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EVALUATION OF RIVERBANK FILTRATION AS DRINKING WATER TREATMENT PROCESS USING BACK-PROPAGATION TECHNIQUE

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Riverbank filtration (RBF) is a natural process, using alluvial aquifers to remove contaminants and pathogens in river water for the production of drinking water as a low-cost water treatment technology. This study illustrates the development and application of feed-forward back-propagation network (BPN) as a type of artificial neural networks. The BPN prediction results produced good agreement with measured data at a correlation coefficient above 0.98 for filtrate water quality parameters, including temperature as well as turbidity, heterotrophic bacteria, and coliform removal.

KEYWORDS: *Riverbank, filtration, drinking water and back-propagation*

INTRODUCTION

Harmful contaminants often taint drinking water drawn directly from a river, but a low-cost natural filter may lie just beyond the banks. The soil alongside a river can remove dangerous microbes and organic material as water flows through it. The cleaner water is then pumped to the surface through wells drilled a short distance from the river. This technique, called riverbank filtration (RBF, **Fig. 1**), has been used in Europe for more than 100 years to improve the taste and smell of drinking water and to remove some hazardous pollutants such as industrial solvents [1].

During this process most contaminants present in the surface water are filtrated and attenuated. RBF is a highly efficient method for significant removal of turbidity [2]; natural organic matter, pest sides, herbicides, hydro-chemical, and pharmaceuticals [2, 3]; microorganisms [4]; salinity [5] and taste and odor which may not be removed from the surface water by conventional treatment methods [6].

Recently, riverbank filtration is applied in the United States as a treatment technology due to its removal efficiency and cost-effectiveness in drinking water treatment [7]. In riverbank filtration, the physical, chemical, and microbiological qualities of bank filtered water primarily depend on the quality of river water. In a situation where chemical pollution is not serious in river, bank-filtered water can be used directly as drinking water after disinfection. However, if contamination of river is serious due to chemicals discharged from industries, additional treatments are required to achieve drinking water standards. The quality of bank-filtered water is also affected by the riverbed sediment, the aquifer media, the infiltration velocity, and the residence time in the aquifer [8].

The organic compounds discharged from chemical plants and industries are the major contaminants to cause river pollution and subsequently to impact on the quality of the bank-filtered water. In riverbank filtration, the fate and transport of organic contaminants are mainly affected by microbial degradation, sorption to solid matrix, and attachment to colloidal particles.

The effectiveness of RBF for removing surface-water contaminants largely depends on hydrologic conditions, including well type and well location with respect to the river, river water temperature, characteristics of the riverbank material and streambed, riverbed scouring, and raw water source characteristics. Wang et al. [2] reported that at the RBF facility in Louisville, river water infiltration into the well is 10% more during summer than during winter because of decreased water viscosity with increasing water temperature. The results suggest that seasonal variation in water temperature should be considered when evaluating RBF effectiveness.

SETUP AND EVALUATION OF BPN MODEL

An ANN consists of a set of nodes (neurons) organized into (1) an input layer, which receives the input data; (2) one or more hidden layer(s), which process the data; and (3) an output layer, which produces the network output. Many ANN structures have been proposed and explored since the 1950s. Among the most researched and widely used structures in hydrology and water-resource problems are multi-layer feed-forward networks (MFNs) with back-propagation (BP) training algorithms [9]. The present study uses the feed-forward back-propagation network (BPN) to measure the efficiency of the ANN model. The BPN consists of three or more layers. The typical topology is shown in **Fig. 2**. The nodes of one layer are connected to the nodes of another layer with connection weight, but they are not connected to nodes of the same layer. Thus, each node in a layer receives signals from nodes of the previous layer with connection weights, adds the weighted inputs of all nodes, converts the weighted sum into an output signal, and transmits the output signal to the nodes of the following layer.

The connection weights between nodes are optimized using the known input and target values through an iterative process and error-minimization technique, so that the network produces outputs close or equal to the known target values. The process is called training of the network. The trained network with an optimized set of connection weights is then applied to the validation data set to estimate the output. The network where data flow is in one direction is known as the feed-forward network; on the other hand, the network where the error estimated between the target and ANN-predicted values is propagated backward for connection weight optimization is called the feed-forward with back-propagation network. The *newff* subroutine available in the Neural Network Tool box of MATLAB was used to create BPN model [11].

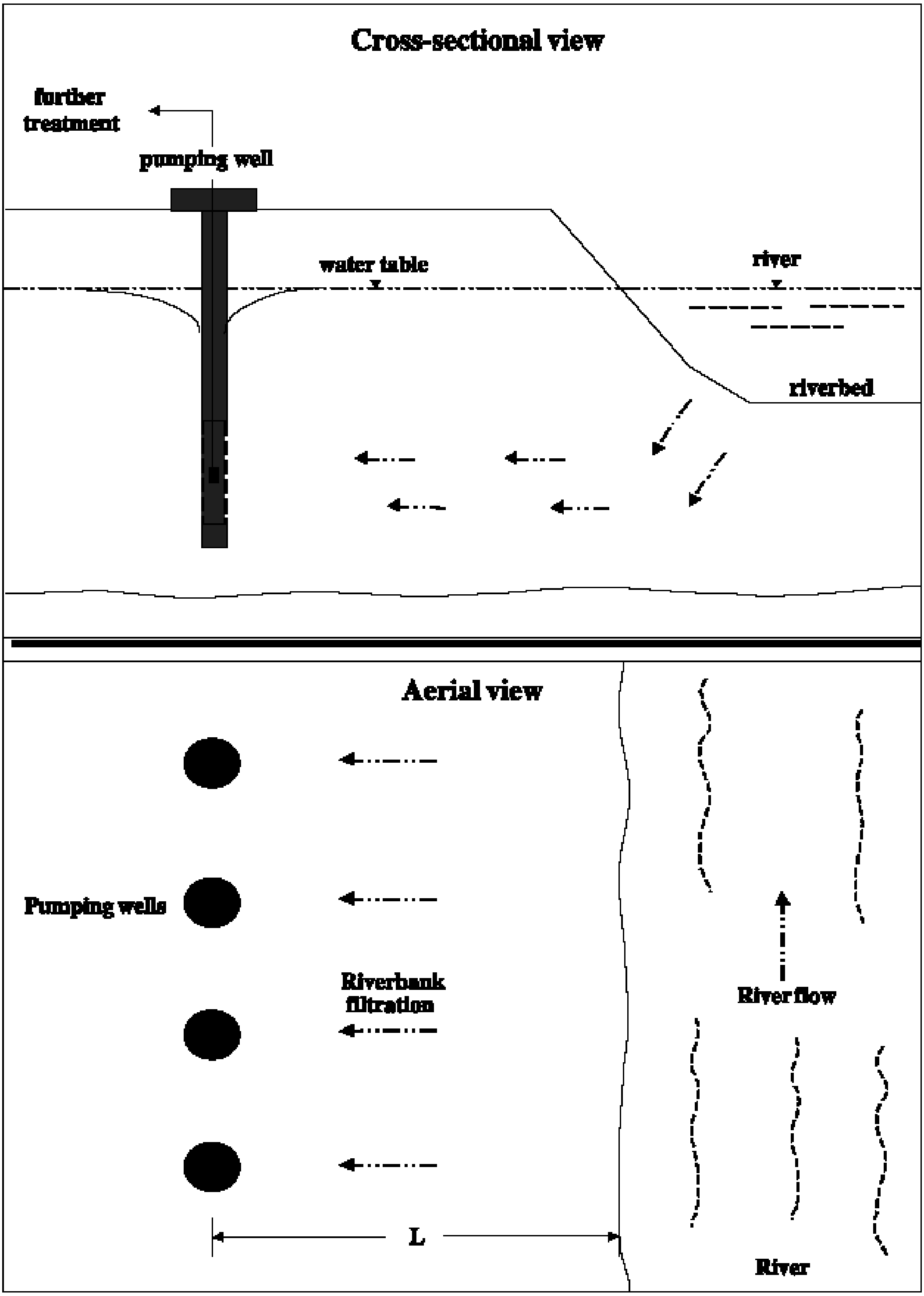

Fig. 1: Schematic drawing of riverbank filtration [10].

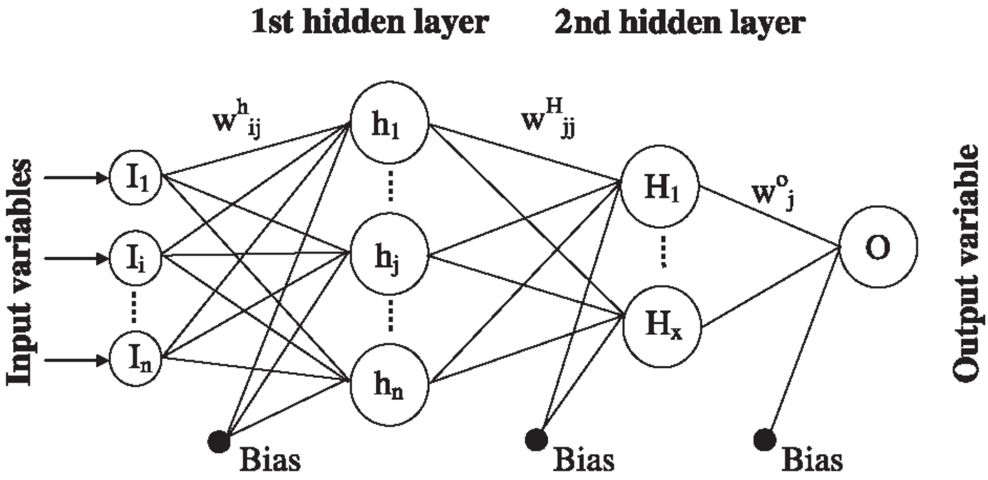

Fig. 2: Schematic diagram of BPN model.

The predictive performances of BPN are measured by four efficiency terms: the correlation coefficient (R); the mean error (ME), i.e., the systematic difference between the predicted and measured values; the mean square error (MSE); and the root mean square error (RMSE). The ANN responses are more precise if R, MSE, RMSE, and ME are found to be close to 1, 0, 0, and 0, respectively. In the present study, MSE is used in the network-training phase, whereas R, RMSE, and ME are used in the network-testing phase. A value of 10^{-8} is used as the threshold MSE for the training phase. The training is conducted iteratively until the network MSE decreases to the threshold MSE value.

INPUT AND OUTPUT OF BPN MODEL

In this study, a data from RBF database published by Wang et al. [2] was used to test the objective of this paper. In that database, daily observations of water flow, temperature, turbidity, heterotrophic bacteria (referred to as HPC) and coliform count for the Ohio River are available. Also, daily observations of temperature, turbidity removal, HPC removal and coliform removal for the well are available. The database is prepared by the Lousville Water Company (LWC). By using the river date, well data could predict using the ANN model and for each element want to predict, one or more element used as input data as in **Table 1**.

Table 1. Input parameters of the BPN model and the predicted output results.

Input parameters (for river)	Output results (for well)
Water temperature for the last four days	Water temperature
Water flow and turbidity for the last four days	turbidity removal
Water flow and coliform for the last four days	Coliform removal
Water flow and HPC for the last four days	HPC removal

Despite numerous studies, no systematic approach has been developed so far for the optimal division of data for the training and validation sets for ANN models [12]. However, training and validation sets must be representatives of the same population [13]. Having too few samples in the training set will lead to poor generalization by the network. Schaap and Leij [14] showed that 35–37% of the data can be in the validation set and the rest can be in the training set. Note that training and validation data sets are independent of each other.

RESULTS AND DISCUSSION

Sahoo et al [15] reported that a rise in river flow causes a corresponding rise in river turbidity. A similar trend is visible for HPC and coliform. It is clear from these study that, increased concentrations of turbidity, HPC, coliform are positively correlated with the flow in the river. They stated that, the effectiveness of the RBF facility for filtering each water quality parameter at the well should be estimated from the corresponding river water quality parameter and flow.

The BPN-estimated temperature, HPC, log coliform removal, and turbidity were compared against the respective measured values of the LWC RBF facilities in **Fig. 3**. The prediction performance efficiencies (i.e., R, RMSE, and ME) are shown in this figure. BPN performed well in predicting the filtrate temperature, heterotrophic bacterial counts, turbidity content, and coliform removal (**Fig. 3**). The BPN predictions for turbidity, HPC removal and coliform removal were nearly identical, each with an R value close to 1.0. The predicted temperature of the filtrate is fairly good (R = 0.989).

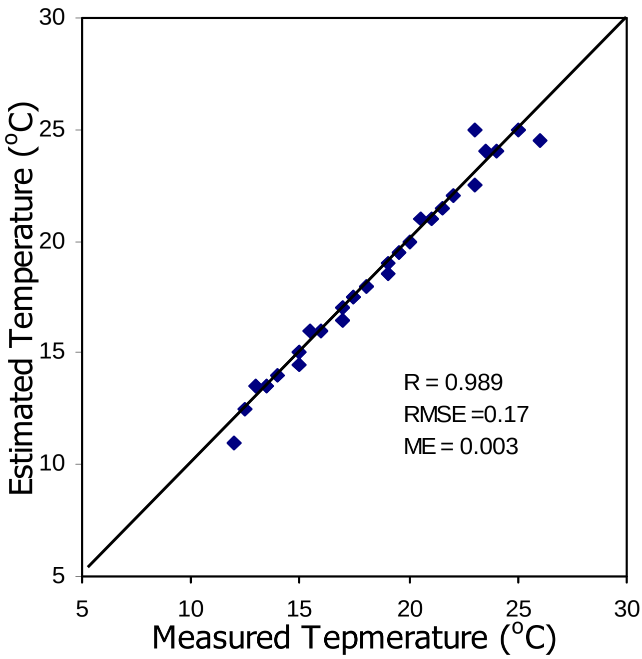

Fig. 3.a: Comparison between measured and estimated temperature of water.

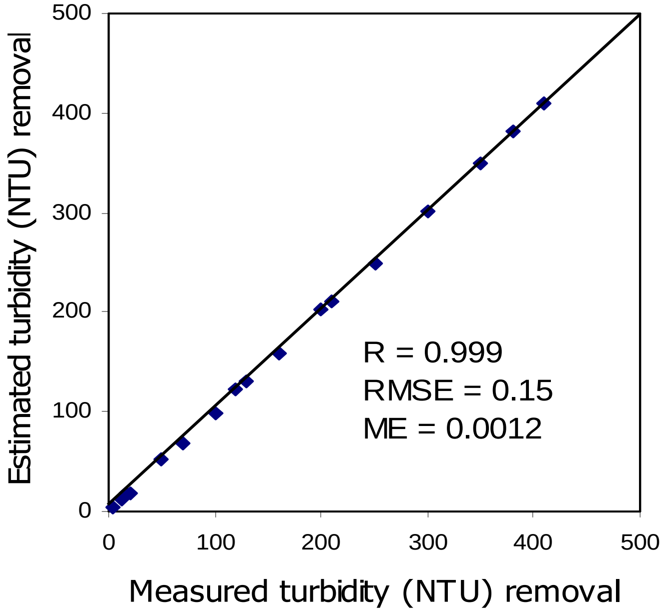

Fig. 3.b: Comparison between measured and estimated turbidity removal from water.

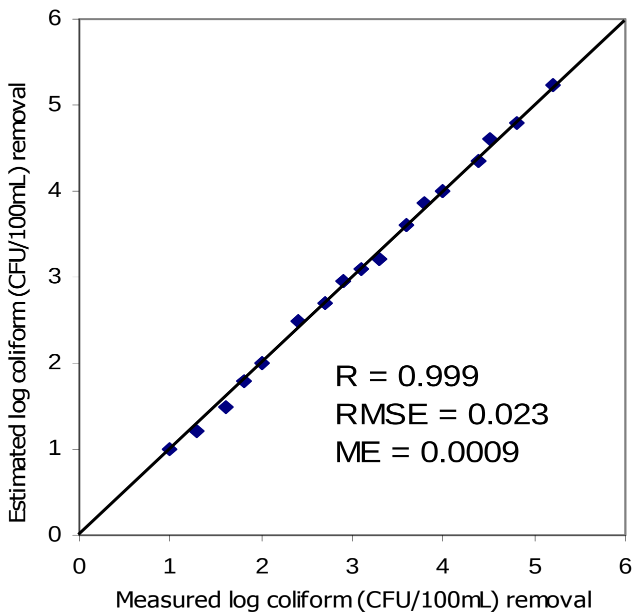

Fig. 3.c: Comparison between measured and estimated log coliform removal from water.

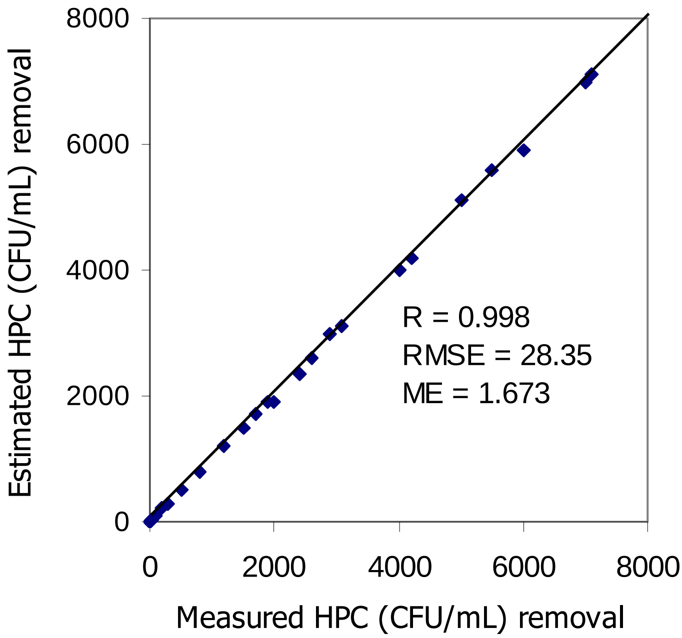

Fig. 3.d: Comparison between measured and estimated HPC removal from water.

CONCLUSIONS

This study examined the potential application of BPN to predict the filtrate water quality parameters, including temperature, turbidity, coliform and HPC removal at RBF facility. The BPN model prediction results produced good agreement with measured data at correlation coefficient above 0.98 for all cases. It is clear that BPN is capable of predicting the efficacy of an RBF facility.

In the absence of detailed underlying physics expressed explicitly in mathematical equations for the development of a mathematical model and due to the lack of detailed time series data to calibrate and validate the mechanistic model, BPN is found to be viable alternatives for evaluating the efficacy of an RBF facility to predict the trend of well water quality parameters. Although BPN model is not a substitute for a mathematical model, it was found to be promising in predicting filtrate water quality. However, BPN model is empirical and do not has the ability to explain the underlying physics of the system because it produce results (effects) from the set of input parameters that cause the effects.

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تقييم طريقة الترشيح عبر ضفة النهركطريقة لمعالجة مياه الشرب باستخدام تقنية التقدم الخلفى

ترشيح المياه المستخدمة في الشرب باستخدام ضفة النهر أو المجرى المائي هي عملية طبيعية وذلك بمرور المياه من المجرى السطحي المفتوح إلى الآبار المجاورة لضفة هدا المجرى. أثناء مرور المياه خلال تربة الضفة يتم إزالة الملوثات والبكتريا والفيروسات وتعتبر هده الطريقة رخيصة التكاليف إذا ما قورنت بالطرق التقليدية لتنقية المياه. في هدا البحث تم استخدام تقنية التقدم الخلفي **(back-propagation)** لاستنتاج ومعرفة كفاءة هدا النوع من الترشيح. تم استنتاج أن تطبيق هذه التقنية أعطى توافق جيد **(Good agreement)** بين القيم المقاسة والقيم المناظرة لها من درجات الحرارة والعكارة وكذلك كمية البكتريا المزالة حيث أن كل قيم معامل الارتباط **(Correlation Coefficient)** لم يقل عن 0.98 لكل عامل من عوامل التلوث المرصودة