Chance-Constrained Pumping Optimization in Saltwater Intruded Aquifers by Simple Genetic Algorithm—Stochastic Model

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EXTENDED ABSTRACT

This paper develops a management model with the economic objective of maximizing the benefit from pumped freshwater volume and minimizing the utility cost in coastal aquifers threatened by saltwater intrusion. In a previous paper, “Pumping optimization in saltwater intruded aquifers by simple genetic algorithm—deterministic model” we assumed that the aquifer parameters, such as the hydraulic conductivity, the recharge rate, the freshwater outflow rate, etc., were known with certainty. In reality, however, information about aquifer parameters is often uncertain. The aquifer management model then needs to address the uncertainty issues and to provide solutions with respect to different reliability requirements. In the optimization model, the uncertainty is handled using chance-constrained optimization. Cases presented in the previous paper, particularly the Miami Beach (Spain) case, are re-examined. It is shown that the allowable pumping rate is decreased with increasing uncertainty level in the input and higher demand of confidence level in the prediction.

1 INTRODUCTION

Due to the increased population in coastal zones, many communities are faced with water shortage problems. The shortfall in water supply is often met by pumping groundwater, which sometimes leads to the over-exploitation of aquifers [Bear and Cheng; 1999]. The extraction of groundwater from coastal aquifers reduces freshwater outflow to the sea and creates local water table depression, causing seawater to migrate inland and rising toward the wells. The increase in salinity renders the water undrinkable or unusable; and wells have to be abandoned. To avert this trend, which is unsustainable in the long-term, many coastal water management agencies have implemented policies to regulate groundwater withdrawal. The goal is to achieve the maximum utilization of fresh groundwater with minimum cost, and without damaging the aquifers as a long-term source of water supply.

In a previous paper [Benhachmi, et al., 2003] we developed a coastal aquifer management model based on the assumption that aquifer parameters, such as the hydraulic conductivity, the recharge rate, the freshwater outflow rate, etc., are known with certainty. A sharp interface model is used to predict the location of saltwater front and invasion of wells. A simple genetic algorithm (GA) is used to solve the optimization problem that maximizes the economic benefit of pumped freshwater and minimizes the utility cost, under the constraint of no saltwater intrusion in pumped wells.
In real life, however, aquifer information and hydrological conditions are often uncertain or random. For example, we may not have sufficient data to accurately determine aquifer parameters such as hydraulic conductivity and thickness. Hydrological conditions such as precipitation recharge, freshwater outflow rate, and sea level, cannot be predicted in the future. Even anthropogenic operation conditions such as pumping extraction and artificial recharge cannot be precisely planned. These input data required for the management model are random variables. At best they can be estimated as a mean, a standard deviation, and covariances. A realistic aquifer management model must be able to handle these uncertain conditions.

The purpose of this paper is to extend the capability of the previous deterministic management model in order to deal with the uncertainty issues. Particularly, we utilize the chance-constrained programming (CCP) [Charnes and Cooper, 1959; 1963] methodology to model uncertainty. This GA-CCP optimization model allows us to use stochastic parameters as input data and provides an output prediction with desirable reliability level. Cases presented in the previous paper, particularly the Miami Beach (Spain) case, are re-examined to demonstrate the effects of uncertainty in aquifer management. The results show that the net benefit of pumping decreases with increasing data uncertainty and higher demand of output reliability.

2 CHANCE-CONSTRAINED GROUNDWATER MODELS

Charnes and Cooper [1959, 1963] studied chance constrained programming by solving a stochastic optimization problem by its deterministic equivalent. The chance-constrained programming can easily incorporate reliability measures imposed on the decision variables. A number of chance-constrained models have been proposed for solving groundwater management problems. Tung [1986] developed a chance-constrained model that takes into account the random nature of transmissivity and storage coefficient by using a first-order uncertainty analysis. Wagner and Gorelick [1987] presented a modified form of the chance constrained programming to determine a pumping strategy for controlling groundwater quality. Hantush and Marino [1989] presented a chance-constrained model for stream-aquifer interaction. Morgan, et al. [1993] developed a mixed-integer chance-constrained programming and demonstrated its applicability to groundwater remediation problems. Chance-constrained groundwater management models have been applied to design groundwater hydraulics [Tiedman and Gorelick, 1993] and groundwater quality management strategies [Gailey and Gorelick, 1993]. Chan [1994] developed a partial infeasibility method for chance-constrained aquifer management that uses heuristic methods requiring the design reliability level to be satisfied for a training set consisting of multiple realizations of uncertain transmissivity. Datta and Dhiman [1996] utilized a chance–constrained model for designing a groundwater quality monitoring network. Wagner [1999] employed the chance-constrained model for identifying the least cost pumping strategy for remediating groundwater contamination in the presence of simulation model uncertainty. This model is combined with the network design model for identifying the groundwater sampling strategy with maximum information contents. Previous research on chance-constrained groundwater management models dealt with uncertainty in the constraint coefficients. The work of Sawyer and Lin [1998] extends previous studies by considering the
combination of uncertainty in the cost coefficients and constraints of the groundwater management model.

3  CHANCE-CONSTRAINED OPTIMIZATION

In this paper a chance-constrained optimization model is formulated to account for uncertainties in the model coefficients. The chance constrained programming method transforms the probabilistic constrained model to an equivalent deterministic one. Solving the deterministic equivalent problem becomes much easier than the probabilistic one.

First, we recall the optimization statement for the deterministic problem as stated in the previous paper [Benhachmi, et al., 2003] as

\[
\text{Maximize } Z = \sum_{i}^{m} \sum_{k=1}^{n} \frac{1}{(1+r)^{k}} (B_{p}Q_{i} - C_{p}Q_{i}(L_{i} - h_{i}))
\]

with respect to \( Q_{i} \) and other design variables, where \( Z \) is the objective function, subject to the constraints:

i) The saltwater toe must not invade the well:

\[
X_{\text{toe},i} < X_{i} \quad i = 1, m
\]

ii) The pumping capacity limits should not exceed the equipment or operation limits:

\[
Q_{i}^{\text{min}} \leq Q_{i} \leq Q_{i}^{\text{max}} \quad i = 1, m
\]

In the above \( Q_{i} \) is the discharge rate of well \( i \), \( X_{w}^{i} \) is the distance of well \( i \) from the coast, \( X_{\text{toe}}^{i} \) is the toe location from the coast in front of well \( i \), \( Q_{i}^{\text{min}} \) and \( Q_{i}^{\text{max}} \) are respectively the minimum and maximum discharge of a well constrained by equipment capacity, \( h_{i} \) is the hydraulic head at well point \( i \), \( L_{i} \) is the ground elevation at well point \( i \), \( B_{p} \) is the benefit per unit supply of water at well point \( i \), \( C_{p} \) is the cost of pumping a unit volume of water per unit head at well point \( i \); \( r \) = interest rate; \( n \) = periods management; and \( m \) is the number of wells. For existing wells at fixed locations, the design variable is the pumping rate \( Q_{i} \). For new wells to be installed, the design variables can include the number of wells, their discharges, and well locations in terms of \( x \)- and \( y \)-coordinates. The main constraint of the problem is the absence of saltwater invasion of the wells.

For the stochastic problem, consider that the saltwater toe location \( X_{\text{toe}} \) is a random variable due to the uncertainty in input conditions. The constraint (2) then needs to be described in the probability sense:

\[
\text{Pr}\{X_{\text{toe},i} < X_{i}\} \geq R_{\text{toe},i} \quad i = 1, n
\]

The above condition says that the probability that the saltwater toe does not reach the well location is greater than a prescribed reliability level \( R_{\text{toe},i} \). This reliability is set by the water manager depending on the importance of each well to be protected. The left side of
(4) is random because the toe location is dependent on the random variables of freshwater outflow rate, hydraulic conductivity, pumping well discharge, etc. Since the compliance of constraints at each pumping well cannot be ensured with certainty, it is more appropriate to examine the constraint performance probabilistically.

A probabilistic statement of toe location constraint in (4) is not mathematically operational. Further modification or transformation is needed. To make (4) mathematically operational, it is necessary to assess statistical properties of the random variables in the constraint equations. The chance constraint model converts the above probabilistic constraint into a deterministic one as:

$$E\left[X_{\text{toe}}\right] + N^{-1}(R) \sigma_{X_{\text{toe}}} \leq X_i$$  \hspace{1cm} (5)

The first term in the above is the expected value (mean) of the toe location, $N^{-1}$ is the standard normal cumulative distribution corresponding to a reliability level $R$, and $\sigma_{X_{\text{toe}}}$ is the standard deviation of the toe location. Equation (5) reflects the uncertainty in the toe location due to the random freshwater outflow rate, hydraulic conductivity, and pumping well discharge, etc. If all these conditions are known with certainty, then (5) reduces to (2), the deterministic condition.

4 STOCHASTIC SIMULATION MODEL

In the previous paper [Benhachmi, et al., 2003], the saltwater intrusion simulation model is based on the analytical solution by Strack [1976]. Particularly, the toe location $x_{\text{toe}}$ is solved from the following equation

$$\Phi_{\text{toe}} = \frac{q}{K} x_{\text{toe}} + \sum_{n=1}^{\infty} \frac{Q_n}{4\pi K} \ln \left[ \frac{(x_{\text{toe}} - x_n)^2 + (y_{\text{toe}} - y_n)^2}{(x_{\text{toe}} + x_n)^2 + (y_{\text{toe}} - y_n)^2} \right]$$  \hspace{1cm} (6)

with given $K$, $Q_n$, $q$, $\Phi_{\text{toe}}$, $x_n$, $y_n$, and $y_{\text{toe}}$ values. Equation (5) shows, however, that in the case of probabilistic modeling, the statistical information of the mean and standard deviation of the simulation under random input is needed. Hence a stochastic simulation model is needed. This is accomplished by the methodology introduced by Cheng and Ouazar [1995] and Naji, et al. [1998].

In the stochastic solution, we assume that the fluctuation of a random variable from its mean is not too large such that the perturbation technique can be used to give a good approximate solution. This a common practice in stochastic groundwater modeling. Utilizing Taylor’s series, the mean toe location is found as

$$\bar{x}_{\text{toe}} = x_{\text{toe}} + \frac{1}{2} \left[ \frac{\partial^2 x_{\text{toe}}}{\partial q^2} \sigma_q^2 + \frac{\partial^2 x_{\text{toe}}}{\partial Q_w^2} \sigma_{Q_w}^2 \right]$$  \hspace{1cm} (7)

and the variance of the toe location is given by

$$\sigma_{x_{\text{toe}}}^2 = \left[ \frac{\partial x_{\text{toe}}}{\partial q} \right]^2 \sigma_q^2 + \left[ \frac{\partial x_{\text{toe}}}{\partial Q_w} \right]^2 \sigma_{Q_w}^2$$  \hspace{1cm} (8)
In the above, $x_{\text{toe}}$ is obtained from (6) using mean values of $K$, $Q_w$, $q$, etc. The partial derivatives $\frac{\partial x_{\text{toe}}}{\partial q}$, $\frac{\partial x_{\text{toe}}}{\partial Q_w}$, $\frac{\partial^2 x_{\text{toe}}}{\partial q^2}$, $\frac{\partial^2 x_{\text{toe}}}{\partial Q_w^2}$ need to be obtained numerically. They are found by perturbing the independent variables $q$, $Q_w$, etc. by a small amount $\Delta q$ and $\Delta Q_w$, and then evaluate the changes of toe location $\Delta x_{\text{toe}}$. Finite difference formulae are employed to approximate the partial derivatives. The variances $\sigma_q^2$ and $\sigma_Q^2$ are given as input data.

5 UNCONSTRAINED OPTIMIZATION BY GENETIC ALGORITHM

The underlying ideas of genetic algorithm (GA) and its methodology has been discussed in the previous paper [Benhachmi, et al., 2003], hence will not be repeated here. It is however necessary to modify the cost function used in the GA unconstrained optimization. To allow a genetic algorithm to be used, the constrained problem in (7) is first transformed into an unconstrained one. This is accomplished by imposing penalty for the constraints in the objective function. In the previous paper, the deterministic constraint of no saltwater intrusion (2) was used. In the current paper, the chance constraint (5) should be used. The benefit function is then modified to:

$$F = \sum_{i=1}^{n} B_i Q_i - C_p Q_i (L_i - h_i) - r \left[ \sum_{i=1}^{m} \left( \frac{1-E[x_{\text{wc}}]+N^{-1}(R)\sigma_{x_{\text{wc}}}}{x_{\text{wc}}} \right)^2 \right]$$  \hspace{1cm} (9)$$

where $r$ is the penalty factor and $m$ is the number of violated constraints. If a well is invaded, then the well should be shut down. If it is not invaded, then we have options of pumping and shutting down. The constraint in (3) is not included in (9) because it is automatically satisfied in genetic algorithm by properly selecting the search space of $Q_w$. The function $F$ is then maximized in an unconstrained optimization procedure.

6 EXAMPLES

The proposed stochastic optimization model is applied to the two problems investigated in the previous paper [Benhachmi, et al., 2003], namely a test problem and the Miami Beach aquifer in northeast Spain.

6.1 Test Problem

The first case examined is an unconfined aquifer with the mean hydraulic parameters as $K = 100$ m/day, $q = 0.6$ m$^3$/day/m, $d = 14$ m, $\rho_s = 1.025$ g/cm$^3$, and $\rho_f = 1$ g/cm$^3$. The are seven wells in the field with their coordinates, pumping limits, and pumping lift summarized in Table 1 of the previous paper [Benhachmi, et al., 2003]. The uniform benefit rate of pumped water is assumed to be $0.16$ per m$^3$, and the cost is $0.00024$ per m$^3$ per m lift.

We assume that the freshwater outflow, hydraulic conductivity and the pumping rates are random variables. We shall test three cases with different levels of uncertainty with the coefficients of variation of these quantities, defined as the normalized standard deviation, to be $c_q = c_Q = c_K = 1\%$, $5\%$, $10\%$, respectively. We further assume that the
Figure 1: Saltwater intrusion front for the optimal pumping pattern with $c_q = c_Q = c_k = 10\%$ and $R = 90\%$.

pumping rate, hydraulic conductivity and freshwater outflow rate are not correlated; hence $\sigma_{qQ} = \sigma_{kQ} = \sigma_{qk} = 0$.

In Figure 1 we present the case of $c_q = c_Q = c_k = 10\%$. We further assume that the reliability level of the prediction is $R = 90\%$. After the GA optimization, the best case gives the total pumping rate of $Q = 2,752$ m$^3$/day and the net benefit $146,478$/yr. We notice that in the optimal solution, only three inland wells are pumping and four wells are shut down. In the figure, the middle solid line shows the mean location of the predicted saltwater front, and the two envelopes are plus/minus one standard deviation of the mean location. We also presented the case of deterministic solution, corresponding to of $c_q = c_Q = c_k = 0$, as the line with symbols in Figure 1. As reported in the previous paper, the optimal pumping rate was $Q = 3,771$ m$^3$/day. We clearly observe that the uncertainty in aquifer information tends to decrease the allowable pumping rate.

Next, we examine the effect of increasing reliability in prediction. Figure 2 presents the result using the same data set, except that the demand for reliability in prediction is increased to $R = 95\%$. In this case, the optimal total pumping rate is given as $Q = 2,580$ m$^3$/day and the net benefit $137,824$/yr. The pumping rate and the benefit decrease because the increasing reliability is needed. In Figure 3, we present the case of further increasing the reliability level to $R = 99\%$. The optimal allowable pumping rate is now $Q = 811$ m$^3$/day and the net benefit $125,704$/yr.

In the next example, we investigate the effect of input data uncertainty level. In Figure 4, we present the case of decreasing uncertainty to $c_q = c_Q = c_k = 5\%$, and Figure 5 the case $c_q = c_Q = c_k = 1\%$. In both cases, the reliability level is fixed to $R = 90\%$. As compared to result reported in Figure 1, we observe that the pumping rate and benefit increases due to the reduction of data uncertainty. For Figure 4, we obtain $Q = 3,330$ m$^3$/day and the net benefit $176,788$/yr; and in Figure 5, $Q = 3,658$ m$^3$/day and the net benefit $196,870$/yr.
The above results show that the total pumping rate and its net benefit decreases with the increasing data uncertainty and required confidence level in prediction. Hence the water manager has the option of investing more money in geological and hydrogeological survey to have a better understanding of the aquifer. These actions can either increase the confidence level of prediction, or at the same confidence level, increase the allowable pumping rate. On the other hand, depending on the sensitivity of an aquifer to survive short-term damage and be restore from it, and the availability of temporary alternative source of water, the manager may take a less conservative approach by decreasing the required confidence level, hence increase the pumping rate.
Figure 4: Saltwater intrusion front for the optimal pumping pattern with $c_q = c_Q = c_K = 5\%$ and $R = 90\%$.

Figure 5: Saltwater intrusion front for the optimal pumping pattern with $c_q = c_Q = c_K = 1\%$ and $R = 90\%$.

6.2 Miami Beach, Spain

The geological and hydrogeological conditions of the Miami Beach aquifer in northeast Spain have been discussed in the previous paper [Benhachmi, et al., 2003]. Figure 6 shows the geographical location of the 25 pumping wells. The unconfined aquifer of Miami Beach is modeled with the following mean properties: $K = 14$ m/day, $q = 1.2$ m$^3$/day/m, $d = 30$ m, $\rho_s = 1.025$ g/cm$^3$, and $\rho_f = 1$ g/cm$^3$. The uniform benefit rate is 1.5 pts per m$^3$ of water and the pumping cost is 0.03 pts per m$^3$ per m lift of water.
Figure 6: Location of pumping wells (red dots) and observations wells (blue dots) in Miami Beach aquifer.

In this paper, the freshwater outflow rate, hydraulic conductivity, and pumping rates are considered as random variables. First, we estimate that the uncertainty in the
data provided are \( c_q = 25\% \), \( c_Q = 10\% \), and \( c_K = 10\% \). In Figure 7, we present the optimal pumping pattern given the reliability level of 90\%. The saltwater intrusion front is presented as the mean location plus/minus one standard deviation in solid lines. The optimal pumping under the deterministic conditions, as obtained from the previous paper [Benhachmi, et al., 2003] is shown as the line with symbols. We observe the most of the wells near the coast are shut down, as well as some of the wells inland. The total allowable pumping rate is \( Q = 3,623 \text{ m}^3/\text{day} \), which is compared to the rate 4,196 m³/day of the deterministic case. Hence the uncertainty is aquifer data input and the required reliability of prediction forced the reduction of pumping rate by about 14\%. The benefit rate for the current case is 69,568 €/yr, as compared to 75,488 €/yr of the previous case.

Next, we investigate the same case by increasing the required reliability level to \( R = 95\% \). The result is presented in Figure 8. We observe in this case the optimal total pumping rate is \( Q = 2,748 \text{ m}^3/\text{day} \) and the benefit rate is 59,279 €/yr. Comparing to the deterministic case, this is a 34\% reduction in pumping rate. In the next case, we further increase the reliability level to \( R = 99\% \) and the result is shown in Figure 9. As expected, we see further reduction in pumping rate to \( Q = 1,717 \text{ m}^3/\text{day} \) and the benefit is 40,711 €/yr.

In the next set of simulation, we fix the reliability level to the more reasonable value of \( R = 90\% \), and assume that we can reduce the data uncertainty level by performing additional hydrogeological survey. With the following two sets of coefficients of variation, \( c_q = 15\% \), \( c_Q = 10\% \), \( c_K = 10\% \), and \( c_q = 1\% \), \( c_Q = 1\% \), \( c_K = 1\% \), we present the simulation results as Figure 10 and 11. With the decreased data uncertainty, we expect the allowable pumping rate should increase. Indeed, the pumping rates are respectively increased to \( Q = 4,045 \text{ m}^3/\text{day} \) and 4,196 m³/day, and benefit rate to 71,899 €/yr and 75,489 €/yr. We notice that there is a rather significant increase in
pumping rate, from $Q = 3,623 \text{ m}^3/\text{day}$ to $4,045 \text{ m}^3/\text{day}$, by simply decreasing the data uncertainty of $c_q$ from 25% to 15%. Hence the investment in gaining more data accuracy may be worthwhile. On the other hand, if the data accuracy is pushed further, from $c_q = 15\%$, $c_Q = 10\%$, $c_K = 10\%$ to $c_q = 1\%$, $c_Q = 1\%$, $c_K = 1\%$, there is only a slight gain in pumping rate, from $Q = 4,045 \text{ m}^3/\text{day}$ to $4,196 \text{ m}^3/\text{day}$. This high data accuracy is practically impossible, hence will cost huge sum of investment. In addition, we notice
Figure 10: Saltwater intrusion front for the optimal pumping pattern with $c_q = 15\%$, $c_Q = 10\%$, $c_K = 10\%$ and $R = 90\%$.

Figure 11: Saltwater intrusion front for the optimal pumping pattern with $c_q = 1\%$, $c_Q = 1\%$, $c_K = 1\%$ and $R = 90\%$.

that $Q = 4,196$ m$^3$/day is just the optimal pumping rate for the deterministic case. This is the upper bound pumping rate, which cannot be exceeded even with 100% data accuracy. This shows that improving data accuracy will be economically desirable only up to a certain point, beyond which the cost of conducting the hydrogeological survey will be large and the return in increased pumped water will be small. In the current optimization model we did not incorporate a model of hydrogeological survey costs versus reduction of data uncertainty. If desirable, such costs can be included as a part of objective function for optimization.
### Table 1: Optimum pumping pattern for the Miami Beach aquifer for different sets of data uncertainty and prediction reliability.

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In Table 1 we summarize the pumping pattern for the five cases simulated. Based on the above results and the current pumping practice in Miami Beach, we conclude that this aquifer system at its present state is over-exploited. Indeed, the continual decline of potentiometric head and consequent increase in pumping cost were observed from 1989 to 1995. Without curtail of pumping and importing water from other sources, the long-term outlook of the health of the aquifer system at Miami Beach is grim.
7 CONCLUSION

The work presented in this paper demonstrates the importance of treating physical parameters and boundary conditions for coastal aquifer as random variables. Since uncertainty in data always exist in real world, implementing coastal aquifer management policy based on deterministic model using average values of aquifer parameters can lead to failure of the system. Conservative management policies by arbitrarily imposing a safety factor can improve the reliability of prediction, but it is a qualitative measure and likely not an efficient scheme. The stochastic modeling, on the other hand, can explicitly take into consideration of the statistics of data input and producing an output with a reliability that can be quantified.

In this paper, we have presented an optimization model for maximizing the financial benefit of pumping freshwater in a saltwater invaded coastal zone with input data uncertainty. The deterministic aquifer simulation model for saltwater intrusion is accomplished by the single potential, sharp interface model of Strack [1976]. To take into consideration of stochastic input conditions and produce stochastic predictions, the perturbation based stochastic solution method by Naji, et al. [1998] is utilized. To convert the stochastic optimization constraint to an equivalent deterministic one, the chance-constrained methodology of Charnes [1959] is used. Finally, the optimization was conducted using the genetic algorithm of Holland [1975]. Using two examples, one involving the real aquifer of Miami Beach, Spain, we have demonstrated that the increasing data uncertainty causes a decrease in allowable pumping rate, and increasing reliability level in prediction also leads to a reduction of pumping. This implies that the investment in hydrogeological survey to reduce the data uncertainty can increase the allowable pumping rate and the benefit of freshwater production. There however exists a tradeoff between the cost of survey and the benefit of production, which is a quantity that can be further optimized.

REFERENCES


