Conjunctive Use of Surface and Groundwater Resources with Emphasis on Water Quality

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Abstract
In this paper, a methodology for conjunctive use of surface and groundwater resources with emphasis on water quality is developed using Genetic Algorithms (GAs) and the Artificial Neural Networks (ANNs). Water supply with acceptable quality, reduction of pumping costs, and controlling the groundwater table fluctuations are considered in the objective function of the model. In the proposed methodology, the results of a groundwater simulation model are used to train the ANNs based simulation model. This model is then linked to the GA based optimization model to develop the monthly conjunctive use operating policies. The proposed model is applied to the surface and groundwater allocation in the irrigation networks in the southern part of Tehran, the capital city of Iran. Tehran metropolitan area has annual domestic water consumption close to one billion cubic meters. The sewer system is mainly consisted of the traditional absorption wells. Some part of this sewage is drained into local rivers and drainage channels and partially contaminates the surface runoff and local flows. These polluted surface waters are used in conjunction with groundwater for irrigation purposes in the Southern part of the Tehran. The results of the proposed model show the significance of an integrated and systems approach to surface and groundwater resources allocation in the study area. For example, the cumulative groundwater table variations in each zone, which has experienced a total fluctuation of more than ±20 meters in the last 20 years, is limited to ±5 meters over the planning horizon

Keywords: Conjunctive Use, Artificial Neural Network, Genetic Algorithms, Groundwater Modeling, Water Quality

Introduction
Many investigators such as Maddock (1974); Onta et al. (1991); Yeh (1992); Fredericks et al. (1998); Loaiciga and Leipnik (2001); and Karamouz et al. (2004a, b) have used the systems approach and mathematical models in conjunctive surface and groundwater management. Most of the previous studies, presents the application of classical optimization models in conjunctive use planning. They also usually
consider the simplified groundwater equations due to the computational burden of the problem. This paper deals with the development and application of an optimization and simulation models for analyzing regional water resources issues. In this paper, the PMWIN (Processing Modflow for Windows, developed by Chiang and Kinzelbach, 2001) model simulates the groundwater quantity and quality and then the groundwater response equations are explicitly developed by training a selected ANN. The proposed model is applied for conjunctive use of surface and groundwater resources considering the water quality in the southern part of Tehran. Considering the number of decision variables and the complexity of the system, a GA based optimization model is used to develop monthly operating policies.

Model Framework

The main objectives of the conjunctive use models are usually as follows:

- Water supply to the agricultural demands
- Improving the quality of allocated water
- Minimizing the pumping costs
- Controlling the groundwater table fluctuations

The model formulation for a 15-year planning horizon is as follows:

\[
\text{Minimize } \sum_{i=1}^{4} \alpha_i Z_i \\
\text{Subject to :}
\]

\[
Z_1 = \begin{cases} 0 & \text{if } D_{imy} \leq Q_{imy} + G_{imy} \quad i = 1, \ldots, n \quad m = 1, \ldots, 12 \\
\sum_{i=1}^{n} \sum_{y=1}^{15} \sum_{m=1}^{12} \left( (D_{imy} - Q_{imy} - G_{imy}) / D_{imy} \right) \left( n \times 15 \times 12 \right) & \text{otherwise}
\end{cases}
\]

\[
Z_2 = \sum_{i=1}^{n} \sum_{y=1}^{15} \sum_{m=1}^{12} \left( G_{imy} \cdot H_{imy} / \left( (G_{imy} \cdot H_{imy})_{\text{max}} \right) \right) \left( n \times 15 \times 12 \right)
\]

\[
Z_3 = \left( \sum_{i=1}^{n} \sum_{y=1}^{15} \sum_{m=1}^{12} \Delta L_{imy} / \Delta L_{\text{max}} \right) / n
\]

\[
Z_4 = \left( \sum_{i=1}^{n} \sum_{y=1}^{15} \sum_{m=1}^{12} C_{imy} / c_{\text{max}} \right) / n
\]

\[
\Delta L_{imy} \leq \Delta L_{\text{max}} \quad y = 1, \ldots, 15 \quad m = 1, \ldots, 12
\]

\[
RD_{imy} = R_{imy} - Q_{imy}
\]

\[
\sum_{i=1}^{2} RD_{imy} \geq E_{my, \text{min}}
\]

\[
\sum_{i=1}^{4} \alpha_i = 1
\]

\[
Q_{imy} \leq R_{imy} \quad i = 1, \ldots, n \quad y = 1, \ldots, 15 \quad m = 1, \ldots, 12
\]

\[
\Delta L_{imy} = f(\bar{G}_{my}, \bar{O}_{my}, \bar{M}_{my})
\]
\[ \Delta C_{imy} = f' (\tilde{G}_{my}, \tilde{O}_{my}, \tilde{M}_{my}, c_{my} ) \]  

(7)

Where:

- \( G_{imy} \): The volume of groundwater extracted in the agriculture zone \( i \) in month \( m \) of year \( y \) (\( m^3 / \text{day} \))
- \( Q_{imy} \): The volume of surface water allocated to agriculture zone \( i \) in month \( m \) of year \( y \) (\( m^3 / \text{day} \))
- \( C_{imy} \): The average concentration of the water quality indicator in the allocated water to agriculture zone \( i \) in month \( m \) of year \( y \) (mg/L)
- \( c_{imy} \): The average concentration of the water quality indicator in the return flow to agriculture zone \( i \) in month \( m \) of year \( y \) (mg/L)
- \( D_{imy} \): Agricultural water demand in zone \( i \) in month \( m \) of year \( y \) (\( m^3 / \text{day} \))
- \( \Delta L_{imy} \): Variation of the groundwater table level in month \( m \) of year \( y \) in the agriculture zone \( i \) (m) (draw down is considered to be negative).
- \( \Delta L_{\text{max}} \): Maximum allowable cumulative groundwater table fluctuation (m)
- \( C_{\text{max}} \): Maximum allowable concentration of water quality variable in allocated water (mg/L)
- \( G_{im} \): The volume of groundwater extracted in the agriculture zone \( i \) in month \( m \) (\( m^3 / \text{day} \))
- \( H_{imy} \): The groundwater table level in agriculture zone \( i \) in month \( m \) in year \( y \)
- \( (G_{im} \times H_{im})_{\text{max}} \): Maximum value of \( (G_{im} \times H_{im}) \) in different years
- \( R_{imy} \): Surface water flow rate in zone \( i \) in month \( m \) of year \( y \)
- \( E_{my,\text{min}} \): Environment water demand in month \( m \) of year \( y \)
- \( RD_{imy} \): Unused Surface water in zone \( i \) in month \( m \) of year \( y \)
- \( Z_1 \): Loss function of water allocation
- \( Z_2 \): Loss function of pumping cost
- \( Z_3 \): Loss function of groundwater table fluctuation
- \( Z_4 \): Loss function of the quality of allocated water
- \( \alpha_i \): Relative weight of the objective function \( i \)
- \( m \): Number of months in the planning horizon
- \( n \): Number of agricultural zones in the study area
- \( y \): Number of years in the planning horizon

The objective functions \( Z_1 \) to \( Z_4 \) should be normalized between 0 and 1. For this purpose the relative weights \( \alpha_i \) can be assigned much easier based on the relative...
importance of the objectives. Based on the constraint (1), the monthly variation of the water table level is limited to a maximum level. Equation (6), which is called the response function, presents the monthly groundwater table variations in each zone which is a function of the set of the volumes of the groundwater extracted in month $m$ of year $y$ in the agricultural zones ($\tilde{G}_{my}$), the outflow at the boundaries, and the groundwater discharge through springs and qanats in month $m$ of year $y$ ($\tilde{Q}_{my}$), recharge by direct precipitation, allocated surfacewater, and also recharge by absorption wells ($\tilde{M}_{my}$). This equation should be formulated using a comprehensive groundwater simulation model.

**GAs based Optimization Model**

GAs use a random search technique that evolves the potential solution at a system using the genetic operators. Generation of the initial population, representation and encoding, selection, crossover, and mutation are the main steps in the GA based optimization models. The main characteristic of the Genetic Algorithms is presented by Gen and Chang (2000). In this study, the gene values are the monthly allocated ground and surface water to the agricultural zones. For example, when there are three agricultural zones and two surface water resources only for zones 1 and 2, the number of genes in a chromosome for a 15-year planning horizon is equal to $15*5*12=900$, where 5 is the number of decision variables.

**Groundwater Simulation using Artificial Neural Network**

The groundwater table and quality variation equations are necessary for the proposed conjunctive use model (Equations 8 and 9). Considering the complexity of the system, the aquifer should be modeled using a comprehensive simulation model. As most of the groundwater quantity and quality simulation models (such as PMWIN) can not easily linked with optimization models, in this study a selected Artificial Neural Networks (ANNs) is trained using the results of the groundwater simulation. In this study, different ANNs have been tested and the multilayer feed forward networks have shown the best performance. Figure 1 shows the components of a typical three-layer feed forward artificial neural network. As it can be seen in this figure, each node $j$ receives incoming signals from every node $i$ in the previous layer. Associated with each incoming signal ($x_i$) to node $j$, is a weight ($w_{ji}$). The effective incoming signal ($s_j$) to node $j$ is the weighted sum of all the incoming signals:

$$s_j = \sum_{i=0}^{n} w_{ji} x_i$$

Where $x_0$ and $w_{j0}$ are called the bias ($x_0 = 1.0$) and the bias weight, respectively. The outgoing of node $j$ is $y_j$. More detailed information about the training of the ANNs can be found in Hsu et al. (1995).
Case Study
The proposed model is applied to the conjunctive use of the surface and groundwater resources in the southern part of Tehran. Tehran plain is bounded by the Kan River in the West and the Sorkhehesar River in the East. About one billion cubic meters of water per year is provided for domestic consumption of over 8 million people. Figure 2 shows a map of the surface water resources of Tehran Plain. As it can be seen in this figure, several rivers are located, form the West to the East, which are considered, as local rivers in this study. These rivers partially supply water to the agricultural lands in the Southern part of Tehran.

Figure 1. Typical three-layer feed forward artificial neural network (Hsu et al., 1995).

More than 60 percent of the water consumption in Tehran returns to the Tehran Aquifer via traditional absorption wells. Three major agricultural zones namely Eslamshahr-Kahrizak (zone 1), Ghaleno (zone 2) and Khalazir (zone 3) are the main users of surface and groundwater resources in the study area (see Figure 2). Tehran aquifer is mainly recharged by inflow at the boundaries, precipitation, local rivers, and return flows from domestic, industrial, and agricultural sectors. The discharge from the aquifer is through water extraction from wells, springs, and qanats as well as groundwater outflow and evapotranspiration. The latest and the most complete water resources data and information (such as flow rate measurements in the pumping wells, springs and qanats) are for 1993-94 water year, which is used for estimation of different terms of water balance and groundwater simulation of Tehran aquifer. More detailed information about the study area and water balance of aquifer is presented in Karamouz et al. (2002, 2004) To simulate the groundwater table elevation in this study area, the PMWIN model is used. Tehran aquifer is considered as a single-layered aquifer, and therefore only the horizontal hydraulic conductivity is estimated. Figure 3 shows the generated grid as well as the boundary conditions in the PMWIN model. For detailed information about the calibration and modification of the Tehran Aquifer please see Karamouz et al. (2004). Based on the available water quality data NO₃ that usually deviates from the standards is selected as indicator water quality.
variables. Figure 4 and 5 presents the comparison between computed and historical groundwater table elevation and NO$_3$ concentration in the study area.

Figure 2. Surface water resources and the agricultural zones in the study.

These figures show how closely the model can reproduce the monthly water table and NO$_3$ concentration variations. The response functions in the optimization model show the monthly groundwater table variations in Tehran aquifer. They are functions of discharge, recharge, inflow, and outflow at the boundaries as well as physical characteristics of the aquifer. The linkage of the optimization and simulation models will significantly increase the computational problems and also the time needed to achieve the optimal solution of the model. In this study, the response functions of the aquifer are developed and used in the optimization model. The results of the frequent execution of the groundwater simulation model (PMWIN) for different sets of recharge-discharge values, and by considering the principle of superposition, the selected ANN is trained for estimating monthly water table variations that have been obtained for each agricultural zone. The suitable variables which significantly affect the groundwater table variations have been selected using a trial and error process. Finally, the total monthly groundwater discharge and the average groundwater table level in aquifer at the beginning of the month have been considered as variables and the other factors that have a negligible effect on the groundwater table variations are assumed to be constant in each month. The general form of the response function of the average groundwater table variation in month $t$ in each zone is estimated as follows:
\[ \Delta H_t = purelin(w_2^t \times \text{tansig}((w_1^t \times h_t) + b_1^t) + b_2^t) \]

Where:

- \( \Delta H_t \): The vector of the ground water table variations in month \( t \) (m) (negative values refer to water table drawdown)
- \( w_2^t \): Weight parameter in the second layer of the ANN developed for month \( t \)
- \( w_1^t \): Weight parameter in the first layer of the ANN developed for month \( t \)
- \( h_t \): Input matrix which consists of the average groundwater table at the beginning of each month and discharge average from agriculture zones.
- \( b_1^t \): Bias parameter in the first layer of the ANN developed for month \( t \)
- \( b_2^t \): Bias parameter in the second layer of the ANN developed for month \( t \)

Figure 3. The generated grid and boundary conditions in the PMWIN model.

Figure 4. Comparison between observed and simulated groundwater table (March 1993).
The developed ANN-based response functions can be used in the GA-base optimization models. Figure 6 shows the result of testing the trained ANN for simulating the groundwater table variations. As shown in this figure, the PMWIN model can be replaced with the trained ANN.

**Results and Discussion**

In this study, the conjunctive use policies for surface and groundwater resources are developed using a GA based optimization model. In this paper, the cumulative groundwater table variations in each zone, which has experienced a total fluctuation of more than ±20 meters in the last 20 years, is limited to ±5 meters over the planning horizon (15 years). The relative weight of $Z_1$ to $Z_4$ are considered to be 30, 10, 35 and 25, respectively. Table 1 presents the reliability of the water supply to the agricultural water demands, and the share of ground and surface water resources allocation. Based on the results of this study, presented in Table 1, only 79 percent of the total water demand can be allocated and more than 64 percent of the allocated demand is supplied by the groundwater resources. Figure 7 shows the cumulative variation of groundwater table in the agricultural zones based on the optimal operating polices. In zone 2, less groundwater is extracted because of a lower concentration of water quality variable in the surface water of this zone (see Figures 8 and 11). As it can be seen in Figure 8, most of the allocated water to zone 2 is supplied from surface water resources due to the availability of the surface water and best water quality in this zone as well as to reduce the pumping cost. Figure 9 presents the total allocated water to zone 1. The peak value (in Figure 9 is due to the over allocating the groundwater to zone 1 to control the groundwater table in this zone. Based on the conjunctive use polices, the groundwater is allocated to zone 3 to control the increasing level of the groundwater table in this agricultural zone. Results of this study show that the proposed model can be effectively used for conjunctive use of surface and groundwater resources considering the water quality issues.
Figure 6. The results of testing the trained Artificial Neural Network for groundwater table.

Table 1. The share of surface and groundwater resources in water allocation to different zones.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Percent of Demand supplied by groundwater</th>
<th>Percent of Demand supplied by surfacewater</th>
<th>reliability of water supply (without quality)</th>
<th>reliability of water supply (with quality)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>79</td>
<td>21</td>
<td>99</td>
<td>95</td>
</tr>
<tr>
<td>2</td>
<td>14</td>
<td>86</td>
<td>85</td>
<td>77</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>0</td>
<td>75</td>
<td>65</td>
</tr>
</tbody>
</table>

Figure 7. Cumulative variation of the groundwater water table level in the agricultural zones.
Figure 8. The monthly allocated surfacewater to agricultural zones 1 and 2.

Figure 9. Monthly allocated water to agricultural zone 1.
Figure 10. Average annual concentration of NO₃ in the allocated water to the agricultural zones.

Figure 11. Average monthly NO₃ concentration in the allocated water to agricultural zones.
References