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Analysis of Changes in Turbidity in the Surface Water Treatment Technological Process

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ABSTRACT
Increasingly wider application of artificial neural networks (ANN) in researches and analyses of unit and technological processes related to the water treatment was a reason of creating ANN model for predicting of treated water turbidity in newly operating water treatment technological system for surface and retention water in "Sosnówka" water reservoir. For modeling of water turbidity during water treatment process for the selected technological system the following programme was applied Flexible Bayesian Models on Neural Networks (FBM). There was a model created which allows to forecast turbidity of water pretreated through a specific technological system and the basis of which are information coming out from monitoring of physicochemical parameters of water drawn from the reservoir as well as from monitoring process parameters of water treatment systemabstract should summarize the content of the paper.
Keywords - water treatment, water turbidity, technological system, artificial neural network

I. INTRODUCTION

The basic problem at taking water from rivers and mountain torrents for pipeline distribution is excessive periodical turbidity of water. The water turbidity is caused by the sudden intensive rainfalls or spring thaws which increase the water level in rivers and amount of suspended solids and solids carried out in river water. The amount of these solids depends *inter alia* from the climatic, geological, geomorphological, hydro-biological and biological conditions and it is also caused by the human activities. The period of high water turbidity may last from several dozen of hours to one month. Changes in water turbidity in mountain rivers can be very fast and the turbidity may achieve the level of a few thousand NTU[1].

Turbidity of mountain river waters depends on water level, i.e. at the high levels is much higher than during lower levels. Water turbidity is also affected by bottom sediments and splashing suspended solids transported at the high speed f water flow. It is observed that the increase of water turbidity in river on which water reservoir is located analogically results also in turbidity level increase in the water reservoir. Waters coming from rivers and mountain torrents are of a relatively good quality. In case of high turbidity water reservoirs are used for storing water. The advantageous solution are water storage and water storage and balancing reservoirs. In water storage reservoir, depending on its location, raw water as well as treated water can be stored. Using of water storage reservoirs allows for cutting-off the water intake in case of water turbidity increase or presence of contamination which makes the proper treatment of water impossible. Water is stores in reservoirs in order to be used in different circumstances, e.g. in case of periodic water turbidity increase. If water reservoir is installed in the technological system before the water intake, water monitoring system must be applied to control the water being taken. Such system is used to detect occurred contamination. Water storage reservoir, depending on their location in the water pipeline system, can store raw or treated water. Water storage and balancing reservoirs, except for the storage capabilities, may also be used to balance water quality. More and more often integrated (hybrid) processes are being applied in water treatment in which standard water treatment technologies are combined with unconventional methods resulting in achieving higher level of contamination removal. The example can be the systems where coagulation is combined with membrane filtration [2]. Despite the significant increase in development in the recent years of the hybrid processes and methods of defining their process parameters (coagulant dose, power consumption, rinsing methods) there are still many unsolved issues related with the expected treated water quality, *inter alia* depending on the methods applied for carrying out the experiment and the used modeling method [3]. The artificial neural networks (ANN) can be applied for this purpose as the mathematical modeling with their application allowing for limitation of time consuming and expensive laboratory researches which are used in order to determine quantitative and qualitative parameters of technological processes. Information transfer in the artificial neural networks imitates the human nervous system [4]. Neurons of which the network is built of are the data processing units. The artificial neural network calculates the outgoing values on the basis of the information given at the incoming side of the network. There are many types of the ANN but currently the most popular kind of the neural network is the multi-layer perceptron with one incoming layer, one (or more) hidden layer and single outgoing layer. Attractiveness of the ANN application is mainly related with possibility of approximating of any nonlinearity. It is not necessary to know the function describing the modeled variable to create the network model. Moreover, the artificial neural networks easily adapt to variable environmental conditions [5]. Due to that fact modeling with application of the artificial neural networks is being recognized as "black box" type of approach and it is not possible to determine *a priori* the optimal network's architecture. The trial and error method is used to achieve the suitable networks structure in order to solve the specific engineering problem. There are many known examples with application of mathematical simulations which involve the ANN for predicting values of varied parameters. Water treatment in membrane processes is the field in which modeling through the ANN is very popular. By using the ANN models based on quantitative equations describing correlations between process variables it is possible to envisage the level of removal of natural compounds on polyamide nanofiltration membranes and through revert osmosis process [6]. The level of topsoil substance's removal and ultra-filtration membrane blocking phenomenon were predicted with the application of the most popular network learning algorithm, i.e. the method of error backward propagation [7]. Monograph [8] presents very interesting approach to the subject of water collection prediction in which the stochastic methods of water collection from city mains are compared with the results of the ANN models. Due to the high variability in the water collection time series the ANN turned out to be a very promising tool for short-time predictions. Modeling of energy return from heat converter used in water treatment station was proposed in elaboration [9], in which thermodynamic model was compared with the ANN model. Both models proved sufficient similarity of measurement and simulation results. In the broadly-taken area of the environmental engineering the artificial neural networks are often used as modern mathematic tool which can supersede the laborious and expensive laboratory measurements. Due to the lack of unambiguous information on predicting water turbidity changes in water treatment technological process, this elaboration deals with the problem of modeling turbidity changes in treated water in the integrated technological system comprising of the following main stages: straining, primary ozonation, filtration through antacid-sand filters, secondary ozonation, sorption on active carbon.

II. RESEARCH METHODOLOGY

In the 90's of the last century in Jelenia Góra in order to supply the city with water, the water reservoir "Sosnówka" was built. Water resources in this reservoir are being the source of raw water for the water treatment plant (WTP). "Sosnówka" water reservoir stores waters from the catchment of Czerwonka torrent and Sośniak torrent as well from its small tributary Sosonówka, with the overall catchment area of 15,3 km^2 [10]. Water treatment process on the WTP equipment has been carried out since 2007. Since then measurements are being carried out in continuous system enabling application of the following processes: straining, primary ozonation, coagulation, pH correction, flocculation, rapid filtration through anthracite-sand filters, secondary ozonation, sorption on active carbon, final pH and water hardness correction and disinfection of treated water [11]. Within the automatic monitoring of raw and treated water in WTP in Sosnówka the following water quality indicators are being continuously measured: temperature, pH, turbidity and conductivity. Moreover, during research period, i.e. from November 2007to October 2008 water physical analyses were carried out in few-day cycles. The scope of analysis covered measurement of parameters such as water temperature, turbidity, colour, pH, general hardness, basicity, ferrum, manganese, chloride, ammonia and nitrate nitrogen, oxidability, dissolved oxygen, conductivity, phosphates. Quality composition of water taken for treatment during research period was balanced and typical for the specific season of the year. Table 1 below presents minimum, maximum and average values of analyzed water quality indicators. Taking into account relatively good quality of raw water, the technological tests were carried out on the system including: screening, initial ozonation, rapid filtration through anthracite-sand filters, secondary filtration and sorption on active carbon marked, without final water quality correction. In the second phase of the research the technological system was expanded to include the final water quality correction. Results of raw and treated water analyses allowed for determination of the reduction level of monitored parameters. Possibility of providing the continuous monitoring allowed for carrying out analyses on changes of parameters such as temperature, pH, turbidity in one-day cycles.

Table No 1

Characteristic values of the selected quality parameters of treated water during the research period

Parameters of analyzed water	Unit	Reservoir			
		S_{Min}	S_{Max}	$\overline{S}$	σ
Temperature	^{o}C	4	22	11,7	6,12
Turbidity	NTU	1,0	12,0	5,2	2,47
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	$mg\ N\cdot dm^{-3}$	0,01	0,11	0,05	0,004
Nitrate nitrogen	$mg\ N\cdot dm^{-3}$	2	5	2,44	1,300
Chlorides	$mg\ Cl\cdot dm^{-3}$	4	6,8	4,95	1,321
Oxidability	$mg\ O_2\cdot dm^{-3}$	1,0	5,22	3,458	1,532
Conductivity	$\mu s\cdot cm^{-1}$	98,28	122,50	110,88	6,692
Dissolved oxygen	$mg\ O_2\cdot dm^{-3}$	9,4	12,4	11,18	1,172
Fe	$mg\ Fe\cdot dm^{-3}$	0,05	0,136	0,066	0,027
Mn	$mg\ Mn\cdot dm^{-3}$	0,012	0,036	0,021	0,007

III. RESEARCH RESULTS

During research period water flow at the level of 172÷202 $m^3\cdot h^{-1}$, at the same speed of filtration on anthracite-sand filters and active carbon of 4,9÷5,7 $m^3\cdot h^{-1}$ and with dosing of the following substances into the technological system: during primary ozonation: ozone – dose 1÷2 $mgO_3\cdot dm^{-3}$; during secondary ozonation: ozone – dose from 1 $mgO_3\cdot dm^{-3}$; for correction of treated water: sodium carbonate – dose 1,0 $mgNa_2CO_3\cdot dm^{-3}$; for stabilization of treated water: magnesium chloride - dose 1,0 $mgMgCl_2\cdot dm^{-3}$; during disinfection: sodium hypochlorite – dose 0,8÷0,9 $Cl_2\cdot dm^{-3}$. Water quality composition during research period was balanced and typical for the specific season of the year. Water temperature varied from 4 ^{o}C during winter to 22 ^{o}C during summer. Turbidity of water taken from the water reservoir was at the level from 1 to 12 NTU (Fig.1), colour from 5 to 14,9 $mgPt\cdot dm^{-3}$, pH in the range of 7,2- 8,40 and conductivity from 98 to 122 $\mu s\cdot cm^{-1}$. Obtained results of monitored parameters allowed for creating daily data base for the whole research duration, i.e. from November 2007 to October 2008. Effectiveness of water turbidity reduction was determined on the basis of the raw water turbidity measurements taken from the reservoir (M_s) and treated water turbidity measurements (M_p), as per the correlation: $R_m = 1 - (M_p/M_s)$ [3]. During the research period the average water turbidity reduction index *Rm* was 0,63, with the standard deviation of σ = 0,21. According to the changes of *Rm* index presented in the Fig. 2 below, it appears that the technological system was operating unstable. It was observed in particular during thaws and heavy daily rainfalls. The mountain type of the catchment area from where water flows into to the water reservoir results in water coming into the reservoir in the amount of even 1,5$m\cdot s^{-1}$, during thaws, with the increased turbidity reaching even up to 27 NTU.

The above conditions were the reason for the *Rm* index decrease to 0,2. In those periods treated water turbidity was higher than 1NTU, periodically reaching 4 NTU. It is also to be mentioned that during the research period interferences occurred in water treatment process. This was noted in spring when treated water turbidity was even higher than turbidity of water flowing into the technological system (raw water turbidity from 3,0 NTU was increasing to 4,09 NTU after the treatment). Results on raw and treated water turbidity allowed for generation of the daily data base for the whole research period. The optimum prediction model shall in any moment allow for determination of projected effects in water treatment, on the basis of the information coming from the monitoring of the hydrological conditions of the catchment area, the meteorological observations and physical and chemical analyses of taken water.

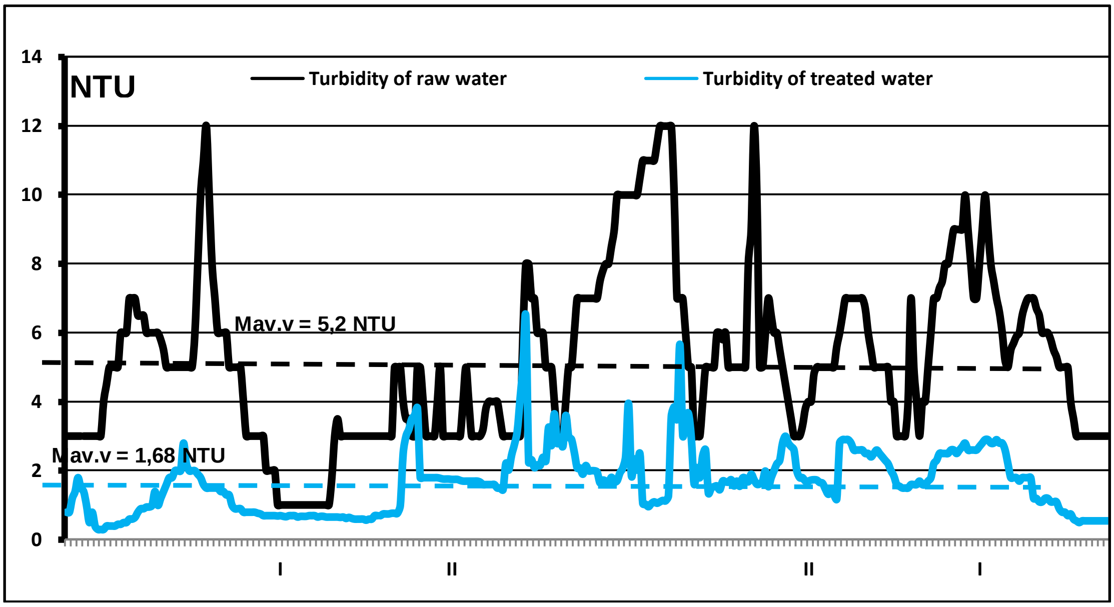

Fig. 1. The turbidities of raw water and treated water

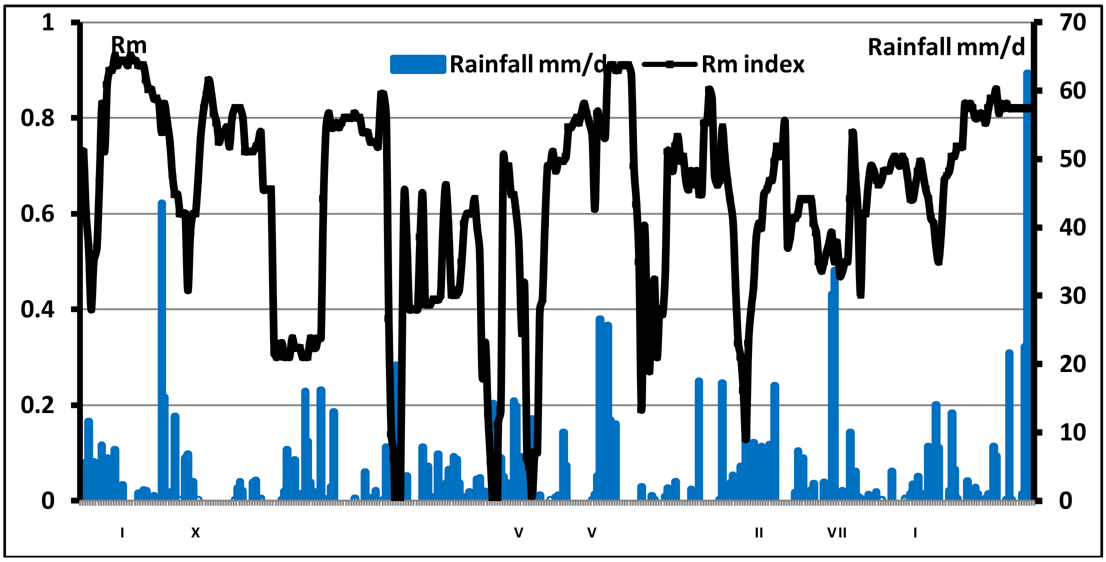

Fig. 2. Changes in the turbidity reduction index (R_m) compared with the daily rainfall in the catchment area

For modeling changes of the treated water turbidity on the program „*Flexible Bayesian Models on Neural Networks*" (FBM) was used, operating in UNIX/Linux environment, version 1999-03-13 [12]. Neural networks models were described in the elaboration titled "*Bayesian Learning for Neural Networks*" published by Springer-Verlag (ISBN 0-387-94724-8) [13]. The neural analyses was carried out on MLP (*Multi Layer Perceptron*) model of neural networks. The structure of the MPL model is based on the numeric analyses in which the target variables are the continuous variables such as: treated water turbidity and five so called input variables, i.e. raw water turbidity, water flow to reservoir, water retention level, daily rainfall and water temperature in reservoir. Learning of networks was based on the collected historical data for 366 numbers of fully described cases from November 2007 to 31st October 2008. Verification of each structure of the numeric model was carried out on the same research group. Parameters of the network architecture were defined for the levels assuring the lowest value of errors achieved in prediction through the control of *inter alia* so called rejection rate being at the level close to 0,5 and selected hyper-parameters optimizing the process of learning the networks. The numeric simulation was carried out for 100 iteration steps and after rejecting of the first 20% so-called burn-in steps. For evaluation of assumed parameters of the neural networks model the RMSE was selected described by the following function (1):

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}\left(S_P - S_R\right)^2} \qquad (1)$$

where N is the number of data, S_P the projected turbidity values after water treatment and

S_R the measured turbidity values (observed) of the treated water.

The second evaluation criteria was defining the correlation factor R between projected and the observed water turbidity. The value of linear correlation on the basis if the n-elements sample was calculated in accordance with the following formula (2):

$$R = \frac{\sum_{i=1}^{N}(S_{Pi} - \overline{S}_P)(S_{Ri} - \overline{S}_R)}{\sqrt{\sum_{i=1}^{N}(S_{Pi} - \overline{S}_P)^2 \sum_{i=1}^{N}(S_{Ri} - \overline{S}_R)^2}} \qquad (2)$$

where $\overline{S}_R$ is the observed average value of the turbidity of the treated water and $\overline{S}_P$ the predicted average value of the turbidity of the treated water.

The correlation factor R presents the linear correlation between two variables. The closer the factor is to 1, the stronger the linear correlation is. Marking the generated MLP model for prediction of treated water turbidity, as per the specification: net-spec sun 5 100 20/-5:50 - 5:50 - 5:50 – 100, the architecture of assumed neural networks can be described as follows: one incoming layer with 5 explanatory variables, 100 of hidden layers, one outgoing layer with 20 units within the range of defined values based on the measured data, number of learning cycles 366, number of edited predictions 948846. For polarization of input data the standard deviation of 100 was assumed. The range of data in incoming layer was 5:50, in hidden layers 5:50 and in outgoing layer 5:50. It was assumed that the neural networks' architecture for the analyzed time series is to be marked with the following sequence: abbreviation of networks name: MLP - perceptron multi-layer networks; number of incoming variables, after colon number of explanatory variables; number of hidden layers; number of outgoing layers, after hyphen number of units from the range of projected index. Taking the above into account, the architecture of the MLP model was described as follows: MLP 1:5 100 1-20. Results on effectiveness analyses of MLP model of projected treated water turbidity are presented in Figure 3, 4 and 5.

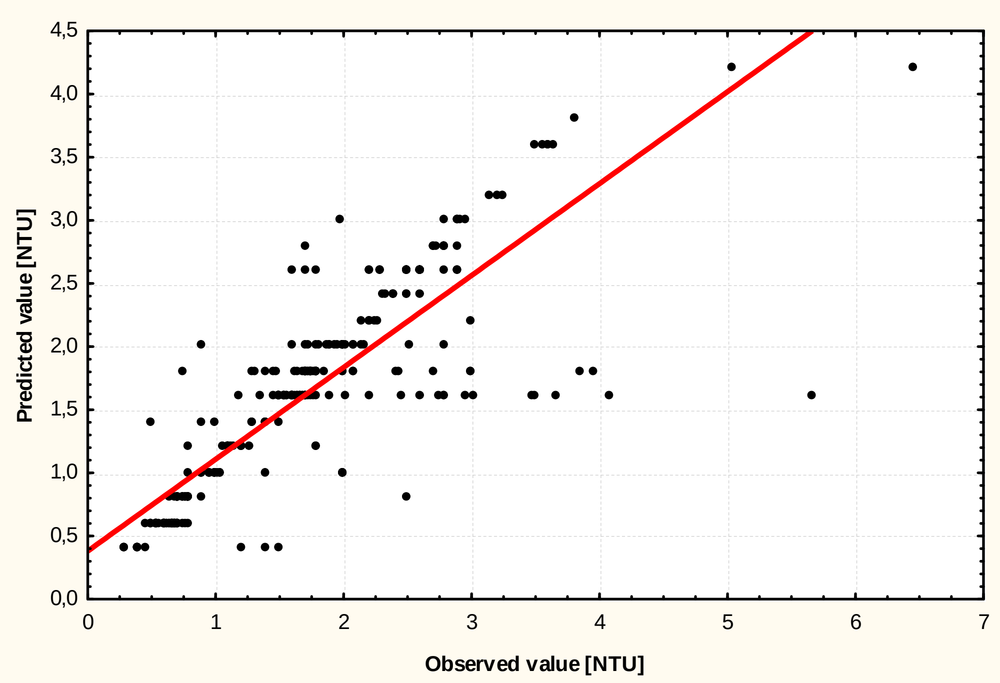

Fig.3. Correlation between projected and observed values of the turbidity of water treated

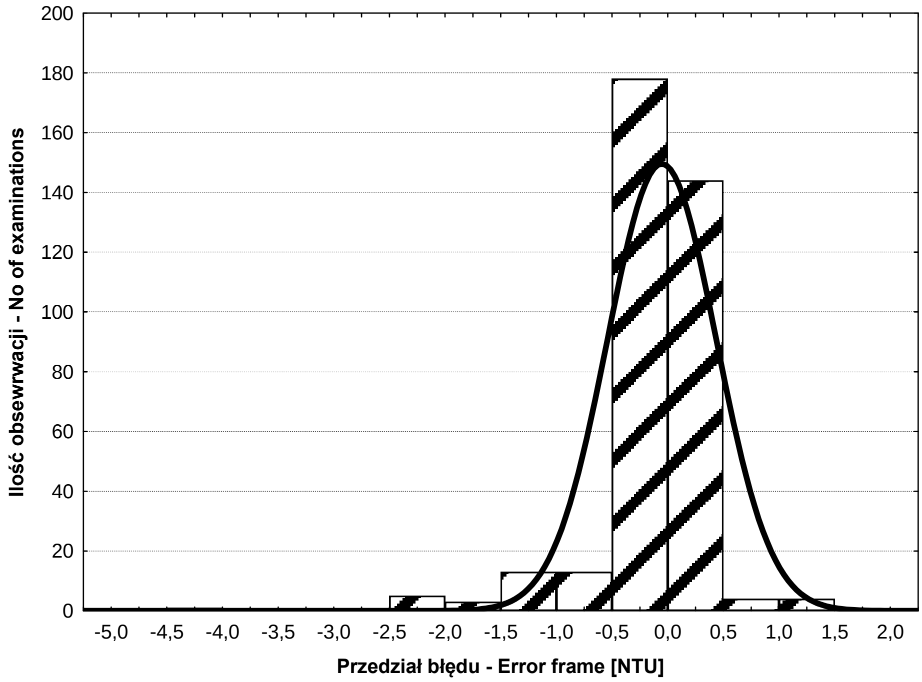

Fig. 4. Histogram of errors of treated water turbidity prediction

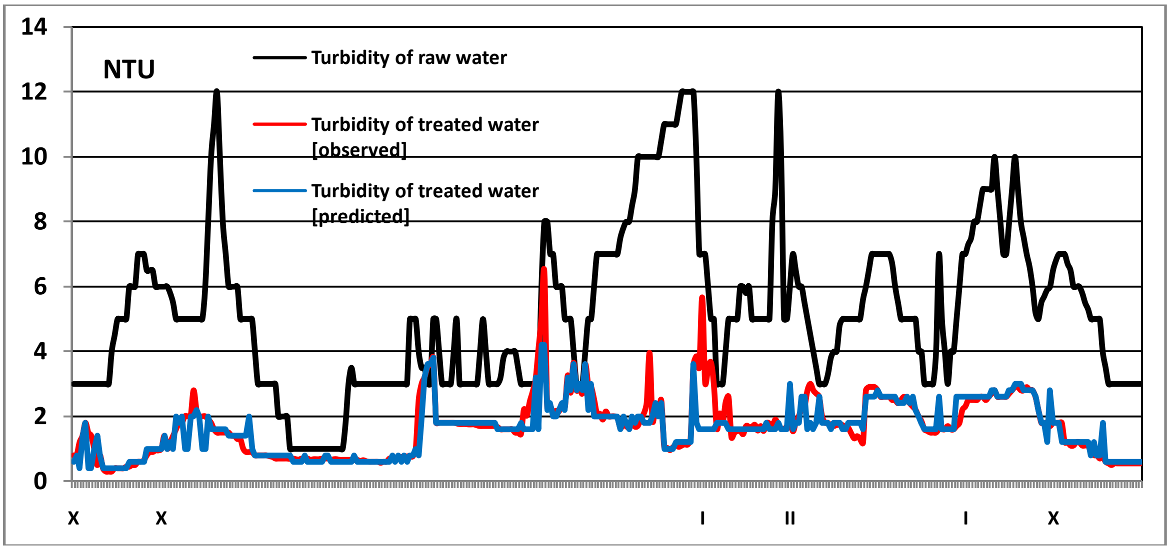

Fig. 5. Changes in the measured turbidities of the raw and treated water and the projected turbidity of the treated water

IV. DISCUSION OF RESEARCH RESULTS

Analyses on the neural network effectiveness in predicting of the water contamination indicators in the reservoir showed relatively good quality of prediction in each analyzed MLP model. The calculated value of RMSE is 0,49 NTU. The calculated correlation factor R equals 0,84. From the carried out analyses it results that, at predicting of the water turbidity, defining of the parameters characterizing the water inflow as the explanatory variables increases the accuracy of projected water quality indicators. The selected model of neural networks shall complement the algorithm of projected informatics systems as well as the algorithm of modernized systems which are applied for managing and controlling of the water intake and treatment processes of water used for potable, industrial and agricultural purposes. Creation of model for predicting of quality indicators requires a number of researches and analyses to be carried out individually for each object of the water management. The result of those researches shall be determination of the criterion water quality indicators which define tested water characteristics and determine expected water parameters, in the aspects of its current and planned usage. Prediction of the selected water quality indicators on the neural networks shall be carried out in stages. Flowchart of the process is presented on Figure 6.

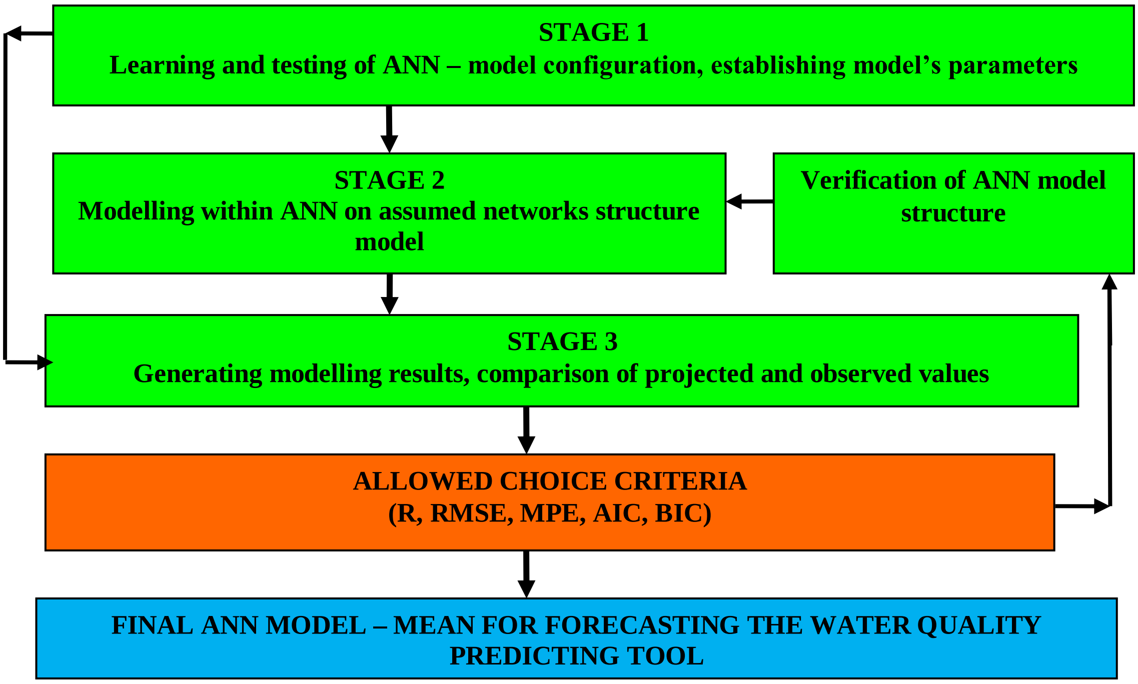

Fig. 6. Diagram of the steps for predicting water quality indicators with an ANN application

REFERENCES

[1] Pawełek J. Turbidity of water in rivers and mountain torrents in the aspect of water treatment for water mains purposes). Environmental Protection 4(51), pp. 69-73, **1993**.

[2] Adamski W., Majewska-Nowak K. Application of multifunction reactors for water purification. Environmental Protection, vol. 32, nr 1, pp. 3–8, **2010**.

[3] Kabsch-Korbutowicz M., Kutyłowska M. Application of artificial neural networks for predicting of water turbidity changes in coagulation/ultrafiltration process. Environmental Protection, vol. 32, nr 2, pp. 15-20, **2010**.

[4] Tadeusiewicz R. Neural networks. Academic Publisihng House RM, Warsaw, **1993**.

[5] Cieżak W., Siwoń Z., Cieżak J. Application of for predicting of time series of short-lived water intake in selected water mains. Environmental Protection, vol. 28, no 1, pp. 39–44, **2006**.

[6] Yangali-Guintanilla V., Verliefde A., Kim T., Sadmani A, Kennedy M., Amy G. Artifi cialneural network models based on QSAR for predicting rejection of neutral organic compounds by polyamide nanofiltration and reverse osmosis membranes. Journal of Membrane Science, Vol. 342, pp. 251–262, **2009**.

[7] Al-Abri M., Hilal N. Artificial neural network simulation of combined humic substance coagulation and membrane filtration. Chemical Engineering Journal, Vol. 141, pp. 27–34, **2008**.

[8] Siwoń Z., Łomotowski J. Cieżak W., Licznar P., Cieżak J. Analysis and prediction of water distribution in water mains. Polish Academy of Science, Civil and Water Engineering Committee, Institute of Basic Technical Problems, Warsaw, **2008.**

[9] Hernandez J., Romero R., Juarez D., Escobar R., Siqueiros J. A neural network approach and thermodynamic model of waste energy recovery in a heat transformer in a water purification process. Desalination, Vol. 243, pp. 273–285, **2009**.

[10] Rak A., Konarczak T. Pilot studies as method of determining surface water treatment technology typical for mountain catchment area stored in water reservoir. Water Supply and Water Quality. Published by PZITS, pp. 641-657, **2008**.

[11] Rak A. Prediction of criterion water quality indicators in reservoir for water treatment plant. Monograph "Supply in water, water quality and protection – modern subjects." Vol. I. Published by ISBN 978-83-89696-33-9, PZITS o/ Poznań, pp. 43-60, **2010**.

[12] Neal R.: Flexible Bayesian Models on Neural Networks, Gaussian Processes, and Mixtures v 2000-08-13. University of Toronto, p. 1-82. Programe availabe to general public; http://www.cs.utoronto.ca/~ radford/, **1999**.

[13] Neal R.: Bayesian Learning for Neural Networks. Wyd. Springer-Verlag (ISBN 0-387-94724-8, p. 10-22, p.99-136. Programe availabe to general public; http://www.cs.utoronto.ca/~carl/, **1996**.