonlinear neurons, with the logistic function, were used in the hidden layer:

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

where:
β – is a numerical factor, usually with the value of 1,
S – the value of the post-synaptic potential function (PSP).

In the output layer of the network, the Softmax activation function was used, according to the formula:

$$y = \frac{e^{\mathrm{S}}}{\sum_{m=1}^{\mathrm{M}} e^{\mathrm{S_m}}} \qquad y = (0...+1) \tag{3}$$

where:
M – the number of neurons of the output layer,
S – the value of the post-synaptic potential function.

The Softmax type activation function is used in classifying tasks; this is an exponential function that assumes values to make the sum of the activation all M neurons in the network output layer, equal to 1. In addition to the fact that network signals are the basis for recognising the appropriate class, the output values, for individual neurons, can be interpreted as an estimation that they probably belong to a given class (Bridle 1990).

The set of all training examples has been divided into training, validation and testing subsets. The basis for selecting neural networks is the error obtained in the validation set. The backpropagation method was applied initially, followed by the Quasi-Newton Method. In the network training process, the Entropy Multiple Error Function was adopted (EME) where each class corresponds to one neuron in the output layer (M> 1) (Bishop 1996):

$$\mathbf{E_{EME}} = -\sum_{t=1}^{\mathrm{T}} \sum_{m=1}^{\mathrm{M}} d_m^{(t)} \log y_m^{(t)} \tag{4}$$

where:
M – the number of neurons of the output layer.
T – the number of examples in the training subsystem,
t = 1, …, T - the number of training examples,
d – the reference value (set) of the neural output signal,
y – the calculated value of the neuron in the output layer.

The artificial neural network was also evaluated on the basis of the accuracy of classification η, defined as:

$$\eta = \frac{\mathrm{n}_{cor}}{\mathrm{n}_{all}} \tag{5}$$

where:
$n_{cor}$ – the number of correctly classified training examples.
$n_{all}$ – the number of all training examples subjected to classification.

Detailed classification results for the training, validation and testing subsets are included in the confusion matrix. This is a square matrix in which information, regarding the individual classes that the examples actually belong to, is given in rows, while information, as to the classes into which they were classified, by the classifier, is given in columns. The diagonal contains examples that have been correctly categorised, while those located beyond the diagonal have been incorrectly classified. At the same time, examples beyond the diagonal, indicate the classes into which they were incorrectly classified.

## 4. Evaluation of design solutions for water distribution systems

At the design stage, for water distribution systems, it is necessary to evaluate the results of the calculation and design solutions, covering technical, economic and reliability issues. The basic technical parameters, determining the correct operation of a water supply network, are the flow velocity, through the pipelines and the pressure levels in the nodes. It is possible to indicate other issues that should be taken into account when assessing the design, as is shown in Fig. 1 (Czapczuk, 2013).

Currently, when choosing water pipe diameters, the basic parameter is flow velocity. It seems that such parameters as linear pressure losses, which largely determine the pressure level in the individual nodes of the network, are also of importance. In the final phase of the calculation, it should be checked as to whether the pressure loss is not too high, thus causing a rapid drop in the pressure line, or whether it is too low, which may be due to the over-sizing of the diameters of the pipework. Currently, this problem remains the designer's responsibility only, for it is he/she who assesses the values obtained, on the basis of his/her own experience and knowledge. The wide range of economic velocity levels, often makes it possible to adjust the diameter while maintaining a favourable flow rate, thus obtaining better network conditions from the point of view of losses to linear pressure.

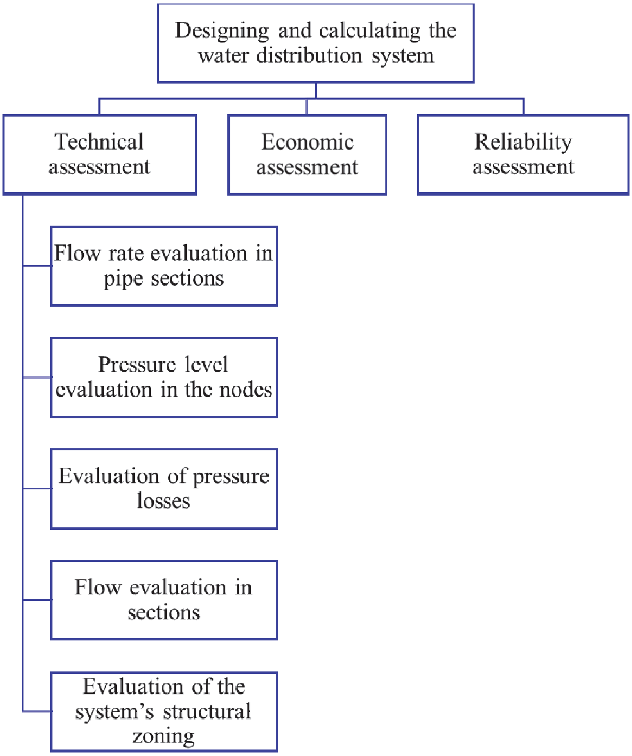


**Fig. 1.** Evaluation of the design solution and of the calculation results of the water distribution system (Czapczuk 2013)
**Rys. 1.** Ocena rozwiązania projektowego i wyników obliczeń systemu dystrybucji wody (Czapczuk 2013)

The pressure level in the nodes ensures that the supply of water is provided under the required pressure, however, at the same time, this pressure should be as low as possible. This is governed by a reduction in water loss and a reduction in pumping costs.

Factors determining levels of pressure loss are the diameter of the water pipe $D_{in}$, the length of the pipeline section L, the flow velocity V and, indirectly, the coefficient of absolute roughness k. Pressure losses in the pipeline, $\Delta h_l$ are calculated on the basis of the Darcy-Weisbach Formula in the form (Knapik & Bajer 2010).

In the literature (Knapik & Bajer, 2010), the economic velocity levels, resulting from the economic and operational conditions of water supply networks. It should be emphasised that the given speed ranges are indicative and require correction, in many cases, due to the working conditions of the entire water distribution system.

When evaluating pressure losses, it is necessary, initially, to determine whether $\Delta h_l$ is correct for a given condition, that is, to determine whether it is too low or too high and what the reason might be for this situation. A review of the results for individual sections, especially in the case of large water distribution systems, can be tedious, time consuming, and confusing. For the purposes of this work, four classes, namely, DH2-DH5 have been defined, describing the reasons for the incorrect value of pressure losses $\Delta h_l$ – while one class, namely, DH1, corresponds to the range of appropriate values.

Class DH1 corresponds to the range of correct values of pressure losses in the section calculated, taking into account not only flow velocity and diameter, but also the length of the section and the absolute roughness coefficient k [mm]. It is assumed that the range of permissible pressure losses occurs when the following conditions are met (Czapczuk 2013):

- the flow rate is higher than 0.5 [m/s],
- the flow velocity for individual diameters does not exceed the recommended values for individual diameters,
- the coefficient of absolute roughness does not exceed k = 1.5 [mm],
- pressure losses resulting from the length of the calculation, at section L will not cause a pressure line drop below 25.5 [m], assuming that the losses resulting from the absolute roughness coefficient k are normal. The initial value of the pressure level is assumed to be 40 [m], hence pressure losses resulting from this, cannot exceed 14.5 [m].

The DH2 class describes a case, where small pressure losses are caused by too large a diameter in the water pipe, or a small flow at the end of the water supply network. Flow rate is less than 0.5 m/s.

The DH3 class characterises a variant in which pressure losses are due to too small a diameter in the water pipe. The value of the absolute roughness coefficient is below the upper limit where k = 1.5 [mm].

The DH4 class describes the conditions in which pressure losses, resulting from the high value of the absolute roughness coefficient k, are above the k limit of 1.5 [mm].

The DH5 class describes a case where the reduction in pressure is below the required pressure loss value, associated with the length of the calculation section of the pipeline. This variant indicates the need for zoning, throughout the system. This length, depending on diameter, flow rate and roughness, is different each time.

The above classes will be assigned to individual calculation sections of the water distribution system, using an artificial neural network. Training examples, in the form of calculation results for sections of the water distribution system have been prepared, using EPANET software and the Excel spreadsheet.

This step was introduced since variability, throughout the whole range of possible attributes, must be taken into account in the examples. Some of the hydraulic calculations were deliberately incorrect, but these examples were described in the appropriate DH classes, so that the expert system could identify the cause of the incorrect losses in pressure.

SDR17 series, PE100 polyethylene plastic pipelines, based on the standard EN 12201-2:2011 were assumed for the calculations.

Hydraulic calculations were made using the following assumptions:

- internal diameters of the pipelines, $D_{in}$ [mm] were taken for the calculations,
- the minimum pipeline diameter DN110 [mm],
- the maximum pipeline diameter DN630 [mm],
- the following absolute roughness coefficients were assumed: k = 0.01; 0.1; 0.5; 1.0; 1.5; 2.0 [mm],
- the maximum length of the calculation sections – 3000 [m].

The training examples relate to the individual sections of the water supply network and were developed in such a way that they can be used to assess pressure loss according to the DH1-DH5 classes. In order to generate a decision tree, the problem domain was defined according to the following attributes:

- the length of the computational line L [m],
- calculation flow in the $Q_m$ section [l/s],
- the absolute roughness coefficient of the pipeline, in a given section k [mm],
- linear pressure losses on the computational section $\Delta h_l$ [m].

All training examples were described using the DH1-DH5 label, indicating that they belong to a specific classification, characterising pressure losses. A collection of 17018 training examples, representing all of the DH1-DH5 classes described above, was obtained.

## 5. The application of artificial neural networks in assessing pressure losses

The search for the proper structure of the neural network, with one hidden layer, began with 9 neurons in the hidden layer. A larger network was constructed where the neural network had not undergone any improvement or only an insignificant improvement, after long training cycles. This suggested that an insufficient number of neurons, processing layers, or learning algorithms had become stuck in the local minimum. Networks with the same structure were trained several times to prevent them from becoming stuck in the local minimum (Hornik 1991).

A list of multi-layer perceptrons with one hidden layer for the assessment of pressure losses, is given in Table 1. The neural network with one hidden layer, is placed in pos. 5.

The above neural network has the lowest number of the Entropy Multiple Error Function $E_{EME}$ for validation subset and a very high accuracy of classification.

**Table 1.** Artificial neural networks for the assessment of pressure losses in water supply pipelines
**Tabela 1.** Sztuczne sieci neuronowe do oceny strat ciśnienia w przewodach sieci wodociągowej

| No. | K | $E_{EME}$ (L) | $E_{EME}$(V) | $E_{EME}$(T) | η(L) | η(V) | η(T) |
|---|---|---|---|---|---|---|---|
| 1 | 9 | 0.435014 | 0.616146 | 0.484385 | 0.778587 | 0.777908 | 0.772033 |
| 2 | 18 | 0.312509 | 0.373041 | 0.488254 | 0.842167 | 0.837368 | 0.838073 |
| 3 | 27 | 0.304561 | 0.368381 | 0.763289 | 0.860266 | 0.853584 | 0.857109 |
| 4 | 36 | 0.279509 | 0.598582 | 0.808997 | 0.899283 | 0.882726 | 0.884371 |
| **5** | **45** | **0.275838** | **0.362148** | **0.660753** | **0.934893** | **0.928555** | **0.932785** |
| 6 | 54 | 0.436712 | 0.503457 | 0.700952 | 0.57022 | 0.557697 | 0.560517 |

where:
K – the number of neurons in the inner layer of the multi-layered perceptron [-],
$E_{EME}(L)$ – the error for the training subset [-],
$E_{EME}(V)$ – the error for the validation subset [-],
$E_{EME}(T)$ – the error for the test subset [-],
$\eta(L)$ – the relevance of the classification of the training subset [-],
$\eta(V)$ – the relevance of the classification of the validation subset [-],
$\eta(T)$ – the relevance of the classification of the testing subset [-].

The neural network adopted, consists of the following elements:

- an input layer with neurons for 4 input variables: L, $Q_m$, k, $\Delta h_l$,
- one hidden layer, constructed of 45 neurons with a logistic activation function (2),
- an output layer, composed of 5 neurons, with the Softmax activation function (3), corresponding to DH1-DH5 classes.

Figure 2 shows the network diagram for the assessment of pressure losses by means of a classification in which activation of the neuron, in the output layer, is visible, indicating the selection of the class DH3 assigned to it.

Tables 2 to 4 show the results of the classification in the form of an error matrix for the neural network, from Tab. 3, pos. 5 for the training, validation and testing subsets.

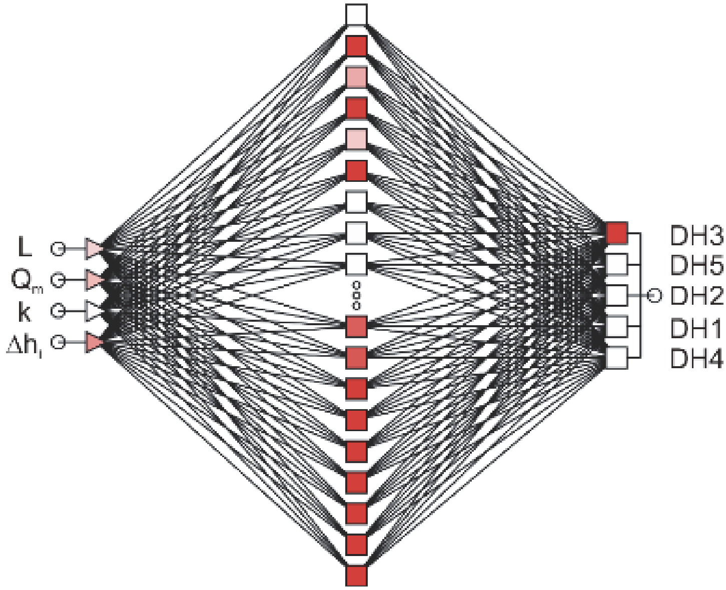


**Fig. 2.** A schematic diagram of a neural network for calculating pressure losses in water pipes
**Rys. 2.** Schemat sieci neuronowej do oceny strat ciśnienia w przewodach wodociągowych

**Table 2.** Results for the classification of pipeline diameters for the training subset
**Tabela 2.** Wyniki klasyfikacji średnic rurociągów dla podzbioru uczącego

| | DH3 | DH5 | DH2 | DH1 | DH4 |
|---|---|---|---|---|---|
| Total | 2081 | 372 | 1945 | 2876 | 1235 |
| Correct | 1985 | 338 | 1865 | 2574 | 1193 |
| Incorrect | 4 | 1 | 13 | 7 | 2 |
| Undetermined | 92 | 33 | 67 | 295 | 40 |
| DH3 | 1985 | 0 | 0 | 4 | 0 |
| DH5 | 3 | 338 | 0 | 3 | 2 |
| DH2 | 0 | 0 | 1865 | 0 | 0 |
| DH1 | 1 | 1 | 13 | 2574 | 0 |
| DH4 | 0 | 0 | 0 | 0 | 1193 |

**Table 3.** Results for the classification of diameters for the validation subset
**Tabela 3.** Wyniki klasyfikacji średnic rurociągów dla podzbioru walidacyjnego

| | DH3 | DH5 | DH2 | DH1 | DH4 |
|---|---|---|---|---|---|
| Total | 1066 | 163 | 1014 | 1388 | 624 |
| Correct | 1006 | 151 | 955 | 1237 | 602 |
| Incorrect | 1 | 3 | 9 | 3 | 0 |
| Undetermined | 59 | 9 | 50 | 148 | 22 |
| DH3 | 1006 | 2 | 0 | 1 | 0 |
| DH5 | 1 | 151 | 0 | 2 | 0 |
| DH2 | 0 | 0 | 955 | 0 | 0 |
| DH1 | 0 | 1 | 9 | 1237 | 0 |
| DH4 | 0 | 0 | 0 | 0 | 602 |

**Table 4.** Results for the classification of pipeline diameters for the testing subset
**Tabela 4.** Wyniki klasyfikacji średnic rurociągów dla podzbioru testowego

| | DH3 | DH5 | DH2 | DH1 | DH4 |
|---|---|---|---|---|---|
| Total | 979 | 184 | 1014 | 1450 | 628 |
| Correct | 935 | 171 | 967 | 1280 | 616 |
| Incorrect | 2 | 3 | 6 | 6 | 0 |
| Undetermined | 42 | 10 | 41 | 164 | 12 |
| DH3 | 935 | 2 | 0 | 4 | 0 |
| DH5 | 1 | 171 | 0 | 2 | 0 |
| DH2 | 0 | 0 | 967 | 0 | 0 |
| DH1 | 1 | 1 | 6 | 1280 | 0 |
| DH4 | 0 | 0 | 0 | 0 | 616 |

Determining the affiliation to one of the classes consists in selecting the neuron of the output layer, in which a value, close to 1, appears; with other neurons, the values should be close to 0, however this is practically impossible to obtain. For this reason, two threshold values are introduced, *viz.,* the acceptance threshold and the rejection threshold, to which the activation level of the neurons of the output layer, is compared. The activation level above the acceptance threshold results in the object being accepted into the class, while the activation value below the reject threshold indicates that the object is not affiliated to any class. In this task, the acceptance threshold is set at 0.95, while the rejection threshold is at 0.05. If this condition is not met, the case is described as indefinite, meaning that the network is unable to classify the object, at all. Table 5 presents the activation values of neurons with the Softmax (3) function of the neural network output layer, for one of the training examples in which the DH3 class was selected.

**Table 5.** Activation values of neurons of the neural network output layer, in the assessment of pressure losses in water Pipes
**Tabela 5.** Wartości aktywacji neuronów warstwy wyjściowej sieci neuronowej do oceny strat ciśnienia w przewodach wodociągowych

| Pipeline diameter, assigned to the output layer neuron | Activation of the output layer neuron |
|---|---|
| DH3 | 0.999999900 |
| DH5 | 5.33E-12 |
| DH2 | 1.33E-21 |
| DH1 | 5.81E-08 |
| DH4 | 1.75E-22 |
| Activation sum: | 1.000000000 |

## 6. Summary and conclusions

The process of creating a set of training data and searching for the appropriate structure of an artificial neural network is complicated and time-consuming. Training artificial neural networks should be carried out repeatedly, in order to avoid the local minimum of the error function. The artificial neural network was developed for computer programmes, in order to calculate hydraulic water distribution systems, in which it acts as an additional module, in the assessment of the results obtained. After completing the calculations, additional DH1-DH5 classes will be assigned to each calculation section. The proposed solution is to indicate the pipelines where it would be possible, or recommended, to adjust the diameter, in order to ensure adequate linear pressure losses and therefore more favourable operating conditions, from the point of view of the network pressure level. The neural network obtained is highly accurate at classifying. Using the previously prepared neural network should not cause users much trouble, as it is intended to be part of a computer programme.

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# Zastosowanie sztucznych sieci neuronowych do oceny strat ciśnienia w przewodach wodociągowych

## Streszczenie

System dystrybucji wody stanowi jeden z najważniejszych elementów wodociągu, którego budowa pochłania największą część kosztów, a jednocześnie w głównej mierze decyduje o możliwościach dostawy wody. Rurociągi wodociągowe powinny spełniać swoją rolę przez wiele lat. W związku z powyższym bardzo ważnym zadaniem jest poprawne zaprojektowanie i wykonanie obliczeń hydraulicznych. Podczas realizacji obliczeń najczęściej konieczne jest wielokrotne korygowanie danych w celu uzyskania poprawnego rozwiązania. W procesie obliczeń ocenie podlega wiele parametrów, w tym prędkość przepływu przez rurociągi wodociągowe, natężenie przepływu, wysokość strat ciśnienia oraz ciśnienie w poszczególnych węzłach sieci. Istotnym parametrem, często niedocenianym, jest wysokość strat ciśnienia na odcinkach obliczeniowych przewodów wodociągowych. W niniejszej pracy zaproponowano metodę oceny strat ciśnienia a pomocą sztucznych sieci neuronowych. W tym celu zdefiniowano jedną klasę DH1 opisującą poprawne warunki oraz cztery DH2-DH5, charakteryzujące problemy związane z wysokością strat ciśnienia w przewodach wodociągowych. Sztuczna sieć neuronowa na podstawie parametrów charakteryzujących pracę przewodu wodociągowego dokonuje wyboru jednej z klas, wskazując w ten sposób na występowanie określonego problemu lub jego brak.

## Abstract

The water distribution system is one of the most important elements of the water supply system, the construction of which accounts for the largest part of the costs involved, while at the same time, being the determining factor in the supply of water. Pipelines should be equipped to continue fulfilling their role for many years. In connection with the above, a very important task is the correct design and execution of hydraulic calculations. During the implementation of calculations, it is often necessary to correct data frequently, in order to obtain the correct solution. Numerous parameters are evaluated in the calculation process, including flow velocity through water supply pipelines, flow rate, pressure loss and pressure in individual, network nodes. An important parameter, often underestimated, is the level of pressure loss in the calculation sections of water pipes. This paper proposes a method for the assessment of pressure loss and for the use of artificial neural networks. For this purpose, one DH1 class, describing the correct conditions and four DH2-DH5 classes, characterising problems related to the amount of pressure losses in the water pipes, have been determined. Based on the parameters characterising the operation of the water pipe, the artificial neural network, selects one of the classes and thus indicates the occurrence of a specific problem, or gives the 'all clear'.

**Słowa kluczowe:**
system dystrybucji wody, obliczenia hydrauliczne, liniowe straty ciśnienia, sztuczne sieci neuronowe

**Keywords:**
water distribution system, hydraulic calculations, pressure losses, artificial neural networks