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Using artificial neural network models to assess water quality in water distribution networks

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Abstract

The purpose of the research is to assess chlorine concentration in WDS using statistical models based on ANN in combination with Monte-Carlo. This approach offers advantages in contrast to the generally use methods for modeling of chlorine decay in drinking water systems until now. The model was tested on one specific location using the hydraulic and water quality parameters such as flow, pH, temperature, etc. The model allows forecasting chlorine concentration at selected nodes of the water supply system. The results obtained in these selected nodes allow then to compare the chlorine concentration with EPANET in the system under assessment.

Keywords: Water Distribution Systems; Chlorine decay; Artificial Neural Networks; Monte Carlo Method

1. Introduction

The purpose of a Water Distribution System (WDS) is to make water available to customers with at least acceptable pressure, flow, continuity and water quality. Water quality can be measure in terms of taste, odor, appearance and chlorine concentration between others parameters. Maintaining water quality through the WDS until the point of consumption is one of the most challenging task faced by the water utility industries (Clement et. al., 2004), taking in consideration the components of the WDS, such as pipe materials, tanks, valves etc. and other risks related to water distribution. Inside the Water Treatment Plant (WTP) there is a combination of processes for

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drinking water treatment. Principal processes of a conventional WTP include; aeration, coagulation, sedimentation, filtration and disinfection. A disinfectant residual should be maintained throughout the distribution system at all times.

Although it is recognized that excessive levels of disinfectant may result in taste and odor problems, it is therefore recommended that a disinfectant residual be maintained and monitored daily throughout the entire system. The most common disinfectant used in water management is chlorine. The concept of Residual Chlorine Concentration is associated with disinfection durability. There is, however, another problem regarding disinfection in a WDS. It is a phenomenon known as chlorine decay; chlorine reacts with other components along the system and its concentration decrease (Castro and Neves, 2003). Knowing the physic-chemical aspects behind chlorine decay is important in order to develop a strategy capable of disinfecting a WDS and at the same time, preserving water quality until the point of use, without using more disinfectant than necessary (Bowden et. al., 2006). The objective of this research is to develop an Artificial Neural Network (ANN) model in combination with Monte Carlo Method that can simulate residual chlorine decay at selected nodes under a special zone of the WDS in the district of Brno-Kohoutovice, Czech Republic, with the advantages of a simple functional form and good accuracy. In addition, it can also be employed to estimate residual chlorine decay in the rest of points inside the network and remark the affected areas in which high or low levels of chlorine are presented in the system by using the computational model EPANET 2.0. The ANN model was developed and tested for the selected pressure zone *1.3.2 Zemní VDJ Kohoutovice.*

2. Methods

Different topologies of feedforward ANNs using the backpropagation learning algorithm were studied to approach the behavior of chlorine decay for varying levels of chlorine residual in several nodes inside the water distribution system of the district of Brno-Kohoutovice, in addition, some physic-chemical input parameters (e.g. pH, Temperature, turbidity and flow) were also assessed as they can affect chlorine decay. The systematic modeling procedure proposed and implemented in this research can be seen in Fig. 1. The main steps for modeling chlorine residual in a WDS using ANN involve: Data preparation, Input selection, Monte Carlo simulation for missing values, Data division and selection of subsets, Model creation, Model calibration and Performance evaluation

Another important step for the creation of ANN models for chlorine decay prediction in a WDS is the creation of the hydraulic model. The hydraulic model was also calibrated in the best possible way since the water quality studies required high level calibration to avoid misleading data or error in the research (Rossman L. 1999). ANN uses historical data for prediction of parameters. When creating ANN models, some data may be missing from the original database. Modelers usually replace the missing data with the average of the sample or simply delete or ignore the complete row, causing the loss of important data. The Monte Carlo (MC) method can be used to generate a database of each parameters affecting chlorine decay in the several nodes studied inside the WDS. Monte Carlo simulation can be performed to fulfill the missing values (if any) in the original database, as it provide flexibility, manage the uncertainty and even provide more accurate results that simple descriptive statistics (e.g. the average value). The objective is to create a big database for each input and output parameter. The results obtained from MC method can be again analyzed with descriptive statistics (average, standard deviation and confidence interval). This analysis can be done again for each input and out parameter of the model.

2.1. Data preparation for ANN models and hydraulic model

Historical data of several parameters that influence chlorine decay should be gathered to be successful in the application of ANN models. Usually utilities measure parameters such as pH, temperature, turbidity, color, manganese, iron, conductivity, e. coli, coliform bacteria etc. Care must be taken in how the data was collected, the format given, the supplier of the data and it must be verified whether the information is current and accurate. Seasons also influence in the value data, so the approach can be taken in two ways. First divide the data for each season and run the study for different seasons as in each season, the variables such as temperature and pH have great changes or the second way, create a big database and run the analysis for all the data available. ANN will find the relationship between the changes, but a big amount of data is required to get better results.

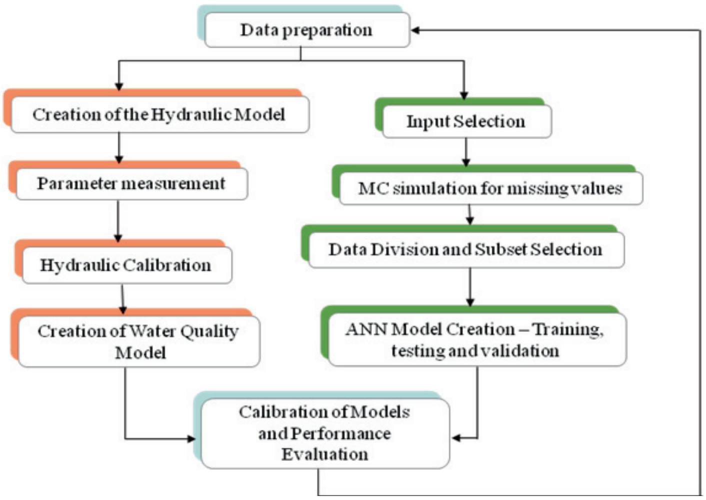


Fig. 1. Modeling methodology

2.2. Selection of inputs and outputs for the ANN model

Successful application of artificial neural network model requires proper input data selection. The better way to choose the inputs for the ANN model is to minimize the size of the network and at the same time maintaining acceptable performance (Lingireddy and Brion, 2005). The better way to choose the inputs in practice is related to two primary considerations:

- Prior knowledge about the process
- Availability and quality of the required data in the training set

Recent studies (Gibbs et. al. 2006, Rao and Alvarruiz, 2007) have shown physic-chemistry parameters such as temperature, pH, turbidity, and natural organic matter (NOM) between other that affect the chlorine decay, also hydraulic parameters as flow, pressure and properties of the pipe line as pipe material, diameter and age of pipes should also take into account as an influence to the chlorine decay.

2.3. Construction of the input database using Monte-Carlo method

Initial Chlorine, pH, pipe roughness, Turbidity between others parameters of the initial conditions of the water distribution system were generated by Monte Carlo simulation technique that requires the use of random number generator. It generates the numbers that follow a normal distribution and uniform distribution depending of the parameter simulated. Generated factors are then to be compared with the actual factor to check the significance of the simulated parameters such as chlorine added to water, pH, flow, turbidity, temperature, etc. For analyzing the factors affecting chlorine decay the general Monte Carlo steps are modified as given below:

- Domain of possible inputs – Varies from minimum to maximum values of Chlorine added to water (initial chlorine), Flow, pH, Temperature, Turbidity, as per historical data received from water utility.
- Random Number Generator – The Software STATISTICA 10 will be used to generate random numbers within the domain.

- Artificial Neural Network – To aggregate the results Artificial Neural Network is plotted in order to calculate the chlorine decay.

An initial simulation was performed starting with the hydraulic parameters followed by the physic-chemical parameters. A normal distribution was follow for the generation of the random number. For the analysis of the measured data, the software Statistica 10 from Statsoft uses a function called Distribution Fitting, this option allows verifying whether the measure values follow a normal distribution and after the confirmation it was run a simulation using the Monte-Carlo Method proposed.

2.4. Creation of the ANN model, division of models into subsets of parameters and performance evaluation

The selection of the ANN type depends on the characteristic of data obtained (Abdi et. al., 1999). To create a database of parameter that can influence chlorine decay the best way is to divide the data into subset and then build several ANN models combining the parameters until find the better results. It is recommended to divide the data depending on the section where the data was gathered. The criteria to divide the parameters into subsets of models are the following:

- Run a preliminary ANN model which includes all the parameters suspected to influence chlorine decay.
- Run a Sensitivity Analysis of each parameter to obtain a better view of the influence weight.
- Based on the sensitivity analysis create a second model with only the parameters that have high influence on chlorine decay.
- Create a third model based on the Initial parameters with high influence in chlorine decay and only those local parameters.
- Continue with a combination of input parameters to compare the model performance.

There are several ways to combine the input parameters. Only the experience and the availability of data can suggest a good combination and provide good performance in the models (Rodriguez and Sérodes, 1998). The ANN model will predict chlorine decay concentration only in few selected points or nodes inside the WDS. The second step is to compare the results from ANN model with the entire system using the computational program EPANET 2.0. The objective of this analysis is to explore the system response to changes during a period of time and to check if there exist some zones affected with high or low among of chlorine. These two computational models (ANN and EPANET) will be weighed against.

3. Results and discussion

The goal is to determine the factors influencing chlorine decay for the case study in the pressure zone of Brno, Kohoutovice. These factors are based on local measurements of residual chlorine. For determining factors affecting chlorine decay in WDS, under different parameter conditions, values of historical data are required. Initial Chlorine, pH, Flow, Temperature and turbidity between other factors are used in this study as input for forecasting chlorine decay in Brno, Kohoutovice - pressure zone, Czech Republic Case Study.

3.1. Case study

City District Brno-Kohoutovice lies approximately 7.3 km west of Brno-center. The water supply system is operated by Brněnské vodárny a kanalizace, a.s. (BVK). The total population in the urban area is 13 338. The Vir Regional water main system (VOV) under reservoir Čebín currently brings the water by gravitation to the Bosonohy tank. From the Bosonohy tank the water is pumped to the tanks Kohoutovice and Myslivna. The drinking water is distributed by gravity to the pressure zone *1.3.2 Zemní VDJ Kohoutovice* (Qh,max = 22,2 L/s) using pipes that ranges from steel, PVC, fiberglass, cast and ductile iron, in diameters as 80, 100 and 300 mm. Bosonohy tank has two chambers and the volume is 6550 m3 with maximum water level of 320 MSL, the water column height is of 6.5 meters. Kohoutovice tank has two chambers and volume is 3000 m3 with maximum water level of 415 MSL, the water column height is of 5 meters.

3.2. Results from the hydraulic model calibration

The hydraulic model for the studied pressure zone inside the water distribution system involved the following steps:

- The base model was taken originally from the General Plan of the 2008 water supplied system, Brno. The model does not contain coordinates.
- Using the software Mike Urban with the export function from the original file GDB, it was created a new file INP and NET that has the possibility to be read by the computational software EPANET 2.0.
- Spatially was allocated customer demands in the network nodes and also it was incorporated two new pumps to pump the water from Bosonohy to Kohoutovice.
- Characteristics as the elevation in nodes, tanks and some valves were already in the base model.
- In the pressure zone 1.3.2 VDJ Zemní Kohoutovice there are connected via pressure reduce valves (PRV) two sub zones: *1.3.2.3 PRV in Kohoutovice-Potocka* and *1.3.2.2 PRV for the down town zone. Settlement Kohoutovice*

The base model had not been properly calibrated but in this study it was performed calibration and quality control review of the resulting model. This model covered only 1 hour in time but the roughness coefficients and demands were already calculated. A quasi-dynamic analysis was performed, i.e. the simulation took place in the time step - in this case was 1 hour time step for two days (48 hrs) using EPANET 2.0. See Fig. 2 (b). The most common parameters to analyze and measure for hydraulic model calibration are; pressure, flow and water level in tanks (Rossman, 1999).

(a) (b)

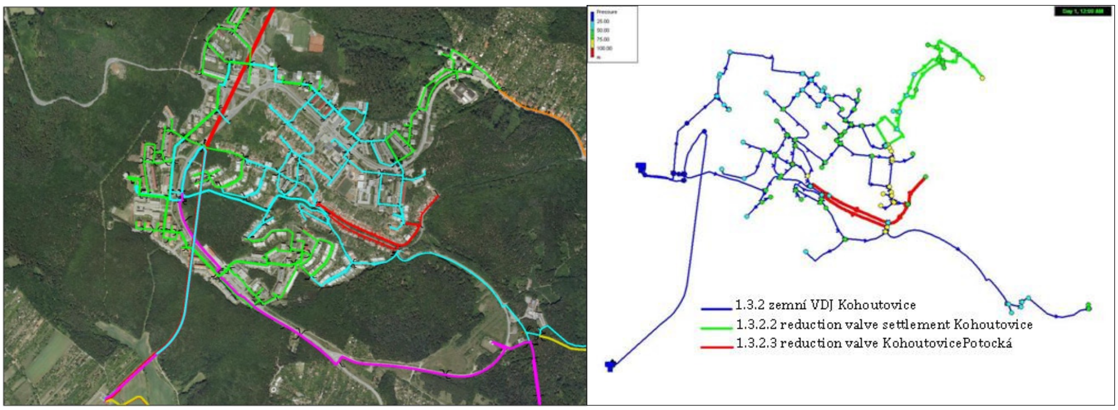


Fig. 2. (a) Water supply scheme, (b) Hydraulic model run in EPANET 2.0

For the model calibration it was used the time series data in tank Bosonohy and the pump station from Bosonohy to Kohoutovice. The data was provided by BVK and it contains out-flow to Kohoutovice distribution network from the tank, water levels in tanks Bosonohy and Kohoutovice, in-flow to Bosonohy tank and pumped water from Bosonohy tank to Kohoutovice tank. For model calibration it was used the measured data obtained by BVK during September and October 2011. The parameters chosen for calibration were flow and water level in Kohoutovice tank, as they are straightforward for measurement and calibration.

The calibration involved adjustments to model input parameters that match best with field observations (Izquierdo, 2004). EPANET 2.0 allows the user to compare results of a simulation against measured field data. This can be done via Time Series plots for selected locations in the network or by special Calibration Reports that consider multiple locations (Vasconcelos and Boulos, 1996).

3.3. ANN model for simulation of residual chlorine concentration

The selected output parameter to be studied in this model is residual chlorine. For the given case, 18 available parameters were used to construct the raw database. In the model for chlorine decay simulation in the pressure zone 1.3.1 Kohoutovice it was choose 15 input parameters and 3 outputs parameters. The model inputs were selected from the available parameters. Input parameters where divided into Initial condition parameters (Initial chlorine in Bosonohy tank, free chlorine in Kohoutovice tank, pH in Kohoutovice tank, temperature in Kohoutovice tank, flow measured at the out flow of Kohoutovice tank and turbidity in Kohoutovice tank) and Local condition parameters (pH node 1, temperature node 1, turbidity node 1, pH node 2, temperature node 2, turbidity node 2, pH node 3, temperature node 3 and turbidity node 3). The Output Parameters are Free Chlorine node 1, Free Chlorine node 2 and Free Chlorine node 3. Chlorine residual was proposed to be simulated in three nodes inside the pressure zone of Brno-Kohoutovice. See Fig. 3. Node 1 represents junction 290172 (street Libusina tr.4) Node 2, junction 291750 (Street Libusino udoli 66) and Node 3 junction 294526 (Street Nad Pisárkami 2).

Nine input parameters were selected and several subsets were constructed for each node by combining the inputs to obtain the best-fitting model and results. See Fig. 4 to check the architecture of the ANN used in modeling chlorine decay for the pressure zone in Kohoutovice.

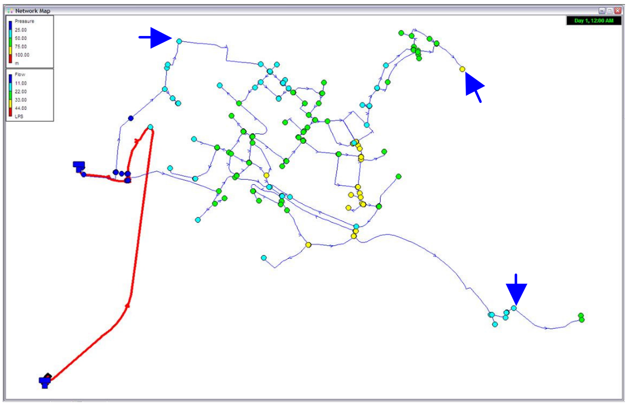


Fig. 3. ANN simulation of residual chlorine in nodes 1, 2 a 3

3.4. Monte-Carlo method for simulation of some input parameters and creation of the ANN model

The original database obtained from BVK for parameters in Kohoutovice Pressure zone 1.3.1 had 667 values for all the parameters including initial condition parameters, local parameters and output parameters. An initial simulation was performed using the historical parameters measured in Kohoutovice pressure zone 1.3.1; Initial Chlorine, pH, Flow, Turbidity, Temperature and residual chlorine in three points inside the pressure zone. A normal distribution was followed to fit the distribution of the data measured and then a MC calculation was run. For the analysis of the measured data the computational software Statistica 10 from Statsoft will be used. Physicochemical parameters show a continuous probability distribution. Normal distribution can be used for each of the parameters to generate the database

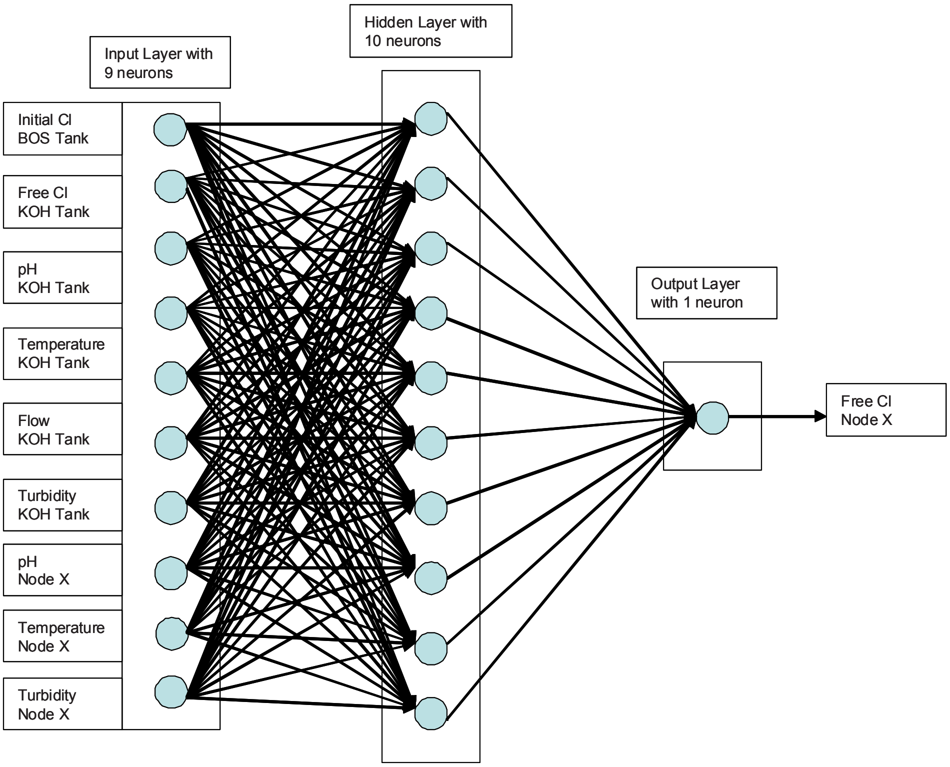


Fig. 4. ANN Structure for residual chlorine modeling

The data set for each parameter were obtained from the data received by BVK and the missing parameters in a row were completed by the Monte Carlo calculations using the Software STATISTICA 10 from Statsoft. The Monte Carlo calculation uncertainty was kept below 2%. Table 1 shows the statistics of the MC calculation for each parameter simulated.

Table 1. Statistics of the parameters calculated by MC method

Parameter	Mean	Standard Dev.	Max.	Min.	Conf. limits for means Interval 95%	
Input Parameter:						
pH Node 1	7,73	0,16	8,11	7,35	7,72	7,74
Temperature (° C) Node 1	18	3	26	9	18	18
Turbidity (NTU) Node 1	1,37	1,04	5,44	0,03	1,34	1,41
pH Node 2	7,60	0,15	7,97	7,29	7,59	7,60
Temperature (° C) Node 2	18	4	22	7	18	19
Turbidity (NTU) Node 2	0,95	0,85	15,66	0,06	0,92	0,98
pH Node 3	7,65	0,07	7,89	7,50	7,65	7,65
Temperature (° C) Node 3	11	2	17	4	11	11
Turbidity (NTU) Node 3	0,69	0,22	2,28	0,46	0,68	0,70
Output Parameter:						
Free Chlorine (mg/l) Node 2	0,0124	0,0063	0,0325	0,0011	0,0122	0,0127
Free Chlorine (mg/l) Node 3	0,0137	0,0089	0,0445	0,0163	0,0134	0,0141

It was then possible to generate ANN model combinations of different input parameters for the three nodes inside the pressure zone. The combination of these parameters for the three nodes inside the pressure zone 1.3.1, produced a data set of 900 input values. The data set composed by these input and output parameters are referred in this work as the training, testing and validation data set. This procedure allows the use of a suitable number of parameters for each model generated with acceptable uncertainties (May et. al., 2008).

Table 2. Details of the seven input subsets (in grey color) selected for the ANN model

Parameter / Input subset #	Node 1			Node 2		Node 3	
	1	2	3	4	5	6	7
Initial Chlorine BOS Tank	■	■	■	■	■	■	■
Free Chlorine KOH Tank	■	■	■	■	■	■	■
pH KOH Tank	■	■		■	■	■	
Temperature KOH Tank	■	■	■	■	■	■	■
Flow KOH Tank	■	■	■	■	■	■	■
Turbidity KOH Tank	■			■		■	
pH Node 1	■						
Temperature Node 1	■		■				
Turbidity Node 1	■						
pH Node 2				■			
Temperature Node 2				■	■		
Turbidity Node 2				■			
pH Node 3						■	
Temperature Node 3						■	■
Turbidity Node 3						■	■
Total	540	300	300	540	360	540	360

The type of ANN model used was the well known Multilayer Perceptron (MLP). The MLP is a feed forward ANN model that maps the sets of input data onto a set of appropriate output (Powell et. al., 2000). The 50% (training) of the data set was used to determine the best configuration of the ANNs and the rest 25% (test) and 25% (Validation) of data set was used to confirm the subsets chosen. After some initial observation it could be noticed that the default learning rate led to a slow reduction in the mean squared error (MSE).

Based on the performance from each model combination it was selected 7 model results of ANN type MLP (Three models for node 1, two models for node 2 and two models for node 3), which performed the best results for each subset of input and output values. See Table 2.

The training, testing and validation results for each of the ANN subset are given in Table 3 (Models 1-7). By the virtue of the MLP architecture, the training set can be predicted to a high level of accuracy. MLP achieved a significantly lower error for the training, testing and validation sets proving that the ANN models are able to find nonlinear relationship between variables.

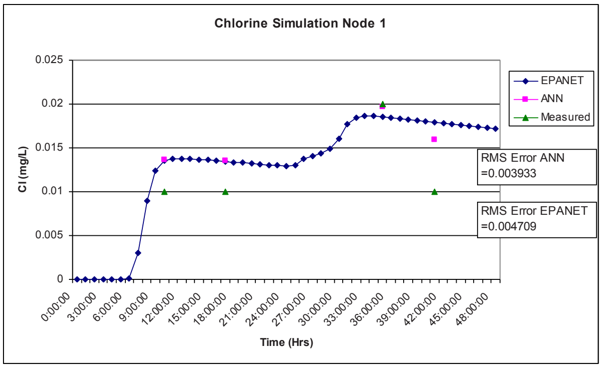
Table 3. Model Performance of each phase of the seven selected parameters

	Subset	Model Type	Training perf.	Testing pef.	Validation perf.
Node 1	1	MLP 9-8-1	0,9343	0,9154	0,9077
	2	MLP 5-5-1	0,8983	0,9083	0,9442
	3	MLP 5-5-1	0,9467	0,9072	0,9284
Node 2	4	MLP 9-8-1	0,9778	0,4072	0,7034
	5	MLP 6-11-1	0,9876	0,4219	0,6672
Node 3	6	MLP 9-9-1	0,9990	0,5338	0,5387
	7	MLP 6-10-1	0,9841	0,4026	0,7811

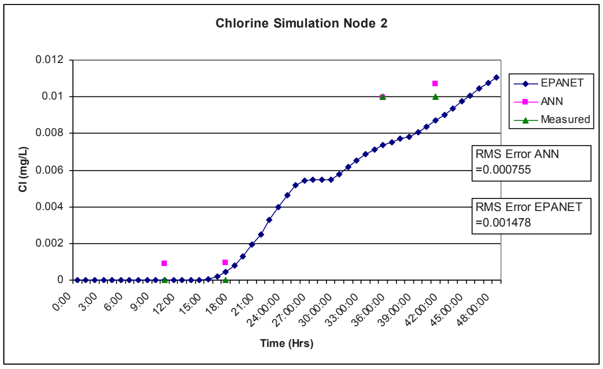
The subset 1, 2 and 3 are those that had attained the lowest values for the mean squared error. A combination of input subsets was chosen to get an overview of the influence of the parameters in the chlorine decay. The three ANN models achieved good and accurate results for the three subsets proposed in Node 1. Subset 4 and 5 correspond to Node 2 where is shown a poor performance in the testing phase (0,4072 and 0,4219) even though the training and validation have better results. The subset 4 was created using all the parameters available that could directly influence chlorine decay. To check which parameters affected the most chlorine at Node 2 it was decided to create subset 5 with more influential parameters including only six inputs the initial condition parameters plus local Temperature at Node 2. The results only increased a bit more in the training and testing while the validation stayed in 0,6672. The subsets 6 and 7 at Node 3 as well achieve varying results from 0,4026 to 0,9990. This behavior must be directly related with the low data availability and it could indicate that different ANNs should be tested for different input subset. Nevertheless the performance values for every network subset in the training data set achieved good and accurate results, showing that the simulated and predicted data are strongly correlated.

Particularly using the Custom Predictions tool in Statistica 10 from statsoft it is possible to predict chlorine in Nodes 1, 2 and 3 with the known conditions of input parameters introducing the values to the ANN model proposed. The data obtained from the ANN can be compared with the results from the EPANET and used as calibration in the three nodes and at the same time providing more reliable results of the final model. Fig. 5 illustrates the forecasting values between ANN prediction and EPANET model compared with the data observed at each selected Node in Kohoutovice pressure zone. The simulated free chlorine concentrations at these select Nodes are in good agreement with the data obtained from ANN models. The models provide practical values by reasonably predicting locations of low chlorine residual and help to establish programs for measurement campaign in the network and residual chlorine assessment including additional parameters such as temperature, turbidity, pH and flow that were not taken into account with the first order simulation by EPANET.

(a)



(b)



(c)

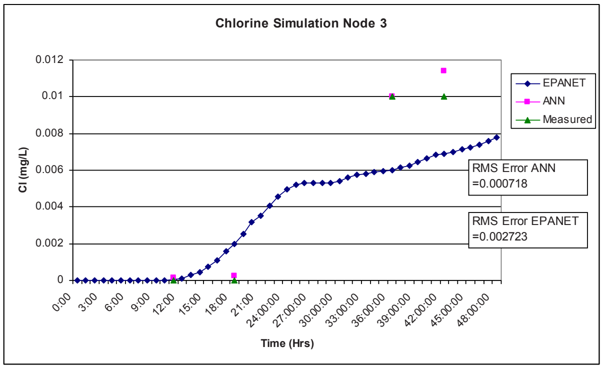


Fig. 5. ANN and EPANET Simulation in (a) node 1; (b) node 2; and (c) node3

4. Conclusion

The use of ANN for evaluation of historical data and chlorine decay prediction was assessed in three points inside the pressure zone in Kohoutovice, Czech Republic. Initial chlorine, pH, flow, turbidity and residual chlorine in three nodes inside the pressure zone were used as dataset in this model. Because prior information is available about some parameters, then this information was used to assess chlorine residual in Nodes 1, 2 and 3. Continual distributions are used to quantify, evaluate and fit these parameters. Basic statistics such as mean, standard deviation and confidence intervals were used for evaluation of these parameters calculated with Monte Carlo method. 3000 readings were generated. The use of the Monte Carlo calculations in combination with artificial neural network have been proven to be a powerful tool to perform chlorine residual prediction in three nodes inside the Kohoutovice pressure zone. Several ANN topologies have responded accurately to the values of the training data set and also to testing and validation data set of value calculated using the MC method. Network topologies (Subset 1) can be fully used to predict the values of chlorine residual concentration in Node 1. Results show that the problem dealt within this paper is indeed very complex because chlorine decay is depending on several parameters such as temperature, pH, turbidity between others. For training the ANN performed was very accurate, even though it could not be achieved the same results in Subsets 4 to 7 in testing and validation phase, as already written in the evaluation of the data obtained section. Therefore, the training data set should be chosen to best represent the expected chlorine residual in the selected Nodes inside the pressure zone Kohoutovice. The present findings suggest that:

- ANNs is capable to predict free chlorine at Kohoutovice pressure zone using historical data and data generated by MC method.
- The key parameters Initial chlorine, flow and temperature have the most influence in the chlorine decay prediction in the pressure zone 1.3.1 Kohoutovice.
  Recommendations for the use of this model are following:
- The present model can only be used for chlorine decay prediction in Kohoutovice pressure zone.
- This methodology can be use to assess chlorine decay behavior in different pressure zones of any water distribution system, following the procedure shown in Fig. 1.
- Creation of a complete database based on the measurements of the parameters affecting chlorine decay in the same places inside the pressure zone.
- Temperature measured in several locations has a high influence in chlorine decay. Ideal calibration should take into account the behavior of chlorine at different temperature values in different season.
- Create a large database which include parameters from all the season and study different model subset for each season.

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