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Original article

The impact of weather conditions on the quality of groundwater in the area of a municipal waste landfill

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ABSTRACT

The quality of groundwater in the source area of pollution depends on many factors, including the weather and hydrogeological conditions within the given area. Anassessment of water quality can be carried out based on data obtained from sensors placed in boreholes. This research examined the influence of air and water temperature, groundwater table position and precipitation on the value of electrical conductivity in groundwater in a selected piezometer belonging to the monitoring network of the Quaternary aquifer in the area of a waste landfill site in Tychy-Urbanowice in southern Poland. The influence of individual factors was checked by using twenty neural network architectures of a Multilayer Perceptron Model (MLP). Each of these indicated factors were selected as input variables. Ultimately, three neural networks were selected, which were characterized by the smallest validation and test errors and showed the highest learning quality. The significance of individual variables for the effectiveness of the model was checked using a global sensitivity analysis. Three selected MLP models contained seven to nine neurons in the hidden layer and used a linear or exponential function as the hidden and output activation. The maximum test quality was 0.8369, while the smallest test error was 0.0011. The results of the sensitivity analysis highlighted the important role of water temperature and water table position on the conductivity value. The obtained goodness of fit results of the models to the input data allowed us to conclude that the MLP was applicable to such forecasts and can be extended by the analysis of further factors.

KEY WORDS: hydrogeology, landfill, artificial neural networks, MLP, Tychy, Poland

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1. Introduction

Groundwater quality assessment plays a key role in groundwater assessment and protection (Liu et al., 2023). Groundwater quality testing also allows for rational resource management and contributes to a reliable assessment of the susceptibility of groundwater to pollution (Weber et al., 2002; Witkowski et al., 2003; Kabbour et al., 2006; Boderna, 2011; Li et al., 2012; Zhang et al., 2021; Xiao et al., 2021; Turan et al., 2022).

The reliable monitoring of groundwater quality conducted in an area of pollution sources, such as landfill sites, will facilitate a proper assessment of the impact of the facility on the groundwater and will assist in the planning of ways to counteract the negative effects of pollution (Grath et al., 2000; Quevauviller et al., 2009; Dąbrowska et al., 2018). Factors affecting the reliability of groundwater monitoring have been studied for many years (Heron et al., 1998; Mikac et al., 1998; Mato, 1999; Nunes et al., 2004; Lasagna & De Luca, 2016; Maleki et al., 2023).

As part of the research, the selection and location of piezometers, the depth and length of the filtered zone, the sampling technique and their preparation

for analysis, the type and construction of the measurement point were evaluated (NIELSEN, 2005; WITCZAK ET AL., 2013). Due to the possible contact of surface and groundwater, and thus changes in groundwater quality, it is important to determine the factors affecting groundwater quality (KORTASI, 2006; RAJU, 2006; KUMAR ET AL., 2014; MA, 2016; ABANYJE ET AL., 2023).

In addition to factors such as geogenic and natural processes (groundwater velocity, groundwater contact with the rock medium, lithological properties, aquifer linkage) and anthropogenic factors (urbanization, industrial and agricultural activities, waste disposal), atmospheric factors also need to be taken into account (JIANG ET AL., 2009; AMUAH ET AL., 2022). The impact of such factors can of course be considered in the short and long term. Climatic factors, such as precipitation and temperature, affect the hydrological cycle, and this affects the composition of groundwater (ABBAS ET AL., 2016). Extreme climatic events can have significant consequences for water quality in urban areas (KHATAMI & KHAZAEI, 2014; MCGILL ET AL., 2019; SITEK ET AL., 2023). Extreme rainfall and flooding can be key conditions for changes in the amount of groundwater pollution, and mostly such events are monitored and modeled due to significant changes in the relationship between surface water and groundwater (SIMPSON & MEIXNER, 2012), but even in the case of small changes in the amount of e.g., precipitation or temperature, changes in the degree of water pollution can be observed.

The influence of various atmospheric factors and the position of the groundwater table on the degree of pollution can be determined using various statistical methods (ZHANG & CI, 2020). In addition, the potential of machine learning and artificial neural networks can be used to create such models (VERMA ET AL., 2020; POLAP, 2021). The quality of predictive models based on artificial neural networks is determined by their input parameters, model structure and learning algorithm. The article aims to test various architectures of the Multilayer Perceptron network (ALAMEER ET AL., 2019; GUPTA & NIGAM, 2020) using air temperature, precipitation, water temperature and water table depth and their influence on the value of electrolytic conductivity (EC). The EC baseline parameter was used as an indicator to reflect the amount of water mineralization, which primarily depends on the concentration of the main ions.

The study used the data from the sensors installed in the nested piezometer and data from the weather station. The research was carried out in the area of the municipal waste landfill site in Tychy (southern Poland). The test results indicate the existence of a relationship between the analyzed data and give good model parameters.

2. Study area

The research was carried out in the area of an inactive since 1994 municipal waste landfill site located in the eastern part of Tychy, in southern Poland (Fig. 1). Groundwater monitoring of the Quaternary aquifer consists of: P1, P2, P10, P16, P17, P17A, P18, P19 and P19A piezometers (DĄBROWSKA ET AL., 2018a).

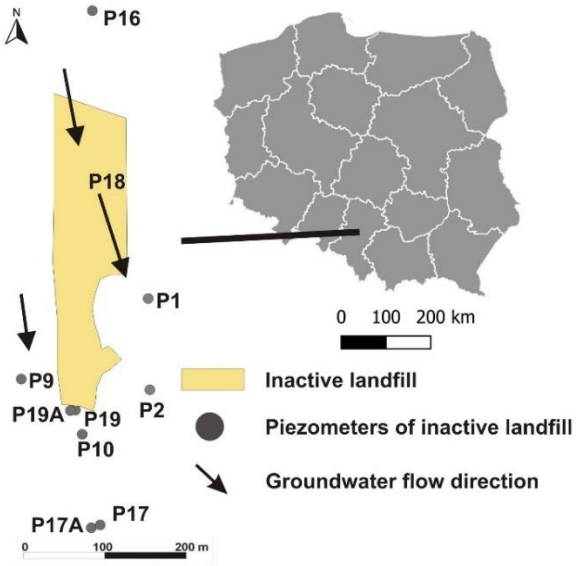


Fig. 1. Study area

The average annual air temperature in this area is 8.1˚C, the lowest temperatures are recorded in January (average 2.4˚C), the highest in July (average 17.8˚C), and the average annual rainfall is 675 mm (WOS, 2010). Precipitation is recorded throughout the year, but most falls in July (about 40% of annual precipitation).

The study area is located in the Upper Silesian Coal Basin, in the vicinity of the Carpathian Foredeep. The geological profile distinguishes Carboniferous, Triassic and Quaternary deposits. Groundwater occurs in this area in three levels: Quaternary (Pleistocene), Triassic (local) and Carboniferous (CZERMIŃSKI ET AL., 1993).

The water table within the Quaternary aquifer is mostly unconfined and, according to the results of the measurements from 2022, it is located at a depth of about 3.1 m in the region of the P17A piezometer and up to about 6.2 m in the region of the P19A piezometer (WITKOWSKI, 2023).

3. Methodology

The study of the impact of atmospheric factors, technical factors of the borehole or the location of

the piezometer against the background of the hydrodynamic system on the obtained results of monitoring measurements allows us to improve the quality of the assessment of the chemical state of the groundwater, especially in the area of pollution sources (WITKOWSKI, 2008). After the removal of the P9 piezometer located at the groundwater outflow from the closed landfill in Tychy, one of the nested piezometers (P19) was selected for testing as a piezometer that may be under the influence of a variable hydrodynamic system in the area of the landfill site in Tychy.

The assessment of the impact of weather data and the height of the groundwater table on the value of specific electrical conductivity (EC) was tested with data from the P19 piezometer capturing the upper part of the aquifer. The results of synoptic research from the nearest weather station in Pszczyna and the results read from the mounted sensor of soil parameters were taken into account. Data collection was carried out from June 29, 2021 to January 26, 2023. Data on the maximum temperature during the day as well as the amount of precipitation were collected from the weather station.

A Levelogger 5 LTC (solinst.com) was installed in the P19 piezometer, which enabled the measurement of conductivity, pressure and temperature. The temperature inside the piezometer, the value of the electrical conductivity and the depth of the water table were used as variables taken from the sensor. The reading from the sensor took place every hour. The sensor was installed at a depth of 8 meters below ground level. In addition, a Barogger 5 was installed, which made it possible to compensate for atmospheric pressure and obtain more reliable results from the Levelogger.

The assessment of the influence of air temperature, precipitation, water temperature inside the borehole and depth of the water table (input variables) on the EC value (output variable) was determined using the Statistica Automatic Neural Networks module (statsoft.pl). Artificial neural networks are an example of an alternative method to standard statistical modeling techniques that are used to solve many environmental problems (JHARIYA ET AL., 2026; CHEN ET AL., 2019; ARABAMERI ET AL., 2020; NGUYEN ET AL., 2020; PANAHI ET AL., 2020;). In the analysis, a model based on the Multilayer Perceptron (MLP) was built. MLP is one of the forms of neural networks with three layers: input, hidden and output (Fig. 2). Outside the input layer, each node is a neuron with a non-linear activation function. By choosing appropriate weights and activation functions, the MLP can approximate any non-linear function. The process of learning and training this network aims to continuously optimize and adjust the connection weight and offset (LEE ET AL., 2017; LEE ET AL., 2018).

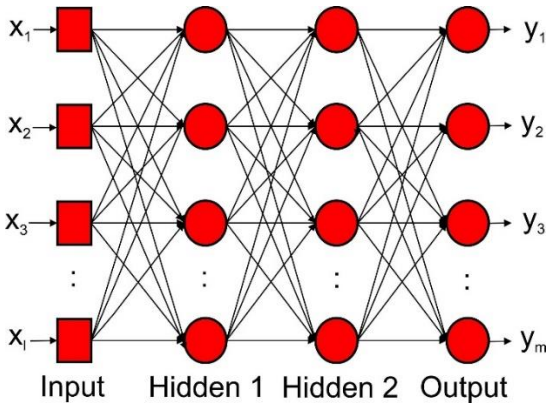


Fig. 2. An example of a neural network architecture

The case file included 13,813 records. The division of cases was divided in such a way that 70% was a training sample, and 15% was a test sample and 15% a validation sample. The division of cases into these three subsets allowed the construction of a properly functioning neural network. The first set was used to teach the network, the second to control the learning process, and the third to verify the results of the work and to choose the best solution (OGRETIM ET AL., 2006; LAPEYRE ET AL., 2019). The sum of squares was chosen as the error function. The error here is calculated as the sum of the squared differences between the set points and the values obtained at the outputs of each output neuron (VENKATESAN & ANITHA, 2006).

As the activation function, i.e. the function to transform the activation level of the unit (neuron) into the output signal, the linear, logistic, hyperbolic and exponential functions were tested (BISHOP, 1995). Activation functions are especially used in an artificial neuron networks to convert the input signal into an output signal which in turn is given as the input to the next layer in the stack (KARLIK & OLGAC, 2011). The accuracy of the neural network prediction depends on the number of layers used and the type of activation function used.

As a learning algorithm, the method of backward error propagation - BFGS (Broyden-Fletcher-Goldfarb-Shanno) was used. This algorithm modified the weights and threshold values of the network to minimize errors made by the network. Within this algorithm, gradient optimization methods were used (DAI, 2002; ANDREI, 2007).

In total, twenty different architectures were tested, which had from four neurons in the input layer and from three to nine neurons in the hidden layer. In the end, the three that gave the best results were kept. Sensitivity analysis was then performed

(SALTELLI, 2005). The sensitivity analysis method answered the question of how the uncertainty of the model output can be attributed to various sources of uncertainty in the model input (SALTELLI ET AL., 2005). The analysis can include a local or global approach. Local sensitivity analysis examines the response of the model's output to a small change in a parameter relative to its nominal value. However, when input parameters have a strong non-linear or coupled effect on the results, local methods may produce unreliable results. Global sensitivity analysis estimates the influence of input parameters across the uncertainty space on model predictions (PIEKUTOWSKA ET AL., 2021).

In Statistica, sensitivity analysis determined the increase in error while eliminating individual variables from the input data. This analysis was accomplished using the error quotient represented by the applied rank. The error ratio expressed the ratio of the error to the total error of all independent variables. If the quotient value for any of the independent variables is less than 1, the variable is removed from the model to improve its quality. A rank value of 1 means that this variable determines the variability of the dependent variable to the greatest extent (NOURANI ET AL., 2012).

4. Results and discussion

The study used data on the depth of the water table (depth), water temperature (temp_in), air temperature (temp_out), electrolytic conductivity (EC) and precipitation (precipitation). Basic statistics on the dataset are presented in Table 1.

Table 1. Basics statistics on the dataset

Variable	N	Mean	Minimum	Maximum	St.dev.
Depth	13813	6.08	6.06	6.51	0.174
Temp_in	13813	10.15	9.59	14.23	0.364
EC	13813	0.58	0.00	0.78	0.086
Temp_out	13813	14.56	-6.30	33.30	9.291
Precipitation	13813	2.22	0.00	62.20	5.438

Electrical conductivity is one of the most frequently measured physical and chemical parameters of groundwater, which is used to indirectly assess the mineralization of these waters. In shallow groundwater that has been exposed to anthropogenic factors, EC values greater than 1000 µS/cm indicate contamination (WITKOWSKI ET AL., 2023). In the case of heavily polluted groundwater in the area of pollution sources, the conductivity values can reach up to 20,000 µS/cm, which gives values comparable to leachates. The monitoring data from the P19 piezometer show that in the measurement series from October 2022, the value of electrical conductivity was equal to 771 µS/cm. At this point, it should be noted that the monitoring data refer to the water after pumping out three volumes of the stagnant water column in the piezometer. However, these data can be compared with data from sensors due to the fact that it has been proven in previous studies that the P19 piezometer water maintains a stable conductivity value during pumping (DĄBROWSKA ET AL., 2018a). The maximum conductivity value recorded by the sensor was 780 µS/cm. This suggests, firstly, that the mounted sensors are working properly, and secondly, that the water in this piezometer are not as polluted as is the case of waters in deeper piezometers. The recorded conductivity values, however, cannot, suggest that these are unpolluted waters. Long-term observations show that due to exceeding the permitted values of total organic carbon, ammonium ions, iron and manganese, these waters should be classified as quality class V on the basis of the Regulation of the Minister of Maritime Economy and Inland Navigation of October 11, 2019 on criteria and method of assessing the status of groundwater bodies (https://isap.sejm.gov.pl/isap.nsf/DocDetails.xsp?id=WDU20190002148).

Evaluation of the quality of the obtained results from sensors and the selection of the best models included the assumption that the validation and testing error was as small as possible, the quality of validation and testing was as high as possible, and that there were no unnecessary input variables.

The first element of the analysis was to determine the relationship between the data. For this purpose, correlation coefficients were determined (Table 2). From the preliminary analysis, it can be seen that the value of the electrolytic conductivity is dependent on all variables. The EC value increased with increasing depth and decreased with decreasing air temperature and with precipitation.

The selection of the best neural network to describe the influence of selected variables on EC value was based on the analysis of the values of basic qualitative measures and error values for the training, validation, and test sets. The overall results for the network were taken into account (Table 3).

Analyzes indicate that for the data used, all selected network architectures show good results. The model errors achieved were very low and the learning quality of all three models was quite high. This study showed that using a multilayer perceptron is comparable for a different architectures for the data from Tychy. The three models show that their predictions were very close. They were also close to the predicted values. Sensitivity analysis was also performed, in order to indicate which of the variables could be rejected for forecasting the EC value and whether removing any of the variables would improve the quality of the model. The results of the sensitivity analysis are presented in Table 4.

Table 2. Correlation coefficients of variables

Variables	Marked correlation coefficients are significant with p < .05000				
	Depth	Temp_in	EC	Temp_out	Precipitation
Depth	1.000	0.014	0.653	0.092	-0.030
Temp_in	0.014	1.000	0.516	-0.850	-0.133
EC	0.653	0.516	1.000	-0.303	-0.084
Temp_out	0.092	-0.850	-0.303	1.000	0.092
Precipitation	-0.030	-0.133	-0.084	0.092	1.000

Table 3. The results of the network performance

Name	Quality (train)	Quality test	Quality (validation)	Error (train)	Error (test)	Error (validation)	Hidden activation	Output activation
4-7-1	0.8424	0.8319	0.8356	0.0011	0.0011	0.0011	Exp	Identity
4-9-1	0.8457	0.8369	0.8413	0.0010	0.0011	0.0011	Identity	Exp
4-7-1	0.8424	0.8335	0.8375	0.0011	0.0011	0.0011	Exp	Exp

Table 4. Sensitivity analysis results

Model	Temp in	Depth	Temp out	Precipitation
1.MLP 4-7-1	4.5731	4.6882	2.3130	1.0432
2.MLP 4-9-1	3.0131	2.4355	1.2440	0.9990
3.MLP 4-7-1	2.5135	2.4792	1.0964	0.9998
Mean value	3.3666	3.2010	1.5512	1.0140

The sensitivity analysis shows that the variable relating to water temperature had the greatest value for the model's efficiency, while the variable determining the amount of precipitation was on the borderline of effectiveness. The most important factor is the one that, if fixed, would lead to the greatest reduction in the uncertainty of the output. The description of these factors is a preliminary step before the calibration of model inputs using some available information.

It has been proven that the EC value prediction model is primarily sensitive to temperature changes. The quotient of the mean square error of the network built without the variable describing the water temperature to the error of the network with all variables ranged from about 4.57 in the case of the first model to about 2.51 in the case of the third model. These analyzes allowed us to show the relationship between the EC value in the waters of this piezometer and atmospheric factors.

Currently, analyzes of climate change are very often performed based on hydrological data (Holman 2006), and take into account such parameters as precipitation and evapotranspiration, snow cover and melting of ice and glaciers, or water content in the soil. Analyzes of changes not only in climate, but also in atmospheric conditions in relation to groundwater are much less frequent (GLEESON ET AL., 2012). This is due to the fact that the relationships between atmospheric parameters and groundwater quality are more complicated. However, models for these relationships should

be developed, not only for water catchments, but also for areas where groundwater pollution sources are located.

Note that for the first network architecture, the depth of the water table factor was the most important. This was confirmed by results of groundwater quality monitoring conducted for about 30 years in the area of municipal waste landfill sites in Tychy-Urbanowice (SITEK ET AL., 2010; DĄBROWSKA ET AL., 2018a; DĄBROWSKA ET AL., 2018b; WITKOWSKI, 2023).

The atmospheric parameters selected for this analysis (precipitation and temperature) are particularly important because they affect groundwater recharge (GREEN ET AL., 2007). Changes in temperature can cause changes in physical, chemical and microbial processes in the subsurface environment, resulting in changes in groundwater quality (CHAPMAN ET AL., 2004; BANKS, 2008; WERNER ET AL., 2009; BONTE ET AL., 2011; GREEN ET AL., 2011; GUNAWARDHANA & KAZAMA, 2012; HÄHNLEIN ET AL., 2013). These relationships were also reflected in the results of the presented models.

Currently, artificial neural networks show great abilities in modeling and forecasting nonlinear time series. The application of this methodology to hydrological and hydrogeological studies gives good matching results (ALTUNKAYNAK, 2007). Depending on the amount of data and their quality, simple models can be extended to more complex architectures.

5. Summary and conclusions

The use of sensors that continuously monitor selected groundwater quality parameters allows for the creation of non-linear forecasting models. This article presented research aimed at finding the structure of an artificial neural network to assess the value of electrical conductivity in water with the P19 piezometer at the Tychy landfill site.

The results obtained from the models has provided grounds for the applicability of artificial neural networks in the case of determining the influence of variables related to temperature, precipitation and the position of the groundwater table on the value of the electrical conductivity of water in the area of the described dump. The obtained error values for neural networks indicated that the models used worked well for the introduced variables.

Research was carried out on the structures of multilayer perceptron neural networks, looking for a solution that would provide the best results. A sensitivity analysis of the input variables was performed. It was found that all adopted input variables affected the result of the neural network operation. All selected neural network architectures were the most sensitive to the value of water temperature and the position of the groundwater table.

As a result of the conducted analyzes, it can be concluded that artificial neural networks should be used when determining changes in selected water quality parameters over time.

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