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APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN THE DIMENSIONING OF RETENTION RESERVOIRS

WYKORZYSTANIE SZTUCZNYCH SIECI NEURONOWYCH W WYMIAROWANIU ZBIORNIKÓW RETENCYJNYCH

Abstract: One of the essential needs for retention reservoirs is to reduce the volume of wastewater flows in sewer systems. Their main advantage is the potential to increase retention in the system, which in turn improves hydraulic safety by reducing the risk of node flooding and the emergence of the phenomenon of "urban flooding". The increasingly common use of retention reservoirs, the observed changes in the climate and the development of dedicated software tools necessitate the updating of the methods used to dimension retention reservoirs. So far, the best known procedures in this regard involve the application of analytical formulas and tools in the hydrodynamic modelling of current sewage systems. In each case the basis for the retention facility design is the evaluation of rainfall in terms of the probability of occurrence and duration that would result in a critical rainwater flow condition in the sewer system in order to define the required reservoir retention capacity. The purpose of this paper is to analyse of the feasibility of applying artificial neural networks in the preliminary estimation of the duration of critical rainfalls. Such an application of these networks is essential to the process of hydrodynamic modelling of the system and to determining the required retention capacity of the reservoir. The study used an artificial neural network model typically used as part of planning processes, as well as the Statistica software suite.

Keywords: retention reservoir, critical rainfall, rainfall distribution, retention reservoir dimensioning

Introduction

The development of urbanised areas [1] and the related "sealing" of green areas that had previously been biologically active [2] results in an increase of wastewater volumetric flow rate through the water drainage systems [3]. A frequently negative effect of this is the hydraulic overload of the sewer system, leading to wastewater spillage and hence "urban flooding".

The most effective method of adapting sewer systems suffering from hydraulic overloads to the new hydraulic conditions is to apply rainwater retention at the various stages of rainwater handling and disposal [4-7]. The retention scheme is facilitated by the use of retention reservoirs, a technology that allows a reduction of the wastewater volume flow upstream of hydraulically overloaded sewer system components [8, 9]. However, the

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implementation of such solutions requires reliable procedures to determine the necessary retention capacity. The retention facility dimensioning methods developed so far are based on the analysis of the hydrograph evolution of retention reservoir waste water inflow and outflow [10-15]. A criterion for the production of hydrographs in hydrodynamic simulation programs [12, 16] is to adopt a reliable and accurate rainfall that has a defined probability of occurrence within a critical duration.

The procedures for retention facility dimensioning most popular in Poland are based on methods that involve the time-invariable characteristics of rainfall, e.g. the Blaszczyk model for rainfall [12, 17]. The model largely simplifies the rainfall and leads to disturbance in the hydrological processes within the rainfall (sewer system) retention reservoir system [18, 19]. A frequent consequence of this is the underestimation of the required retention facility volume, which increases the risk of wastewater overflow from the sewer system, resulting in local flooding.

Investigations so far into the retention of rainwater [10, 20] have facilitated the development of analytical methods that permit the determining of the design parameters for reliable rainfalls.

These studies helped to define the relation (1) that determines reliable rainfall duration, *TDM*, for the dimensioning of high-capacity retention reservoirs [10]:

$$TDM = \left(\frac{0.667 \cdot K_d}{\left[\left(0.67 \cdot Q_o \cdot T_d \cdot K_d^{-1} \right)^2 + 1.33 \cdot K_d \cdot Q_o \right]^{0.5} - 0.67 \cdot Q_o^{\,2} \cdot T_d \cdot K_d^{-1}} \right)^3 \tag{1}$$

where: K_d - characteristic parameter of the geographical location, catchment size and sewage system reliability, determined from the relation (2) [$m^3 s^{1-n}$]; T_d - rainfall duration for the sewage system [min]; Q_o - outflow from retention reservoir [m^3/s].

$$K_d = 6.63 \cdot H^{0.67} \cdot c^{0.33} \cdot F_{zr} \tag{2}$$

where: H - height of normal annual rainfall [mm]; c - frequency of precipitation [-]; F_{zr} - reduced catchment area [ha].

The presented relations facilitate determination of the critical rainfall duration with a time-invariable characteristic [21, 22]. As shown by preliminary simulation runs with various distributions of rainfall in time, the necessary retention reservoir capacity V_u [23] varies with the rainfall distribution in time. Time-variable rainfall distribution requires higher necessary retention capacities at the same levels of rainfall probability. This justifies the use of time-variable rainfall distribution to assure the hydraulic safety of catchments.

Objective of the study

The objective of the study is to analyse the feasibility of applying artificial neural networks as a tool to determine the time-variable critical rainfall duration for the process of dimensioning the required retention capacity.

The study is based on a synthetic rainfall, the time distribution of which is expressed by the equation:

$$h_{o(t)} = a \cdot t^2 \tag{3}$$

The characteristics of the rainfall is expressed by the quadratic function (3) with one decimal place in the coordinates (0.0). According to the assumptions, the precipitation begins with the rainfall height $h_o = 0$, which increases in time t in the quadratic function across the entire the rainfall duration t_{op} (Fig. 1).

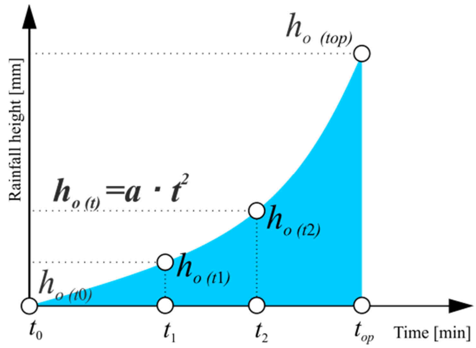

Fig. 1. Characteristics of precipitation for the distribution of C4 ($t_{0,1,2}$ - time of rainfall, $h_o(t_{0,1,2})$ - the amount of rainfall in time, $t_{0,1,2}$)

This rainfall distribution satisfies the conditions expressed by the relations (4) and (5):

$$t_0 < t_1 < t_2 < t_{op} \tag{4}$$

$$h_{o(t0)} < h_{o(t1)} < h_{o(t2)} < h_{o(top)} \tag{5}$$

The rainfall height h_o at the defined probability of occurrence p at any point in time t is expressed by the relation:

$$h_{o(t)} = \frac{3 \cdot h_{\max}}{t_{op}^3} \cdot t^2 \tag{6}$$

The relation is the result of the equation (7), the solution of which facilitated the determination of the parameter a of the function (3). The solution of the equation is expressed by the formula (8):

$$\begin{cases} \dfrac{\int_0^{t_{op}} a \cdot t^2 dt = \dfrac{a}{3} \cdot t_{op}^3}{\int_0^{t_{op}} a \cdot t^2 dt = h_{\max}} \end{cases} \tag{7}$$

$$a = \frac{3 \cdot h_{\max}}{t_{op}^3} \tag{8}$$

Methodology and case study

The investigations were based on a model of a retention reservoir connected to a sewer system, where the model features defined the technical parameters, such as: the required retention reservoir capacity V_u, the maximum design accumulator fill level h_s of wastewater, and the retention reservoir plan surface area A_1.

The retention reservoir area A_1 and its maximum design fill level h_s need to be chosen according to the actual local conditions. The required retention reservoir capacity V_u includes the hydraulic parameters of the catchment and of the sewer system, as well as the critical rainfall parameters.

Based on the developed qualitative characteristics of the model parameters [24], the parameters can be investigated as independent variables. All input variables (independent parameters) of the analysis, the output value (dependent variable) and the constants are shown in Figure 2, and fully represent the contemplated problem.

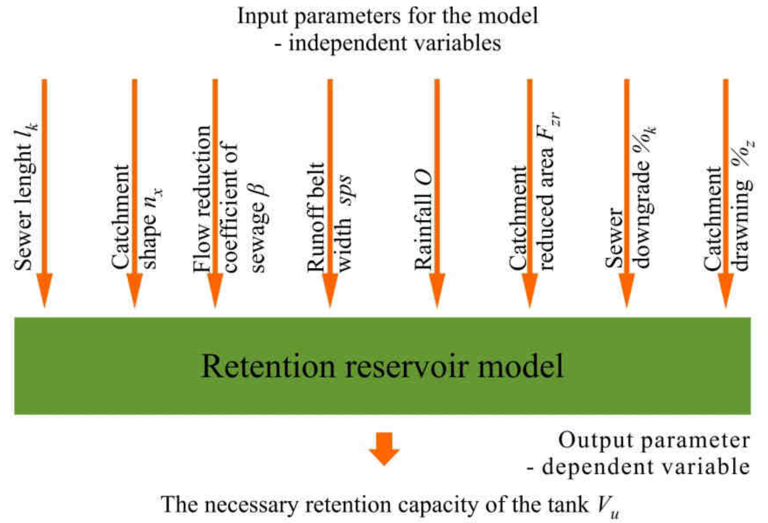

Fig. 2. Test object qualitative model

Table 1 presents the input parameter values of the model as applied in the study. The parameter n_x was implemented due to the variety of possible catchment shapes and the required unification thereof. The parameter value is the ratio of the short catchment side to the long catchment side.

Table 1

Test object characteristic values

Designation		**Minimum**	**Maximum**
O	**Rainfall**	**Tested parameter**	
F_{zr}	Catchment reduced area [ha]	0	50
sps	Runoff belt width [m]	200	4000
l_k	Sewer length [m]	100	2000
β	Flow reduction coefficient of sewage	0.1	0.9
n_x	Catchment shape	1	8
$\%_k$	Sewer downgrade [‰]	1	10
$\%_z$	Catchment downgrade [‰]	1	10

The qualitative model also identified constant values, i.e. h_k/D (sewer wastewater fill to sewer diameter ratio) and the maximum design fill level of the retention reservoir, all of which affect the retention facility volume. The sewer fill level was determined at the preliminary assumption stage to have a ratio of the wastewater volumetric flow Q to total volumetric flow Q_c approximating to 1.

The tests at this stage were to ensure a sufficient number of sewer system models, characterised by various hydraulic parameters of the system and/or of the catchment, followed by loading the models with the assumed rainfall characteristics.

The first phase of the study was to establish the input data for the model, which were modified as the analysis progressed to represent the various catchment configurations.

The following parameters were modified as designed during the study:

- The wastewater flow reduction factor β, determined from the maximum wastewater inflow of the reservoir and the wastewater outflow.
- The catchment shape n_x, which represents the ratio of sides of the tested catchment, when approximated to a rectangular form.
- The sewer downgrade $\%_k$, which represents the differential height between the sewer bottom start and end levels.
- The catchment reduced area F_{zr}, which is the plan surface area of the catchment with the surface run-off coefficient effect, depends on factors like the basin downgrade $\%_z$ and the catchment usage.
- The sewer length l_k, representative of the sewer system length from the start node to the cross-section at which the retention reservoir is located.
- The run-off belt width *sps*, which is the length over which the wastewater is released into the sewer system.

The parameters may have very different values, depending on the actual local conditions. Hence the preparation of a finite number of sewer system models (i.e. the complete design) to represent every possible case is overly complicated and irrational. This is due to the extremely high number of input parameters that characterise the sewer system, and the high number of possible parameter values. As a consequence, the number of sewer system models, and their hydraulic parameter values required for the analysis, was determined on the basis of design of experiment theory.

One of the conditions that prevent application of the design of experiment theory is the interdependencies present between the input parameters. The developed sewage system and catchment model features certain parameters that remain in a close relationship. This applies to the following independent variables:

- catchment reduced area F_{zr},
- sewer length l_k,
- runoff belt width *sps*.

The run-off belt width *sps* is closely related to the sewer length l_k. The SWMM guidelines [25, 26] indicate that it is possible to determine the run-off belt width *sps* as double the design length l_k of the sewer system. The catchment reduced area F_{zr} and the sewer length l_k also exhibit a similar relation. This is due to the sewers having high l_k in catchments with large areas F_{zr}.

Hence it was decided to replace the parameters with a novel synthetic substitute, designated as 'catchment load', O_z. The dimension of this parameter is a physical magnitude that defines the surface area per each kilometre of sewage system length.

The new parameter, catchment load O_z, resulted in a change to the test object model, as shown in Figure 3.

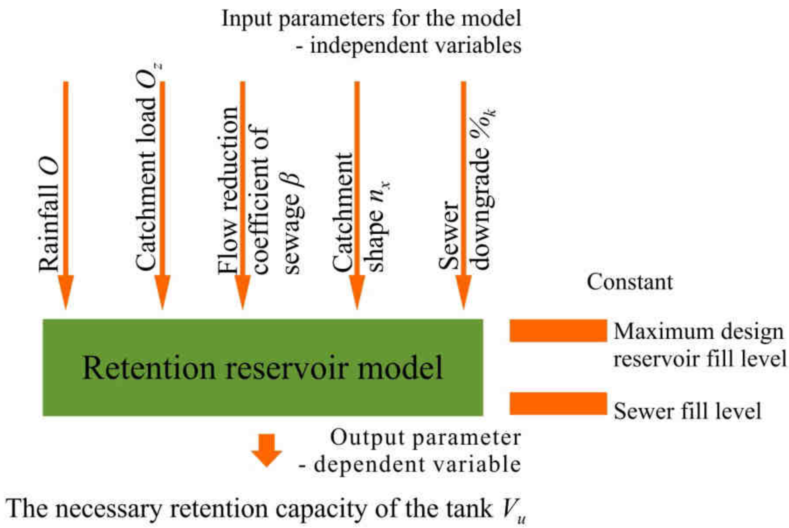

Fig. 3. Updated test object model

The values of catchment load O_z, catchment shape n_x and sewer downgrade $\%_k$ were determined directly based on design of experiment theory. The sewer length l_k values and the run-off belt width values *sps* were determined indirectly by applying the equations (9) and (10):

$$O_z = \frac{F_{zr}}{l_k} \tag{9}$$

$$sps = 2 \cdot l_k \tag{10}$$

Based on the plan construction guidelines from Polanski [24] and the essential understanding of sewer systems, limit values were applied to the analysed parameters as shown in Table 2.

Table 2

Minimum and maximum values of the model input parameters

Parameter	Parameter minimum	Parameter maximum
Catchment shape n_x [-]	1	7
Sewer downgrade $\%_k$ [‰]	2	8
Catchment load O_z [ha/km]	5	30

The adopted values allowed compliance with the calculation feasibility criterion and the effectiveness criterion, which permit a major reduction of the number of necessary simulations.

The systems and number of investigated catchments and sewer networks were defined using the *Statistica* software suite. The test assumed a three-factor central composition design with double iteration at the central point [26].

The applied method allowed the determination of the tested parameter values in the form of coded values from the formula (11) [2, 26].

$$\hat{x}_i = \frac{2 \cdot \alpha \cdot \left(x_i - \overline{x}_i\right)}{\left(x_{i,\min} - x_{i,\max}\right)} \tag{11}$$

where: $\hat{x}_i$ - coded value [-], α - design star arm; the α in the design is 1.7 [-], x_i - subsequent variable actual value [-], $x_{i,\min}$ - minimum value of the determined actual variable [-], $x_{i,\max}$ - maximum value of the determined actual variable [-], $\overline{x_i}$ - mean value of the determined actual variable [-].

The calculation results both produced by and forming the design of the experiment represented by the coded values are shown in Table 3.

Table 3

Design of the experiment with coded values for the catchment and sewer system hydraulic parameters

System number	**Catchment shape n_x**	**Sewer downgrade $\%_k$**	**Catchment load O_z**
	$x1$	$x2$	$x3$
1	–1.0	–1.0	1.0
2	–1.7	0.0	0.0
3	0.0	0.0	–1.7
4	–1.0	–1.0	–1.0
5	1.7	0.0	0.0
6	0.0	0.0	1.7
7c	0.0	0.0	0.0
8	0.0	–1.7	0.0
9	1.0	1.0	1.0
10	1.0	1.0	–1.0
11c	0.0	0.0	0.0
12	1.0	–1.0	–1.0
13	1.0	–1.0	1.0
14	–1.0	1.0	1.0
15	–1.0	1.0	–1.0
16	0.0	1.7	0.0

Table 3 shows the coded values of the hydraulic parameters for the catchment and for the sewage network, namely and respectively: 0, ±1, ±1.7.

The coded values were converted into the actual values with the equation (12) and the conversion results are shown in Table 4 as the actual design of the experiment.

$$x_i = \overline{x}_i + \frac{\hat{x}_i}{\alpha} \cdot \left(x_{i,\max} - \overline{x}_i\right), \ i = 1, 2, ... \tag{12}$$

The developed design forms sixteen catchment systems defined as a set of hydraulic parameters that determine the configuration of the studied sewer system.

The last stage of the study, focused on the estimation of the critical rainfall duration for a catchment characterised by the defined hydraulic parameter values, was completed using the artificial neural network wizard in the *Statistica* software suite.

Table 4

The design of the experiment with the actual values of hydraulic parameters of the catchment and the sewer system

System number	Catchment shape n_x	Sewer downgrade $\%_k$	Catchment load O_z	Sewer system length l_k for a catchment of 5 ha	Sewer system length l_k for a catchment of 10 ha	Sewer system length l_k for a catchment of 20 ha	Sewer system length l_k for a catchment of 35 ha	Sewer system length l_k for a catchment of 50 ha
	[-]	[‰]	[ha/km]	[m]	[m]	[m]	[m]	[m]
1	2	3	25	201	401	802	1404	2005
2	1	5	18	286	571	1143	2000	2857
3	4	5	5	1000	2000	4000	7000	10000
4	2	3	10	497	993	1987	3477	4967
5	7	5	18	286	571	1143	2000	2857
6	4	5	30	167	333	667	1167	1667
7c	4	5	18	286	571	1143	2000	2857
8	4	2	18	286	571	1143	2000	2857
9	6	7	25	201	401	802	1404	2005
10	6	7	10	497	993	1987	3477	4967
11c	4	5	18	286	571	1143	2000	2857
12	6	3	10	497	993	1987	3477	4967
13	6	3	25	201	401	802	1404	2005
14	2	7	25	201	401	802	1404	2005
15	2	7	10	497	993	1987	3477	4967
16	4	8	18	286	571	1143	2000	2857

Test results and discussion

The aim of the tests was to develop a method for determining reliable rainfall duration with time-variable distribution using sixteen catchment systems at various values of wastewater flow reduction factor. The results formed a dataset of 1350 cases. The results were derived from the simulations of reliable rainfall duration applied in the dimensioning of retention reservoirs within the rainwater sewer systems. The simulation runs were completed using the SWMM 5.0 hydrodynamic modelling software package, and the results are shown in Figure 4.

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The test results were divided into five groups depending on the wastewater flow reduction factor β value.

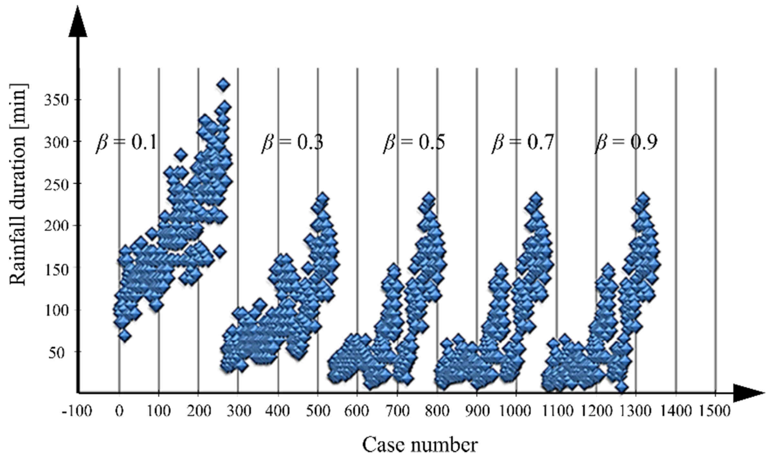

Fig. 4. Results of the rainfall duration test for retention reservoir dimensioning

Further investigations included the application of artificial neural networks [27-29]. A sufficiently large representative dataset was necessary to determine the expected dependent variable value.

The artificial neural network was generated in *Statistica*. The output data were input into the software and then the software artificial neural network wizard was used to define the settings for the division of the collected data into the following groups:

- Test data - 70 % of the total,
- Teaching data - 15 % of the total,
- Validation data - 15 % of the total.

The neural network wizard selected the 25 best neural network matches, which were subject to further selection to single out the network with the lowest error value and the highest match rating.

The neural network model (ANN) proposed for the prediction of results was an MLP (Multi-Layered Perceptron) with 6-8-1 architecture. The network chosen had the lowest teaching, testing and validation error rates of all the neural networks proposed by the software.

The proposed MLP network, the architecture of which is shown in Figure 5, features six neurons in the input layer, eight neurons in the hidden layer and one neuron in the output layer.

The operating concept of the developed neural network was to have each neuron calculate the weighted mean of the input values. Then the result of the operation was multiplied by a function of transition and passed to the output. The activation functions for the hidden and output layers are the hyperbolic tangents (tanh), while the function of error was determined with the SOS (sum of square) method.

The generated simulation results and the neural network outputs allow the conclusion that the presented model achieves a high accuracy. This is shown in Figure 6, which lists the expected values as rainfall duration *TDM* from the computer simulation runs and the values from the developed artificial neural network model.

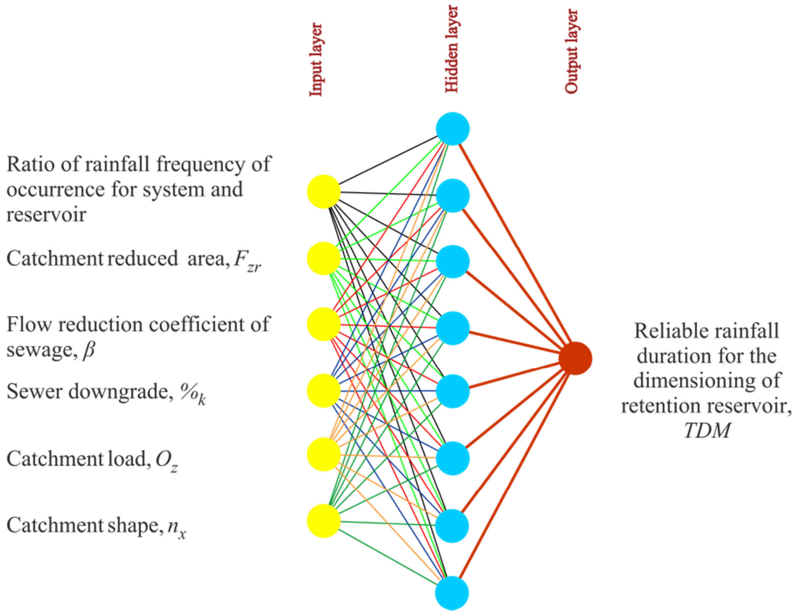

Fig. 5. Diagram of the artificial neural network used in the determination of reliable rainfall duration, *TDM*

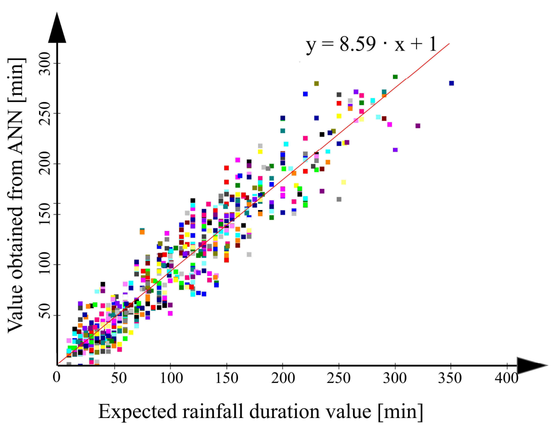

Fig. 6. Analysis of the linear regression between the experimental data and the ANN model output data

The Pearson correlation factor *r* calculated for the results is 0.955. The determination factor R^2 is 0.913, which gives a very good linear dependence between the expected and modelled values, according to the Stanisz's scale.

The developed neural network model was applied in the check calculations for selected catchments in the city of Przemysl, Poland. Three partial catchments with sewers were chosen with the design parameters listed in Table 5.

Table 5

Design parameters of control sewer systems

	Catchment reduced area F_{zr}	Catchment shape n_x	Catchment load O_z	Sewer downgrade $\%_k$
	[ha]	**-**	**[ha/km]**	**[‰]**
Catchment One	6.42	5	3.4	2.83
Catchment Two	22.82	14	5.88	3
Catchment Three	37.85	12.5	9.4	4.2

The design parameters of the selected catchments and sewer systems are characterised by values that differ from the parameters applied to build the artificial neural network model.

Each of the presented catchments were simulated in the SWMM software package to facilitate the determination of the required retention reservoir capacity V_u. The analyses were carried out for the wastewater flow reduction factor β values of 0.2, 0.35, 0.55, and 0.8, as well as the sewer system to volumetric structure ratios of rainfall frequency of 0.2 and 0.4. The results are shown in Figure 7.

The accuracy check analysis of the test results demonstrated that the expected values of the reliable rainfall duration for the necessary retention reservoir capacity largely reflect the values produced from the neural networks. Moreover, a linear regression equation, expressed by the relation (13), was established for the test results. The Pearson correlation r for the equation is 0.84 with R^2 = 0.7057.

$$y = 0.6 \cdot x + 47 \tag{13}$$

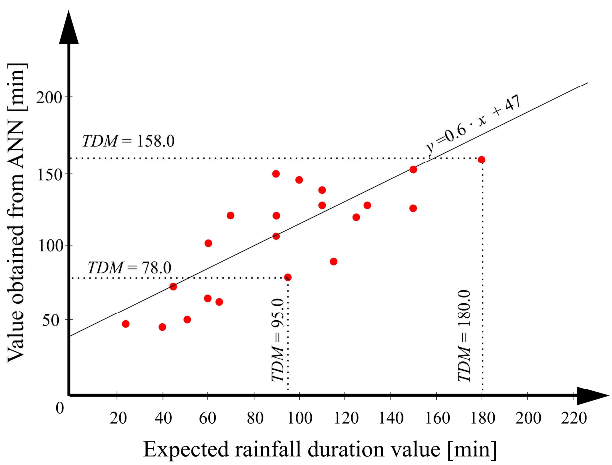

Fig. 7. Analytical results for the expected and actual rainfall duration for the control data

Figure 8 shows the values of the necessary retention reservoir capacity V_u produced from the simulations in the SWMM hydrodynamic modelling suite.

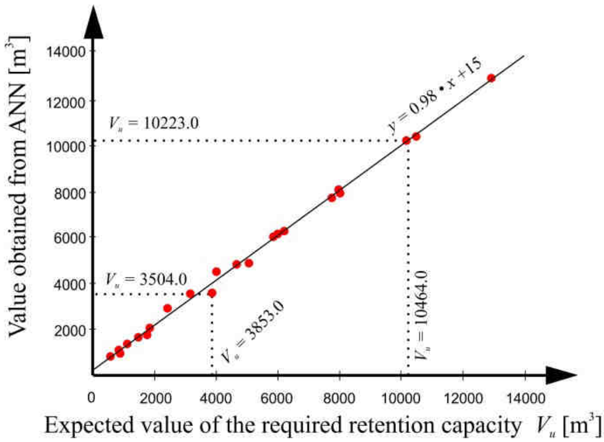

Fig. 8. Analytical results for the expected and actual values of the required retention reservoir capacity V_u for the control data

The expected values of the required retention reservoir capacity largely reflect the values produced by loading the catchment with the rainfall duration determined using the artificial neural networks. Moreover, a linear regression equation, expressed by the relation (14), was established for the results.

$$y = 0.98 \cdot x + 15 \tag{14}$$

The Pearson correlation r was 0.99904 and R^2 = 0.998081 for the required retention reservoir capacity data. The values are indicative of a very good linear dependence between the expected and modelled values. The investigation also included a test for the difference between the actual required retention reservoir capacity V_u results and the results defined for reliable rainfall duration, established with the artificial neural networks. A retention capacity underestimation of 12 % was calculated for the worst case scenario.

To conclude, the application of neural networks in the determination of reliable rainfall duration *TDM* facilitates the production of extremely satisfactory results.

Summary and final conclusions

The availability of mathematical apparatus that permits the development and distribution of hydrodynamic modelling software facilitates the use of more reliable rainfall data in the process of required retention reservoir dimensioning.

The investigations have confirmed that artificial neural networks are the best tool to define the critical rainfall duration. The results obtained with ANN can be applied in the simplified method for direct estimation of the reliable rainfall duration or, when precision methods are applied, to reduce the necessary iterations required to obtain the exact result.

The completed investigation, coupled with an in-depth analysis of the results for this research, allows the conclusion that the reliable rainfall duration *TDM* for retention reservoirs is best obtained by iteration of an algorithm based on an MLP 6-8-1 artificial neural network.

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