ARTIFICIAL NEURAL NETWORK MODELING OF SALTWATER UPCONING

Ferenc Szidarovszky, Department of Systems and Industrial Engineering, University of Arizona, Tucson, Arizona 85721-0020 U.S.A., szidar@sie.arizona.edu.
Emery A. Coppola Jr., NOAH, L.L.C., 610 Lawrence Road, Lawrenceville, New Jersey 08648 U.S.A
Charles F. McLane, McLane Environmental L.L.C.,707 Alexander Road, Suite 206, Princeton, New Jersey 08540-6331 U.S.A.
Mary M.Poulton, Department of Mining and Geological Engineering, University of Arizona, Tucson, Arizona, 85721-0012 U.S.A.
Robin D. Magelky, McLane Environmental L.L.C., 707 Alexander Road, Suite 206, Princeton, New Jersey 08540-6331 U.S.A.

ABSTRACT

Salt-water upconing and intrusion into freshwater groundwater systems can result in serious water quality problems, affecting potable supplies in coastal areas around the world. In this study, artificial neural networks (ANNs) were developed to accurately predict highly time-variable specific conductance values in a real-world unconfined coastal aquifer. Unlike physical-based models, which require hydrologic parameter inputs, such as horizontal and vertical hydraulic conductivities and porosity, ANNs can “learn” system behavior from easily measurable variables. In this study, the ANN input predictor variables were the initial specific conductance (a measure of dissolved ions) measured at a monitor well, total precipitation, mean daily temperature, and total pumping extraction. The ANNs predicted conductance at a single monitoring well located near a high capacity municipal-supply well over time periods ranging from 30-days to several years. Model accuracy was compared against measured/interpolated values and predictions made with linear regression (LR), and in general, achieved excellent prediction accuracy. The ANNs were also used to conduct a sensitivity analysis that quantified the importance of each of the four predictor variables on final conductance values, providing valuable insights into the dynamics of the system. The results demonstrate that the ANN technology can serve as a powerful and accurate prediction and management tool, minimizing degradation of ground-water quality to the extent possible by identifying appropriate pumping policies under variable groundwater system and weather conditions.

INTRODUCTION

Effective ground-water management often requires models that can accurately predict system responses under spatially and temporally variable conditions like climate and pumping. In coastal areas where populations are increasing rapidly, a critical ground-water management issue is degradation of water quality due to saltwater upconing and/or intrusion. These phenomena are caused primarily by excessive ground-water pumping withdrawals which change the natural dynamic equilibrium between the freshwater-saltwater interface, allowing saltwater containing high concentrations of dissolved ions to migrate upward and/or inland, contaminating portions of the fresh ground-water supply.

Accurate prediction and management models can delay if not eliminate the need for expensive mitigation measures, and may even prevent loss of an irreplaceable ground-water resource. There are, however, significant challenges in developing a ground-water model with limited field data that is capable of making accurate predictions in both space and time (Anderson and Woessner, 1992; Coppola et al., 2003). Typically, modeling the physical flow conditions of a real-world ground-water system is inherently difficult because of the complexity and variability of natural systems (Gelhar, 1993). Modeling and accurately predicting movement of the brackish zone and freshwater-saltwater interface under conditions of variable density flow can be even more difficult. For all their importance, these conditions are difficult and expensive to field-characterize (Voss and Souza, 1987), and computationally intensive, thereby constraining efforts to accurately simulate the transport phenomena with a physical-based model.

As an alternative "learning" modeling paradigm, artificial neural networks (ANNs) do not require explicit representation of the physical laws and conditions governing the system behavior of interest. Instead, the ANN obtains a complex mathematical relationship that predicts outputs, constituting the system behavior of interest, in response to predictor input variables (Poulton, 2001). This functional mapping is done in a manner analogous to human learning, where observation data is processed through its internal architecture in an effort to learn relationships between cause and effect variables. Thus, for this ground-water quality prediction problem, the need to represent relatively complex processes with physical-based equations, as well as quantify aquifer properties and boundary conditions, many of which may be highly variable over space and/or time, is virtually eliminated.

In this study, ANN predictive capability to accurately predict conductance in the vicinity of a municipal supply well in a coastal aquifer is compared against linear regression and measured/interpolated conductance values. The ANNs were also used to conduct sensitivity analyses which quantified important cause and effect relationships, increasing system understanding. Overall, the ANN modeling approach achieved excellent prediction capability and provided valuable insights into system dynamics, demonstrating strong potential for appropriately managing vulnerable groundwater resources in coastal areas.

STUDY AREA

The study area is located within the Pamet Lens, a freshwater lens aquifer on the northern tip of the Cape Cod, Massachusetts peninsula. Figure 1 show both the general site location and a cross-section of the study aquifer, which is unconfined, and consists predominantly of coarser glacial sand and gravel outwash deposits, interbedded with silt and clay. Overpumping of a municipal well (Test Site No. 4 Production Well) from the late 1970's to mid 1980's resulted in saltwater upconing, which was monitored via conductance levels measured in nearby observation well TSW-235.

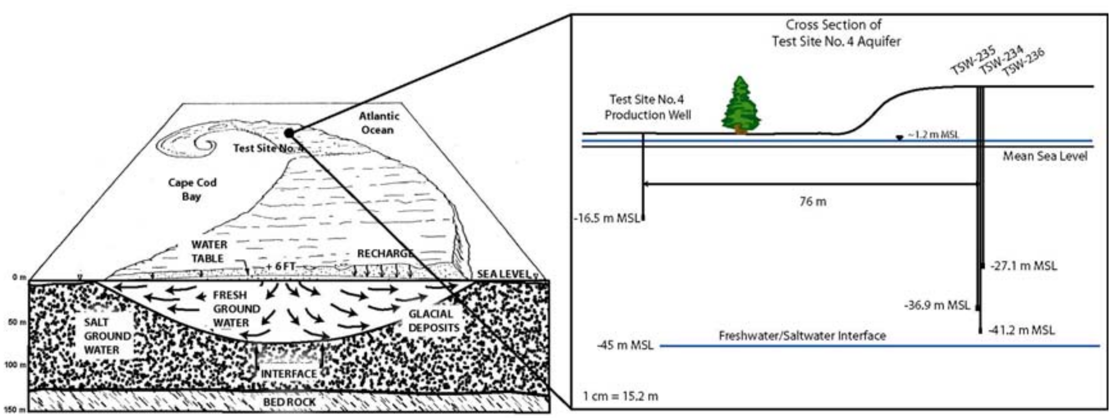

FIGURE 1. The study area and aquifer cross-section in both regional and local view

MODELING APPROACH AND RESULTS

For this ground-water management problem, three different prediction periods consisting of 30, 60, and 90 days were initially used, with a separate ANN trained and tested for each of these three prediction periods. The ANN inputs were initial conductance measured at beginning of prediction period, mean daily temperature, total precipitation, and total groundwater pumping extraction over pumping period. The single ANN output was the conductance value at the conclusion of the prediction period, measured in microsiemens/cm. The daily data set used for ANN development and validation spanned the period from June 1, 1981 to January 31, 1985.

As a benchmark for ANN performance, linear regression (LR) was also conducted on the data sets, and a comparison in predictive accuracy between the two methods is shown in Table 1.

TABLE 1. Mean Absolute Error Achieved with ANN and Linear Regression for All Data

Prediction Period (days)	ANN	LR
30	61.8	148.5
60	67.6	168.9
90	25.4	99.7

Note: Model conductance error values in units of μS/cm.

Figure 2 is a representative figure comparing the ANN against the linear regression for the 90-day prediction period. As shown by Table 1 and Figure 2, both models achieved excellent performance, but the ANN consistently outperformed LR.

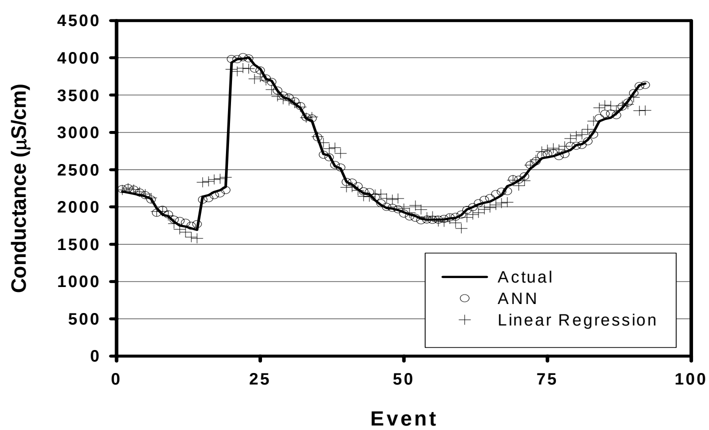

FIGURE 2. ANN and linear regression versus measured/interpolated conductance values for the 90-day prediction period

To further test the ANN approach, an extended period simulation was conducted, where both models were used to predict conductance values over 46 consecutive months. As shown by Figure 3, unlike LR, the ANN model achieved excellent predictive accuracy, and was able to accurately predict conductance values based upon pumping and climate conditions several years into the future, demonstrating that ANN is not limited to serving as only a real-time groundwater management tool, but can be also employed as a longer-term forecasting model.

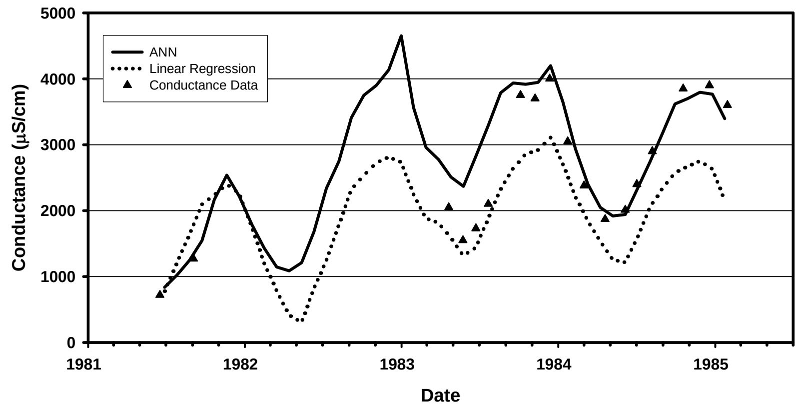

FIGURE 3. ANN versus Linear Regression over the multi-year prediction period

SENSITIVITY ANALYSIS

A sensitivity analysis was conducted to assess the interrelationships between the input predictor variables and the output variable conductance in order to foster a deeper and more complete understanding of aquifer system behavior.

The sensitivity analysis results obtained from the data used to validate the ANNs are presented in Table 2 for the 30-, 60-, and 90-day prediction periods.

TABLE 2. Sensitivity Matrix for ANN Prediction Periods (Validation Data Set)

	Initial Conductance	Total Ground Water Extraction	Mean Temperature	Total Precipitation
Importance Rank	1	2	3	4
30-Day RMSE Ratio	13.3	5.8	3.6	1.3
60-Day RMSE Ratio	10.2	5.1	2.7	2.1
90-Day RMSE Ratio	25.5	17.6	14.4	4.9

Note: Units are in µS/cm.

Sensitivity analyses quantify and rank the importance of each of the four input variables by examining the change in root mean squared error (RMSE) if the particular input variable is eliminated. For example, for the 30-day prediction period, eliminating the total monthly precipitation input variable nominally increases the RMSE for the validation data set by a factor of 1.3 (i.e. RMSE ratio), which ranks this predictor variable as the least important (4); in comparison, eliminating the initial conductance input variable increases the RMSE during validation by a factor of 13.3, ranking this variable as the most important predictor (i.e. 1).

The relative importance (ranking) of the four prediction variables remains the same for all three prediction periods. Generally, all four predictor variables become significantly more important for accurately predicting final conductance levels over the 90-day prediction period, as reflected by the increasing RMSE ratio values. For the three source/sink terms (i.e. precipitation, temperature, and pumping extraction), this is likely due to an increased correlation between these variables and conductance levels over longer-periods. For example, during the summer season, characterized by higher temperatures, pumping extraction increases to meet greater consumer demand, increasing conductance levels. There is a natural temporal correlation, therefore, between temperature and pumping extraction, which becomes stronger over 90-day periods, and both variables correlate strongly with conductance levels. In addition to correlating with pumping extraction, temperature also strongly influences evapotranspiration rates and soil-moisture deficits, which, in combination with precipitation, determine recharge rates. Recharge rates affect ground water levels, which in turn influences conductance levels. Over the longer 90-day prediction period, precipitation or lack thereof would be expected to have a relatively larger effect on ground water levels, again influencing conductance levels. By contrast, over relatively shorter periods, precipitation is not expected to have as much of an effect on ground water levels due to the relatively high specific yield value (0.25) of the aquifer. There is likely some correlation between precipitation and pumping extraction, but over the relatively long time periods considered, it does not appear to be important. Collectively, the three source/sink variables have an implicit relationship with ground water level changes, which in accordance with the well known Ghyben-Herzberg relation, induces vertical displacements of the brackish zone and freshwater-saltwater interface, which affects conductance levels.

CONCLUSIONS

ANN technology was used to accurately predict conductance values due to vertical displacements in the brackish zone and saltwater-freshwater interface in a freshwater lens aquifer in response to variable pumping and climate conditions. The results were compared against both linear regression and measured/interpolated values. In addition, the ANN models were used to conduct important sensitivity analyses to increase system understanding.

The ANN approach provides a number of advantages over linear regression and physical modeling approaches. First, as non-linear behavior becomes more pronounced, such as at the pumping well, or under higher groundwater extraction conditions, the discrepancy between the ANN approach and other models (i.e. linear regression and linearized approximate analytical solutions) is expected to increase. Second, as the hydrogeology becomes more complex, with greater heterogeneity and/or less “ideal“ environments (e.g. fractured rock, limestone, etc.), the assumptions of analytical and standard numerical models become less appropriate, which is further exacerbated by the uncertainty regarding model parameter inputs. Accordingly, the ANN would again be expected to provide superior real-time predictions.

This type of real-time prediction and management system can help the operator identify appropriate pumping extractions that meet expected demand requirements, but do not pose an unacceptable risk to water quality conditions or the environment in the long-term. As water demand increases in coastal areas and water supplies diminish, this type of forecasting and management tool will likely prove to be of great benefit in many areas around the world.

A more extensive overview of the site history, its hydrogeology, and the ANN modeling with more detailed results can be found in the work of Coppola et al. (2005).

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