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A COMPARATIVE SIMULATION-OPTIMIZATION STUDY ON EFFECTIVE MANAGEMENT OF SALTWATER INTRUSION IN COASTAL AQUIFERS

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ABSTRACT

This study outlines the general performance of two different simulation-optimization (S/O) models developed to examine the capabilities of the new proposed management scenario to control seawater intrusion (SWI) in coastal aquifers. In the first S/O model, a finite element (FE) simulation model is directly linked with a multi-objective genetic model. In the second model a trained surrogate model is linked to the same optimization model. The simultaneous abstraction of saline water near the coast and artificial recharge of treated wastewater into the aquifer are the main principles used in the proposed management scenario. The recharge is implemented using a surface pond and therefore unsaturated flow theory is utilized in the simulation. The objective functions include minimization of the total economic cost of the management scenario and also the minimization of the total amount of salt in the aquifer. The results show that implementation of the surrogate model in the S/O framework results in a significant reduction in CPU time.

Keywords: *seawater intrusion; coastal aquifer; simulation-optimization; EPR*

1. Introduction

Saltwater intrusion is a common contamination problem in developed and urbanized coastal areas especially in arid and semi-arid regions of the world. In critical cases SWI may be followed by abandonment of production wells of freshwater, human health problems and damage to natural ecosystem [1,5]. Therefore, appropriate management strategies should be implemented to control SWI with acceptable limits of economic and environmental costs. In parallel with raising awareness of the concerns on management of coastal groundwater resources, there has been a growing need to find optimal solutions for controlling the SWI problem. The problem is a multi-objective optimization problem that aims to find the trade-off relationship between conflicting objectives. In the early stages of this advancement, different linear/nonlinear programing optimization tools were incorporated with simulation models. However, the problematic features of the traditional optimization techniques in attaining the correct optimal solutions for multi-objective complex problems have triggered the demand for innovation and use of other types of optimization tools such as evolutionary algorithms [5]. In the S/O process the numerical simulation model is linked with a chosen optimization model. In cases with computational complexity some works have attempted to link surrogate models with the optimization algorithms. A recent review of the research efforts related to the application of S/O modelling in management of SWI in coastal aquifers has been presented in [2] and [4].

This paper presents the development and application of two S/O models to assess the efficiency of a new management method for controlling saltwater intrusion while satisfying water demands, and with acceptable limits of economic and environmental costs. The first S/O model (FE-GA) is developed by direct linking of a finite element (FE) simulation model with a multi-objective genetic algorithm. In order to reduce the computational burden the numerical simulation model is replaced by an Evolutionary Polynomial Regression (EPR) based surrogate model in the next S/O model (EPR-GA). A comparison is made between the capabilities of both schemes in capturing the optimal results in hypothetical coastal aquifers.

2. Evolutionary Polynomial Regression (EPR)

EPR [7] is a relatively recent hybrid data mining method that integrates the best features of the conventional numerical regression with the effectiveness of genetic programming. In EPR, the created models are presented in the form of mathematical expressions which are easily accessible to the user. This important feature, however, is not available in other black box data driven methods such as artificial neural networks. The possibility of getting a set of models (not only one) for a complex phenomenon is the other important feature of EPR. The level of accuracy for each model is evaluated based on the coefficient of determination (*COD*):

$$COD = 1 - \frac{\sum_{N}(y_{EPR} - y_a)^2}{\sum_{N}(y_a - avg(y_a))^2} \tag{1}$$

where y_a is the actual output value; y_{EPR} is the predicted value that is computed by the trained EPR model; and N is the number of data points on which *COD* is computed. Detailed explanation of the EPR methodology can be found in [7].

3. Model Description

The studied aquifer system is a 2D hypothetical unconfined aquifer with 200 m × 40 m dimensions. A density dependent FE model SUTRA (Saturated-Unsaturated TRAnsport) [3] is used for the numerical simulation of this flow system. The hydrostatic water heads of 31 m and 30 m are assigned to the left and right sides of the domain respectively to represent the freshwater and seawater pressure boundaries of the aquifer system (Figure 1). The aquifer is discretised into 2000 elements and 2091 nodes. The presence of an unsaturated flow layer in the model requires simulating this layer with finer spatial and temporal discretization in order to limit the instability and oscillation resulting from calculated pressure and saturation values which may change drastically during wetting events [3]. To simulate a plan for future demand, a local production well screened at coordinates (40, 10) m is incorporated into the model (see Figure 1). It is assumed that 26 m^3/day of groundwater is continuously pumped from this well. The total calculated mass of solute in the aquifer would be raised from 27 tons prior the pumping to 98 tons after pumping. Consequently, a management action is required to comply with the planned demand for water while protecting the aquifer against SWI.

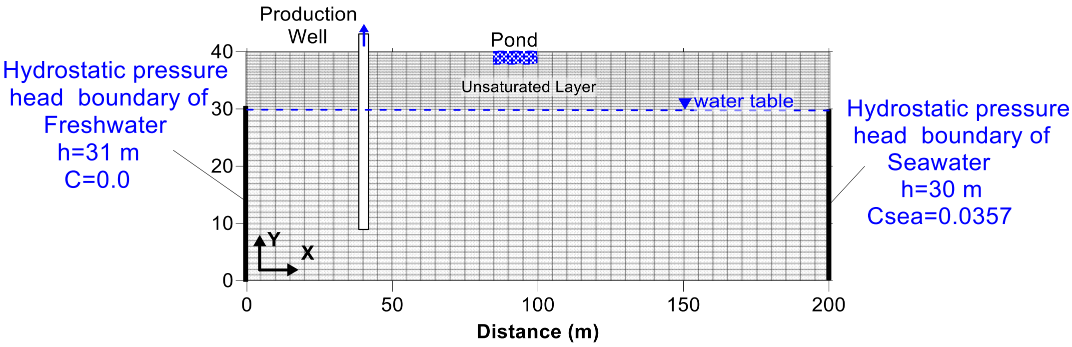

Figure 1: Model geometry and boundary conditions

A new management scenario called ADRTWW [1,6] is proposed to restrict the negative impacts of the intruded saline wedge and the pumping of freshwater from production well. This methodology consists of three steps; Abstraction of brackish water from the saltwater wedge, Desalination of the abstracted brackish water to meet a part of the projected water demand, and artificial Recharge of the aquifer using Treated Waste Water [1,6]. A pond system with dimensions 15m×2m located 65 m from the shoreline is used to collect the reclaimed water and then recharge the aquifer. The calculated recharge rate under this pond system is 0.35 m/day.

4. Simulation-Optimization models:

In order to investigate the cost-effectiveness of the ADRTWW management scenario in different arrangements of its recharge/abstraction components and also in a wider range of optimal solutions, two different S/O frameworks are developed. In the first S/O framework, so called FE-GA, the FE based numerical model (SUTRA code) is directly linked with non-dominated sorting genetic algorithm, NSGA-II [8]. NSGA-II is a popular, fast and elitist multi-objective genetic algorithm. In FE-GA, the numerical model (SUTRA) is repeatedly called by NSGA-II to calculate state variables (pressures and concentrations) in response to each set of generated design variables. After evaluating the corresponding fitness of the objective functions and passing through multiple elitism and evolutionary processes, the trade-off curve of optimal solutions is captured. In the second framework (EPR-GA) a suitably trained EPR is linked with the same multi-objective algorithm. Prior to its linking, the developed surrogate (EPR) model is trained and tested externally on the inputs/outputs of the SUTRA model describing the response of the aquifer system. The results of the EPR-GA model are compared with those obtained by direct integration of the numerical simulation model into the optimization (FE-GA) model. In both FE-GA and EPR-GA, the S/O process aims to minimize the total mass of salt (f_1) in the aquifer as well as minimizing the costs (f_2) of construction and operation of the management process subjected to several side constraints.

5. Results and Discussion

The values of the main parameters adjusted for the optimization algorithm in both developed S/O models are the population size = 50, total number of generations=100, probability of crossover = 0.9 and probability of mutation = 0.0025. Figure 2 shows the results of the trade-off between the two objectives of the management scenario using both FE-GA and EPR-GA models. It can be seen that the captured non-dominated fronts in both models are very close to each other. In the FE-GA model, the optimal points on the Pareto front correspond to abstraction rates in the range of 9.7-25.50 m^3/day and the location of the abstraction well at a distance of 10-20 m from the sea boundary and at the depth of 36-37 m. Figure 3 shows the final steady state distributions of salinity throughout the system for one of the optimal solutions selected based on engineering judgment in terms of the objective functions along the Pareto front (marked in Figure 2). In this selected solution, the optimal location of abstraction well, determined by FE-GA, is 15 m from the sea boundary abstracting the groundwater at the optimal rate of 15.5 m^3/day. The optimal depth of the well is 37 m below the top boundary. The great performance of this optimal solution in controlling SWI is compared with the no-management scenario. The 10%, 50% and 90% salinity contours of the no-management scenario are illustrated as dashed lines.

The total computational time of the analysis by FE-GA is 16 days on an Intel(R) Core(TM) i7-2600 CPU @ 3.40GHz (8 CPUs) with 16 GB RAM in this small aquifer system. The application of fine spatial and temporal discretization of the unsaturated flow zone increased the computational complexity of the simulation process. Under this circumstance, the multiple calls of the SUTRA in the optimization framework make the S/O method by FE-GA computationally inefficient. Consequently in the second scheme of the S/O framework it has been replaced by a metamodel (EPR). Horizontal (*Xa*) and vertical (*Ya*) coordinates of the abstraction well, and also its pumping rate (*Qa*) are the input parameters considered in EPR-GA. A database of 500 cases of these input variables is randomly generated with a uniform probability distribution. Then, by multiple runs of the SUTRA code the outputs (total mass of salinity, f_1) corresponding to each set of these data are calculated as the response of the system in each control scenario. The required database for training and validation of the EPR models is developed using the created sets of input and output. In each scenario 400 cases of data are used to train the EPR model and the remaining 100 cases (that are kept unseen to EPR during the model development process) are used for validation of the developed model. The following best EPR model (Equation 2) with high levels of fitness (*COD* values) is selected for prediction of total mass of solute (f_1) in ADRTWW scenario. The *COD* values of this EPR model are 94.9% and 93.1 % in training and testing datasets respectively. The input data of this equation were used concurrently to evaluate the second objective function (cost function, f_2) as well. The average time required to complete the analysis using EPR-GA (including the time to generate the database) is less that 10 % of the time required by FE-GA on the same CPU core that can be considered as a very significant difference.

$$\begin{aligned} f_1 = {} & 30.966\text{-}24.936\mathrm{Ya}^{0.5} + 7.827\mathrm{Ya}\text{-}(7.053\times10^{-2})\mathrm{Ya}^2 + \\ & 56.411\mathrm{Qa}^{-1}\text{-}12.204\mathrm{YA}^{0.5}\mathrm{Qa}^{-1} + 343412.244\mathrm{Qa}^{0.5}\mathrm{Xa}^{-2}\text{-} \\ & 2.069\mathrm{Qa} + (2.605\times10^{-2})\mathrm{Qa}^2 - 105.069\mathrm{YA}^{0.5}\mathrm{Qa}^2\mathrm{Xa}^{-2} \end{aligned} \tag{2}$$

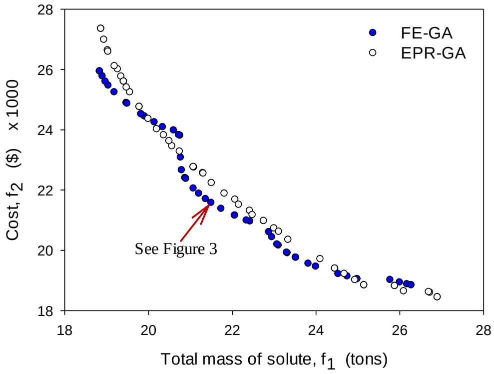

Figure 2: Optimal solutions obtained using both S/O models

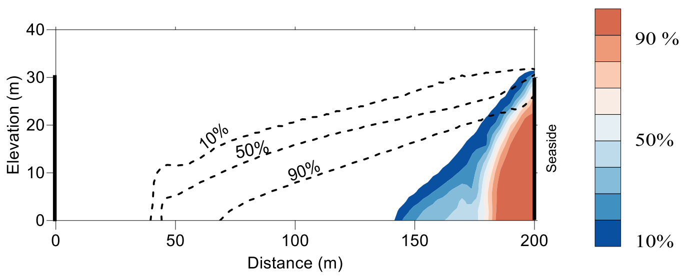

Figure 3: Steady state salinity map (%) of the system for the selected optimal solution compared with the case of no-management scenario (dashed lines)

6. Conclusions

This paper presented the results of an investigation into the capabilities of two different S/O models to find the set of optimal solutions for a new management scenario for controlling saltwater intrusion in coastal aquifers. The results showed that the two S/O schemes were in excellent agreement in terms of capturing the Pareto front of the system in the management scenario. The application of EPR-metamodel in the S/O framework (i.e linking of EPR with optimization tool) resulted in significant reduction of the overall computational complexity and CPU time compared with those obtained by direct linking of the numerical simulation model with the optimization tool.

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