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An artificial neural network model for the effects of chicken manure on ground water

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ABSTRACT

In the areas where broiler industry is located, poultry manure from chicken farms could be a major source of ground water pollution, and this may have extensive effects particularly when the farms use nearby ground water as their fresh water supply. Therefore the prediction the extent of this pollution, either from rigorous mathematical diffusion modeling or from the perspective of experimental data evaluation bears importance. In this work, we have investigated modeling of the effects of chicken manure on ground water by artificial neural networks. An ANN model was developed to predict the total coliform in the ground water well in poultry farms. The back-propagation algorithm was employed for training and testing the network, and the Levenberg–Marquardt algorithm was utilized for optimization. The MATLAB 7.0 environment with Neural Network Toolbox was used for coding. Given the associated input parameters such as the number of chickens, type of manure pool management and depth of well, the model estimates the possible amount of total coliform in the wells to a satisfactory degree. Therefore it is expected to be of help in future for estimating the ground water pollution resulting from chicken farms.

1. Introduction

Chicken farms, amounting to nearly 400, widely exist in the province of Corum and have become an important source of ground water pollution in the area. In these farms the manure is transferred by means of pressurized water to the manure pool. In the course of this transfer and following operations, chicken manure penetrates into the ground water by runoff, flooding and diffusion. Furthermore farms get their water supply from 20 to 90 m deep wells.

For predicting the degree of pollution for major pollutant constituents in ground water wells in poultry farms, one approach could be the identification of an input–output relationship between the involved variables based on the field measurements. From this perspective, artificial neural networks (ANNs) are powerful tools that have the abilities to recognize underlying complex relationships from input–output data only [1]. ANN models have been widely used tools in the field of water quality prediction [2–6]. An artificial neural network is an information processing system that imitates the behavior of a human brain by emulating the operations and connectivity of biological neurons [7]. It performs a human-like reasoning, learns the attitude and stores the relationship of the processes on the basis of a representative data set that already exists. In general, the neural networks do not need much of a detailed description or formulation of the underlying process, and thus appeal to practicing engineers who tend to rely on their own data [1].

1.1. ANN modeling

Depending on the structure of the network, usually a series of connecting neuron weights are adjusted in order to fit a series of inputs to another series of known outputs [1]. When the weight of a particular neuron is updated it is said that the neuron is learning. The training is the process that neural network learns. The adaptability, reliability and robustness of an ANN depend upon the source, range, quantity and quality of the data set.

The feed forward neural networks consist of three or more layers of nodes: one input layer, one output layer and one or more hidden layers. The input vector passed to the network is directly passed to the node activation output of input layer without any computation. One or more hidden layers of nodes between input and output layers provide additional computations. Then the output layer generates the mapping output vector. Each of the hidden and output layers has a set of connections, with a corresponding strength-weight, between itself and each node of preceding layer.

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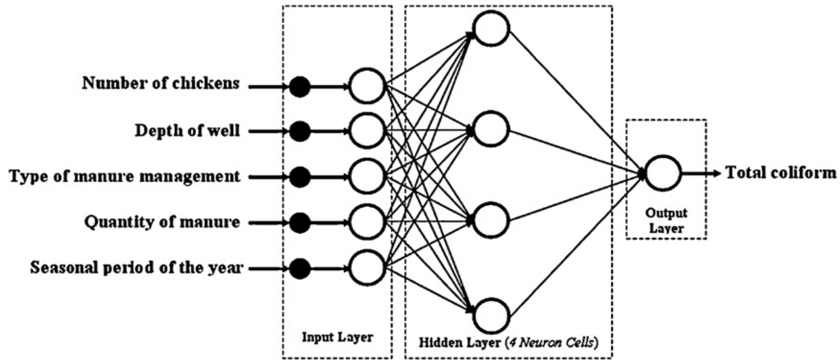

Fig. 1. ANN architecture.

Such structure of a network is called a multi-layer perceptron (MLP) [1].

A feed-forward back-propagation artificial neural network (BPNN) is chosen in the present study since it is the most prevalent and generalized neural network currently in use, and straightforward to implement. Fig. 1 illustrates the basic configuration of the network model. Each interconnection in the model has a scalar weight associated with it, which modifies the strength of the signal. The function of the neuron is to sum the weighted inputs to the neuron and pass the summation through a non-linear transfer function. In addition, a bias can also be used, which is another neuron parameter that is summed with the neuron s weighted inputs. Back-propagation refers to the way the training is implemented and involves using a generalized delta rule [1]. A learning rate parameter influences the rate of weight and bias adjustment, and is the basis of the back-propagation algorithm [8]. The set of input data is propagated through the network to give a prediction of the output. The error in the prediction is used to systematically update the weights based upon gradient information [9].

The network is trained by altering the weights until the error between the training data outputs and the network predicted outputs is small enough. There are many back-propagation training algorithms available. The choice of algorithm depends on the type of problem and may require experimentation of different algorithms. The algorithms have different computation and storage requirements, and train data at different speeds [10]. The goal of selection is to efficiently and accurately train the network while keeping the speed of training relatively fast.

After generating sets of training patterns, appropriate NN architecture and associated parameters must be chosen for the particular application. The main design parameters are the number of hidden layers, number of neurons in each layer, and the neuron processing functions. The choice of these parameters will depend on the complexity of the system being modeled and they will affect the accuracy of the model. If the number of hidden neurons is too high, the network may over fit the data. On the other side if the number of hidden neurons is small, network may not have sufficient degrees of freedom to learn the process correctly [11]. There is no exact guide for the choice of the numbers. The architecture of most ANN model is designed by trial and error [12].

In this work, we have investigated the modeling of the effects of chicken manure on ground water by artificial neural networks. An ANN model was developed for predicting the total coliform in the ground water well in poultry farms. The back-propagation algorithm was applied to training and testing the network. Levenberg–Marquardt algorithm [13] was used for optimization. The model holds promise for use in future in order to predict the degree of ground water pollution from nearby chicken farms.

2. Methods and materials

2.1. Experimental

In this study 20 chicken farms, comprising a chicken population of 10 000–40 000 and a manure quantity between 2.4 and 7.0 tons/day, were picked from the area. Geographical coordinates, types, design capacity, operation capacity of the farms; geographic features of the land, depth of well, distance to the Derincay river, ways and capacity of manure stocking, number of chicken and feeding type were followed during a period of 8 months at 5 different times. Water samples were taken from the wells, and pH, electrical conductivity, salinity, total dissolved solid, turbidity, nitrite nitrogen, nitrate nitrogen, ammonia nitrogen, organic nitrogen, total phosphor, total hardness and total coliform analysis were performed. The analysis results were in the range of 0.5–5.2 mg NO_3-N/L, 0.02–3.90 mg NH_3-N/L, 0.51–1.89 mg total PO_4/L, 481.0–1852.0 mg/L total dissolved solid, 93–1100 MPN (most probable number)/100 mL total coliform.

2.2. Modeling procedure

An artificial neural network (ANN) model was constructed by using the experimental observations as the input set in order to identify the possible effects of chicken manure resulting from the farms on the ground water. A three-layered feed forward and back propagation algorithm with 5 neurons in the first layer, 4 neurons in the interim layer and 1 neuron in the last was chosen. The network had one input layer, one hidden layer and one output layer as represented in Fig. 1.

The output of a neuron can be defined as:

$$\text{out} = f(m) \tag{1}$$

where

$$m = \sum_{i=1}^{N} w_i x_i + b \tag{2}$$

where x_i and w_i are the input signals and the weights of neuron, respectively. b is the bias, $f(.)$ is the activation function.

The most common used activation functions in configuration of ANNs are sigmoid and linear functions:

$$\text{Linear transfer function}\,(\mathit{purelin}) : f(m) = m$$

$$\text{Log-Sigmoik transfer function}\,(\text{log}\mathit{sig}) : f(m) = \frac{1}{1 + e^{-m}}$$

$$\text{Hyperbolic tangent sigmoid transfer functions}\,(\mathit{tansig}) : f(m)$$

Table 1
The training parameters.

Parameters	Properties
The number of layers	3
Network configuration	5-4-1
Transfer function	*tansig, logsig, purelin*
Learning rate	0.1
Training algorithm	Levenberg–Marquardt
Epochs	500
Training pattern	60
Testing pattern	20

$$= \frac{2}{1+e^{-2m}} - 1$$

logsig function produces outputs in the range of 0 to 1, *tansig* function produces outputs in the range of −1 to +1 and *purelin* function produces outputs in the range of $-\infty$ to $+\infty$ [14].

A transfer function determines the relationship between inputs and outputs of a neuron and a network. Selection of transfer function for layers is an important parameter. The best structure of transfer functions is evaluated on the basis of mean square error (MSE) of the training data set. In this work, the optimum configuration is achieved by using *purelin* transfer function in output layer and using *tansig* and *logsig* in hidden layer. The first layer has five hyperbolic tangent sigmoid neurons, the second layer has four logsigmoid neurons and last layer has one linear neuron. In the course of training, which was based on Levenberg–Marquardt method, the number of secret layers, the number of neurons in the hidden layer, training accuracy and number of iterations were determined by trial and error. Levenberg–Marquardt algorithm is similar to the quasi Newton method in which a simplified form of the second derivative is used. Hessian matrix can be approximated as:

$$H = H^T J \tag{3}$$

and the gradient can be calculated as:

$$g = J^T e \tag{4}$$

where J is the Jacobian matrix, The Jacobian matrix can be computed with a back propagation method. The Levenberg–Marquardt algorithm uses this approach to the Hessian matrix in Eq. (5):

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{5}$$

where μ is the learning rate and I is the identity matrix. When the μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size.

The learning rate (lr) multiplies the negative of the gradient to determine the changes to the weights and biases. If the learning rate is set too high, the algorithm become unstable and, if the learning rate is too small, the algorithm will take too long to converge. It is not practical to determine the optimal setting for the learning rate before training and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface [10].

The learning parameters of the proposed ANN structure are given in Table 1.

The ANN model consists of five input nodes corresponding to

(a) Number of chickens
(b) Depth of well
(c) Type of manure management
(d) Quantity of manure
(e) Seasonal period of the year

The single output was the total coliform concentration in the system (MPN). Thus a three layer feed-forward neural network was chosen for modeling purposes. In the hidden layer, four hidden neurons were used. For training, the classical back-propagation algorithm was employed. Activation functions used were logarithmic sigmoid and tangent sigmoid. Fig. 2 illustrates the progress of a typical training session for proposed network structure. Performance function (MSE) value is calculated about 0.01 for 500 epochs.

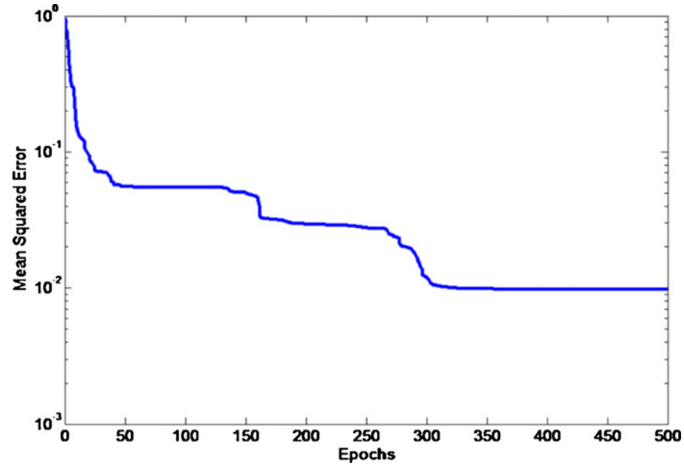

Fig. 2. Performance function evaluation for network training.

A data set including 80 data samples. The available set of data was divided into two sections randomly; a training set and a testing set which consisted of 60 and 20 data, respectively. Basic statistics of the measured data is presented in Table 2. The performance function was the sum of the squares of the difference between ANN output and laboratory analysis results. The network was trained for 500 epochs. The computation was performed in MATLAB 7.0 (Mathworks, 2003) environment.

3. Results and discussion

The model developed in this study aims at assessing the effects of chicken manure on the level of pollution in ground water. Thus the model was created by considering the total coliform concentration in the chicken manure on ground water as the output variable.

For development of neural network models the Neural Network Toolbox 4 and MATLAB 7.0 [15] were used. A MATLAB script was written, which loaded the data file, trained and validated the network and saved the model architecture. The input data (which was composed of the number of chickens in the farm considered, depth of well where the measurements were taken, type of manure management, quantity of manure and seasonal period of the year) and output data were normalized and de-normalized before and after the actual application in the network. The model was trained for input–output behavior of the system, whose results are shown in Fig. 3. The behavior of the network for the test data is reflected in the following Fig. 4. As can be detected from Fig. 4, the network model captures the general trend in the output. The ANN has been shown to provide prediction results according to statistical parameter values (R and MAPE).

Two statistical performance criteria, MAPE (mean absolute percent error) and R(correlation coefficient), were calculated for

Table 2
Basic statistics of the input and output variables.

Variable	Min	Max	Mean	SD
The number of chickens	10000.0	40000.0	19150.0	9007.9
Depth of well (m)	15.0	90.0	32.2	15.1
Management type of manure pool	1.0	9.0	3.9	2.1
The quantity of manure (ton/day)	0.16	7.0	3.1	1.8
The seasonal period of the year	3.0	12.0	5.6	3.3
Total coliform (MPN/100 ml)	93.0	1100.0	456.1	379.7

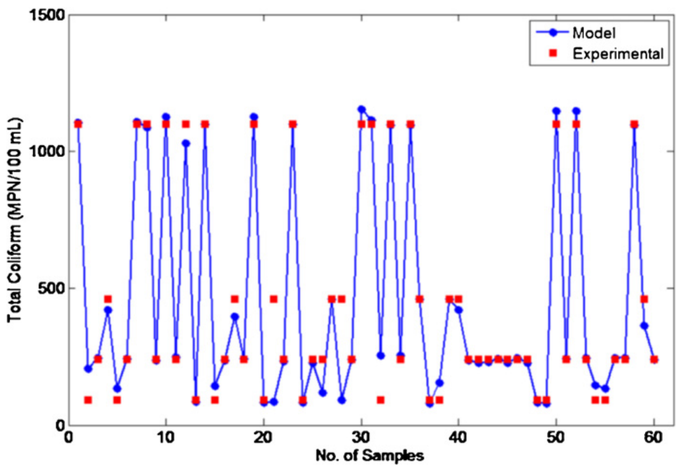

Fig. 3. ANN model for learning data.

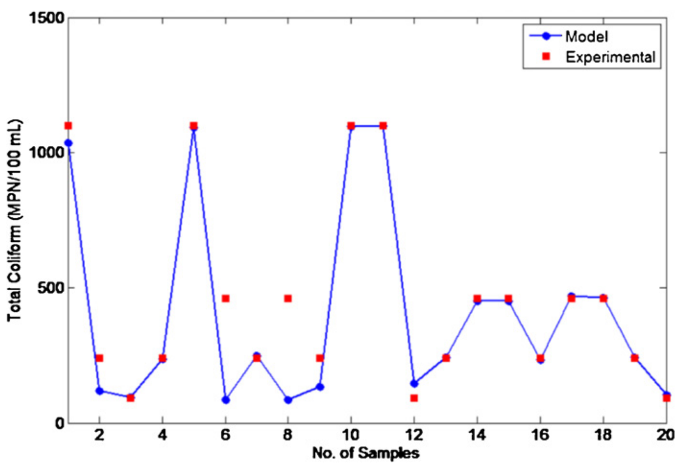

Fig. 4. ANN model for test data.

Table 3
Statistical parameters of the ANN used for prediction of total coliform.

Performance	Training phase	Testing phase
Correlation coefficient, *R*	0.98	0.95
MAPE (%)	0.072	0.387

assessing the network performance (Table 3). Correlation coefficients calculated for training and testing of network were 0.98 and 0.95, respectively. MAPE values were found as 0.072% and 0.387%. As magnitudes of both errors were quite small for prediction of total coliform, this was considered as an indication of a reliably performing model.

4. Conclusions

An artificial neural network model for the estimation of total coliform in the ground water was examined by comparing the modeling results with the observed total coliform values. The developed ANN model predicts the possible amount of total coliform in the ground water well in poultry farms, when the number of chickens, depth of well, management type of manure pool, the quantity of manure and the month of the year are given. Encouraged by the results, the model is expected to be of use in future for predicting the degree of ground water pollution from nearby chicken farms.

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