This article was downloaded by: [Heriot-Watt University]
On: 06 January 2015, At: 14:30
Publisher: Taylor & Francis
Informa Ltd Registered in England and Wales Registered Number: 1072954
Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK

ISH Journal of Hydraulic Engineering
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/tish20

PARAMETER ASSESSMENT IN FLOW THROUGH POROUS MEDIA

A. K. Rastogi [a] & V. P. Huggi [b]

[a] Department of Civil Engineering , Indian Institute of Technology Bombay , Mumbai E-mail:

[b] Department of Civil Engineering , BLDEA College of Engineering and Technology , Bijapur

Published online: 07 Jun 2012.

To cite this article: A. K. Rastogi & V. P. Huggi (2009) PARAMETER ASSESSMENT IN FLOW THROUGH POROUS MEDIA, ISH Journal of Hydraulic Engineering, 15:sup1, 272-296, DOI: 10.1080/09715010.2009.10514980

To link to this article: http://dx.doi.org/10.1080/09715010.2009.10514980

PLEASE SCROLL DOWN FOR ARTICLE

Taylor & Francis makes every effort to ensure the accuracy of all the information (the “Content”) contained in the publications on our platform. However, Taylor & Francis, our agents, and our licensors make no representations or warranties whatsoever as to the accuracy, completeness, or suitability for any purpose of the Content. Any opinions and views expressed in this publication are the opinions and views of the authors, and are not the views of or endorsed by Taylor & Francis. The accuracy of the Content should not be relied upon and should be independently verified with primary sources of information. Taylor and Francis shall not be liable for any losses, actions, claims, proceedings, demands, costs, expenses, damages, and other liabilities whatsoever or howsoever caused arising directly or indirectly in connection with, in relation to or arising out of the use of the Content.

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is

THE INDIAN SOCIETY FOR HYDRAULICS
JOURNAL OF HYDRAULIC ENGINEERING

PARAMETER ASSESSMENT IN FLOW THROUGH POROUS MEDIA

by

A K Rastogi and V P Huggi

ABSTRACT

Effective planning and management of aquifers requires modeling of conceptualized system. Assessment of reliable parameters is vital for meaningful system simulation. Optimisation – simulation models are under continuous investigations to auto – calibrate such models resulting in assessment of hydraulic conductivity, specific yield, dispersivity, recharge estimations and recognition of an acceptable modeled structure. This study assesses parameters in confined and unconfined aquifers by genetic algorithm (GA) and simulated annealing (SA). These heuristic methods are found ideally suited for combinatorial optimization problems involving non-convex objective functions. An inverse parameter identification model based on coupled flow–solute transport simulations is developed. Twenty seven aquifer parameters for the nine zones of the confined aquifer are estimated by the coupled numerical models. Normally distributed noise was added to the data to examine their efficacy in the field problem. Both models based on SA and GA responded to the noisy data well and were also found to be independent to the initial guess of the parameters. Necessary modifications in the coupled parameter inversion algorithms were made to apply it to unconfined aquifer of Mahi Right Bank Canal (MRBC) Command area of Kheda District, Gujarat, India. Estimated zonal hydraulic conductivity, longitudinal and transverse dispersivity values were compared with zonal values of the flow region for the calibrated model.

KEYWORDS : Parameter Inversion, Solute Transport, Simulated Annealing, Genetic Algorithm, Optimization

INTRODUCTION

In the past few decades, distributed parameter models (finite difference and finite element) have become important tool to analyze real groundwater systems. Large

---

1. Professor, Department of Civil Engineering , Indian Institute of Technology Bombay, Mumbai, email : akr@civil.iitb.ac.in
2. Professor, Department of Civil Engineering, BLDEA College of Engineering and Technology, Bijapur.

number of researchers has used various methods for modeling of heterogeneous, leaky, isotropic and anisotropic confined and unconfined aquifers involving complex boundaries (Cooley and Vecchia 1987; Sondhi et al. 1989; Rastogi 1989; Cooley and Naff 1990; Anderson and Woessner1992; Aly 1995; Anderman et al. 1996; Hill et al. 1998; Cheng 2000; Charbeneau 2000; Rastogi and Sulekha 2000; Ukarande and Rastogi 2003). Prasad and Rastogi (2001) stated that model conceptualization, model parameters and boundary conditions must be known correctly to build a good quality model since continuous improvement in the solution techniques alone is not enough for practically useful system simulation of aquifers. Though it is of utmost importance to obtain reliable distribution of parameters in an aquifer, however, it is often a difficult task due to the field problems and costs involved in the direct estimation of the field variables. Consequently these parameters are normally worked out at a few locations in the flow domain and information on their spatial distribution is often inadequate.

Inverse modeling is continuously emerging to estimate the hydraulic conductivity, transmissivity, storage coefficient, specific yield, porosity, dispersivity, aquifer recharge in various sub regions of a system with adequate reliability (Carrera and Neuman 1986, Sun and Yeh 1992, Anderman et el 1996, Zimmerman et el 1998, Prasad and Rastogi 2001). The technique is further applied to investigate a valid model structure to identify number of sub regions in an aquifer with distinct parameters (Sun 1994, Zheng and Wang 1996, Prasad and Rastogi 1999). Quantification of data shortcomings and needs, and comparison amongst alternate models under different conditions are also examined by the inverse solution techniques (Kitanidis 1996, Hantush and Marino 1997, Hill et el 1998). Hence, there is a growing appreciation of inverse modeling in many countries of the world today for an effective simulation of large groundwater systems.

The inverse modeling procedure is based on (1) the formulation of an objective function (2) the parameterization which reduces the number of parameters to be identified and (3) the optimization algorithm which estimates the parameter set. The objective function involves a least squares or maximum likelihood formulation and requires computation of the head and concentration distribution for a set of initially assumed parameters. A simulation algorithm is needed for computing the head and concentration distribution. Since the number of observation is finite and limited, whereas the spatial domain of the parameter field is continuous, parameterization is used to simplify the aquifer structure (Sun 1996, Willis and Yeh 1987). Zonation approach can be applied if variation in aquifer quality is distinctly identified from the bore logs. Alternatively, interpolation techniques are appropriate when parameter values are known at certain locations (nodes) and are required to be projected at other nodes for numerical modeling.

Normally the conventional optimization algorithms of Flecher Reeves, Davidon Flecher-Powel, Gauss Newton, or modified Gauss Newton methods are used for computing optimum parameters. The solutions by these methods however may obtain local optimum values as there may be more than one local optimal point in the solution domain due to the non-convexity inherent in many field problems. As a result there is no guarantee that the solutions based upon these methods are the best ones. More over the solution convergence of these methods depends on the initial guess values for the parameters. Chavent (1974), Neuman and Yakowitz (1979), Carrera and Neuman (1986), Sun (1994) and Poeter and Hill (1997) investigated the uniqueness and stability problems in inverse modeling. They concluded that choosing appropriate optimization technique where results do not depend upon the initial estimate of the parameters, appropriate selection of the upper and lower bounds on the parameters and incorporation of the prior field information can adequately over come these problems of the inverse modeling. This paper, examines the application of simulated annealing and genetic algorithm global optimization tools for estimating aquifer parameters. Aquifer region is simulated by Galerkin's finite elements formulation. The flow domain is parameterized by zonation technique and least squares function is used as performance criterion. The coupled numerical model is then applied for estimating parameter for a synthetic confined aquifer consisting of nine zones. The results of SA and GA are compared with true parameters and also with the Gauss-Newton-Marquardt (GNM) method. Later these soft computing tools are effectively applied to assess parameters of longitudinal, transverse dispersivity and hydraulic conductivity for unconfined aquifer of Mahi Right Bank Canal (MRBC) command region in the State of Gujarat.

APPLICATION OF SA AND GA TO ESTIMATE SOLUTE TRANSPORT PARAMETERS - EXAMPLE PROBLEM

An example problem of mass transport in a two-dimensional confined aquifer is considered to test various aspects of inverse modeling which involves a set of aquifer parameters. A synthetic confined aquifer of area 36 square kilometer has been chosen for the present study. The region is bounded by two impervious, a prescribed head and concentration and one known flow boundaries as shown in fig.1a. The northern part of the aquifer is recharged by two strips at the rate of 0.015×10^{-3} m/d with water of total dissolved solids (TDS) concentration of 1000 ppm and 0.25×10^{-3} m/d with TDS concentration 800 ppm respectively. The aquifer is assumed to have nine zones (Fig 1.b) of different transmissivity, longitudinal and transverse dispersivity values which are listed in Table 1. One recharge well with flow rate of 500m^3/d and TDS concentration of injected water 1000 ppm, and one pumping well with a flow rate of 1200 m^3/d are also considered within the flow domain (Fig.1c). Eighteen observation wells are located within the flow region as shown in fig.1d.

The chosen example represents field applicable conditions and flow region area except for its regular shape. The impervious boundaries represent intersecting faults,

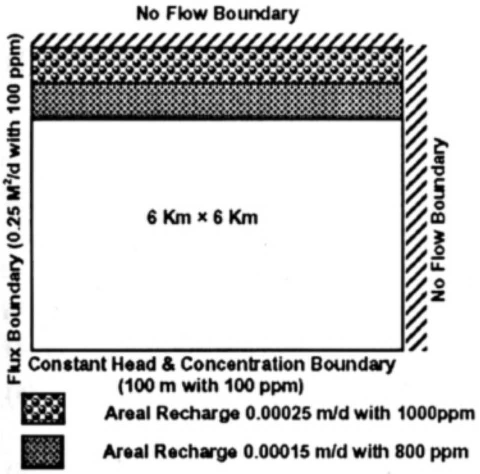

FIG. 1A FLOW REGION

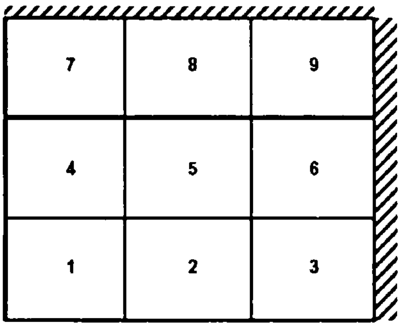

FIG. 1B ZONATION

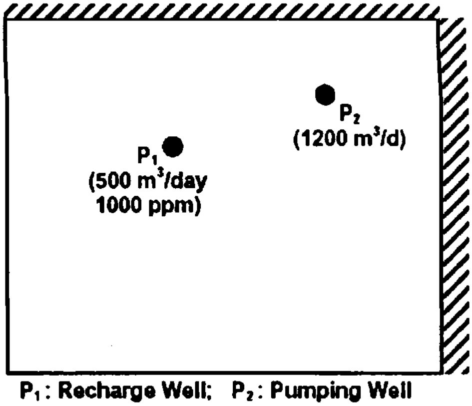

FIG. 1C PUMPING AND RECHARGE WELLS LOCATION

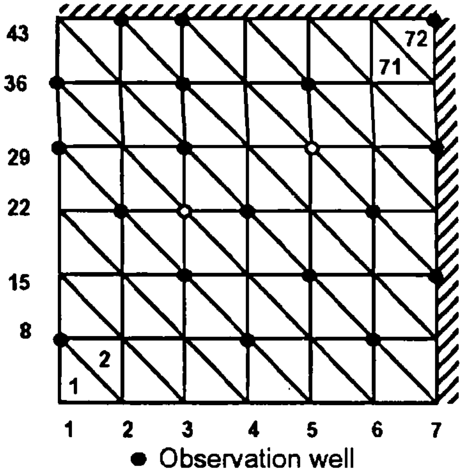

FIG. 1D FINITE ELEMENT DISCRETISATION

a hillock, or a water divide. Variations in recharge on the northern side of the aquifer region may be due to changes in aquitard hydraulic conductivity. Lateral recharge along the western side boundary may originate from a field drain with known head and concentration. Whereas Southern side boundary may approximate representation of a river, reservoir or lake hydraulically connected to the aquifer.

The governing equations describing the groundwater flow and solute transport in a two-dimensional inhomogeneous, isotropic confined aquifer is given by (Anderson and Woessner 1992)

$$\frac{\partial}{\partial x}\left(T_x \frac{\partial h}{\partial x}\right)+\frac{\partial}{\partial y}\left(T_y \frac{\partial h}{\partial y}\right)+W=S\frac{\partial h}{\partial t} \quad \text{(Flow equation) i,j=1,2} \qquad (1)$$

$$\frac{\partial}{\partial x_i}\left(D_{ij}\frac{\partial c}{\partial x_j}\right)-\frac{\partial}{\partial x_j}(cV_i)+\frac{W}{\theta B}c'=\frac{\partial c}{\partial t} \quad \text{(Transport equation) i , j = 1,2} \qquad (2)$$

Following initial and boundary conditions are applicable:

h (x, y, 0) = h_0(x, y) for all x, y ε Ω (3)

c (x, y, 0) = c_0(x, y) for all x, y ε Ω (4)

h (x_B, y_B, t) = h_1(x_B, y_B, t) for all x_B, y_B ε $\partial\Omega_1$, t > 0 (5)

$-T_{ij}\frac{\partial h}{\partial x_j}n_i\big|_{x_B}$ = q(x_B, y_B, t) for all x_B, y_B ε $\partial\Omega_2$, t > 0 (6)

c (x_B, y_B, t) = c_1(x_B, y_B, t) for all x_B, y_B ε $\partial\Omega_1$, t > 1 (7)

$-D_{ij}\frac{\partial c}{\partial x_j}n_i\big|_{x_B}$ = q_c(x_B, y_B, t) for all x_B, y_B ε $\partial\Omega_2$, t > 0 (8)

Where

h_0(x, y) = Initial hydraulic head (m)

c_0(x, y) = Initial TDS concentration (ppm)

h_1(x_B, y_B, t) = Specified head along $\partial\Omega_1$ and x_B, y_B point on the boundary

q(x_B, y_B, t) = flux normal to the boundary $\partial\Omega_2$ and n_i (i = 1,2) are the components of the unit normal vector of $\partial\Omega_2$ and x_B, y_B point on the boundary

c' (x_B, y_B, t)= Specified TDS concentration

q_c(x_B, y_B, t) = dispersive flux normal to the boundary $\partial\Omega_2$ and n_i (i = 1,2) are the components of the unit normal vector of $\partial\Omega_2$

T(x,y) = Transmissivity (m^2/d)

S = Storativity

W = Source or Sink (m/d) (-W for source and +W for sink)

x,y = Horizontal space variables (m)

Ω = Entire domain

∂Ω = Boundary of flow region ($\partial\Omega_1 \cup \partial\Omega_2 = \partial\Omega$)

$\frac{\partial}{\partial n}$ = Normal derivative

Solution of the above governing equation is obtained using Galerkin's finite element approach for the given aquifer geometry, initial and boundary conditions, flux across the boundary, rate of recharge and rate of pumping. Solutions are obtained by solving the following system of equations generated for the flow and transport model. Grid size is kept unchanged for the flow and transport model, for which the entire domain is discretised in 72 linear triangular elements with 49 nodes. Following system of equations are generated:

$$[A]\{h\}+[B]\left\{\frac{\partial h}{\partial t}\right\}=\{f\}\text{(For flow model)} \tag{9}$$

and

$$[G]\{c\}+[P]\left\{\frac{\partial c}{\partial t}\right\}=\{M\}\text{(for transport model)} \tag{10}$$

Where

$[A]$ = Conductance matrix containing transmissivity terms

$[B]$ = Storage matrix depending upon storativity and element configuration

$\{h\}$ = Head vector for the flow domain

$\left\{\frac{\partial h}{\partial t}\right\}$ = Head time derivative vector

$[G]$ = Advection dispersion matrix

$[P]$ = Sorption matrix

$\{c\}$ = Nodal concentration vector

$\left\{\frac{\partial c}{\partial t}\right\}$ = Concentration time derivative vector

Performing the time integration using implicit finite difference scheme the solution of head and concentration are expressed in the matrices form of simultaneous equations as

$$\left[A+\frac{1}{\Delta t}B\right]\left\{h^{t+\Delta t}\right\}=\frac{1}{\Delta t}[B]\left\{h^{t}\right\}+\{F\}\text{ (for flow model)} \tag{11}$$

$$\left[G+\frac{1}{\Delta t}P\right]\left\{c^{t+\Delta t}\right\}=\frac{1}{\Delta t}[P]\left\{c^{t}\right\}+\{M\} \text{ (for transport model)} \tag{12}$$

Where

Δt = Time step size

$\left\{h^{t+\Delta t}\right\}$ = Unknown head vector

$\left\{c^{t+\Delta t}\right\}$ = Unknown concentration vector

$\left\{h^{t}\right\}$ = Known head vector at time t

$\left\{c^{t}\right\}$ = Known concentration vector at time t

At any time step, $\left\{h^{t+\Delta t}\right\}$and $\left\{c^{t+\Delta t}\right\}$are updated by solving a system of simultaneous equations for the previous time (t). Time step size of one day is chosen presently and a total period of 1000 days is simulated. The objective function (performance criterion) considered in the present problem is least squares (WLS) criterion, wherein the functional to be minimized is

$$\underset{T_1 \dots T_M}{Min}\ J(T)=\sum_{L=1}^{L}\sum_{t=t_0}^{t_f}\omega_{h_{(L,t)}}\left(h_{L,t}^{est}-h_{L,t}^{fem}\right)^2+\sum_{L=1}^{L}\sum_{t=t_0}^{t_f}\omega_{c_{(L,t)}}\left(c_{L,t}^{est}-c_{L,t}^{fem}\right)^2 \tag{13}$$

subject to the lower and upper bounds on the parameters

$$T_i^l \le T_i \le T_i^u \tag{14}$$

where $h_{L,t}^{est}$ and $c_{L,t}^{est}$ are computed head and concentration at observation well L at time t for assumed parameters as systems response to various dynamic activities, $h_{L,t}^{fem}$ and $c_{L,t}^{fem}$ are head and concentration at observation well L at time t for true parameters, T_i is transmissivity at block i, M is number of transmissivity blocks (parameter dimension). L is number of observation wells and t_0, t_f are beginning and ending times of observations, and *i,u* are superscripts used to denote lower and upper bounds of parameters. $\omega_{h_{L,t}}$ and $\omega_{c_{L,t}}$ are weighting factors which are applied for accuracy and reliability of field parameters. For the present problem these are taken equal to one for all time steps. (It may be noted that in real problem, bounds on parameters are related with prior information of the aquifer field conditions)

SIMULATED ANNEALING AND GENETIC ALGORITHMS

Dougherty and Marryott (1991) were first to introduce simulated annealing (SA) in the field of water resources research. They laid emphasis on practical algorithmic guidance and demonstrated the technique with the help of simple groundwater management examples. Simulated annealing is a technique that uses an analogy from metallurgical process (Kirkpatrick et.al. 1983) to find near global optimum solutions for real discrete problems. In this method each decision variable is restricted to a set of possible discrete values. Each combination (decision vector) is called a configuration. The set of all possible combinations constitute the configuration space. The basic idea of the method is to generate a random configuration (iteratively referred as chain) through perturbation and evaluate the objective function. For example if there are 4 decision variables and each is allowed to take 10 possible discrete values, there are 10^4 configurations. If the trial point is infeasible, it is rejected and a new point is generated. If the trial point is feasible and objective function value is smaller than current best record, than the point is accepted, and the record for the best value is updated. If the point is feasible but the objective function is higher than the best value, then the point is sometimes accepted and sometimes rejected. The acceptances of uphill moves are based on metropolis criterion (Metropolis, 1953), wherein for computing the probability of acceptance a (temperature like) parameter is used. For the optimization problem, this parameter can be target value for the objective function corresponding to a global minimum. Initially a larger target value is selected and as the trial progresses, this value is reduced (cooling schedule) and the process is terminated after a fairly large number of trial. The acceptance probability steadily decreases to zero as temperature is reduced. Thus in the initial stages, the method is likely to accept worse designs (or configurations) while in the final stages, the worse designs are almost always rejected. This strategy avoids getting trapped at a local minimum.

Genetic algorithms (GA) also belong to the class of evolutionary stochastic search methods (Goldberg and Deb 1991, Charbeneau 2000). In GA, several design alternatives, called a population in a generation, are allowed to reproduce and crossover among themselves, with bias allocated to most fit members of the population. Combination of most desirable characteristics of mating members of the population results in new designs that are better fit than their parents. In GA each design (or configuration) must be represented by a finite length string. Real (Chang and Chen, 1998) or binary strings (Goldberg, 1989) are used for this purpose called encoding. Three operators are needed to implement the algorithm: 1) reproduction 2) crossover and 3) mutation. The three steps are repeated for successive generation of population until certain stopping criteria are satisfied. There are no fixed ways to pick up crossover and mutation probability values which are presently worked out by tuning of algorithm. The reproduction generally involves a selection procedure such as roulette wheel (Goldberg, 1989) or tournament selection (Wang and Zheng, 1998). The members in the final generation with best fitness level suggest the optimum design solution. Efforts are made by researchers to make conventional genetic algorithm more efficient. Real coded genetic algorithm (RCGA) is a step in that direction which uses real parameters without any strings. Problem of hamming cliffs associated with certain strings is successfully tackled by this method. Steady state GA (SSGA) is different to the generational model in that a replacement strategy defines inferior solution which in the current population is forced to move out and replaced by better (offspring) solution. In order to ensure convergence and to accelerate the rate of convergence, elitist genetic algorithm (EGA) is also being used where it is ensured that the population does not deteriorate as the solution advances (Deb 2001). Sharief et al. (2006a and b) have applied the various GAs to problems of optimal design of pump and treat groundwater pollution remediation for synthetic aquifers. They have recommended that all methods of GA require tuning of GA parameters to get the best results. Population size, cross over and mutation probability, maximum reduction in the objective function and maximum number of generations are considered by them in the tuning process.

Although SA has been reported as superior to GA, it uses more empirical control parameters that significantly impact on the solution efficiency but are difficult to determine (Wang and Zheng, 1988).

RESULTS AND DISCUSSIONS

Finite element formulation is used to compute the head and concentration distribution in steady and transient state. Steady state heads are computed prior to pumping with boundary and other conditions of constant flux and areal recharge operative in the flow domain. For this pumping well is off and recharge well is operative. Transient state head and concentration distribution in the aquifer region is obtained for groundwater withdrawal from the pumping well at constant rates when the recharge well is also active. The transient state head and concentration values at all the nodes are computed for the time periods of 50, 200 and 1000 days after pumping is commenced, using a time step size of 1 day. The initial TDS concentration in the flow domain was considered as 100 ppm. As expected the study found a gradual spread of total dissolved solid pollution with time for both, steady state and time variant groundwater head in the system. For steady state heads the groundwater velocity in confined aquifer was uniform, however for time variant head flow through porous media involved a small variation in velocity each day which caused different polluted zones with time compared to steady state velocities. Pollution spread levels after 50, 200 and 1000 days of pumping were analysed and concentration contours after 1000 days are shown in fig. 2. Study found that about 30% aquifer region occupied TDS in excess of initial 100 ppm after 50 days, which grew to occupy 50% region after 200 days and rather slowly to encompass 80% area after 1000 days. However maximum concentration was found to be 300 ppm near recharge well after 50 days, which increased to 700 ppm after 200 days and 950 ppm after 200 days.

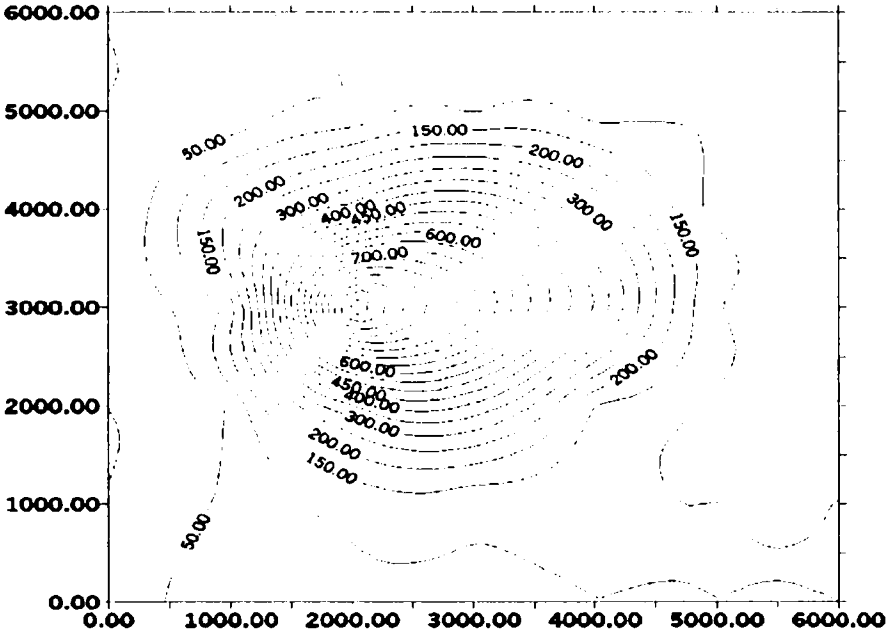

FIG. 2 SOLUTE CONCENTRATION (PPM) OBTAINED FROM THE MODEL FOR TRANSIENT STATE AFTER 1000 DAYS

There was a shift in the spread of TDS contamination towards the pumping well for time variant head whereas this was not present for steady state heads where only the boundary conditions influenced the spread of pollutant.

CASE 1: NOISE FREE HEAD AND CONCENTRATION DATA

For this case groundwater heads and TDS concentrations are computed by the finite element simulation model for the true parameters values within the aquifer. The computed heads and concentrations at the eighteen observation wells are used as observed heads and concentrations without noise (measurement errors). This is a particular advantage of the synthetic problem that the FEM simulated values can be considered as giving the correct distribution of state variables, since the system parameters are defined precisely in the flow region. The aquifer transmissivity, longitudinal and transverse dispersivity values are estimated both, for steady and transient state cases. For solving the inverse problem eighteen observed heads and concentrations at the eighteen observation wells are considered in steady state. For the transient case the observed heads and concentrations at three time periods 50, 200, and 1000 days after pumping at the eighteen observation wells are available. Optimized inverse solution estimate the transmissibility, longitudinal and transverse dispersivity parameters in the nine zones of the aquifer region which are found closer to the true values. This analysis found that the inverse solutions by SA and GA show a very small percentage of error from the true aquifer parameters and therefore are quite acceptable from practical consideration. However, since noise is inherent in the field data, this information may not be adequate when applied to a field problem.

CASE 2: CONSIDERATION OF NOISE (MEASUREMENT ERRORS) IN DATA

In this case the computed aquifer heads and TDS concentrations obtained for true parameters from finite element simulation model are corrupted by adding random noise. The noise (errors) is assumed normally distributed as suggested by Cooley and Naff (1990) and random noise is generated with zero mean and variance equal to n. (n ranging 0.01 to 1). Therefore for this case Observed head = FEM head for true parameters + noise N (0, n) and Observed concentration = FEM concentration for true parameters + noise N (0, n).

These aquifer heads and solute concentrations at eighteen observation points for, both, steady state and transient conditions are used for estimating the transmissivity, longitudinal and transverse dispersivity of the aquifer. In field problems this noise is equivalent to personal and instrument measurement errors which are unavoidable. Three different sets of error distributions N(0,n) are generated with different random seed to obtain three different sets of observed head and concentration data. Thus data set 1, data set 2 and data set 3 are generated for steady and transient states which are used for parameter estimation by simulated annealing and genetic algorithm. The standard deviation of 0.01, 0.1 and 1.0 are used to generate the three data sets. Therefore n = 0.01 suggests very small errors, n = 0.1 indicates medium errors and whereas n = 1.0 implies much larger errors than normally expected in field problems in the data set. Therefore the parameter assessed by N (0,1) are of utmost interest where significant errors in aquifer head ranging from -2.76 to + 2.67 are added in the correct head and TDS concentration values to get severe noisy data. Table 2 considers the transmissivity estimated for nine zones of the aquifer for steady state data sets by SA and GA. Results obtained by Gauss Newton Marquardt (GNM) method are also shown in this table for comparison purpose. In general the results are agreeable, however, the weighted average error is maximum by GNM (14.5%) compared to GA (2.25%) and SA (0.61%). Transmissivity estimated by simulated annealing produced the best results for steady state data set 3. However, when transmissivity parameter was estimated using transient data set (Table 3), the weighted average error was 2.5% by SA and 2.9%, 2.95% by GA and GNM respectively.

Longitudinal dispersivity parameter using maximum noisy steady state data set produced fairly good estimate and the weighted average error for the nine zones of the confined aquifer was only 1.1% by SA and 1.5%, 4.67% by GA and GNM respectively (Table 4). Therefore the SA and GA results are considerably better and both perform better then GNM. Table 5 shows the assessment of longitudinal

TABLE-1

ZONAL DATA FOR THE EXAMPLE PROBLEM

Zone no	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
T(m^2/d)	150	150	50	150	50	15	50	15	5
α_L (m)	60	60	40	60	40	15	40	15	10
α_T (m)	6	6	4	6	4	1.5	4	1.5	1

TABLE-2

COMPARISON OF ESTIMATED TRANSMISSIVITY VALUES IN VARIOUS ZONES USING NOISY STEADY STATE HEAD DATA BY SA, GA AND GNM APPROACH

Zone no	**Estimated transmissivity (m^2/d)**									**True parameter**
	data set 1 N(0, 0.01)			**data set 2 N(0, 0.1)**			**data set 3 N(0, 1)**			
	SA	GA	GNM	SA	GA	GNM	SA	GA	GNM	
1	150.001	149.994	149.873	150.063	149.326	147.805	150.145	149.023	120.915	150.0
2	150.000	149.963	150.214	150.041	149.461	152.192	149.816	148.988	190.435	150.0
3	49.999	50.118	49.854	49.981	49.326	48.616	49.712	49.011	38.850	50.0
4	149.998	150.112	150.248	149.963	149.612	152.125	150.163	149.131	180.645	150.0
5	50.000	49.923	49.898	50.015	49.716	48.946	49.686	48.989	41.215	50.0
6	15.000	14.998	15.021	15.011	14.813	15.164	15.082	13.989	15.995	15.0
7	49.998	49.961	49.998	49.986	49.617	49.712	49.663	49.113	49.485	50.0
8	15.000	14.998	15.010	15.019	14.963	15.031	15.128	14.512	16.125	15.0
9	5.000	4.991	5.002	5.000	4.961	4.999	5.101	4.893	5.425	5.0
						Weighted Average Error	0.61%	2.25%	14.5%	

TABLE-3

COMPARISON OF ESTIMATED TRANSMISSIVITY VALUES IN VARIOUS ZONES USING NOISY TRANSIENT STATE HEAD AND CONCENTRATION DATA BY SA, GA AND GNM APPROACH

Zone no	Estimated transmissivity (m^2/d)									True parameter
	data set 1 N(0, 0.01)			data set 2 N(0, 0.1)			data set 3 N(0, 1)			
	SA	GA	GNM	SA	GA	GNM	SA	GA	GNM	
1	150.001	149.103	149.919	150.893	148.762	148.912	151.143	148.712	147.165	150.00
2	150.000	148.991	149.998	149.116	149.451	148.671	149.131	149.113	142.476	150.00
3	49.998	49.918	49.875	49.611	49.753	49.116	51.016	49.610	51.922	50.00
4	149.999	150.097	149.911	150.421	149.892	148.116	150.992	148.999	146.926	150.00
5	49.997	49.921	49.913	49.563	49.716	48.623	48.936	49.613	52.132	50.00
6	15.000	14.862	14.999	14.513	14.776	13.991	14.162	14.192	15.462	15.00
7	50.001	49.863	49.973	49.113	49.321	49.103	49.149	49.013	50.643	50.00
8	15.000	14.781	15.002	15.068	14.292	14.322	15.167	14.199	15.560	15.00
9	5.000	4.942	4.999	4.718	4.816	4.321	4.616	4.528	4.921	5.00
						Weighted Average Error	2.5%	2.9%	2.95%	

TABLE-4

COMPARISON OF LONGITUDINAL DISPERSIVITY VALUES IN VARIOUS ZONES USING NOISY STEADY STATE HEAD DATA BY SA, GA AND GNM APPROACH

Zone no	Estimated longitudinal dispersivity									True parameter
	data set 1 N(0, 0.01)			data set 2 N(0, 0.1)			data set 3 N(0, 1)			
	SA	GA	GNM	SA	GA	GNM	SA	GA	GNM	
1	60.000	59.436	59.918	59.616	59.773	59.113	58.918	59.183	58.228	60.0
2	60.001	58.999	58.879	59.348	59.819	59.216	59.137	59.591	58.916	60.0
3	39.999	39.163	39.992	39.718	39.698	39.236	39.216	39.463	37.612	40.0
4	60.000	59.495	59.996	59.659	60.158	59.413	59.146	60.153	58.643	60.0
5	39.998	39.664	40.013	39.736	39.768	38.992	40.133	39.196	38.115	40.0
6	14.996	14.863	14.999	14.834	14.697	14.512	15.123	14.269	14.115	15.0
7	40.001	39.766	39.986	39.813	39.598	39.621	39.311	39.110	38.212	40.0
8	15.000	14.968	15.001	15.133	15.281	14.822	15.102	15.293	14.615	15.0
9	10.000	9.866	9.999	10.108	9.739	9.162	9.715	9.642	8.923	10.0
				Weighted Average Error			1.1%	1.5%	4.67%	

TABLE-5
COMPARISON OF LONGITUDINAL DISPERSIVITY VALUES IN VARIOUS ZONES USING NOISY TRANSIENT STATE HEAD AND CONCENTRATION DATA BY SA, GA AND GNM APPROACH

Zone no	Estimated longitudinal dispersivity									True parameter
	data set 1 N(0, 0.01)			data set 2 N(0, 0.1)			data set 3 N(0, 1)			
	SA	GA	GNM	SA	GA	GNM	SA	GA	GNM	
1	60.000	59.436	59.918	59.136	59.330	59.132	58.963	59.138	58.821	60.0
2	60.001	58.999	59.879	59.562	58.992	60.233	59.351	59.973	58.122	60.0
3	39.999	39.163	39.992	39.632	38.997	39.163	40.136	38.961	38.623	40.0
4	60.000	59.495	59.996	59.613	59.321	58.874	59.466	59.181	57.996	60.0
5	39.998	39.664	40.013	39.270	39.438	39.313	39.169	39.319	38.421	40.0
6	14.996	14.863	14.999	14.112	14.392	14.615	15.086	14.129	14.261	15.0
7	40.001	39.766	39.986	40.091	39.439	39.233	39.458	39.322	38.353	40.0
8	15.000	14.968	15.001	14.239	14.693	14.771	15.113	14.392	14.663	15.0
9	10.000	9.866	9.999	9.511	9.569	9.125	9.614	9.116	8.826	10.0
					Weighted Average Error		1.4%	3.05%	4.19%	

TABLE-6

COMPARISON OF TRANSVERSE DISPERSIVITY VALUES IN VARIOUS ZONES USING NOISY TRANSIENT STATE HEAD AND CONCENTRATION DATA BY SA, GA AND GNM APPROACH

Zone no	Estimated transverse dispersivity									True parameter
	data set 1 N(0, 0.01)			data set 2 N(0, 0.1)			data set 3 N(0, 1)			
	SA	GA	GNM	SA	GA	GNM	SA	GA	GNM	
1	6.000	5.821	5.998	5.616	5.663	5.421	4.813	5.479	4.993	6.0
2	6.001	5.879	5.919	5.523	5.712	5.336	5.226	5.513	5.236	6.0
3	3.999	3.906	3.996	3.718	3.823	3.341	3.518	3.628	3.132	4.0
4	5.998	5.913	5.923	5.439	5.772	5.511	4.961	5.419	5.136	6.0
5	3.997	3.958	4.001	3.811	3.797	3.863	3.667	3.568	3.671	4.0
6	1.498	1.473	1.499	1.229	1.382	1.239	0.871	1.319	0.812	1.5
7	4.001	3.962	3.991	3.361	3.699	3.677	3.813	3.598	3.563	4.0
8	1.500	1.493	1.498	1.366	1.412	1.361	0.968	1.393	0.771	1.5
9	1.000	0.995	1.000	0.891	0.928	0.913	0.616	0.910	0.713	1.0
				Weighted Average Error			21.2%	9.4%	23%	

dispersivity values for the nine aquifer zones using transient data set. For this case the weighted average error is minimum (1.4%) by simulated annealing. In case of transverse dispersivity estimation by less noisy data, it was found that the error is very small for data set 1 and 2. However, it shot up considerably (23% - Table 6) by GNM when noise in the data set was increased to maximum. Higher error for this case is attributed to much smaller values of the parameter compared to the errors which have relative lesser influence on the solute transport. Therefore it is observed that in all the cases, the SA and GA model gave better estimates as compared to GNM results. One particular advantage noted in using GA and SA was that a considerable larger range of initial parameters could be used, which did not alter the finally estimated results.

APPLICATION OF SA AND GA MODELS TO MR BC UNCONFINED AQUIFER

The coupled flow-mass transport inverse models as tested above upon a synthetic confined aquifer and based upon GNM, SA and GA are suitably modified for its subsequent application to a field problem. The chosen flow region lies in Mahi Right Bank Canal (MRBC) command area, Anand and Kheda districts, Gujarat State, India (fig.3). Finite element flow modeling of this unconfined aquifer region (fig.4) is done in detail by Prasad and Rastogi (2001). Their model involved irrigation return flow, canal seepage, well withdrawals, river flux, evapotranspiration losses and groundwater outflow, which are also considered in the present model. They also suggested an optimal zonation pattern (fig.5) for the MRBC region which was used presently for the transport model of the flow domain. The solute transport model for the MRBC aquifer was developed and the model was calibrated with the field observations of head and concentration values. The calibrated values of the longitudinal, transverse dispersivity and hydraulic conductivity were used to compare them later with those estimated by SA and GA inverse models for which the field data was available. Due to field data constraints, the study period was confined from June 1999 to May 2000 and June 2003 to May 2004 respectively. The computed head and concentration contours (figs.6 and fig.7) for the estimated parameters showed an acceptable match with the observed head and concentration distribution suggesting the adequacy of the developed model. For inverse modeling the available head and concentration contours (June 1999 and May 2000) of flow region are used simultaneously. The flow region is divided into 10 zones (fig.5) and the zonal hydraulic conductivity, longitudinal and transverse dispersivity values are estimated based on GNM, SA and GA approach. The estimated zonal hydraulic conductivity, longitudinal and transverse dispersivity values agreed closely with zonal values of the flow region. A comparison of TDS concentration contours for the period May 2000 and May 2004 (Figs 7 and 8) shows the gradual growth of pollution in this region and particularly in the southern region where sharper concentration gradients are obtained.

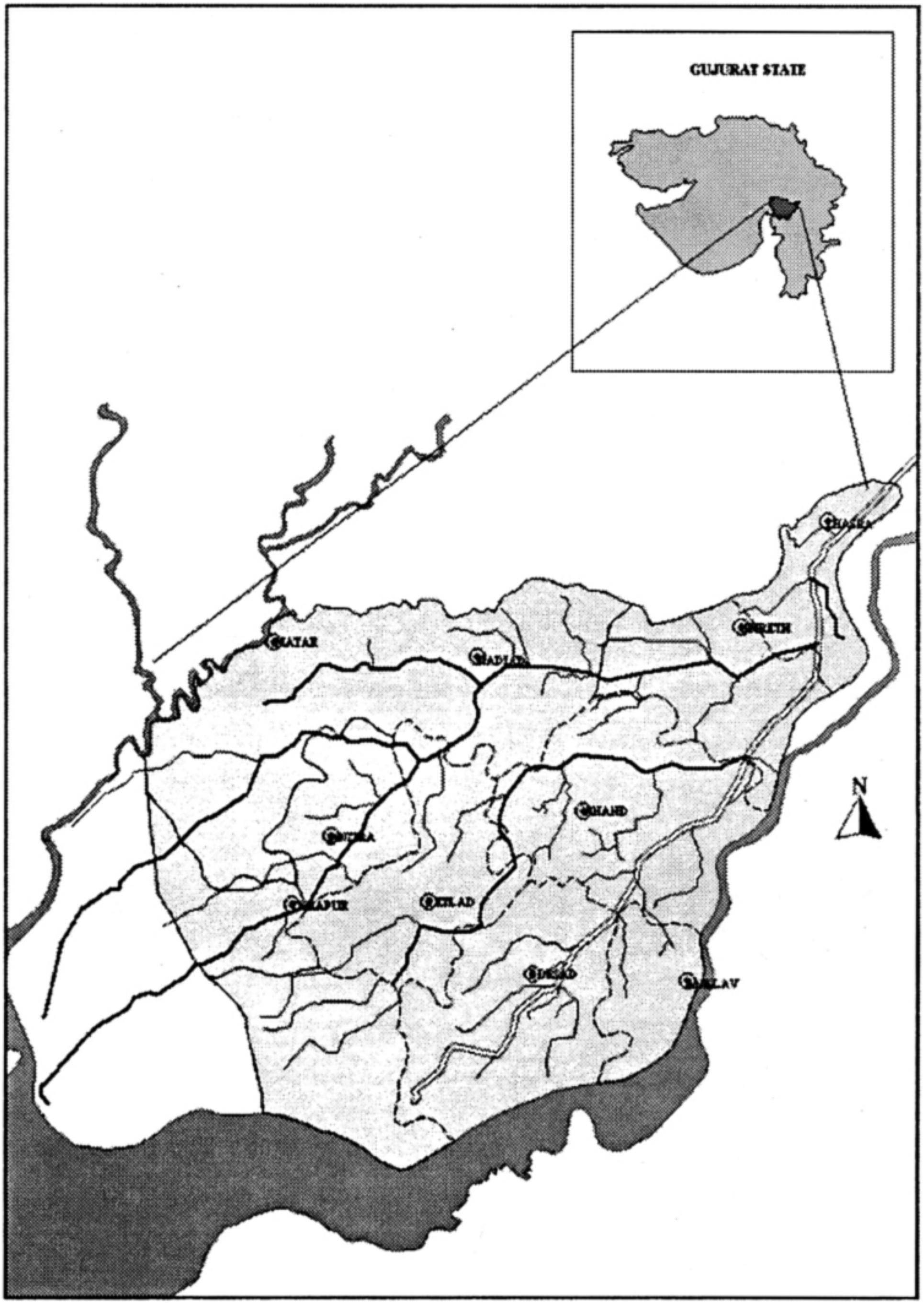

FIG. 3 LOCATION MAP OF STUDY AREA

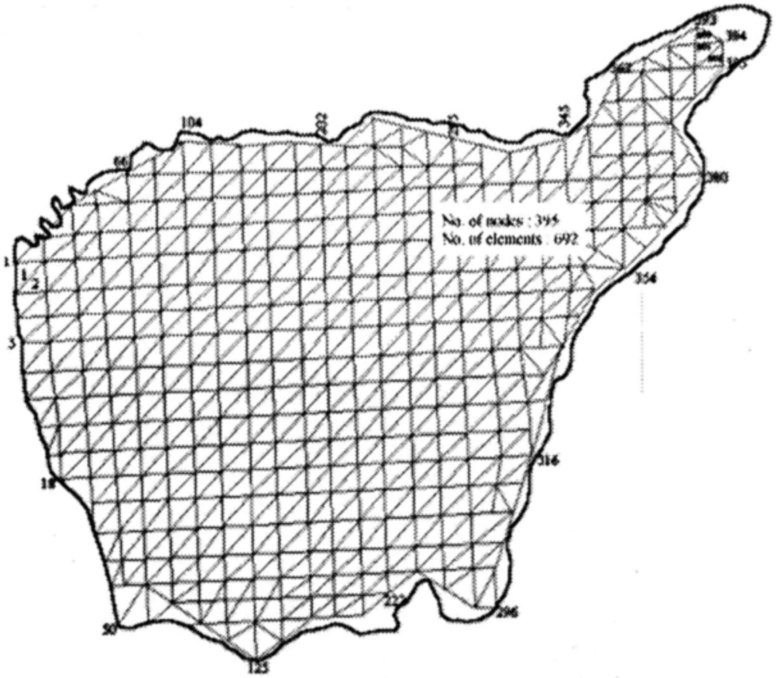

FIG. 4 FINITE ELEMENT DISCRETISATION

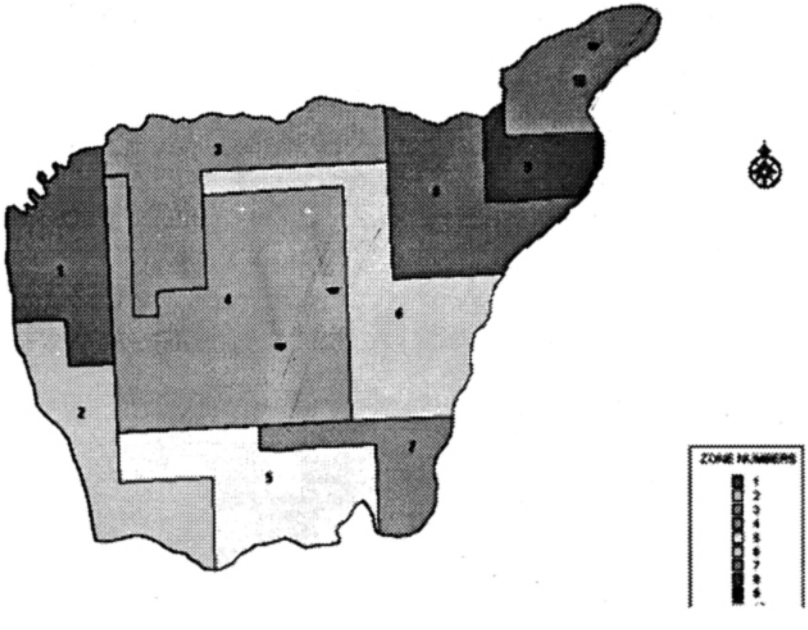

FIG. 5 OPTIMUM ZONATION PATTERN

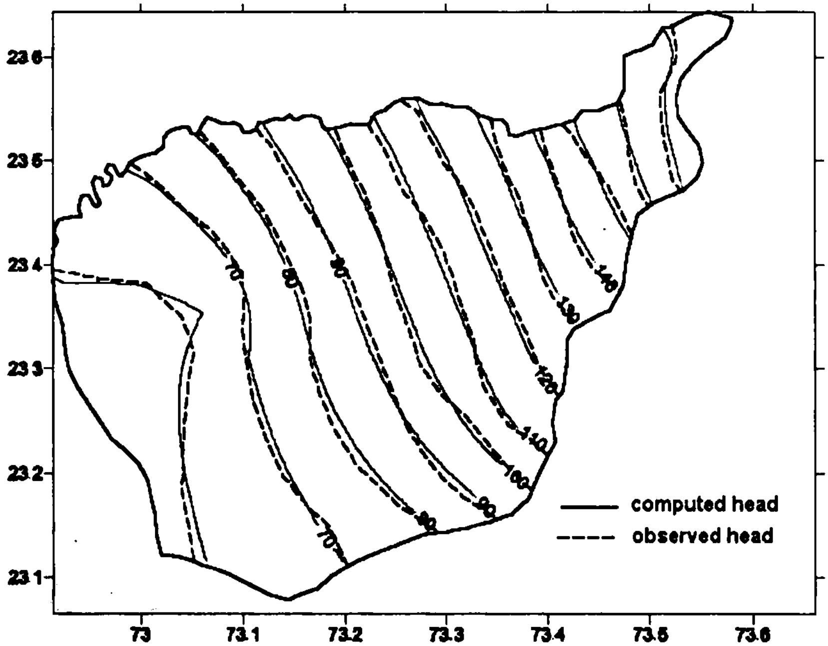

FIG. 6 COMPARISON OF COMPUTED AND OBSERVED HEAD (M) DISTRIBUTION CONTOURS IN THE MRBC REGION (MAY 2000)

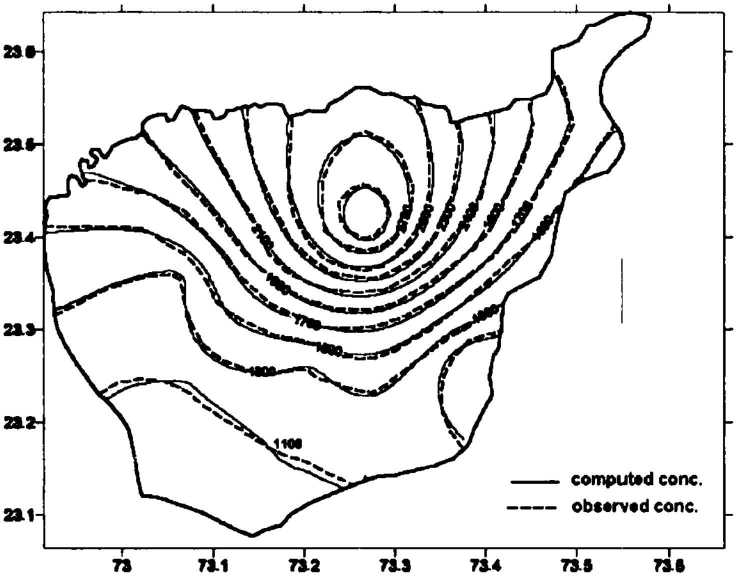

FIG. 7 COMPARISON OF COMPUTED AND OBSERVED CONCENTRATION (PPM) CONTOURS IN THE MRBC REGION (MAY 2000)

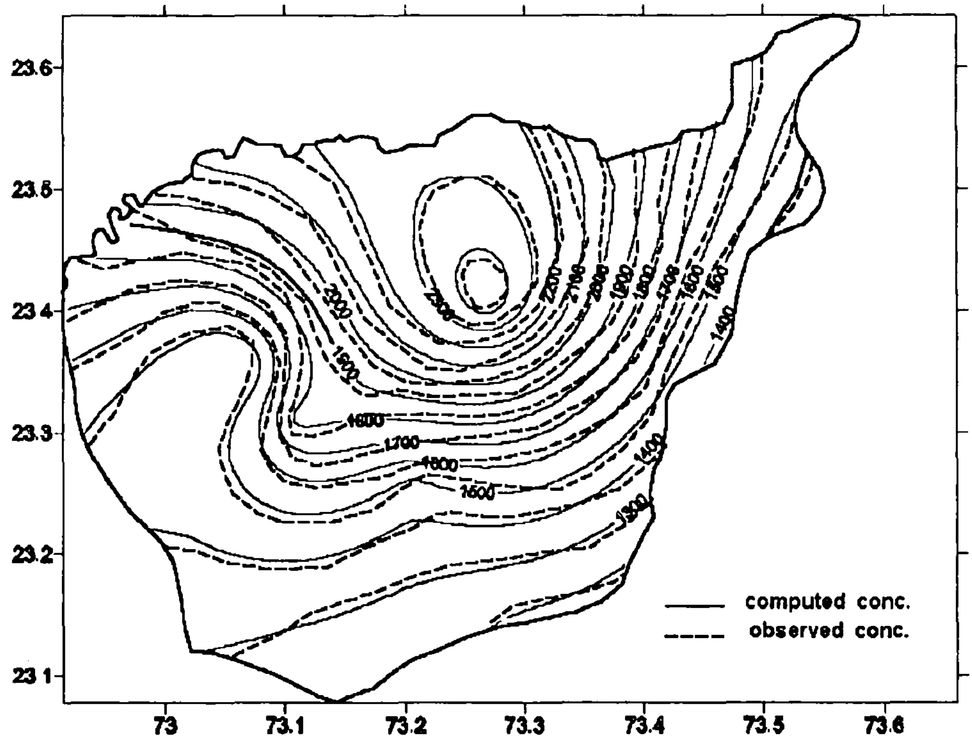

FIG. 8 COMPARISON OF COMPUTED AND OBSERVED CONCENTRATION (PPM) CONTOURS IN THE MRBC REGION (MAY, 2004)

CONCLUSIONS

The study has shown that emerging techniques of simulated annealing and genetic algorithms can be successfully used for parameter estimation in flow through porous media. Presently 27 aquifer parameters (transmissibility, longitudinal and transverse dispersivity) for the nine zones of the confined aquifer are estimated by the coupled (SA + FEM and GA+FEM) models. Different levels of noise distributions are considered and in all cases the model results were found satisfactory and acceptable from field considerations. When compared with conventional numerical GNM optimisation technique it was found that GNM results are marginally better for the noise free data (which is rare for field problem), where as SA and GA results are better for noisy head and concentration data, which encouraged their application for real aquifer system parameter estimation.

Parameters of longitudinal, transverse dispersivity and hydraulic conductivity were estimated for unconfined aquifer of MRBC region. These estimated parameters compared favorably with the known parameters for the calibrated model. Lack of sensitivity of the SA and GA approach for the initial guess of the parameters was established which is a definite merit of these soft computing methods over rigorous numerical schemes. Their advantage over GNM is attributed to no computation of objective function derivative with respect to the estimated parameters, which may cause numerical instability. The study concluded that given the reliable data set of head and concentration distribution in the flow domain the present coupled model estimates the porous media parameters adequately which can be used to predict the groundwater and concentration levels for effective planning and management of groundwater resources. Present study shows the gradual growth of TDS concentration and which calls for appropriate corrective remedial measures in MRBC aquifer region.

REFERENCES

Aly, I. Kadi, El. (Ed.) (1995). Groundwater Models for Resources Analysis and Management, Lewis Publication, Boca Raton.

Anderman, E. R., Hill, M. C. and Poeter, E. P. (1996). Two-dimensional advective transport in groundwater flow parameter estimation, Groundwater, Vol.34, No.6, pp.1001-1009.

Anderson, M. P. and Woessner, W. W. (1992). Applied Groundwater Modeling, Academic press, Inc.

Carrera, J. and Neuman, S. P. (1986). Estimation of aquifer parameters under transient and steady state conditions, 3, Application to synthetic and field data, Water Resour. Res., Vol.22, No.2, pp.228-242.

Chang, F.I. and Chen, L. (1998). Real-Coded Genetic Algorithm for Rule-Based Flood Control Reservoir Management, Water Resour. Manage, Vol.12, pp.185-198.

Chavent, G. (1974). Identification of Functional Parameters in Partial Differential Equations in Identification of Parameters in Distributed Systems, (Edited by Goodson, R.E. and Polis, M. ASME), pp.31-48, New York.

Cheng, H. D. and Alexander (2000). Multilayered Aquifer Systems Fundamental and Applications, Marcel Decker Pub. New York.

Charbeneau, R. J. (2000). Groundwater Hydraulics and Pollutant Transport – Prentice Hall, Upper Saddle River.

Cooley, R. L. and Vecchia, A. V. (1987). Calculation Of Nonlinear Confidence and Prediction Intervals for Groundwater Flow Models, Water Resour. Bull., Vol.23, No.4, pp. 581-599.

Cooley, R. L. and Naff, R. L. (1990). Regression Modeling of Groundwater Flow, U. S. G. S. Techniques of Water Resources Investigations, Book. 3.

Deb, K. (2001). Multi-Objective Optimisation using Evolutionary Algorithms, John Wiley & Sons, England.

Dougherty, D. E., and Marryott, R. A. (1991). Optimal Ground Water Management, 1. Simulated Aneealing,Water Resources Research, and Vol.27, No.10, pp.2493-2508.

Goldberg, D. E. (1989). Genetic algorithms in Search, Optimization, and Machine Learning, Mass., Addison – Wesley.

Goldberg, D. E., and Deb. (1991). Comparative Analysis of Selection Schemes used In Genetic Algorithms. In Foundations of Genetic Algorithms, G.J.E.Rawlins (Ed.), Morgan Kaufmann, Sanmateo, CA, pp. 69-93.

Hantush, M. M. and Marino, M. A. (1997). Stochastic solutions to inverse problem in groundwater, Jr. of Hydraulic Engineering, Vol.123, No.12, pp.1139-1146.

Hill, M. C., Cooley, R. L. and Pollock, D. W. (1998). A Controlled Experiment in Groundwater Flow Model Calibration, Groundwater, Vol. 36, No.3, pp.520-535.

Kirkpatric, S. Gelatt, C. D. and Vecchi, M.P (1983). Optimization by Simulated Annealing. Science, Vol. 220, No.4598, pp. 671-680,

Kitanidis, P. K. (1996): On the Geostatistical Approach to the Inverse Problem - Advances in Water Resources, Vol.19, No.6, pp. 333-342.

Metropolis, N.A., Rosenbluth, M., Rosenbluth A., Teller and Tell, E. (1953). Equation of State Calculations by Fast Computing Machines, Journal of chemical physics, Vol. 21 pp.1087-1092.

Neuman, S. P. and Yakowitz, S. A. (1979). Statistical Approach to the Inverse Problem of Aquifer Hydrology, 1, Theory - Water Resour. Res.,Vol. 15, No.4 pp.845-860.

Poeter, E. P. and Hill, M. C. (1997). Inverse models: A Necessary Step in Groundwater Modeling - Groundwater, Vol. 35, No.2, pp. 250-260.

Prasad, K. L. and Rastogi, A. K.(1999). Selection of Optimal Model Structure Based upon Reliability of Aquifer Parameter Using Genetic Algorithm – Proc. International Conference on Water, Environment, Ecology, Socio- economics and Health Engineering WEE-SHE-99, pp.381 – 394, Oct. 18-21, Seoul, Korea,.

Prasad, K L and Rastogi, A. K.(2000). Estimation of Hydrogeologic Parameters in Ground Water Modeling by Genetic Algorithm - Ground Water Updates, pp. 405 - 410, Springer Verlag, Tokyo,.

Prasad, K. L. and Rastogi A. K.(2001). Estimating Net Aquifer Recharge and Zonal Hydraulic Conductivity Values for Mahi Right Bank Canal Project Area, India by Genetic Algorithm, Jr. of Hydro., Vol. 243, No.138, pp.149-161.

Rastogi, A. K. (1989). Optimal Pumping Policy and Groundwater Balance of Blue Lake Aquifer - California, Involving Non Linear Groundwater Hydraulics- Jr. of Hydro. Vol. 111, pp.177-194.

Rastogi, A. K. and Sulekha. (2000). A Coupled Ground Water Flow And Solute Transport Model To Ascertain Spread Of Pollutants in an Irrigated Area – Proc. Third R & D International Conference on ' Sustainable Development of Water and Energy Resources, (Organiser: Central Board of Irrigation and Power, New - Delhi), Jabalpur. Vol. 1, pp. 54-60.

Sharief, S. M. V, Eldho, T. I. and Rastogi, A. K.(2006a.). Optimal Design Of Pump And Treat Groundwater Pollution Remediation by Steady State Genetic Algorithm – 3rd APHW Conference on Wise Water Resources Management towards Sustainable Growth and Poverty Reduction - 16-18 Oct, Bangkok, (in CD)

Sharief, S. M. V, Eldho, T. I. and Rastogi, A. K.(2006b). Real Coded Genetic Algorithm for Optimal Groundwater Contaminant Remediation using Pump And Treat Method, National and 3rd International Conference on Fluid Mechanics and Fluid Power, Dec. 7-9, I I T Bombay, India, (in CD)

Sondhi, S. J., Rao, N. H. and Sarma, P. B. S.(1989). Assessment Of Groundwater Potential For Conjunctive Water Use in a Large Irrigation Project in India, Jr. of Hydrology, Vol.107, pp.283-295.

Sun, Ne- Zheng (1994). Inverse Problems in Groundwater Modeling, Kluwer Academic Publishers, Netherlands.

Sun, N. Z. and Yeh, W. W. G. (1992). A Stochastic Inverse Solution for Transient Groundwater Flow: Parameter Identification and Reliability Analysis, Water Resour. Res., Vol.28, No. 12, pp .3269-3280.

Sun, N. Z .(1996). Identification and reduction of model structure for modeling distributed parameter systems, Parameter Identification and Inverse Problems in Hydrology, Geology and Ecology, Kluwer academic publishers, Netherlands,. pp. 91-103.

Ukarande, S. K. and Rastogi, A. K.(2003). Modeling of Sea Water Intrusion in Multilayered Coastal Aquifers, Proc. 2nd International Conference on Water Quality Management- part II, pp.12-25, CBIP, New Delhi, Feb. pp.13-15.

Wang, M. and Zheng, C. (1998). Ground Water Management Optimization using Genetic Algorithms and Simulated Annealing: Formulation and comparison, Journal of American Water Res. Assoc., Vol.34, No.3, pp.519-530.

Willis, R. and Yeh, W. W.G (1986). Groundwater Systems Planning and Management, Prentice-Hall, Inc. Englewood Cliffs, New Jersy,.

Zheng, C and Wang, P. (1996). Parameter Structure Identification Using Tabu Search and Simulated Annealing, Advances in Water resources, Vol.19, No.4, pp.215-224.

Zimmerman, D. A., De, Marsily G., C. A., Gotway, M. G., Marietta, C. L., Axness, R. L., Beauheim, R. L., Bras, J., Carrera, G., Dagan, P. B., Davies, D. P., Gallegos, A., Galli J., Gomez-Hernandez, P., Grindrod, A., L., Gutjahr., Kitanidis P. K., Lavenue, A. M., McLaughlin, D., Neuman, S. P., Ramarao, B. S., Ravenne, C. and Rubin, Y(.1998): A Comparison of Seven geostatistically Based Inverse Approaches to Estimate Transmissivities For Modeling Advective Transport By Groundwater Flow, Water Resour. Res., Vol. 34, No.6, pp. 1373-1413.