15

Modelling of Critical Water Quality Indicators for Water Treatment Plant

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1. Introduction

A technology system water treatment requires pre-determined information on critical quality indicators for the water. A neural networks can be designed to assess this.
Use of an artificial neural networks [ANN] to analyse unit and technology processes within water management, treatment and distribution led to consideration of the possibilities of using an ANN for forecasting water quality and creating a model which would permit this. Siwoń et al. (2008) examined the results of experiments carried out using an ANN and indicated that the first use of an ANN in modelling and forecasting water system operation occurred in the 1990s. A lot of work was done to assess whether the ANN might be useful in modelling and forecasting the distribution as well as the sale and production of water. A similar analysis was carried out by Bardossy and his colleagues (2009). Additionally, a Variable Input Spread Inference Training [VISIT] programme was created, which allowed for the automatic examination of the ANN model being suggested for implementation.
Artificial neural networks were also used to establish the essential doses of chloride needed within large water systems and to forecast the contamination amount of left over chloride. Koo et al. (2008) examined the possibility of using an ANN to forecast the amount of chloride remaining in water pipes. A model was then created. It analysed five scenarios regarding the use of chloride subject to a dose of chloride being put into the water system. An established model indicated the amount of chloride to put into a water system, subject to the water temperature and the amount of water being put through the system, so that the amount of chloride remaining does not exceed the allowed dose. The Pearson correlation coefficient, R, between the examined and observed data was calculated; its value for the model being analysed was $R = 0.959$.
An ANN has recently been introduced for the operation of a water system. It has been widely discussed not only in foreign literature (Camarinha-Matos & Martinelli, 1998; Zhou et al., 2000, 2002), but local works as well. For example, Sroczan and Urbaniak (2004) as well as Zimoch and Kłos (2003) suggest using an ANN to monitor, steer and operate water supply systems, and for water protection. Dawidowicz (2005) carried out a number of numerical tests which allowed verification of the idea of using an ANN in assessing the 'Diametre Nominal' (DN) of the water pipes and for taking any hydraulic measurements. Licznar and Łomotowski (2004) obtained very good results in forecasting the daily amount of water distributed in a large scale system of water pipes using various ANN technologies.

Deveughèle and Do-Quang (2005) supplied the results of using an ANN to forecast the use of coagulant in a surface water treatment process. A model was created which enabled the optimal dose of coagulant to be established subject to the parameters of the raw water. The model's prototype was fully implemented in a French water treatment plant. It enabled the amount of coagulant being used to be reduced by approximately 10%. Cougnaud et al. (2005) used an ANN to forecast the absorption capacity of active carbon subject to the concentration of pesticides in the water. It was noted that the operating parameters – contamination, concentration and pace of filtration – had an effect on the efficacy of reducing contamination. The ANN model established the relationship between the features of active carbon and the adsorption of pesticides. There was a mutual relationship noted between the concentration of pesticides, pace and filtration time. It was a strong linear relationship; the coefficient of determination, R^2, being 0.985. An ANN was also used to assess the maximum level of water contamination. Brion and Lingireddy (2003) indicated that an ANN could be useful when examining the micro-biological changes of water. The ANN provided the ability to examine the mutual relationships between large numbers of parameters. It allowed this information on the predicted micro-biological features of the water to be supplied to the system operator. Using an ANN for modelling allowed the highest level of micro-biological water contamination to be assessed with 90% accuracy. Gavin et al. (2003) used an ANN to model water supply systems. The networks were used to predict the salinity of rivers in South Australia. The salinity was forecast 14 days in advance using a linear model. Strugholtz et al. (2009) used an ANN to examine a water treatment process as a subject for both raw water quality and technology process. It established the optimal technology process and predicted its course. That was one stage of the examination. The other stage developed a model to optimise operational costs. The ANN was used to set the parameters of the filtration and to optimise the doses of the reactants; the result was a lowering of the costs by 15%.

These various examinations and analyses have led to the conclusion that ANN models are as good as statistical ones.

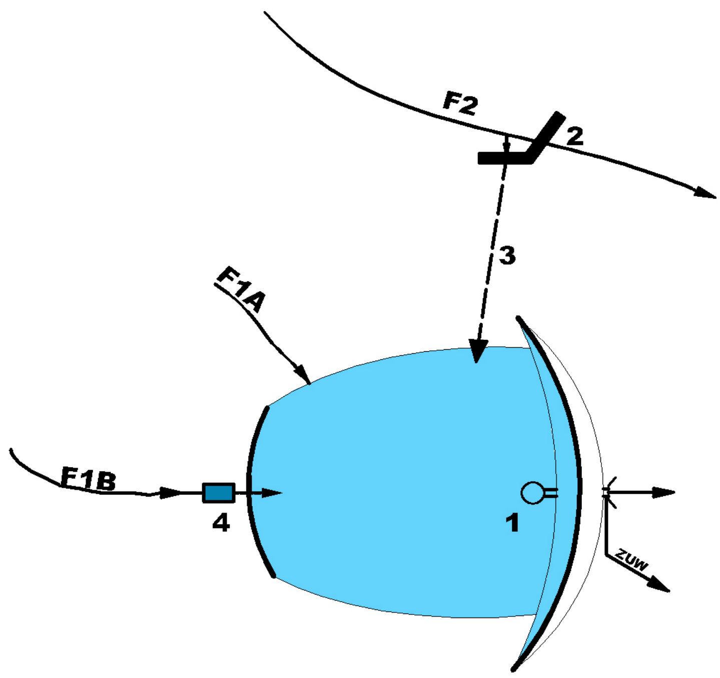
2. Experimental

2.1 The site

The Sosnówka reservoir was constructed in the 1990s to supply water to the municipality of Jelenia Góra. It supplies raw water to a local water treatment plant. Sosnówka reservoir retains water from the catchment areas of the Czerwonka and Sośniak streams and the Sosnówka tributary. The total catchment area is 15.3 km^2.

The flow of the Czerwonka stream within the reservoir's section, Q_{SN}, is 0.038 $m^3 \cdot s^{-1}$, with the average flow, Q_{aver}, being 0.192 $m^3 \cdot s^{-1}$. The Czerwonka stream catchment area is 5.5 km^2 and it is separated from the Sośniak stream by the reservoir catchment area. It indirectly supplies water to the object under study (Figure 1).

The total capacity of the reservoir is 15.4 million m^3 and it has a maximum surface area of 178 ha. The depth at the lower dam is 13.5 m and the total average depth is 8.15 m. The amount of water from the reservoir used for consumption is 11 million m^3 (Photo 1). It is assumed that at least 70% of the total amount of water required can be supplied from the Podgórna river catchment area to the reservoir in the even that the Sosnówka reservoir water is completely used (Photo 2). So the Podgórna River is the main source of water for the reservoir (Rak, 2008).



F1A –Czerwonka stream catchment area; F1B –Sośniak stream catchment area
F2 – Podgórna River catchment area.

1. Extraction construction of the reservoir including the water catchment area.
2. Construction of water distribution system at Podgórna River.
3. Transfer canal.
4. Initial reservoir including a pumping station.

Fig. 1. Schematic of the water distribution of the 'Sosnówka' reservoir:

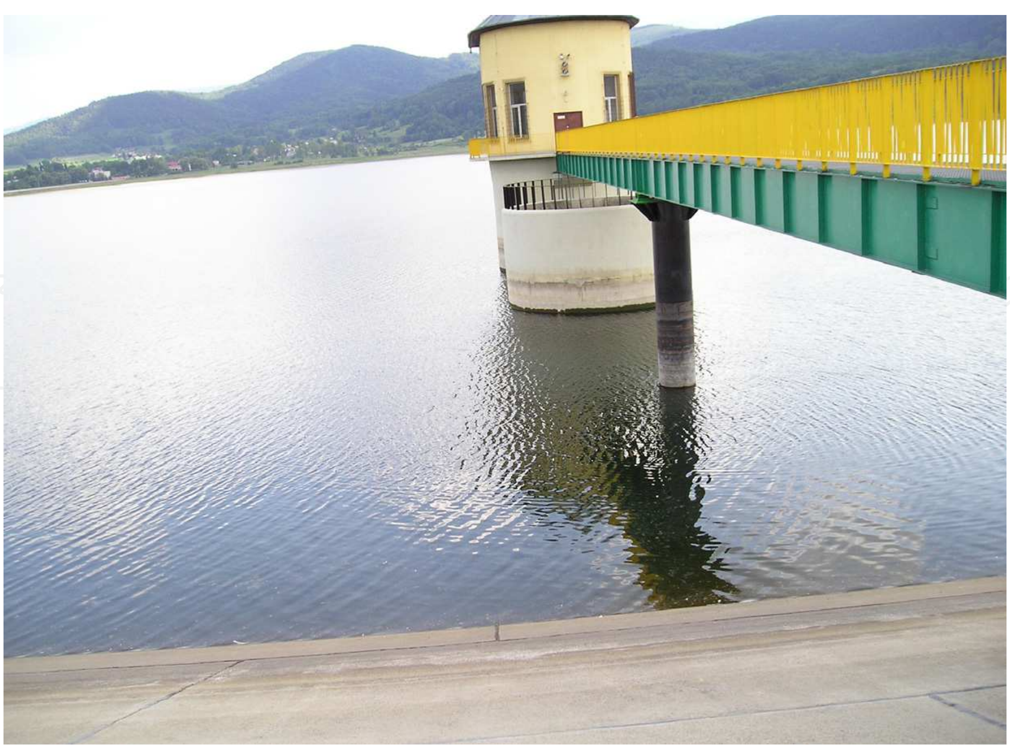


Photo 1. Retention reservoir "Sosnówka"

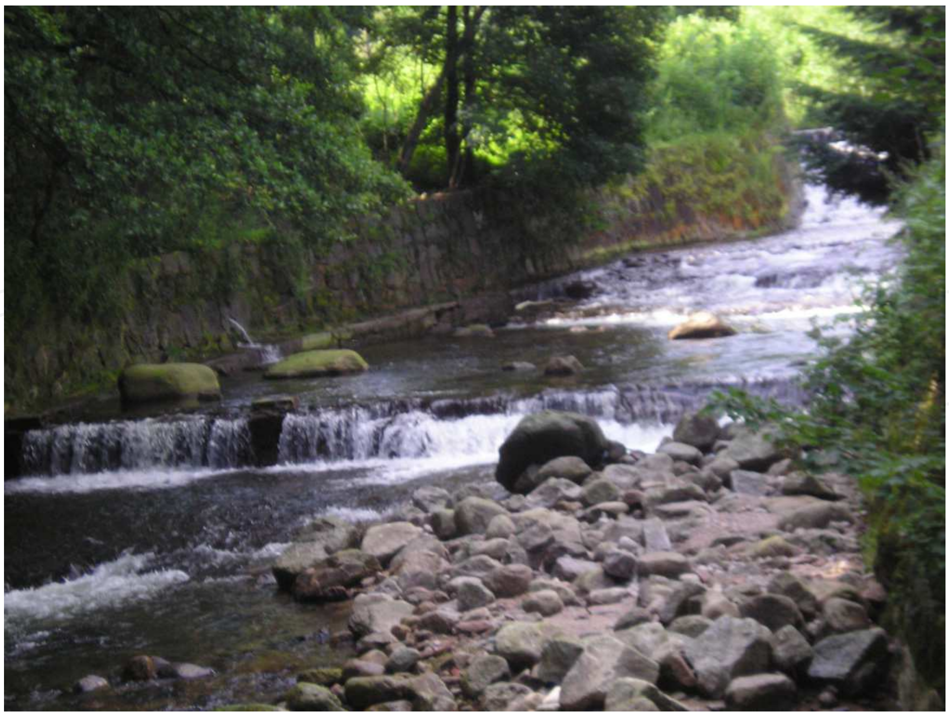


Photo 2. Podgórna River

In the reservoir area there were few anthropogenic contamination sources. The area is a mix of woods and meadows, the soil comprises mountain peat deposits (Institute of Environmental Protection Wrocław [IMGW], 1986). Factors which have a positive influence on changes in reservoir water quality include the wooded character of the terrain, a low annual water exchange rate and an absence of indirect contamination sources. The Schindler index value of 1.39 ranks the reservoir as being in the first category regarding susceptibility to degradation. However, given the increasing amount of water being taken for consumption purposes, more water is being supplied from the Podgórna River. The water factors have change and the Schindler index value has risen to 4.62. This has resulted in the reservoir being downgraded regarding susceptibility to degradation to the second category.

2.2 Methodology

Some parameters of the raw and treated waters at the treatment plant are automatically monitored. These include the temperature, pH, muddiness, colour and conductivity. Between November 2007 and October 2008, the first operational phase of the water treatment plant, certain physical and chemical examinations were conducted every few days. These tests included measuring the water temperature, turbidity, colour, pH, general hardness, alkalinity, iron, manganese, chlorides, ammonium and nitrates levels, oxidisability, dissolved oxygen content, conductivity and phosphates. The technology system allowed examination of such unit processes as sieving, pre-ozonation, coagulation, correction of pH, flocculation, accelerating anthracite and sand deposit filtration, derivative ozonation, sorption on active carbon, final correction of pH and hardness as well as disinfection of the treated water (see Figure 2).

The technology system is designed to allow different combinations of the various unit processes depending on the quality of the water.

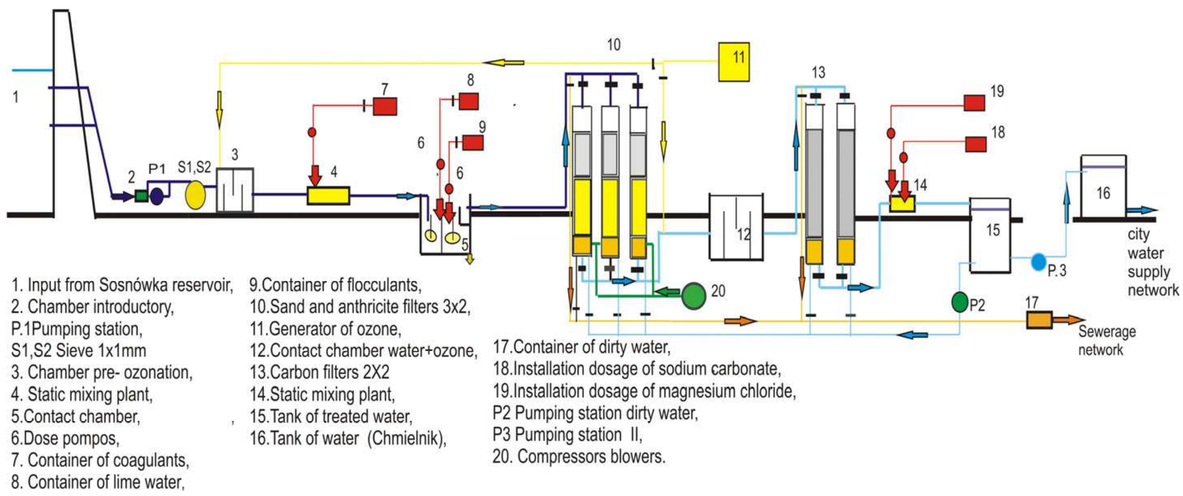


Fig. 2. The technology of the water treatment process

The unit processes available within the technology system are presented in Table 1.

Unit processes	Technology system					
	W1	W1A	W1B	W2	W2A	W3
Sieving with a 1 mm by 1 mm sieve	+	+	+	+	+	+
Pre-ozonation	+	+	+	+	+	+
Coagulation with aluminium sulphate	+	+	+			
Flocculation	+	+	+			
Correction of pH	+	+				+
Anthracite and sand deposit filtration	+	+	+	+	+	+
Derivative ozonation	+		+	+	+	+
Active carbon deposit filtration	+	+	+	+	+	+
Final correction of water pH	+	+	+	+		+
Disinfection	+	+	+	+	+	+

W1, W1A, W1B, W2, W2A and W3 – different possible sequences or systems of unit processes used for treatment of the water

Table 1. The separate unit processes of the technology system

The results of the technology examinations conducted during the first operating period of the water treatment plant resulted in the decision to opt for the W2 sequence. This included such unit processes as sieving, pre-ozonation, accelerating filtration on anthracite and sand deposits, derivative ozonation, sorption on active carbon, final correction of water quality and disinfection. When the pH value was low, technology system W3 was implemented as this included correction of the pH of the water.

3. Results

During the first period of operation of the treatment plant, the water taken from the reservoir was analysed to establish the characteristics of the raw water. Table 2 displays the typical minimum and maximum values of the contamination factors of this water.

Water quality indicators	Unit	Sosnówka reservoir			
		S_{min}	S_{max}	S_{aver}	Standard deviation(σ)
Water temperature	^oC	3	15	9.2	1.620
Turbidity	$mgSiO_2 \cdot dm^{-3}$	0.57	3.81	1.56	1.052
Colour	$mgPt \cdot dm^{-3}$	5	14.9	8.21	2.791
pH	pH	7.2	8.4	7.63	0.366
General hardness	$mval \cdot dm^{-3}$	0.62	1.03	0.85	0.072
Nitrate nitrogen	$mgN\text{-}NO_3 \cdot dm^{-3}$	2	5	2.44	1.300
Chlorides	$mgCl \cdot dm^{-3}$	4	6.8	4.95	1.321
Oxidability	$mgO_2 \cdot dm^{-3}$	1.0	5.22	3.458	1.532
Conductivity	$\mu s \cdot cm^{-1}$	98.28	122.50	110.88	6.692
Dissolved oxygen	$mgO_2 \cdot dm^{-3}$	9.4	12.4	11.18	1.172
Fe	$mgFe \cdot dm^{-3}$	0.05	0.136	0.066	0.027
Mn	$mgMn \cdot dm^{-3}$	0.012	0.036	0.021	0.007

S_{min} – minimum value of the parameter for the Sosnówka reservoir,
S_{max} – maximum value of the parameter for the Sosnówka reservoir,
S_{aver} – average value of 2005-2006 samples of the parameter for the Sosnówka reservoir.

Table 2. Typical values of chosen water quality indicators during initial period of operation

During the first period of operation of the plant, given the good quality of the water being extracted, the technology tests that were carried out within the technology system included sieving, pre-ozonation, accelerating filtration on anthracite and sand filters, derivative ozonation and sorption on active carbon (W2A – excluding final correction of the water pH). During the second period, final correction of water quality was included in the technology system; the W2 system was applied. The flow rate of the water during treatment was between 172 $m^3 \cdot h^{-1}$ and 202 $m^3 \cdot h^{-1}$ and the speed of filtration on the anthracite and sand filters and with the active carbon was between 4.9 $m^3 \cdot h^{-1}$and 5.7 $m^3 \cdot h^{-1}$. Certain amounts of ozone and other substances were applied within the technology system. These included:

- in the pre-ozonation process, between 1 and 2 mg $O_3 \cdot dm^{-3}$ were added,
- in the derivative ozonation process, up to 1 mg $O_3 \cdot dm^{-3}$ was added,
- to correct the pH of the treated water, 1.0 mg dm^{-3} of sodium carbonate was added,
- for stabilization of the treated water: 1.0 mg dm^{-3} of magnesium chloride was added,
- in the disinfection process, between 0.8 and 0.9 mg $Cl_2 \cdot dm^{-3}$ (in the form of sodium hypochlorite) was added.

By examining both the raw and the treated water it was possible to establish the levels of reduction of the indicators being monitored for a particular water temperature and the dose of ozone given relative to the raw water colour. Following the W2 technology system, the water colour was reduced from 65% to 98% at water temperatures between 4^{o}C and 15^{o}C. The average colour reduction level was 80%. The relationship between water colour and the temperature of the treated water was noted. When the temperature was lower, there was a 60% reduction in the water colour. However, when the temperature was 6^{o}C the reduction in water colour increased to 80%. Further reduction in water colour was noticed at temperatures higher than 14^{o}C. The possibility of constant monitoring allowed both the water temperature and pH to be analysed in week long cycles. In spring time, when the level of water in the reservoir was high, the pH value of the water was quite high. In April

the pH value of the water was greater than 8.85 while the water temperature was quite low (between 6°C and 7°C). The high pH value required a technology process without a pH correction stage in it. In May when the temperature increased to 15°C, weather conditions stabilised, and the pH level of the raw water was considerably reduced. However, it was still sufficiently high that a technology system without a pH correction stage could be used.
After each of the unit processes within the water treatment process it was noted that there were changes in the pH of the water. With every test carried out the pH changed. For example, after the pre-ozonation process the pH was increased by about 10%. The filtration processes, in contrast, decreased the pH to between 6.55 and 6.90. Disinfection with sodium hypochlorite increased the pH slightly – to 7.05 (see Figure 3).

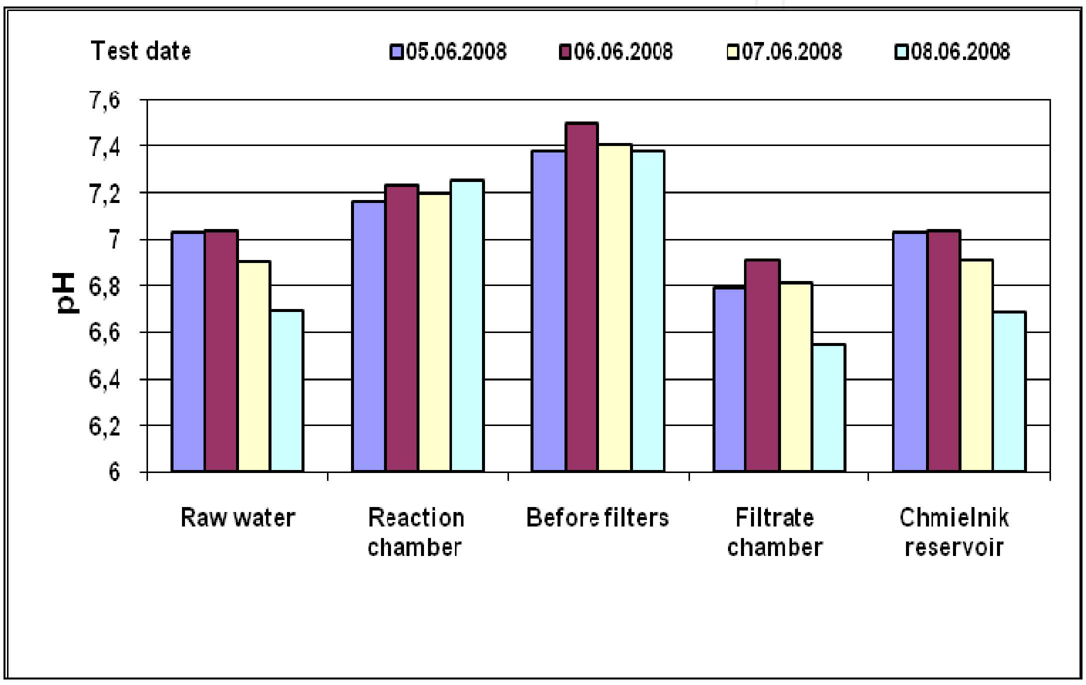


Fig. 3. Changes in the pH of the water at various water treatment processes

Changes in pH, the low general hardness of the water and its alkalinity during the treatment process were analysed to assess the stability and aggressive character of the treated water. The pH at saturation (pH_S) and the Langelier (I_L) and Rezner (I_R) indices were determined. The values of the water temperature, pH, pH_S, I_L and I_R, are shown in Figure 4. It is clear that both the raw and the treated water are aggressive in character in the W2A technology system. These indicators changed their values, particularly in May when the temperature increased from 8°C to 15°C. However, until May when the water temperature was between 4°C and 8°C, there was little increase in the aggressiveness of the character of the treated water compared with that of the raw water. Moreover, with higher temperatures and increasing pH values (up to pH = 8.4), the treated water became unstable and more aggressive in character. At that time the I_L index was negative (- 1.6), while the I_R index value was 10.5. The results of the examinations were the basis for implementing a water stabilization process by dosing the treated water with magnesium chloride and sodium carbonate before it was disinfected. The tests in the W2 technology system were carried out using fixed doses of $MgCl_2$ and Na_2CO_3 – 0.5, 0.75 and 1.0 $mg \cdot dm^{-3}$.

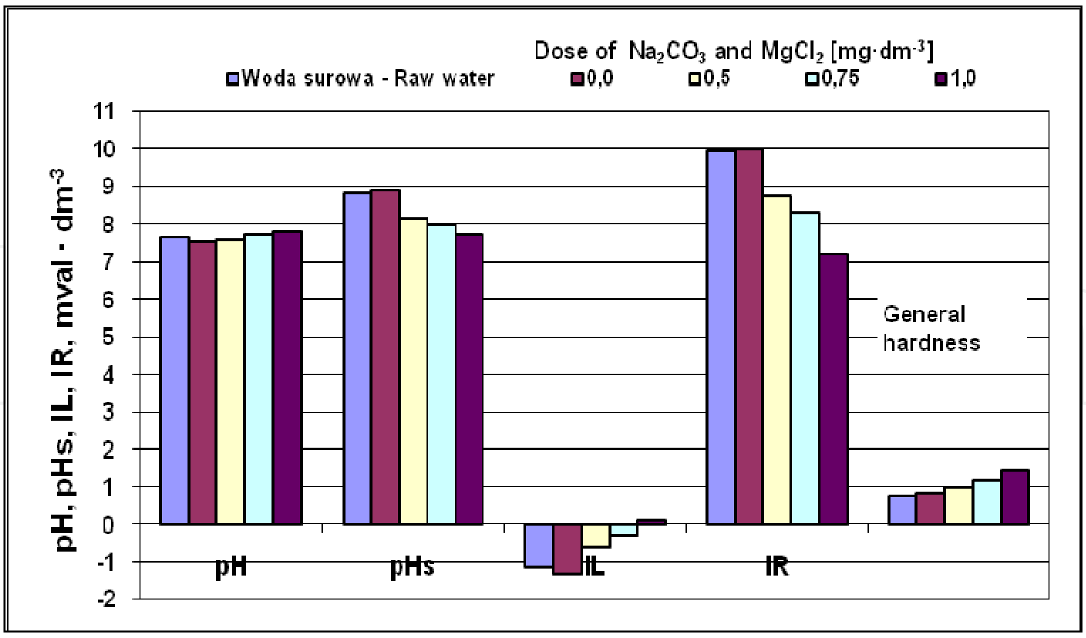


Fig. 4. Changes in pH, general hardness, and the pH_S, I_L, and I_R indices of the water for various doses of $MgCl_2$ and Na_2CO

The results obtained (see Figure 4) show that the treated water is stabilized by increased doses of magnesium chloride and sodium carbonate. Using 0.75 mg·dm^{-3} of both magnesium chloride and sodium carbonate resulted in a general hardness level of 1.2 mval·dm^{-3}. The I_L index reached a value of -0.3 and the I_R index reached a value of 8.3. However, both indices changed their values when the amounts of magnesium chloride and sodium carbonate added reached 1.0 mg·dm^{-3} becoming 0.1 for I_L and 7.2 for I_R.

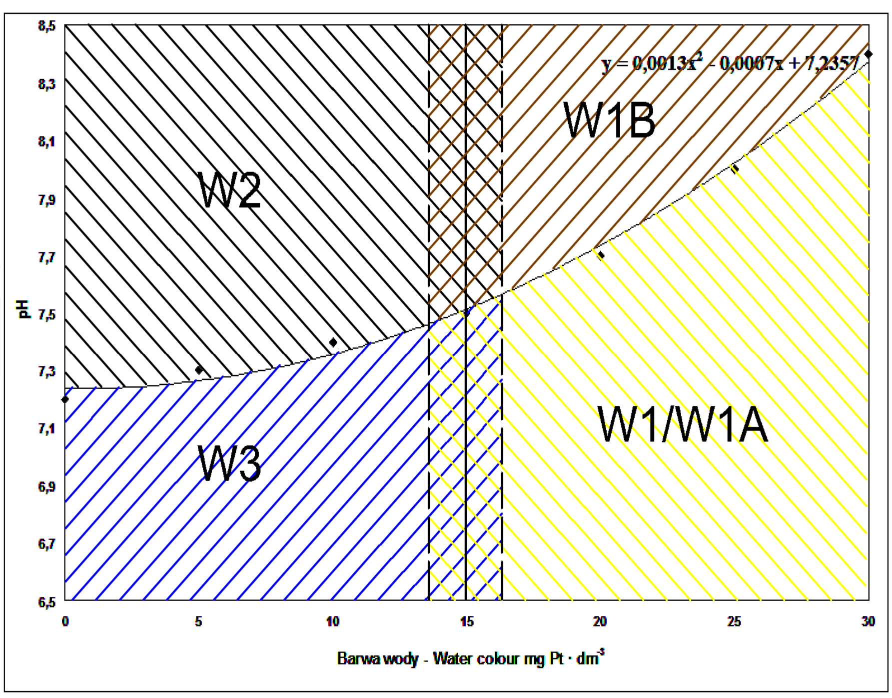


Fig. 5. Nomogram for selecting the technology system subject to raw water colour and pH values

The research identified limit values for the colour and pH of the raw water where there is a possible choice of treatment process. Those areas are shown in Figure 5. The nomogram governs the selection of the appropriate technology system subject to the colour and pH value of the reservoir water. Each of technology systems, W1, W2 and W3, can be modified with the inclusion of the derivative ozonation process, subject to water temperature. In winter time when the temperature drops to between 9°C and 12°C, derivative ozonation does not have to be implemented.

4. Discussion

The analysis led to the conclusion that the critical indicators that have an effect on the selection of the technology system to apply are the water colour, pH and temperature. Other contamination indicators are not relevant to the choice of the technology system of water treatment processes. The study indicated that both the raw and treated water were aggressive and unstable in character. Therefore, each of the technology systems includes processes which make the water stable and harder.

From a water management and distribution points of view, the quality of the water supplied to recipients is as important as the operational costs of the system. The costs depend on the technology system being used within the water treatment process. The technology system selected will generate operational costs subject to certain quality parameters of the raw water and the length of time that they are prevalent. These costs depend on the duration of the water treatment process within the appointed technology system. Therefore, it is important that the water treatment plant's operator be supplied with a prognosis of the contaminants of the raw water, as these determine the choice of technology system to implement. This forecast is critical for the water treatment plant under consideration. Pawełek and Bergel (2008) suggested a methodology to establish the duration time of a critical indicator. This led to the development of a readiness indicator, K_g, for critical water quality indicators. This readiness indictor is defined as:

$$K_g = \frac{T - \sum t_i}{T} \qquad (1)$$

where T is the examination time. For operational cost purposes this is taken to be 365, $\sum t_i$ is the total time for any limit values of the critical indicators designated for a certain type of a technology system.

Based on equation (1), readiness indicators were calculated for the critical indicators of water colour, pH and water temperature. These are shown in Figures 6, 7 and 8. The total duration time of the limit values was calculated for each of the critical indicators as a curve function of time per examination year.

The values for the readiness indicator for pH indicate that technology systems W2 and W3 (Figure 6) can be used for 302 days a year. For the rest of the year, the W1 technology system should be applied as coagulation needs to be implemented. Both W2 and W3 technology systems can be modified with the use of the pH correction. Figure 7 shows that the water pH correction needs to be implemented for 232 days per annum (63%). All technology systems (W1, W2 and W3) can be modified subject to the temperature of the water being treated. Figure 8 shows that the longest that the water treatment process W1A (excluding derivative ozonation) can be applied is 151 days a year.

The readiness indicators for water colour, pH and water temperature allow factors to be set to adjust the operational costs of the technology system appropriate to the critical values of indicators as given in the chart of Figure 5.

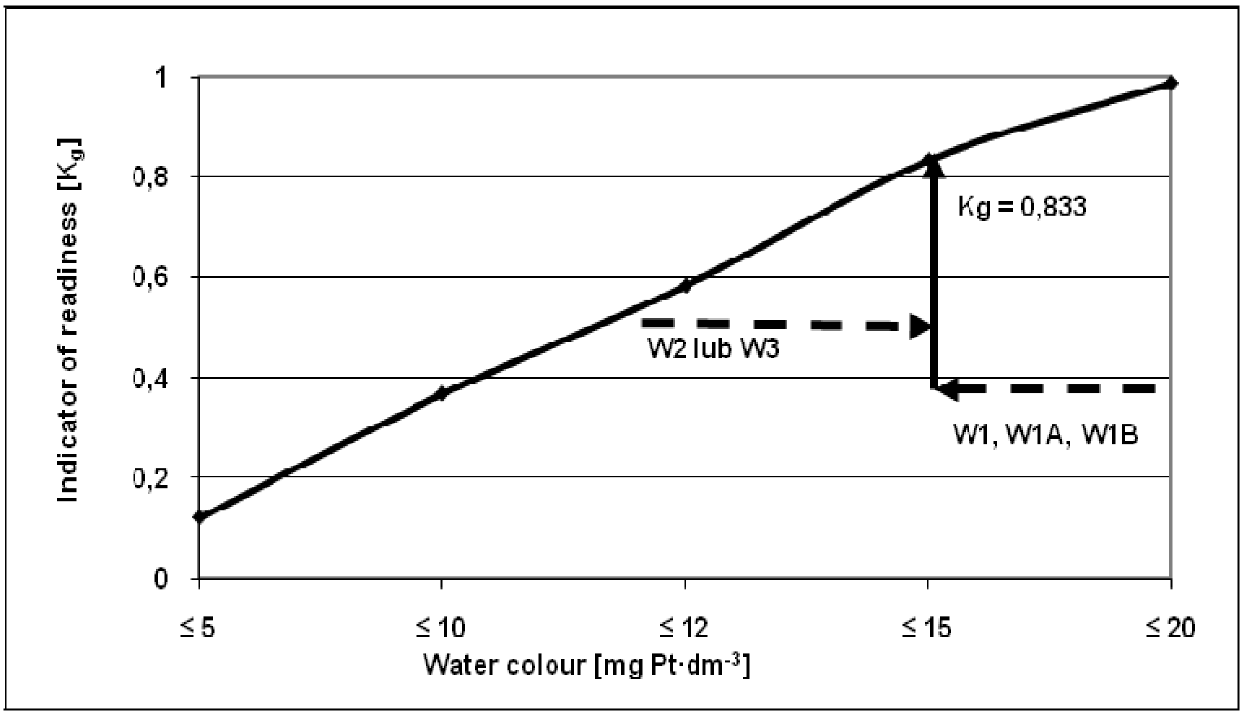


Fig. 6. Readiness indicator for water colour

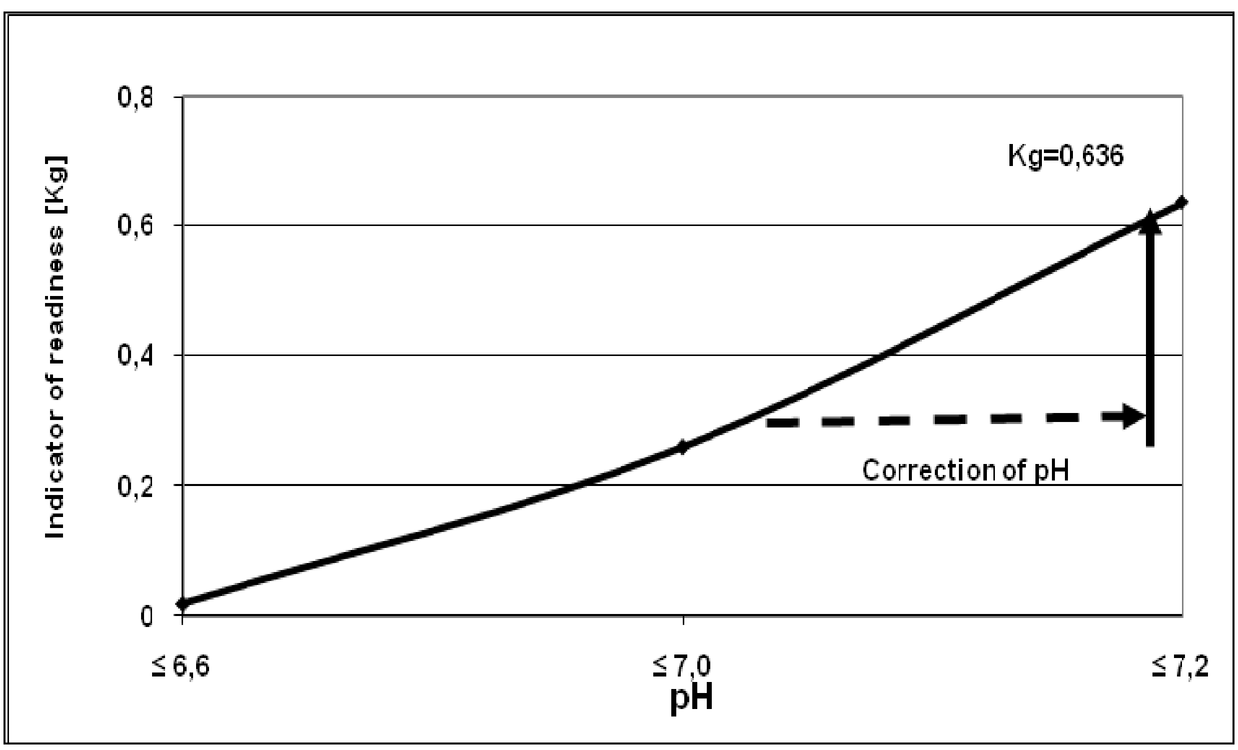


Fig. 7. Readiness indicator for water pH

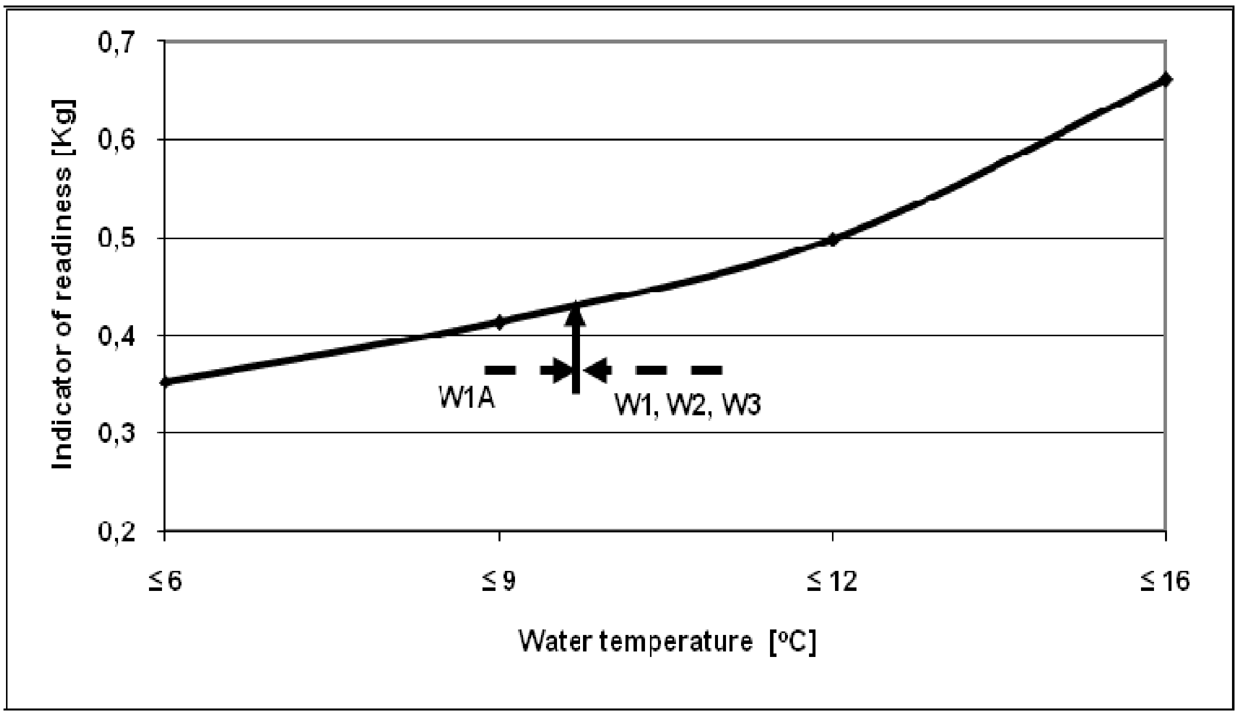


Fig. 8. Readiness indicator for water temperature

It is essential that the operator of the water treatment plant has a prediction of the water quality parameters which govern which type of technology system is set in motion. Short term prognoses of water quality can be used in the modelling of water management in various situations depending on water conditions, the ecological status of the inflow and the amount of water taken out for consumption.

Flexible Bayesian models (FBM) are the neural networks which were used to forecast the reservoir water quality indicators (Neal, 2000). A numerical analysis applied to a regression model in which the target variables, such as colour (S_1), turbidity (S_2), pH (S_3) and water hardness (S_4), are subject to input variables such as time (Z_1), reservoir water level (Z_2), daily precipitation amounts in the catchment area (Z_3) and water temperature (Z_4). Adjustments to the network were based on historic data gathered from assessments carried out for 365 days from November 2007 till 31 October 2008. Verification of the regression model was carried out using the same data. The parameters of the network were established at such levels as to accommodate the lowest values of the predicted errors. The parameters of the network architecture were set at values which allowed acquisition of the smallest values of the prediction errors by control of the rejection rates (value 0.5) of the chosen hyper-parameters that make the network adjustment optimal. A numerical simulation was carried out with 250 iterations after the first 20% of the burn-in steps were rejected.

There are two criteria used to set the final parameters of the neural network. The first is the root mean square error (RMSE). The other is the correlation (R) between the predicted indices and the observed ones. The correlation coefficient shows the strength of the linear relation between two variables. The coefficient of determination, R^2, shows how well future outcomes are likely to be predicted by the model.

Figures 9, 10, 11, 12, 13 and 14 show the results of examinations carried out using of ANN FMB.

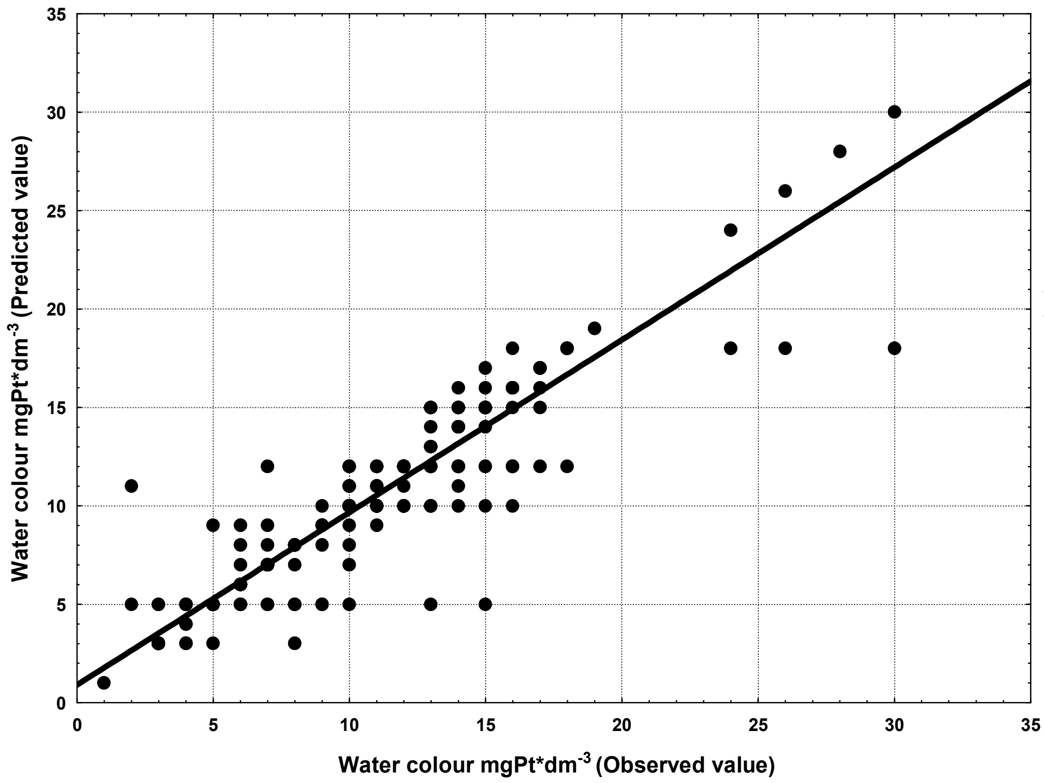


Fig. 9. Correlation between forecasted and observed values for water colour

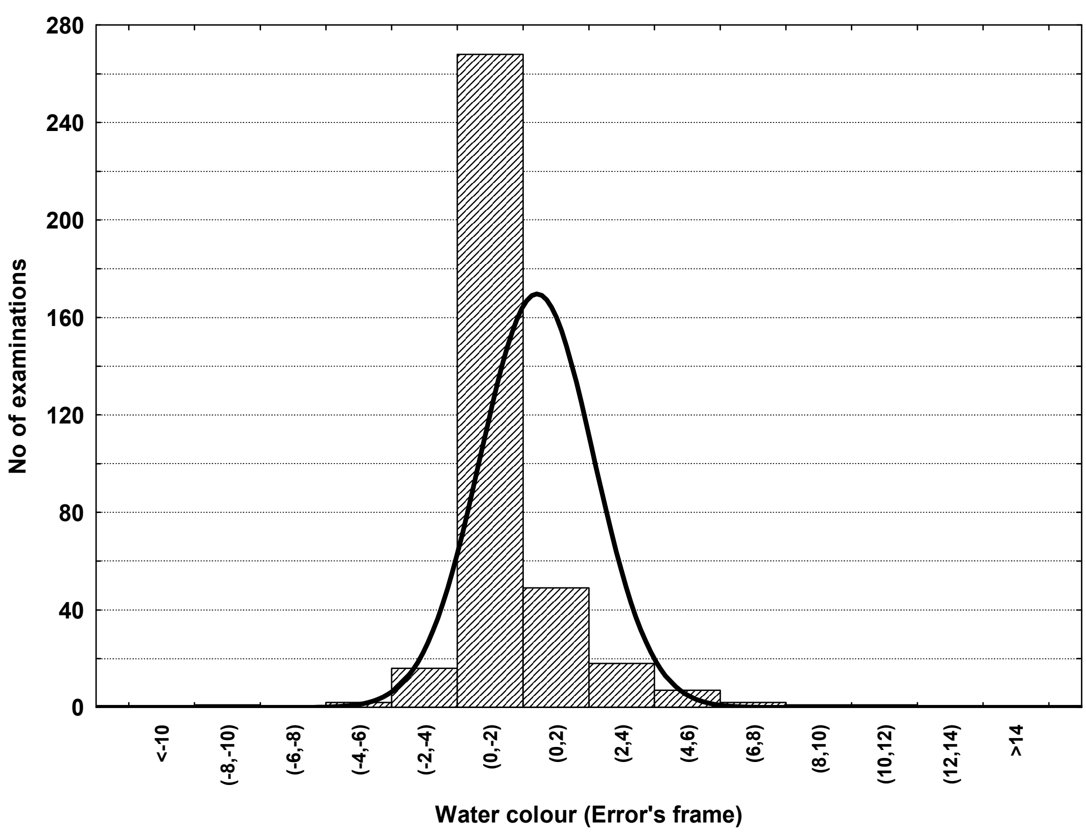


Fig. 10. Histogram of errors for forecasted water colour

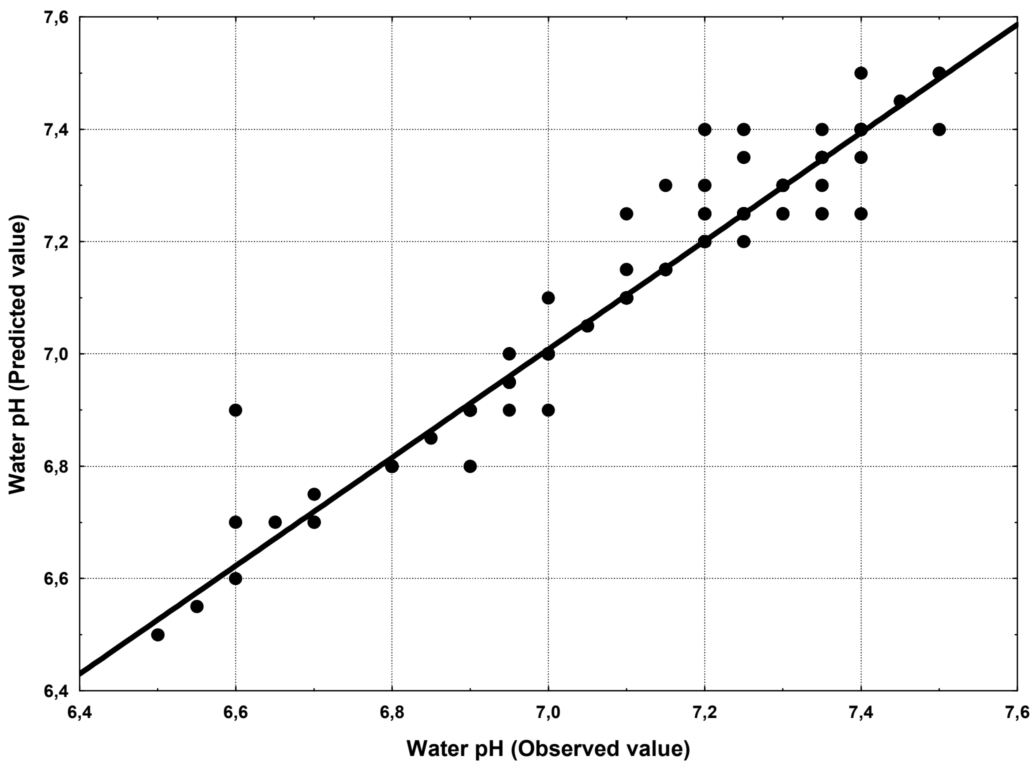


Fig. 11. Correlation between forecasted and observed values of water pH

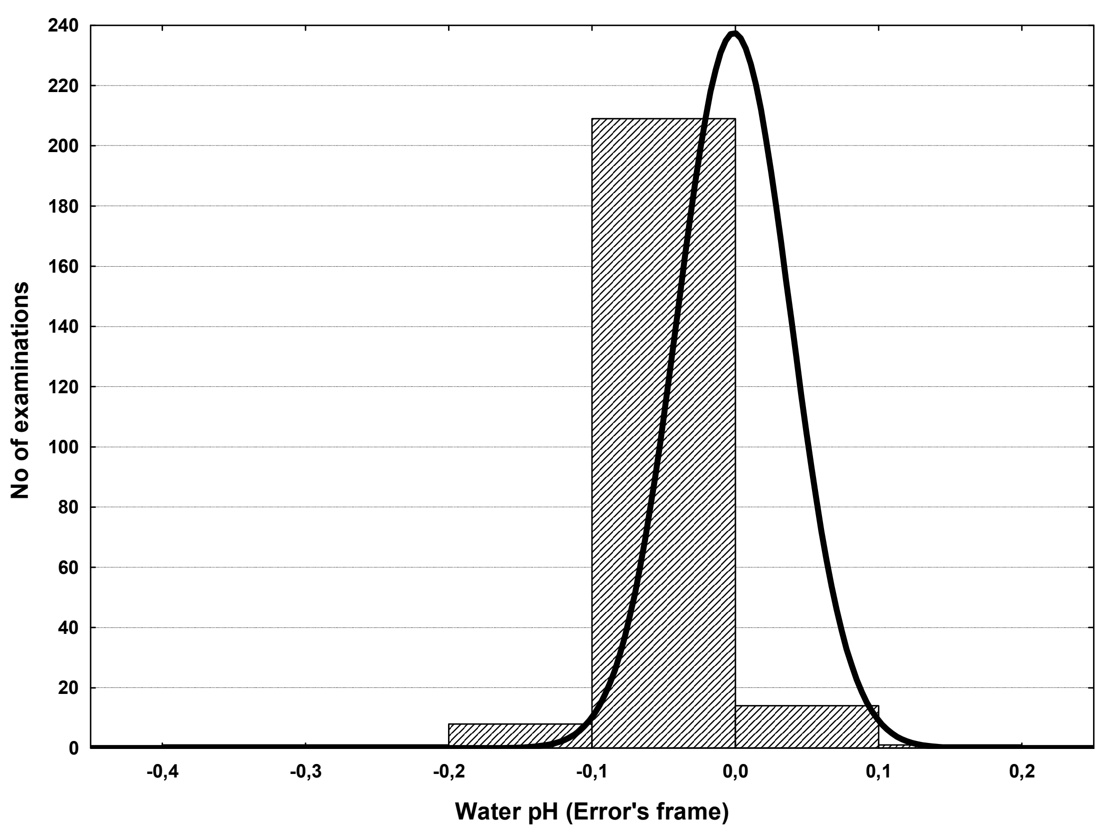


Fig. 12. Histogram of errors for forecasted water pH

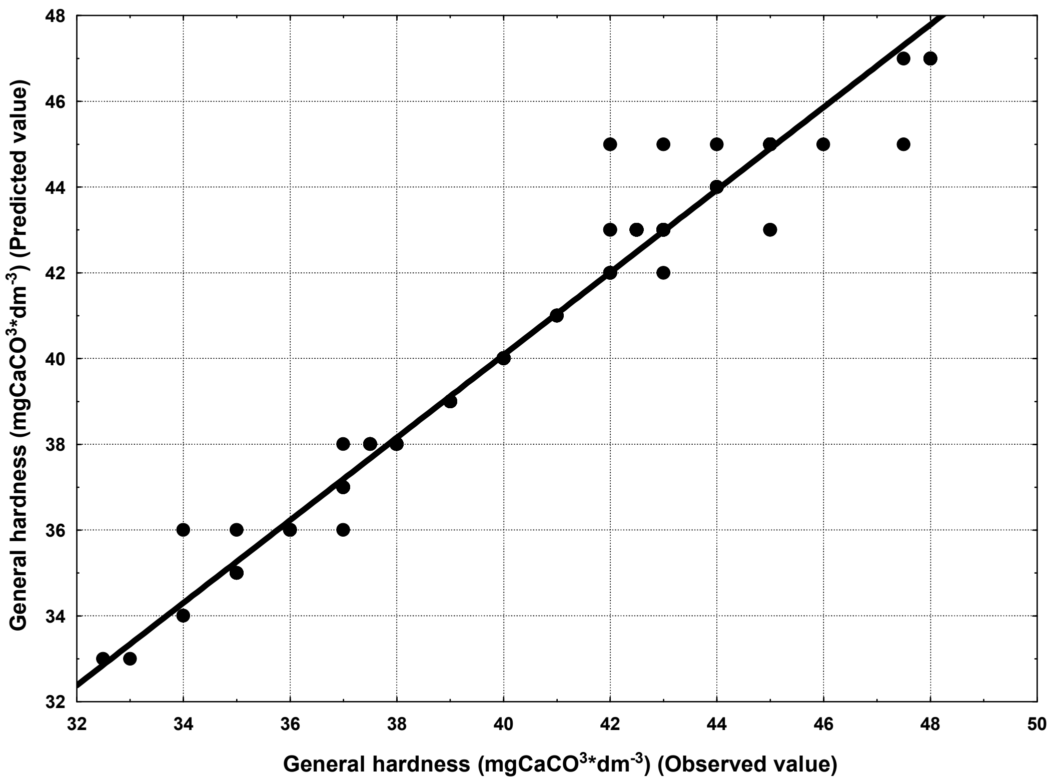


Fig. 13. Correlation between forecasted and observed values of water general hardness

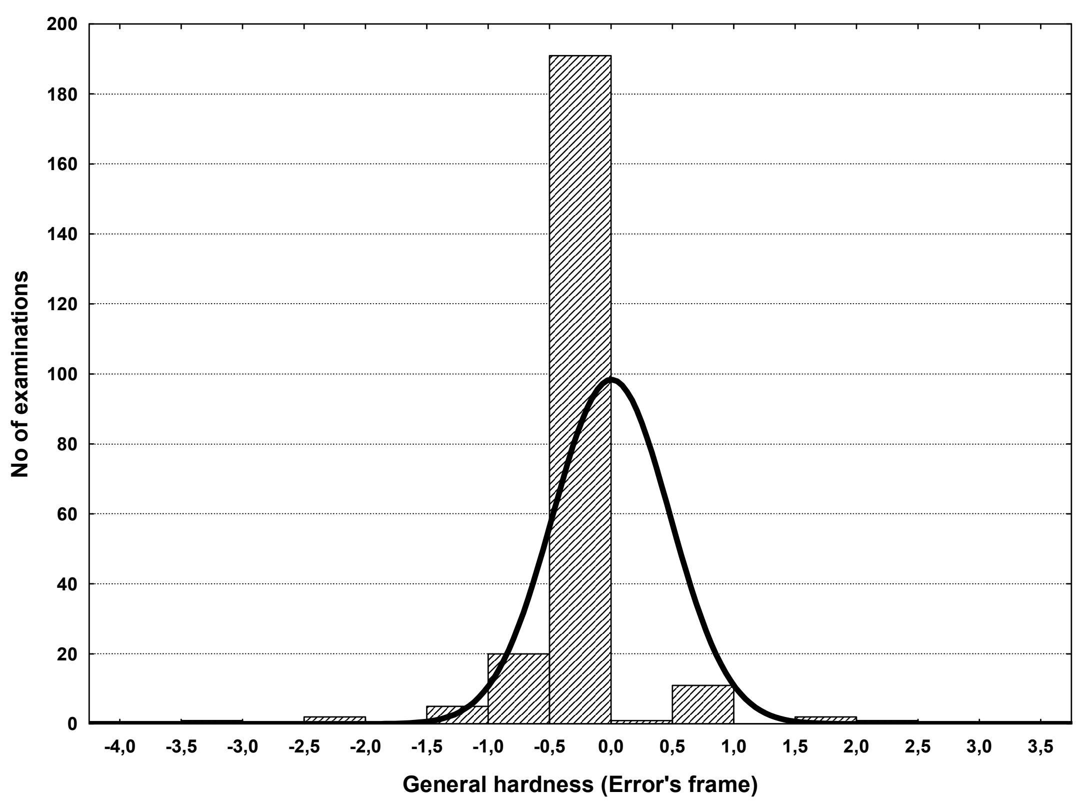


Fig. 14. Histogram of errors for forecasted water general hardness

The calculated RMSE values were 1.69 mg Pt·dm^{-3} for water colour, 0.83 mg SiO_3·dm^{-3} for water turbidity, 0.062 for pH and 1.38 mg $CaCO_3$·dm^{-3} for the general hardness of the water. The correlation coefficients between the assessed and observed indices were 0.9318 for water colour, 0.9448 for water turbidity, 0.9475 for water pH and 0.9177 for the general hardness of the water. Indicators of the chosen water quality parameters were assessed based on the chosen ANN model. The results obtained were grouped into three subsets based on the water temperature. The results are shown in Table 3.

Set	Conditions	Mark	Colour	Turbidity	pH	Hardness	Alkalinity
			mg Pt·dm^{-3}	mg SiO_2·dm^{-3}	pH	mg $CaCO_3$·dm^{-3}	mval·dm^{-3}
Subset **I**	Temp 17-22^{o}C, V_Z 6.4-9.2 mln m^3 rainfall P_{max} = 54 mm·d^{-1}	S_{max} observed	30	12	7.2	48	0.75
		S_{max} forecast	30	12	7.2	45	0.7
		S_{min} observed	10	3	6.9	35	0.5
		S_{min} forecast	5	3	6.9	35	0.5
Subset **II**	Temp. 9-16,9^{o}C, V_Z 6.5-8.9 mln m^3, rain fall P_{max} = 16.6 mm·d^{-1}	S_{max} observed	14	12	7.5	44	0.65
		S_{max} forecast	14	12	7.4	44	0.65
		S_{min} observed	3	3	6.5	33	0.55
		S_{min} forecast	3	3	6.6	33	0.55
Subset **III**	Temp. 3-8,9^{o}C, V_Z 7.8-8.4 mln m^3, rainfall P_{max} = 25.7 mm·d^{-1}	S_{max} observed	16	12	7.5	4.8	0.95
		S_{max} forecast	15	12	7.4	48	0.9
		S_{min} observed	1	1	7	38	0.5
		S_{min} forecast	1	1	7	39	0.5
Total set	Temp. 3-22^{o}C, aver temp. 11.5^{o}C V_Z 6.6-9.2 mln m^3, V_{averr} 8.2 mln m^3, rainfall P_{max} = 54 mm·d^{-1}	S_{max} observed	30	12	7.5	48	0.95
		S_{max} forecast	30	12	7.4	48	0.9
		S_{min} observed	1	1	6.6	33	0.5
		S_{min} forecast	1	1	6.6	33	0.5
		S_{aver} observed	10.2	5.2	7.09	41	0.64
		S_{aver} forecast	9.9	5.1	7.1	41.5	0.64

Table 3. Comparison of results forecasted by an ANN model and the indicators of water quality observed at the retention reservoir

5. Conclusions

The effectiveness of an ANN FBM in establishing the critical indicators of water contamination at the reservoir was relatively good, providing high quality predictions with each of the models. Analysis of the predicted values of the quality indicator variables of the reservoir water and the observed ones was undertaken using Microsoft Access 2007.
The observed and forecasted values of the analysed indicators of water quality were aggregated into a data base for each ANN FBM model. Using the 'filter' function allowed the predicted values of the relevant indicator of water quality to be found once the observed variables were defined.
A suggested methodology for designing an ANN model resulted in an optimal configuration of the particular ANN type in order to establish the predicted values of the quality indicators of the water. The chosen ANN model could replace the current algorithms used in the design of modern systems which are responsible for water management at retention reservoirs. It could also be used to control and direct the processes controlling the abstraction and treatment of water used for consumption and industrial and agricultural purposes.
Designing a model to forecast indicators of water quality requires extensive examination of each water management establishment. The results of the analysis should determine the critical indicators of water quality. These would determine the character of the water being analysed and the characteristics required given the current and planned uses of the water.
A review and analysis of the literature has led to the following conclusions:

- Management of surface water treatment requires constant optimisation given the large number of indicators which influence water quality. It is essential to establish a model which predicts the critical values of the water quality indicators which, in turn, determine the water treatment technology system to apply.
- Having a large set of critical water quality indicators means that it is not possible to operate with just one technology system of water treatment processes. For the retention reservoir considered in this paper, the critical indicators were water temperature, water colour, pH and the general hardness of the water.
- The suggested methodology for creating and verifying ANN models permits the development of an optimised configuration for a particular ANN type to best forecast the quality indicators of the water held in the reservoir.

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