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Elitist Genetic Algorithm For Design Of Aquifer Reclamation Using Multiple Well System

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ABSTRACT

Groundwater contamination is one of the most serious environmental problems in many parts of the world today. For the remediation of dissolved phase contaminant in groundwater, the pump and treat method is found to be a successful remediation technique. Developing an efficient and robust methods for identifying the most cost effective ways to solve groundwater pollution remediation problems using pump and treat method is very important because of the large construction and operating costs involved. In this study an attempt has been made to use evolutionary approach (Elitist genetic algorithm (EGA) and finite element model (FEM)) to solve the non-linear and very complex pump and treat groundwater pollution remediation problem. The model couples elitist genetic algorithm, a global search technique, with FEM for coupled flow and solute transport model to optimize the pump and treat groundwater pollution problem. This paper presents a simulation optimization model to obtain optimal pumping rates to cleanup a confined aquifer. A coupled FEM model has been developed for flow and solute transport simulation, which is embedded with the elitist genetic algorithm to assess the optimal pumping pattern for different scenarios for the remediation of contaminated groundwater. Using the FEM-EGA model, the optimal pumping pattern for the abstraction wells is obtained to minimize the total lift costs of groundwater along with the treatment cost. The coupled FEM-EGA model has been applied for the decontamination of a hypothetical confined aquifer to demonstrate the effectiveness of the proposed technique. The model is applied to determine the minimum pumping rates needed to remediate an existing contaminant plume. The study found that an optimal pumping policy for aquifer decontamination using pump and treat method can be established by applying the present FEM-EGA model.

Keywords: Pump and treat, Finite element method, Simulation–optimization, Aquifer reclamation, Elitist genetic algorithm.

I. INTRODUCTION

World's growing industrialization and planned irrigation of large agricultural fields have caused deterioration of groundwater quality. With the growing recognition of the importance of groundwater resources, efforts are increasing to prevent, reduce, and abate groundwater pollution. As a result, during the last decade, much attention has been focused on remediation of contaminated aquifers. Pump and treat is one of the established techniques for restoring the contaminated aquifers. The technique involves locating adequate number of pumping wells in a polluted aquifer where contaminants are removed with the pumped out groundwater. Various treatment technologies are used for the removal of contaminants and cleanup strategies. Depending on the site conditions, some times the treated water is injected back in to the aquifer. Many researchers found that the combined use of simulation and optimization techniques can be a powerful tool in designing and planning strategies for the optimal management of groundwater remediation by pump and treat method. Different optimization techniques have been employed in the groundwater remediation design involving linear programming [1], nonlinear programming [2-4] and dynamic programming [5] methods. Application of optimization techniques can identify site specific remediation plans that are substantially less expensive than those identified by the conventional trial and error methods. Mixed integer programming was also used to optimal design of air stripping treatment process [4].

Bear and Sun [6] developed design for optimal remediation by pump and treat. The objective was to minimize the total cost including fixed and operating costs by pumping and injection rates at five potential wells. Two–level hierarchical optimization model was used to optimization of pumping /injection rates[6]. At the basic level, well locations and pumping and injection rates are sought so as to maximize mass removal of contaminants. At the upper level, the number of wells for pumping / injection is optimized, so as to minimize the cost, taking maximum contaminant level as a constraint. Recently the applications of combinatorial search algorithms, such as genetic algorithms (gas) have been used in the groundwater management to identify the cost effective solutions to pump and treat groundwater remediation design. Genetic algorithms are heuristic programming methods capable of locating near global solutions for complex problems [7]. A number of researchers have applied genetic algorithms in the recent past to solve groundwater pollution remediation problems [8-19].

Ritzel and Eheart [8] applied GA to solve a multiple objective groundwater pollution containment problem. They used the response matrix approach. Vector evaluated genetic algorithm and Pareto genetic algorithms have been used for maximization of reliability and minimization of costs. The Pareto algorithm was shown to be superior to the vector evaluated genetic algorithm. Genetic algorithms have been used to determine the yield from a homogeneous, isotropic, unconfined aquifer and also, to determine the minimum cost of pump and treat remediation system to remove the contaminant plume from the aquifer using air stripping treatment technology [9].

Wand and Zheng [10] developed a new simulation optimization model developed for the optimal design of groundwater remediation systems under a variety of field conditions. The model has been applied to a typical two-dimensional pump and treat example with one and three management periods and also to a large-scale three-dimensional field problem to determine the minimum pumping needed to contain an existing contaminant plume [10]. Progressive Genetic algorithms were used to optimize the remediation design, while defining the locations and pumping and injection rates of the specified wells as continuous variables [20]. The proposed model considers only the operating cost of pumping and injection. But the pumping and injection rates are not time varying. Real-coded genetic algorithm are also applied for groundwater bioremediation[21].

Integrated Genetic algorithm and constrained differential dynamic programming were used to optimize the total remediation cost[20]. But the decision variables only involve determining time varying pumping rates from extraction wells and their locations. FEM is well established as a simulation tool for groundwater flow and solute transport [22-26].

Many of the research works revealed that the high cost of groundwater pollution remediation can be substantially reduced by simulation optimization techniques. Most of the groundwater pollution remediation optimization problems are non-convex, discrete and discontinuous in nature and GA has been found to be very suitable to solve these problems. GA uses the random search schemes inspired by biological evolution [7]. The present study develops an optimal planning model for cleanup of contaminated aquifer using pump and treats method. This study integrates the elitist genetic algorithm and finite element model to solve the highly nonlinear groundwater remediation systems problem. The proposed model considers the operating cost of pumping wells and subsequent treatment of pumped out contaminated groundwater. Minimizing the total cost to meet the water quality constraints, and the model computes the optimal pumping rate to restore the aquifer.

In the present problem, the genetic algorithm is chosen as optimization tool. GAs are adaptive methods which may be used to solve search and optimization problems. GA is robust iterative search methods that are based on Darwin evolution and survival of the fittest [7, 31]. The fact that GAs have a number of advantages over mathematical programming techniques traditionally used for optimization, including (1) decision variables are represented as a discrete set of possible values, (2) the ability to find near global optimal solutions , and (3) the generation of a range of good solutions in addition to one leading solution. Consequently, GAs is used as the optimization technique for the proposed research. The GA technique and mechanism selected as a part of proposed approach are binary coding of the decision variables, roulette wheel selection, uniform crossover, bitwise mutation and elitism technique. In the present study, a simulation-optimization model has been developed by embedding the features of the finite element method (FEM) with elitist genetic algorithm (EGA) for the assessment of optimal pumping rate for aquifer remediation using pump and treat method. The developed model is applied to a hypothetical problem to study the effectiveness of the proposed technique and it can be used to solve similar real field problems.

II. GROUNDWATER FLOW AND MASS TRANSPORT SIMULATION

The FEM formulation for flow and solute transport followed by genetic algorithm approach is considered in this study. The governing equation describing the flow in a two dimensional heterogeneous confined aquifer can be written as [26]

$$\frac{\partial}{\partial x}\left[T_x\frac{\partial h}{\partial x}\right]+\frac{\partial}{\partial y}\left[T_y\frac{\partial h}{\partial y}\right]=S\frac{\partial h}{\partial t}+Q_w\delta(x-x_i)(y-y_i)-q \qquad (1)$$

Subject to the initial condition of

$$h(x,y,0) = h_0(x,y) \qquad x,y\in\Omega \qquad (2)$$

and the boundary conditions

$$h(x,y,t) = H(x,y,t) \quad x,y\in\partial\Omega_1 \qquad (3)$$

$$T\frac{\partial h}{\partial n} = q(x,y,t) \qquad x,y \in \partial\Omega_2 \qquad (4)$$

where $h(x,y,t)$ = piezometric head (m); $T(x,y)$ = transimissivity (m^2/d); S = storage coefficient; x, y = horizontal space variables (m); Q_w = source or sink function ($-Q_w$ source, Q_w = Sink) (m^3/d/m^2); t = time in days; Ω = the flow region; $\partial\Omega$ = boundary region ($\partial\Omega_1 \cup \partial\Omega_2 = \partial\Omega$); $\frac{\partial}{\partial n}$ = normal derivative; $h_0(x,y)$ = initial head in the flow domain (m); $H(x,y,t)$ = known head value of the boundary head (m) and $q(x,y,t)$ = known inflow rate (m^3/d/m).

The governing partial differential equation describing the physical processes of convection and hydrodynamic dispersion is basically obtained from the principle of conservation of mass [27]. The partial differential equation for transport of total dissolved solids (TDS) or a single chemical constituent in groundwater, considering advection dispersion and fluid sources/sinks can be given [24,28] as follows:

$$R\frac{\partial C}{\partial t} = \frac{\partial}{\partial x}\left(D_{xx}\frac{\partial C}{\partial x}\right) + \frac{\partial}{\partial x}\left(D_{yy}\frac{\partial C}{\partial y}\right) - \frac{\partial}{\partial x}\left(V_x C\right) - \frac{\partial}{\partial y}\left(V_y C\right) - \frac{c`w}{nb} + \frac{W}{\theta}C_0 - \frac{Q}{\theta}C \qquad (5)$$

where V_x and V_y = seepage velocity in x and y principal axis direction; D_{xx}, D_{yy} = components of dispersion coefficient tensor[L^{2}T^{-1}]; C = Dissolved concentration [ML^{-3}]; θ = porosity (dimensionless); w = elemental recharge rate with solute concentration c'; n = elemental porosity; b = aquifer thickness under the element; R = Retardation factor: C_0 = concentration of solute in injected water into aquifer; W = rate of water injected per unit time per unit aquifer volume (T^{-1}) ; Q = volume rate of water extracted per unit aquifer volume.

The initial condition for the transport problem is

$$C(x,y,0) = f \;\; (x,y) \in \Omega \qquad (6)$$

and the boundary conditions are

$$C(x,y,t) = g_1 \qquad (x,y) \in \Gamma_1 \qquad (7)$$

$$\frac{\partial C}{\partial n}(x,y,t) = g_2 \qquad (8)$$

where Γ_1 = boundary sections of the flow region Ω; f = a given function in Ω; g_1 = given function along Γ_1, which is known solute concentration. g_2 = concentration gradient normal to the boundary Γ_2; n = unit normal vector.

For numerical analysis, the finite element method is selected because of its relative flexibility to discretize a prototype system which represents boundaries accurately. The finite element method (FEM) approximates the governing partial differential equation by integral approach. In the present study, two-dimensional linear triangular elements are used for spatial discritization and Galerkin approach [29] is used for finite element approximation. In the FEM, the head variable in equation (1) is initially approximated as

$$\hat{h}(x,y,t) = \sum_{L=1}^{NP} h_L(t) N_L(x,y) \qquad (9)$$

where h_L = unknown head; N_L = known basis function at node L; $\hat{h}(x,y,t)$ = trial solution; NP = total number of nodes in the problem domain. A set of simultaneous equations is obtained when residuals weighted by each of the basis function are forced to be zero and integrated over the entire domain. Applying the finite element formulation for equation (1) gives

$$\iint_\Omega \left[\frac{\partial}{\partial x}\left(T_x\frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(T_y\frac{\partial h}{\partial y}\right) - Q_w + q - S\frac{\partial h}{\partial t}\right] N_L(x,y)dxdy = 0 \qquad (10)$$

Equation (10) can further be written as the summation of individual elements as

$$\sum_e \iint \left(T_x^e \frac{\partial \hat{h}^e}{\partial x}\{\frac{\partial N_L^e}{\partial x}\} + T_y^e \frac{\partial \hat{h}^e}{\partial y}\{\frac{\partial N_L^e}{\partial y}\} \right) dxdy + \sum_e \iint \left(S\frac{\partial \hat{h}^e}{\partial t} \right) \{ N_L^e \} dxdy$$

$$= \sum_e \iint (Q_w)\{N_L^e\}dxdy - \sum_e \iint (q)\{N_L^e\}dxdy \qquad (11)$$

where $\{N_L^e\} = \begin{Bmatrix} N_i \\ N_j \\ N_k \end{Bmatrix}$. The details of interpolation function for linear triangular elements are given among others by [29].

For an element eq(11) can be written in matrix form as

$$[G^e]\{h_I^e\} + [P^e]\left\{\frac{\partial h_I^e}{\delta t}\right\} = \{F^e\} \qquad (12)$$

where I = i, j, k are three nodes of triangular elements and G, P, F are the element matrices known as conductance , storage matrices or recharge vectors respectively.

Summation of elemental matrix equation (12) for all the elements lying within the flow region gives the global matrix as

$$[G]\{h_L\}+[P]\left\{\frac{\partial h_L}{\partial t}\right\}=\{F\} \qquad (13)$$

Applying the implicit finite difference scheme for the $\frac{\partial h}{\partial t}$ term in time domain for equation (13) gives

$$[G]\{h_L\}_{t+\Delta t}+[P]\left\{\frac{h_{t+\Delta t}-h_t}{\Delta t}\right\}=\{F\} \qquad (14)$$

The subscripts t and $t+\Delta t$ represent the groundwater head values at present and next time steps. By rearranging the terms of equation (14), the general form of the equation can be given as[25]

$$[[P]+\omega\Delta t[G]]\,\{h\}_{t+\Delta t}=$$

$$[[P]-(1-\omega)\Delta t\,[G]]\,\{h\}_t+\Delta t\,(1-\omega)\{F\}_t+\omega\,\{F\}_{t+\Delta t} \qquad (15)$$

where $\Delta t =$ time step size; $\{h\}_t$ and $\{h\}_{t+\Delta t}$ are groundwater head vector at the time t and $t+\Delta t$ respectively ; $\omega =$ Relaxation factor which depends on the type of finite difference scheme used. In the present study Crank-Nicholson scheme with ω = 0.5 is used. These global matrices can be constructed using the element matrices of different shapes based on discritization of the domain. The set of linear simultaneous equations represent by eq (15) are solved to obtain the groundwater head distribution at all nodal points of the flow domain using Choleski's method for the given initial and boundary conditions, recharge and pumping rates, transsmissivity, and storage coefficient values. After getting the nodal head values, the time step is incremented and the solution proceeds in the same manner by updating the time matrices and recomputing the nodal head values. From the obtained nodal head values, the velocity vectors in x and y directions can be calculated using Darcy's law. For solving transport simulation, applying Gelarkin's FEM to solve partial differential equation (5), final set of implicit equations can be given as (similar to eq 15)

$$[[S]+\omega\Delta t\,[D]]\,\{C\}_{t+\Delta t}=$$

$$[[S]-(1-\omega)\Delta t[D]]\,\{C\}_t+\Delta t\,(1-\omega)\{F\}_t+\omega\{F\}_{t+\Delta t} \qquad (16)$$

where $[S]$ = sorption matrix; $[D]$ = advection–dispersion matrix; $[F]$ = flux matrix; $\{C\}$ = nodal concentration column matrix and the subscripts t and $t+\Delta t$ indicates the concentration at present and forward time step respectively. Solution of eq (16) with the initial and boundary conditions gives the solute concentration distribution in the flow region for various time steps.

III. ELITIST GA OPTIMIZATION MODEL FORMULATION

Genetic algorithm is a Global search procedure based on the mechanics of natural selection and natural genetics, which combines an artificial survival of the fittest with genetic operators abstracted from the nature [7]. In this paper, elitist genetic algorithm is used as optimization tool. The EGA procedure consists of three main operators: selection, crossover and mutation Elitism ensures that the fitness of the best solution in a population doesn't deteriorate as generation advances Genetic algorithm converge the global optimal solution of some functions in the presence of elitism In order to preserve and use previously best solutions in the subsequent generations an elite preserving operator is often recommended [30]. In addition to overall increase in performance, there is another advantage of using such elitism. In an elitist GA, the statistics of the population best solutions cannot degrade with generations. There exists a number of ways to introduce elitism. In the present study, the best ε% of the population from the current population is directly copied to next generation. The rest (100 - ε) % of the new population is created by usual genetic operations applied on the entire current population including the chosen ε% elite members. In this way the best solutions of the current population is not only get passed from one generation to another, but they also participate with other members of the population in creating other population members. The general scheme for the elitist GA is explained below [31].

1. The implementation of GA starts with a randomly generated set of decision variables. The initial population is generated randomly with a random seed satisfying the bounds and sensitivity requirement of the decision variables. The population is formed by certain number of encoded strings in which each string has values of '0's and '1's, each of which represents a possible solution. The total length of the string (i.e., the number of binary digits) associated with each string is the total number of binary digits used to represent each substring. The length of the substring is usually determined according to the desired solution accuracy.
2. The fitness of each string in the population is evaluated based on the objective function and constraints. Various constraints are checked during the objective function evaluation stage. The amount of any constraint violation is multiplied by weight factor and added to the fitness value as a penalty. The multiplier is added to scale up the penalty, so that it will have a significant, but not excessive impact on the objective function.
3. This stage selects an interim population of strings representing possible solutions via a stochastic selection process. The selected better fitness strings

are arranged randomly to form mating pool on which further operations like crossover mutation are performed. Reproduction is implemented in this study using the Roulette wheel approach [7]. In roulette wheel selection, the string with the higher fitness value represents a large range in the cumulative probability values and it has higher probability of being selected for reproduction. Therefore, the algorithm can converge to a set of chromosomes with higher fitness values.

4. Crossover involves random coupling of the newly reproduced strings, and each pair of strings partially exchanges information. Crossover aims to exchange gene information so as to produce new offspring strings that preserve the best material from the parent strings. The end result of crossover is the creation of a new population which has the same size as the old population, and which consists of mostly child strings whose parents no longer exist and a minority of parents luckily enough to enter the new population unaltered.

5. Mutation restores lost or unexplored genetic material to the population to prevent the GA from prematurely converging to a local minimum. Mutation is performed by flipping the values of '0' and '1' of the bit that is selected. A new population is formed after mutation. The new population is evaluated according to the fitness, i.e., objective function.

6. The best ε% of the population from the current population is directly copied to next generation. The rest (100- ε) % of the new population is created by usual genetic operations applied on the entire current population including the chosen ε% elite members.

7. The next step is to choose the appropriate stopping criterion. The stopping criterion is based on the change of either objective function or optimized parameters. If the user defined stopping criterion is met or when the maximum allowed number of generations is reached, the procedure stops, otherwise it goes back to reproduction stage to perform another cycle of reproduction, crossover, and mutation until a stopping criterion met.

IV. INTEGRATION OF FEM-ELITISTGA SIMULATION–OPTIMIZATION APPROACH

To clean up the contaminated aquifer by pump and treat, pumping rates are to be optimized to achieve the minimum specified concentration levels within the system after a particular period. Here a coupled FEM-EGA model is developed to find out the optimal pumping rates in the pump and treat method. A binary coded genetic algorithm is embedded with the flow and transport FEM model described earlier, where pumping rates are defined as continuous decision variables. In the optimization formulation, three constraints were considered, which include concentration constraints, constraint for extraction rates and also constraints for nodal head distribution.

In the present study, the objective is to minimize the total cost of groundwater lift and the treatment cost for a fixed remediation period to achieve a desired level of cleanup standards. The appropriate objective function for this remediation is considered as,

$$f = a_1 \sum_{i=1}^{NP} \frac{Q_i \gamma t}{\eta} \left[h_i^{gl} - h_i \right] + a_2 \sum_{i=1}^{NP} Q_i \; t \quad (17)$$

where, f = objective function for minimization of the system cost; Q_i = pumping rate from the well; η = pump efficiency; h_i^{gl} = ground level at well i; h_i = piezometric head at well i; a_1 = cost coefficient for total energy unit in kWhr (INR 20.0/kWhr); a_2 = cost coefficient for treatment (INR 10.0 /m3); t = duration of pumping; γ = unit weight of water; $(h_i^{gl} - h_i)$ = groundwater lift at well i and INR = Indian national Rupees (1US\$ = INR 47/- approximately); and NP number of pumping wells.

Constraints to the problem are specified as Subject to

$$C_i < C^* \qquad i = 1.....N$$

$$h_{min} \le h_i \le h_{max}; \qquad i = 1.....N$$

$$Q_{i,min} \le Q_i \le Q_{i,max} \qquad i = 1.....NP$$

where, i is the node number; N is the total number of nodes of the flow domain;. C^* is specified limit of concentration in the region; and Q_i = Pumping rate at well at i. Decision variables for the pump and treat remediation system include the pumping rates for the wells and the state variables are the hydraulic head and solute concentration which are dependent variables in the groundwater flow and transport equations. For the remediation design, simulation model has to update the state variables, which are passed on to the optimization model to select the optimal values for the decision variables. The flow chart for the developed FEM-EGA model is shown in Fig.1.

V. OPTIMAL REMEDIATION SYSTEM DESIGN WITH FEM-EGA MODEL – A CASE STUDY

A hypothetical problem of solute mass transport in a confined aquifer is considered for remediation of contaminated groundwater. The aquifer is assumed to be homogeneous, anisotropic and flow is considered to be two-dimensional. When the remediation process commences, it is reasonably assumed that the source of pollutants entering in to the aquifer system is stopped.

Important data for the considered aquifer are as follows: The aquifer is discretised into finite element mesh with a grid spacing of 200 m × 200 m. Thickness of the confined aquifer = 25 m; Size of the confined aquifer = 1800 m × 1000 m; storativity = 0.0004; aquifer is recharged through some aquitard in the area of 0.6 km^2 (between node numbers 19 to 42) at the rate of 0.00012 m/d; porosity = 0.2; longitudinal dispersivity = 150 m; transverse dispersivity = 15 m; rate of seepage from the pond = 0.005 m/d; T_{xx} = 300 m ^{2}/d, and T_{yy} = 200 m^2/d. The boundary conditions for the flow model are constant head on east (70 m) and west sides (75 m), and no flow on the north and south sides. For transport model, the boundary conditions are zero concentration on west and concentration gradient is zero on north and south directions. Since the area of the aquifer is relatively small (1.8 km^2) the boundary for the east direction is kept open.

The flow region is discretised into triangular elements consisting of 60 nodes and 90 elements as shown in Fig. 2. The groundwater flow and contaminant spread in the aquifer system is simulated using FEM to obtain nodal heads, velocity vectors and nodal concentration distribution in the aquifer domain. Three production wells extracting water at the rate of 500, 600 and 250 m^3/d respectively are considered in the flow region. These wells are located at nodes 23, 33 and 35 respectively (Fig.2). A recharge well with inflow rate of 750 m ^{3}/d is located at node 21. Three observation wells are located in the aquifer domain at nodes 44, 47, and 52 respectively to monitor the concentration levels during the remediation period. The problem involves seepage from a polluted pond into the underlying aquifer. The bottom of the pond is assumed to be sufficiently close to the groundwater surface so that seepage underneath the pond occurs in a saturated region. The recharge rate (0.005 m/d) from the pond controls the amount of solute introduced into the system with a certain velocity. In this problem, the contaminant is seeping into the flow field from the polluted pond (4000 ppm TDS) and is also added by a recharge well (1000 ppm). Initially the entire aquifer domain is assumed to be uncontaminated $(C = 0)$. This study examines the coupled flow and solute transport problem with these input sources. Pumping wells are also active for a simulation period of 10000 days during which period the aquifer continues to get contaminated. At the end of this simulation period the TDS concentration distribution is considered as initial concentration levels in the aquifer domain before the remediation begins. Concentration distribution at the end of 10000 days of simulation period for these dynamic conditions operative on the system is shown in Fig. 3. Pump and treat method is applied for the aquifer remediation after the sources entering in the system are arrested (i.e., no recharge through the polluted pond and recharge well). From the existing three abstraction wells, the contaminants in the system are pumped out for the treatment. Based on the concentration distribution at the end of the simulation period in the system, the location of pumping wells has been changed, so that the pumping wells are situated in the highly polluted area. Therefore for the aquifer remediation the recharge well at node 21 is converted as a pumping well (pumping well at node 23, 35 closed). Additionally one pumping well and one observation well which is located at nodes 33 and 52 are considered for pumping out the contaminated water for treatment on the ground surface.

The FEM simulation and EGA optimization techniques have been used for obtaining an optimal pumping pattern to cleanup the contaminated aquifer. The optimization of pump and treat remediation design requires that the flow and solute transport model is run repeatedly, in order to calculate the objective function associated with the possible design, and to evaluate whether various hydraulic and concentration constraints are met. In the present work, the compliance requirement for the contaminants concentration level is considered to be lower than 750 ppm everywhere in the aquifer at the end of 3960 days. The objective of the present study is to obtain optimal pumping rates for the wells to minimize the total lift cost of groundwater involving in definite volume of contaminated groundwater for treatment for the specified time period. Three pumping wells scenario is considered for this remediation period to cleanup the aquifer for a fixed cleanup period of 3960 days. The optimal pumping pattern (least cost) for the chosen scenario has been obtained by the coupled simulation optimization model.

Three scenarios have been considered in this study to cleanup the contaminated aquifer for a fixed cleanup period of 3960 days. Three pumping wells, two wells and one well respectively are considered for this remediation period to treat these scenarios. The optimal pumping pattern (least cost) for three scenarios has been obtained by the coupled simulation optimization model.

VI. TUNING OF GENETIC ALGORITHM PARAMETERS

Important genetic algorithm parameters such as size of population, crossover, mutation, number of generations, and termination criterion affect the EGA performance. Hence appropriate values have to be assigned for these parameters before they are used in the optimization problem.

For some parameters several trial runs may be needed to "tune" these parameters. Each parameter was varied to determine its effect on the system within reasonable bounds while keeping remaining parameters at a standard level. The obtained optimal values are used in the simulation optimization model for these scenarios.

Rate of mutation

In the present study for three scenarios, the mutation rate was varied between 0.1%, 1.0%, and 10% per bit. Probability of mutation is usually assigned a low value between 0.001 and 0.01., since it is only a secondary genetic operator. Mutation is needed to introduce some random diversity in the optimization process. However if probability of mutation is too high, there is a danger of losing genetic information too quickly, and the optimization process approaches a purely random search

Rate of crossover

Probability of crossover between 0.60 and 1.0 is used in most genetic algorithm implementations. Higher the value of the crossover, higher is the genetic recombination as the algorithm proceeds, ensuring higher exploitation of genetic information.

Population size

The optimal value of maximum population for binary coding increases exponentially with the length of the string [7]. Even for relatively small problems, this would lead to high memory storage requirements. Results have shown that larger population performs better. This is expected as larger populations represent a large sampling of the design space.

Minimum reduction in objective function for termination

The selection of this parameter is problem dependent, and its appropriate value depends on how much improvement in objective function value may be considered significant. The value of this parameter is determined by trial and error, and a value of 3 to 4 usually quite sufficient. Larger values of this parameter increase the chances of converging to the global optimum, but at the cost of increasing the computational time

Penalty function

Specifying a penalty coefficient is a challenging task. A high penalty coefficient will ensure that most solutions lie with in the feasible solutions space, but can lead to costly conservative system designs. A low penalty coefficient permits searching for both feasible and infeasible regions, but can cause convergence to an infeasible system design [30].

Number of generations

From practical considerations, the selection of maximum generation is governed by the limits placed on the execution time and the number of function evaluations. In each generation, the objective function is calculated maximum population times, (except in the first generation in which the fitness of the initial population is also calculated) and the various genetic operators are also applied several times.

VII. RESULTS AND DISCUSSION

Although the specific test cases are synthetic and relatively idealized, the overall approach is realistic. The installation of pumping wells at appropriate locations may be necessary to prevent further spreading of the contaminants to unpolluted areas. At the end of the remediation period, the concentration levels everywhere in the system are expected to be lower than the specified concentration limit of 750 ppm. In all scenarios a fixed management period of 3960 days is used. Various design strategies for the remediation period are presented in Table.1. The following section provides the details of the results obtained for the chosen problem for various scenarios.

Three wells scenario

In this three well scenario, three pumping wells are considered for pumping out the contaminated groundwater. Lower and upper bounds on the pumping capacity are chosen as 250 m^3/d and 1000 m^3/d respectively. The pumping rates of the three wells are encoded as a 30 bit binary string with 10 bits for each pumping rate. The optimal GA parameters as discussed earlier sections are used in this study. The optimal size of the population is chosen as 30. A higher probability of crossover of 0.85 and lower mutation probability is set at 0.001. A converged solution is obtained after 128 generations. Fig. 4 shows the final concentration contours at the end of 3960 days of remediation period based on the optimal pumping rates achieved by simulation–optimization model (FEM-EGA). A best value of objective function versus number of generations for three well scenarios is presented in Fig.6. The optimal pumping rates for the three wells are 300.58, 260.26 and 275.65 m^3/d respectively as shown in Fig.5.

Although the three wells scenario performs good to cleanup the system to the required concentration level everywhere in the system, as expected it leads to a higher system cost. Also it needs to be emphasized that an increase in the number of pumping wells to pump out the contaminated groundwater is not the first choice. However, if the pumping wells are placed at an appropriate location, a further spreading of the contaminant plume can be minimized. This means that more effective remediation can be achieved by appropriately locating the pumping well. These investigations show that an appropriately designed pump and treat system can have a significant effect on the decontamination of a polluted aquifer and preclude further spreading of contaminant plume.

Two wells scenario

During the remediation period, two abstraction wells are considered for pumping out the contaminated groundwater. The lower and upper bounds of the abstraction wells are 250 m^3/d and 1000 m^3/d respectively. The pumping rates of the two abstraction wells are encoded as a 20 bit binary string with 10 bits for each pumping rate. The optimal size of the population is taken as 30. A higher probability of crossover of 0.85 is chosen and lower mutation probability is set at 0.001. A converged solution is obtained after 30 generations. The progress of the aquifer decontamination for this scenario is shown in Fig 6. The optimal pumping rates obtained for the two wells are 252.199 m^3/d and 260.263 m^3/d respectively. Best values of the objective function versus number of generations for two well scenario is presented in Fig.7.

One well scenario

For this case, the length of the management period is same as that of three and two well scenarios. One pumping well is considered for pumping out the contaminated groundwater during the remediation period. The lower and upper bounds of the pumping well are kept same as for the above two scenarios. The pumping rate of the one abstraction well is encoded as a string length of 10 bits. The optimal size of the population is chosen to be 20. A moderate crossover probability of 0.85 is taken and lower mutation probability is set at 0.001. A converged solution is obtained after 25 generations which is relatively less as compared to the three well scenarios. Results indicate that the optimal pumping rate for one well for this case is 346.77 m^3/d. This pumping rate is much lower compared to other two scenarios. Even for the lower pumping rate the mass remaining in the system (728 ppm) is marginally less than the specified limit (750 ppm). Therefore one well scenario is perhaps the best option to cleanup the aquifer within the specified time period. Fig. 8 shows the final concentration contours at the end of 3960 days of remediation period based on the optimal pumping rate. Values of objective function versus number of generations for one well scenario are presented in Fig. 9. Figure suggests marginal increase in the values after 5 generations and minimum at 25 generations.

The results suggest that, for the remediation of contaminated aquifer using three and two well scenarios, the concentration levels in the aquifer domain is less than that the required value everywhere in the system, where as for one well scenario the maximum concentration level is marginally less than the specified cleanup standard limit for the system. Further results in Table.1 shows that increasing the number of pumping wells is not feasible, since it involves high system cost and less performance. Hence the optimal pumping rate obtained in this one well scenario is the best pumping policy for the chosen problem to cleanup the aquifer with in the specified time period. These investigations show that an appropriately designed pump and treat system can have a significant effect on the decontamination of a polluted aquifer and preclude further spreading of contaminant plume.

VIII. CONCLUSIONS

Here an integrated simulation–optimization model is developed for the remediation of a confined aquifer that is polluted by a recharge pond and injection well operational for a prolonged period of time. The two-dimensional model consists of three scenarios for remediation of contaminated aquifer. Studies demonstrate the effectiveness and robustness of the simulation optimization (FEM-EGA) model. The problem used a cost based objective function for the optimization technique that took into account the costs of pumping and treatment of contaminated groundwater for the aquifer system. Optimal pumping pattern is obtained for cleanup of the aquifer using FEM and EGA for a period of 3960 days. Comparing the total extraction and pumping patterns for the three scenarios, it was found that the one well scenario reduces the total pumping rate and shows the dynamic adaptability of the EGA based optimization technique to achieve the cleanup standards. The total remediation cost for the two well scenarios is relatively less as compared to three and one well scenario. This is due to the pumping well locations which are placed in the highly polluted area, so that removal of contaminant from these pumping wells is effective. The total extraction of contaminated groundwater gives an indication of costs associated with pumping and treatment costs in the system. Hence the optimal pumping rate obtained in this one well scenario is the best pumping policy for the chosen problem to cleanup the aquifer within the specified time period.

The important advantage of using EGA in remediation design optimization problem is that the global or near global optimal solutions can be found. Since there is no need to calculate the derivatives of the objective function which often creates a numerical instability, the GA based optimization model is robust and stable. However, the study found that application of genetic algorithms in remediation design optimization model are computational intensive for tuning of EGA parameters.

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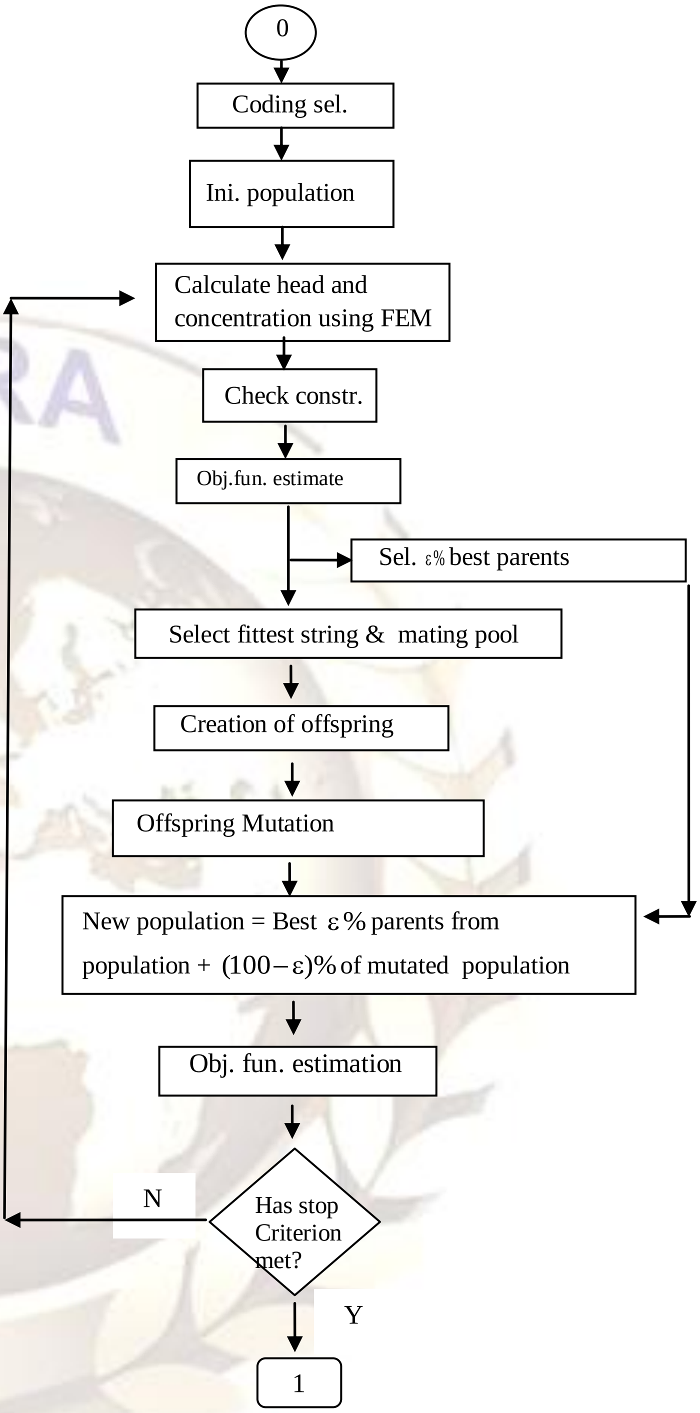


Fig. 1. Flow Chart for Integrated FEM and GA

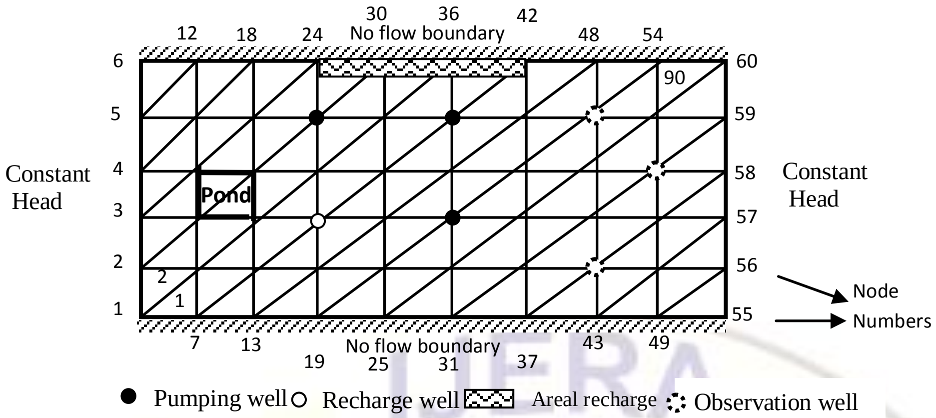


Fig. 2. Finite element discritization

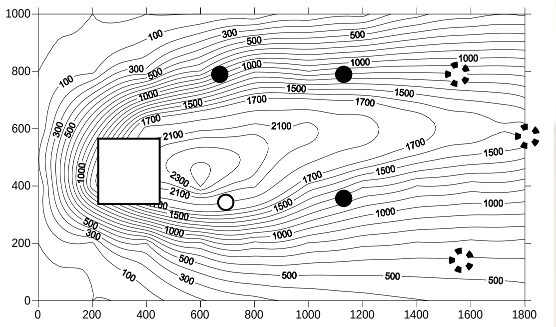
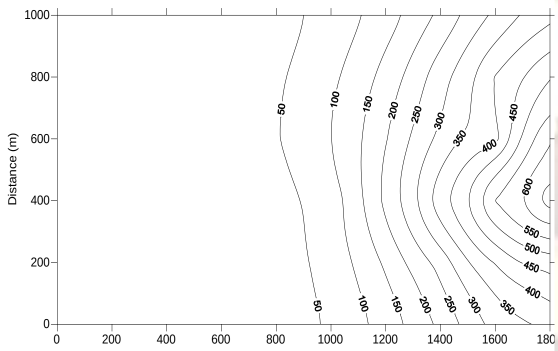


Fig.3. Concentration distribution at the end of 10000 days of simulation (Initial concentration before remediation commences)



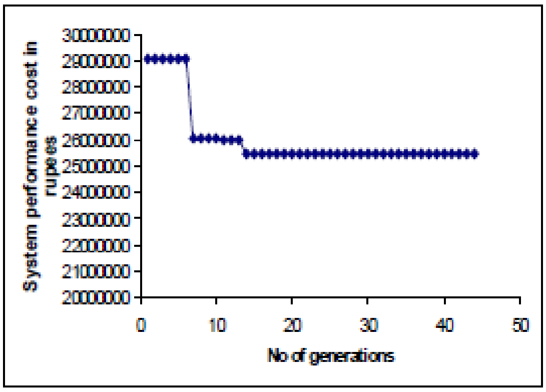


Fig.4. Concentration distribution at the end of 3960 days remediation for three well scenario

Fig.5. Values of objective function versus number of generations for three well scenario

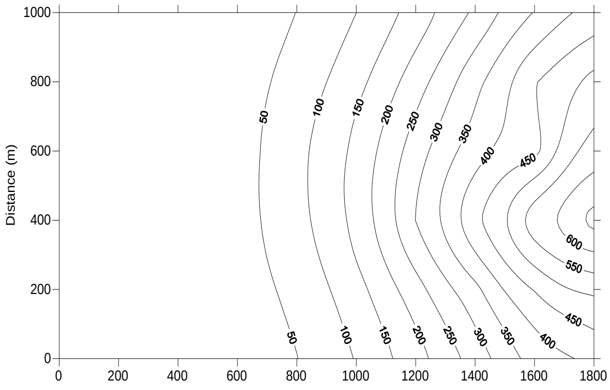


Fig.6. Concentration distribution at the end of 3960 days remediation for two well scenario

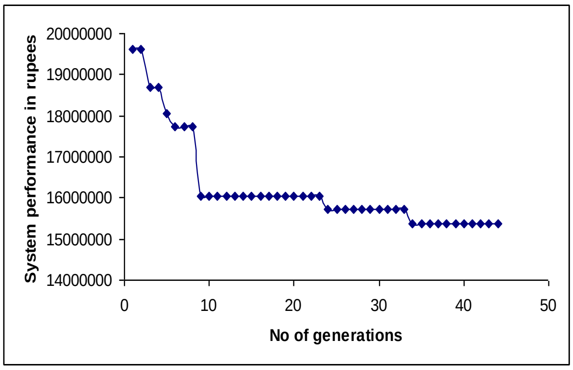


Fig.7. Values of objective function versus number of generations for two well scenario

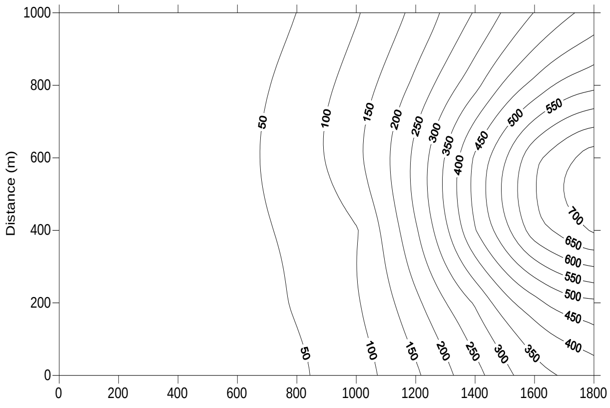


Fig.8. Concentration distribution at the end of 3960 days remediation for one well scenario

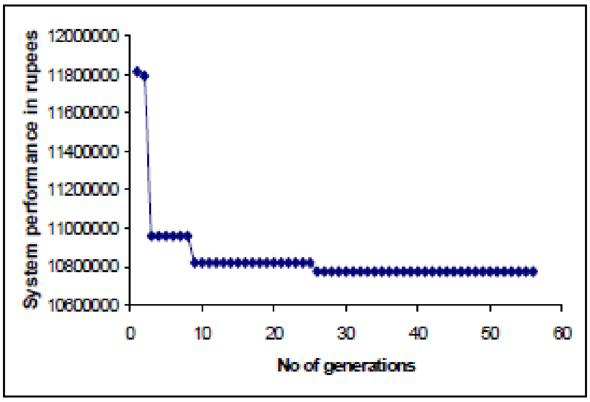


Fig.9. Values of objective function versus number of generations for one well scenario

Table.1. Various design strategies for the remediation period

Design strategies	Pumping rates for each well (m^3/d)	Total pumping for the remediation period. (m^3)	Evaluated cost (Rupees)
Three well	289.58 264.66 279.32	3300897	25459830
Two well	252.19 260.26	2029302	15384529
One well	346.77	1373209	10774175