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RESEARCH ARTICLE

Evaluation of the Effects of Measurement Interval on Artificial Neural Network-Based Prediction for Wireless Water Quality Monitoring Network

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Abstract – Water is the essential element of life, and not only its quantity but also the quality is a vital issue. In modern Lebensraum, the quality of water is ensured by the authorities. In this study, an artificial neural network-based water quality prediction system which relies on data collection through a wireless water quality monitoring network is proposed, and the effects of measurement interval on the prediction accuracy are investigated. In the proposed system, water quality parameters are collected at specified time-intervals and fed into the artificial neural network-based prediction system. The proposed system provides authorities a valuable tool to predict groundwater quality and thereby enables the authorities to take immediate actions for ensuring water quality. With a set of experimental studies, the efficiency and accuracy of the proposed system and the effects of measurement interval on the prediction performance are proved.

Index Terms – Artificial Neural Network, Back Propagation, Groundwater Quality, Wireless Water Quality Monitoring Network, Prediction, Measurement Interval.

1. INTRODUCTION

All around the world, authorities develop a set of standards for water quality and accordingly set limits to the highest concentrations of organic/inorganic chemicals, microbial pathogens, and radioactive elements which may affect the safety of water supplied by public water systems [1-3]. As stated by the directives of the European Parliament and the European Council [4], the maximum permissible limit for commonly used water quality parameters are as follows: Dissolved Oxygen (DO): 5 mg/L, Electrical Conductivity (EC): 2.5 mS/cm, pH: 6.5-8.5 units, nitrate: 10-50 mg/L. Typically, assessment of water quality is a two-step process: 1- analysis in the field and 2- analysis at the laboratory [6, 7]. Although it is highly important for the safety of drinking water, this time-consuming process results in delays. Therefore, taking immediate decisions subject to urgent cases is not generally possible. In this respect, continuous water quality monitoring systems play a key role to ascertain the sources of pollutants and contaminants in order to take preventive measures [5-8].

Since effective water quality monitoring is critical for the environmental protection of watercourses and for wastewater treatment, it should be is undertaken to ensure that consented parameters are below the consented concentrations. While, in the past, it was done using water quality sampling methods, in recent years automatic water quality measurement systems

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have become popular since they are seen as the most reliable and timely means of ensuring water quality. In contrast to manual sampling strategies employed by the traditional water quality monitoring approaches, automatic sampling strategies rely on taking periodic or event driven samples from site for analysis. Typically, automatic monitoring systems currently in use continuously monitor on site and record by a data logger and then manually download the results or automatically sent them back to a website or to a central server.

In contrast to the studies in the literature [9-14] which focus on the use of specific machine learning or artificial neural network (ANN) approaches for water quality assessment, this study mainly focuses on evaluating the effects of measurement interval on the accuracy of ANN-based water quality prediction. In this way, it enables the researchers to choose the best measurement interval for their specific needs. In addition, instead of being based on manual data collection methods, it employs automatic data collection via a wireless water quality monitoring network (WWQMN), and this way both speeds up the evaluation process and offers an automated way of predicting water quality.

In this paper, an ANN-based water quality prediction system which collects data through a WWQMN as shown in Figure 1 is proposed and the effects of measurement interval on the accuracy of the proposed system are evaluated.

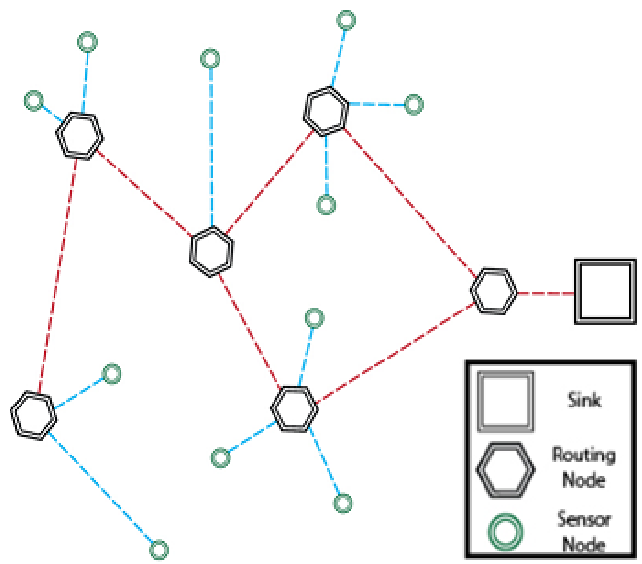

Figure 1 Wireless Water Quality Monitoring Network

The dataset used in the experimental studies was the input of the proposed ANN-based water quality prediction approach and was collected in Edirne, Turkey in May 2015 using off-the-shelf water quality monitoring nodes [15] with wireless interfaces. The nodes formed a WWQMN and sent the collected data to the logging server in real-time [5, 8]. Because of the lack of direct sunlight and unavailability of indoor harvesting almost all the time during the experimental study [16], the measurement interval was set 15 minutes in order to arrange appropriate recharging schedules. Since the batteries of the nodes lasted around 22 days, the batteries were charged every 20 day. In many aspects including rapid assessment, cost-effectiveness, easy-implementation and portability, a WWQMN such as the one used in this study is superior to traditional laboratory-based water quality analyses. The nodes have detachable probes for typical water quality parameters but in this study DO, EC, pH, nitrate, calcium, and temperature probes were used. During the data collection process, the water quality monitoring nodes were placed in a water reservoir found in the basement of an apartment as shown in Figure 2. The water reservoir is directly fed from a water-well without a water treatment system. DO, EC, pH, nitrate, calcium, and temperature values were measured every 15 minutes, and then were fed into the artificial neural network-based prediction system running on the server.

Figure 2 The sensor node used during the data collection process

The rest of the paper is as follows. Section II presents a focused literature survey. Section III explains the approach used in this study. In Section IV, the experimental setup used in this study is presented and the results obtained through a set of performance evaluations carried out using the experimental setup are reported. Finally, the paper is concluded in Section V.

2. RELATED WORK

"Water quality" is a term used to describe the condition of water and includes the water's physical, chemical, and biological characteristics. Since the assessment of water quality based on traditional approaches relies on the collection of water quality parameters at specified time-intervals and takes significant time, the authorities look for alternative approaches

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that can quickly provide the assessments they need. Therefore, in recent years, automatic water quality assessment systems have started to replace the traditional ones. However, although automatic water quality assessment systems provide many benefits over the traditional approaches in terms of timely assessment, accuracy and reliability, reliable and state-of-the art assessment models are needed to predict water quality and reveal possible near future problems. Hence, in recent years, there is a growing interest in the development of automatic water quality assessment systems.

Modelling water quality parameters is a highly important aspect in the analysis of aquatic systems. For appropriate management of water resources, prediction of surface water quality is required so that adequate and rapid measures can be taken to keep pollution levels within permissible limits. Hence, accurate prediction is the key of water resources management.

In the last couple of decades, ANNs were widely employed to model complex and dynamic environmental systems [17-20]. They offer a powerful tool to simulate nonlinear systems and without increasing the mathematical complexity much, they can be coupled with other models to increase the prediction capability. In [21], the training, validation and application of two ANN models for predicting the DO and biochemical oxygen demand levels in the Gomti river in India are presented, and it is shown that the presented ANN models can be successfully used for the computation of water quality parameters. Similarly, since DO concentrations are generally accepted as the primary indicator of stream water quality, in [22] the use of three types of ANN models using different combinations of input variables and input stations to predict the DO concentrations in the River Yamuna in India is presented and it is shown that the predicted values of DO exhibit very high accuracy with correlations up to 0.9 between measured and predicted values.

With their flexible structure that can identify complex nonlinear relationships between input and output data, ANNs have distinct advantages over other classical modelling techniques. To identify the advantages and disadvantages of different modelling methods, linear regression techniques, multilayer ANNs and radial basis function neural network are investigated in [23] and it is proved that radial basis function neural network models can describe the behaviour of water quality parameters better than linear regression techniques and find a solution faster than multilayer ANNs.

It is known that in some countries very high salinity levels may cause serious to water users. In [24] ANNs are used to predict salinity levels in the River Murray in Australia two weeks in advance. The authors prove that the average absolute percentage errors of the independent two-week predictions are between 5.3% and 7.0% and the average absolute percentage error in the real-time simulation is 6.5%.

As abovementioned, the studies in the literature focus on the use of specific machine learning or ANN algorithms for water quality assessments. Contrary to them, we address another important factor, measurement interval, in automatic water quality measurement systems. The contribution of this study is twofold. First, the effect of measurement interval on the accuracy of ANN-based water quality monitoring is analysed. Second, using the methodology and results presented in the paper the practitioners and researchers can choose the best measurement interval based on their specific needs related to the design parameters.

3. ARTIFICIAL NEURAL NETWORK-BASED GROUNDWATER QUALITY PREDICTION

ANNs can be described as a group of statistical learning algorithms inspired by biological neural networks. ANNs consist of simple processing units with an inherent trend for storing experiential knowledge and making it available for use [17-20]. At the beginning, a training pattern is presented to the input layer of the untrained ANN, the signals are passed through the network, and finally the output at the output layer is determined. At the end of each epoch, which can be called iteration, the outputs are compared to the desired values and any difference corresponds to an error. In ANNs, error is some scalar function of the connection weights, and the connection weights are adjusted to reduce the error. The error is at minimum when the network outputs match the target outputs.

The analysis of water resources to determine specific water quality parameters is a complexity problem from some aspects. However, in recent years, ANN-based techniques have already proved successful for water quality monitoring. Especially, when combined with statistics, genetic algorithms, and fuzzy logic, ANNs can automatically find solutions for a wide range of problems without any prior knowledge. With only minimal or no user involvement ANNs can address the issues associated with building robust models from available empirical data. If we analyse input data to identify appropriate transforms, partition the input data into training and test datasets, and select relevant input variables, we can easily construct, train, and optimise an ANN tailored to the target problem.

In the proposed ANN-based prediction approach for water quality prediction, similar to the studies in the literature [9-14], back propagation (BP) ANN and Levenberg-Marquardt algorithm is preferred [25-29]. BP learning uses the gradient descent procedure to train the connection weights. When the input layer of the ANN takes a training pattern, in the hidden layer, the weighted sum of the input to the *j*th node is calculated using Eq. (1) and in the classical BP algorithm Eq. (2) is used to estimate the entire error in the output layer for the *p*th sample pattern, and the error is minimised by means of the weights and biases using gradient descent (Eq. (3)). The structure of the multilayer ANN model is developed in MATLAB [30, 31].

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$$o_j = f(net_j) = f(x)\ then\ \ net_j = \sum_j^i w_{ji} o_i + \theta_j \tag{1}$$

$$E_p = \frac{1}{2} \sum_{j \in out.} (t_{pj} - o_{pj})^2 \tag{2}$$

$$\left.\begin{aligned} \delta_{pj} &= (t_{pj} - o_{pj}) \\ \Delta_p w_{ji} &= -\varepsilon(\frac{\partial E_p}{\partial w_{ji}}) \\ \Delta_p \theta_j &= -\varepsilon(\frac{\partial E_p}{\partial \theta_j}) \end{aligned}\right\} \tag{3}$$

Where i is neuron number, j is layer number, w_{ji} is weight, o_j is neuron output, t_{pj} represents target output, o_{pj} is actual output, δ_{pj} is error value in layer j, net_j is weighted sum, ε is learning rate, and θ_j is bias.

As abovementioned, using Eq. (1) the aggregate input to the neuron can be calculated. The θ_j term represents the weighted value from a bias node, which can be regarded as a pseudo input to each neuron in the hidden layer and the output layer. The aim of using the bias node is to address the problems associated with situations in which the values of an input pattern are zero. When any of the input patterns has zero values, it means that the ANN could not be trained without a bias node. To determine whether a neuron should activate, the net term is passed on to a proper activation function. In this way, the resulting value determines the output of the neuron and becomes the input value for the neurons in the next layer.

4. RESULTS AND DISCUSSION

To satisfy the proposed system's goals, in the training dataset we tried to present every group having its own central tendency toward a particular pattern. We also tried to depict the range of data to the ANN by presenting the entire range of data with noise included and by making it sure that statistical variation is adequately represented. Since the main goal of this study is to evaluate the effects of measurement intervals on the accuracy of the proposed system, we used three different datasets with measurements obtained at different intervals: 60 min, 120 min, and 240 min. 15 rows of the dataset consisting of the measurements are listed in Table I.

We used the datasets obtained at 60, 120 and 240 minutes intervals and tried to address the effect of measurement frequency on the estimation performance. In this study, the dataset had 414 rows for 60 minutes interval, 207 rows for 120 minutes interval, and 104 rows for 240 minutes interval, respectively. Since there is no rule-of-thumb to divide data into training and test sets using specific ratios such as 75:25, 80:20 or 90:10, in this study, for 60 minutes interval, we used 80 rows for testing and 334 rows for training. For 120 minutes interval, 40 rows were used for testing and 167 rows were used for training. For 240 minutes interval, 20 rows were used for testing and 84 rows were used for training. As abovementioned, there is not an ideal ratio between a training set and test set, the choice generally depends on the complexity of the situation, the quantity of the dataset and the number of independent parameters chosen. Traditionally if 5-folders cross validation is used to verify, 80:20 is the typical ratio. Nevertheless, there exist two competing concerns. If less training data is used, the parameter estimates have greater variance. On the other hand, if less testing data is used, the performance statistic will have greater variance. Therefore, the data should be divided such that neither variance is too high. In this study, approximately 80:20 ratio was chosen and nitrate was selected as the output. The predicted and measured values for the output for 60, 120 and 240 minutes intervals by the ANN-based prediction system are shown in Figures 3, 5 and 7, respectively. The performance of the ANN-based prediction system is shown in Figure 4 for 60 minutes measurement interval, in Figure 6 for 120 minutes measurement interval, and in Figure 8 for 240 minutes measurement interval.

It is clear that although the dataset for 240 minutes measurement interval has the least number of measurements, its performance is better than the other measurement intervals in terms of training and performance. Due to the nature of groundwater, water quality does not change drastically. In addition, more data is better up to a point and there is always a risk of over-fitting due to too much training. When the employed dataset is much bigger than necessary and contains a lot of noise, the training must be stopped at a suitable point. In fact, there is really no fixed rule that can be applied to determine the number of training samples for training and it generally depends on the nature of the problem, the number of features, and the complexity of the network architecture.

As it is well known, over-fitting is not caused by optimisation. It generally happens when the employed model is over-complicated and can fit all the data points without learning the actual rule that created them. It can be prevented using a number of ways. The aim should be to optimise the network and make it as accurate as possible, considering those constraints. Since BP ANNs take advantage of what the actual output was supposed to be and adjust the weights in the right direction based on that, they are supposedly much faster than stochastic optimisation techniques, which try completely random changes and ignore that information. Nevertheless, in some cases, Evolutionary Algorithms can do better in the long run by avoiding local optimas, but it takes longer to train them and they have some drawbacks such as algorithm parameters' tuning and computational complexity. Therefore, although ANNs are highly promising, considering the availability of different application scenarios and various requirements, the reliability and accuracy of alternative prediction techniques may be evaluated.

The main drawback of this study is the lack of cross validation. Although not used in this study, cross validation may be highly useful for evaluation purposes, especially when there is no clearly defined train/test data split and there is a desire to calculate statistical significance. In addition, using it more robust model ANN models can be obtained. On the other hand, averaging weights learned during BP can sometimes be useful. It should be noted that in training ANNs some data is often hold out and after each epoch this held out set is tested on. When performance on the set decreases, over-fitting is about to begin and training should be stopped.

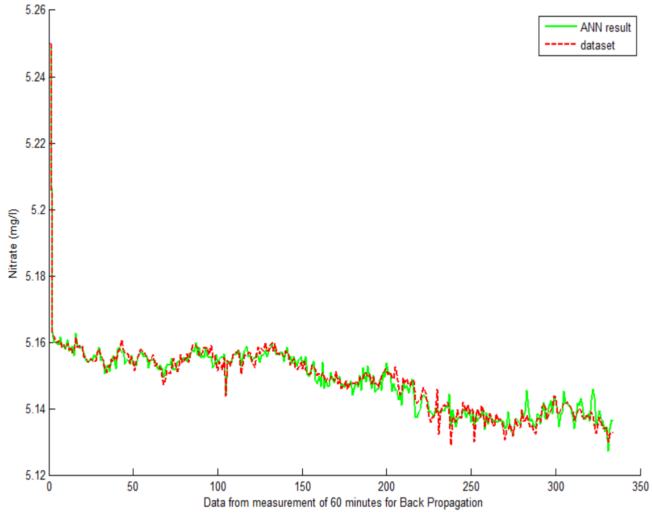

Figure 3 Result of BP neural network for 60 minutes interval

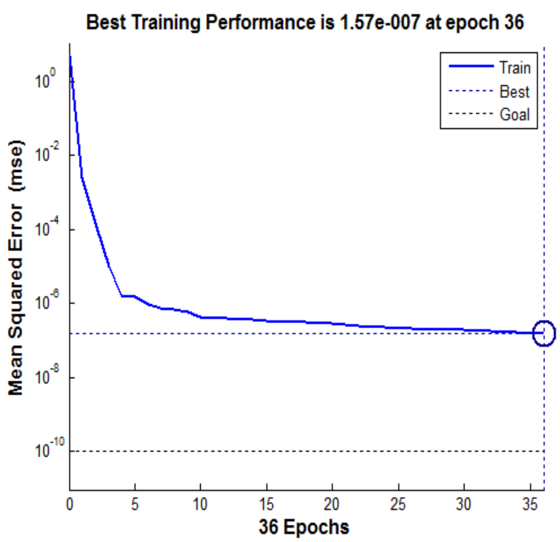

Figure 4 Performance of BP neural network for 60 minutes interval

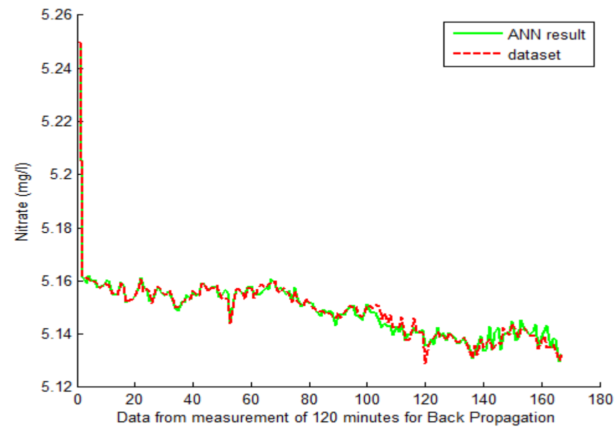

Figure 5 Result of BP Neural Network for 120 minutes interval

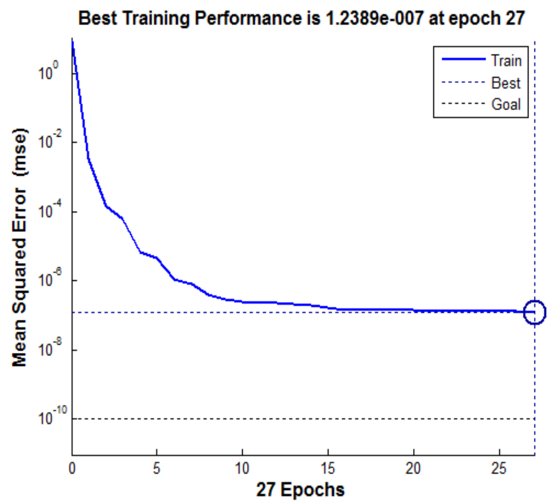

Figure 6 Performance of BP neural network for 120 minutes interval

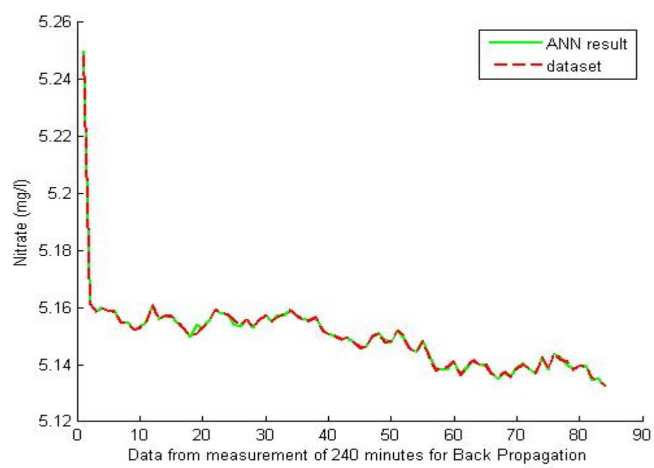

Figure 7 Result of BP neural network for 240 minutes interval

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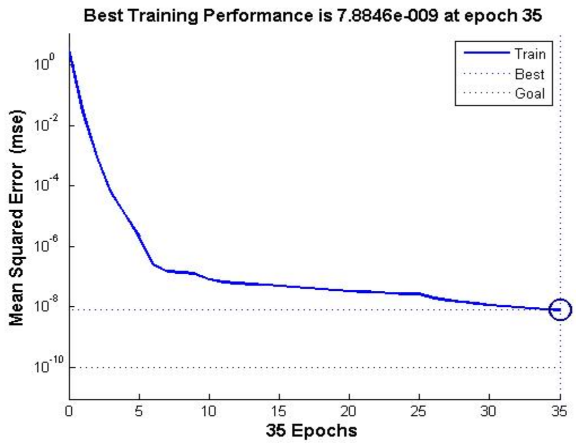

Figure 8 Performance of BP neural network for 240 minutes interval

5. CONCLUSION

Since water is vital for human life, continuous monitoring and analyses of water quality are highly important to ascertain the sources of pollutants and contaminants in order to take preventive arrangements. While authorities assess the quality of water resources through periodical sampling, they do not perform predictions of water quality for future projections.

In this study, an artificial neural network-based water quality prediction system was proposed and the effects of measurement interval on the prediction accuracy were investigated. The proposed system provides real-time water quality data and predicts water quality parameters, and in this way it allows the authorities to take immediate actions for improving groundwater quality. In addition, the results of the experimental study showed that more data is better up to a point but over-fitting resulting from too much training can cause problems.

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