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Optimum Management of Groundwater, Using Genetic Algorithm Technique

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Abstract—**The aim of this research is to develop decision support tools for identifying optimal location for groundwater development to meet the future demands in the Teeb Area. Teeb Area is located in north and north east of Missan Province, south of Iraq. This area is about 1860 km^2. A two-dimensional mathematical model is developed to simulate the flow regime of the upper part of Quaternary Deposits. The suggested conceptual model, which is advocated to simulate the flow regime of aquifer is fixed for one layer, i.e. the activity of the deeper aquifer is negligible. The model is calibrated using trial and error procedure in two stages, steady state followed by unsteady state. This model is integrated with an optimization model which is based on the genetic algorithm (GA). Three management cases were undertaken by running the model with adopted calibrated parameters. In the first case found the optimum value of the objective function is (0.32947E+08 m^3/year), in other words, the pumping rates could be raised to nine times the current pumping rates, with a highest decline in the hydraulic heads of groundwater compared with initial hydraulic heads reached to 6 cm. In a second case twenty six wells out of thirty five can be operated with "on/off" status associated with each well to obtain the maximum value of pumping rate. In third case is allowed to move a location of well anywhere within a user defined region of the model grid until the optimal location is reached. The optimum value of objective function in third case is (0.35539E+08 m^3/year) with 8% increasing of the pumping rates compared with the first case.**

Keywords— **Management, Groundwater, Teeb, Genetic Algorithm.**

I. Introduction

Groundwater is extracted from the ground just as are other minerals, such as oil, gas, or gold. Water typically carries a special constraint.

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It is regarded as renewable natural resources. Thus, when water well is drilled, people presume that production of water will continue indefinitely with time. In fact, this can occur only if there is a balance between water recharged to the basin from surface sources and water pumped from within basin by wells. The demand for groundwater in recent decades has led to development of a variety of strategies for managing subsurface water and making efficient use of the available underground storage space. These may involve shifting of local water sources, changing pumping patterns, limiting pumping, artificial recharge, conjunctive use of groundwater and surface water, and reuse of wastewater [1].

Nonlinear programming techniques have been used to groundwater management problem since the 1980 [2]. These methods employ gradient-based algorithm to adjust decision variables so as to optimize the objective function of a management model. The objective functions and the constraints must be continues and derivable because there require the computation of derivatives of the objective functions. In general, only local optimal solutions can be obtained by these methods. However, groundwater management problems tend to be highly nonlinear and nonconvex mathematical programming problems, especially in the case of unconfined aquifer systems, making it difficult to calculate or estimate the derivatives of the objective function of typical groundwater system components with respect to the decision variables. As such, the conventional gradient-based methods cannot be available for management problems of the complicated groundwater system [3].

The genetic algorithm (GA) is a global search technique based on the mechanics of matured selection and natural genetics, which combines artificial survival of the fittest with genetics operators abstracted from nature. The seminal work on genetics algorithm was done by J. H. Holland, 1970. Since there is no limitation of requiring derivatives with respect to decision variables as in optimization problems, the GA has been utilized in a wide variety of applications including the field of water resources.

The development and application of the coupled simulation-optimization approach has been an active and fruitful research area in recent years (e.g. [4], [5], [6], [7], [8]).

The Modular Groundwater Optimizer (MGO) is a general-purpose simulation optimization code developed for field scale applications [9]. This modular is used in this research. In the proposed model, MODFLOW packages are used to simulate the flow of the groundwater in Teeb area. Teeb area is located in north and north east of Missan province as shown in Fig. 1. This model is then integrated with an optimization model which is based on the genetic algorithm (GA), which is adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics. In the proposed simulation-optimization model, the locations of wells and release of groundwater flow are treated as the explicit decision variables and determined through the optimization model.

II. Optimization Techniques

Groundwater management models fall in two general categories: hydraulics or policy evaluation and water allocation. Groundwater hydraulic management models enable the determination of optimal locations and pumping rates of numerous wells under a variety of restrictions placed upon local drawdown, hydraulic gradients, and water production targets. In groundwater management problems, there are two sets of variables, decision variables and state variables, where the decision variable is the pumping and injection rates of wells. Also other decision variables include well locations and the on/off status of a well. By optimization techniques the decision variables can be managed to identify the best combination of them. Hydraulic head is the state variable, which is the dependent variable in the groundwater flow equation.

The management objectives must be achieved within a set of constraints. The constraints may be decision or state variables, also may be take the form equalities or inequalities.

A general form of the objective function and a set of commonly used constraints suitable for a wide variety of resources management design problems can be expressed as follows, [9].

Maximize (or minimize)

$$J = a_1 \sum_{i=1}^{N} y_i + a_2 \sum_{i=1}^{N} y_i d_i + a_3 \sum_{i=1}^{N} y_i |Q_i| \Delta t_i + a_4 F(q,h) \quad (1)$$

Subject to

$$\sum_{i=1}^{N} y_i \leq NW \quad (2)$$

$$Q_{min} \leq Q_i \leq Q_{max} \quad (3)$$

$$h_{min} \leq h_m \leq h_{max} \quad (4)$$

$$h_m^{out} - h_m^{in} \geq \Delta h_{min} \quad (5)$$

$$Q_m = A \sum_{i=I1}^{I2} Q_i + B \quad (6)$$

Where,
objective function as expressed in equation (1),
J is the management objective in terms of the total costs or in terms of the total amount of pumping or mass removal.
Qi is the pumping/injection rate of well represented by parameter i (negative for pumping and positive for injection). Note that the term parameter is used to represent the pumping/injection rate associated with a particular well location at a specific management period. For an optimization problem with only a single management period, the flow rate of any well is constant and can be represented by a single parameter. However, for an optimization problem with multiple management periods, the flow rate of any well can vary from one management period to another. Thus, multiple parameters are needed to represent the flow rates of the well at different management periods.
F(q,h,) is any user-supplied cost function which may be dependent on flow rate q, hydraulic head h.
N is the total number of parameters (decision variables) to be optimized.
yi is a binary variable equal to either 1 if parameter i is active (i.e., the associated flow rate is not zero) or zero if parameter i is inactive (i.e., the associated flow rate is zero).
di is the depth of well bore associated with parameter i.
Δti is the duration of pumping or injection associated with parameter i (or the length of the management period for parameter i).
a1 is the fixed capital cost per well in terms of dollars or other currency units;
a2 is the installation and drilling cost (dollars or other currency units) per unit depth of well bore (e.g., dollars/m); and,
a3 is the pumping and/or treatment costs (dollars or other currency units) per unit volume of flow (e.g., dollars/m^3).
a4 is the multiplier for an external user-supplied cost function.
Among the constraints equations.
Equation (2) is a constraint stating that the total number of actual wells at any time period must not exceed a fixed number, NW, out of the total candidate wells, N.
Equation (3) is a constraint stating that the flow rate of a well at any specific management period must be within the specified minimum and maximum values (Qmin and Qmax).
Equation (4) is a constraint stating that the hydraulic head at any monitoring location, hm, must be within the specified lower and upper bounds (hmin and hmax).
Equation (5) is a constraint stating that the head difference between an "outside" and an "inside" monitoring wells must be greater than a minimum value, Δhmin.
Equation (6) is a constraint stating that the pumping/injection rate of a well at an arbitrary location, Qm, is proportional to the sum of the optimized flow rates represented by parameters I1 through I2 where A and B are proportional constants.

III. Genetic Algorithms

Genetic algorithms were formally introduced in the United States in the 1970s by John Holland at University of Michigan. The continuing price/performance improvements

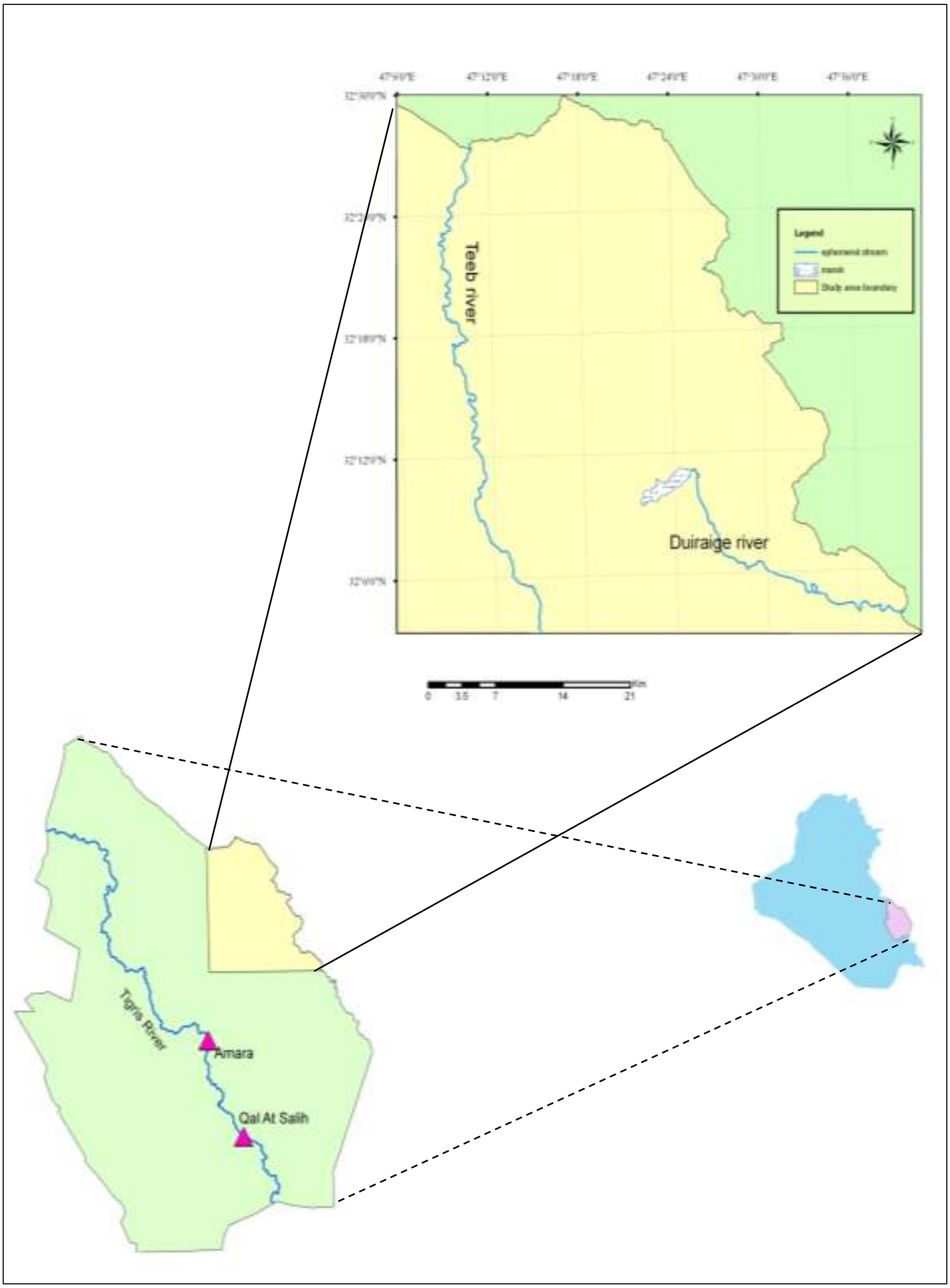

Figure 1. Location of study area in reference to map of Iraq.

of computational systems have made them attractive for some types of optimization. In particular, genetic algorithms work very well on mixed (continuous and discrete), combinatorial problems. The basic steps of GA are explained in the following subsections.

1. Parameter Encoding

The first step in GA is to map the model parameters to be optimized into some digital form suitable for various GA operations. The binary encoding method is commonly used because of its simplicity to program and manipulate. The patterns of 1s and 0s in the individual binary string represent the characteristics of the corresponding solution. For example, the decision variable, i.e., the pumping rates Qi, can be coded in binary alphabet {0,1} by the following string:

0 0 1 1 0 0 1 0 0 1 1 1 0 0 1 ……
Q1 Q2 Q3 ……

The binary string as shown above consists of one or more substrings, each of which represents an individual well rate. By analogy with biological systems, each bit in the binary string is referred to as a "gene" and the length and pattern of the string defines the genetic characteristics of an "individual" of a population. The total length (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 a substring, ki, is dependent on the specified range, Qmin<Qi<Qmax, and the precision requirement for the well rate represented by the substring. The precision requirement, i.e., the minimum allowable variation in the well rate, is controlled by the discretization interval,

$$dQ_i = \frac{Q_{max}-Q_{min}}{N_i-1}, N_i = 2^{k_i} \tag{7}$$

Where:

N_i is possible values of Q_i are given as $Q_i^{min} + jdQ_i$ where, j=0,…, Ni-1.

2. Generation of the Initial Population

The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space). A rule of thumb for selecting an appropriate population size is provided by Carroll (1996) [10].

$$npopsiz = order\left[(l/k)2^k\right] \tag{8}$$

Where: the term order implies an "order-of-magnitude" estimate and npopsiz is the size of population, l is the length of the string, and k is the average size of the schema of interest (effectively the average number of bits per parameter, i.e., approximately equal to the string length l divided by the number of parameters, rounded to the nearest integer).

3. Evaluation of the Strings

The evaluation function is a procedure to determine the fitness of each string in the population and is very much application oriented. Since GA proceeds in the direction of evolving better fit strings and the fitness values is the only information available to GA, the performance of the algorithm is highly sensitive to the fitness values. In case of optimization routines, the fitness is the value of the objective function to be optimized. GA is basically unconstrained search procedures in the given problem domain. Any constraints associated with the problem could be incorporated into the objective function as penalty function. For groundwater hydraulic design, it could be either maximum pumping or minimum costs. Various constraints on hydraulic head, and pumping/injection rates are checked during the objective function evaluation stage. A penalty can be added (or subtracted in a maximizing problem) to the fitness function if any of the constraints is not satisfied.

4. Selection of the Strings for Reproduction

When breeding new chromosomes, we need to decide which chromosomes to use as parents. The selected parents must be the fittest individuals from the population but we also want sometimes to select less fit individuals so that more of the search space is explored and to increase the chance of producing promising offspring. The simplest procedure to select strings to pass into the interim population is known as tournament selection. It is based on relative rank, rather than the absolute value of fitness. It begins by picking two strings at random from the population. These two strings are then pitted against each other based on their objective function values in a tournament and the one with the better value wins. A copy of the winner is then placed in a temporary mating pool. Tournament selection is repeated until a mating pool as large as the original population is selected. In so doing, a string with a better fitness value may be represented multiple times in the mating pool while a string with a poor fitness value may not be represented at all.

5. Crossover of the Selected Strings

After selection of the population strings is over, the genetic manipulation process consisting of two steps is carried out. In the first step, the crossover operation that recombines the bits (genes) of each two selected strings (chromosomes) is executed. Crossover may be performed using either the single-point method or the uniform method.

The uniform crossover operator is probably the most powerful crossover because it allows the offspring chromosomes to search all possibilities of re-combining those different genes in parents [11]. The uniform method works sequentially through every bit in the selected strings. At each bit, a random number between 0 and 1 is generated and compared with the user specified crossover probability. If the random number is smaller than the crossover probability, the selected bit in one string is exchanged with the corresponding bit in the other string. Otherwise, if the random number is greater than the crossover probability, no crossover is performed. For uniform crossover, a crossover probability of 0.5 is recommended [9].

6. Mutation of the Strings

The classic example of a mutation operator involves a probability that an arbitrary bit in a genetic sequence will be changed from its original state. A common method of implementing the mutation operator involves generating a random variable for each bit in a sequence. This random variable tells whether or not a particular bit will be modified. This mutation procedure, based on the biological point mutation, is called single point mutation. Other types are inversion and floating point mutation. When the gene encoding is restrictive as in permutation problems, mutations are swaps, inversions and scrambles.

The purpose of mutation in GAs is preserving and introducing diversity. Mutation should allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other, thus slowing or even stopping evolution. This reasoning also explains the fact that most GA systems avoid only taking the fittest of the population in generating the next but rather a random (or semi-random) selection with a weighting toward those that are fitter [12].

An example for this type of mutation is illustrated below. A selected bit in the old string (shown as underlined) is changed from 1 to 0 to form the new string:

Old String: 0 1 0 1 0 1 0 1 0 1 0 1 1 <u>1</u> 1 0 0 0

New String: 0 1 0 1 0 1 0 1 0 1 0 1 1 <u>0</u> 1 0 0 0

The probability of any bit in a string being selected for mutation is controlled by the mutation probability. Carroll (1996) suggests a rule of thumb for the mutation probability, pmutate:

$$\mathrm{pmutate} = 1/\mathrm{npopsiz} \tag{9}$$

Where:

npopsiz is the size of population as defined earlier.

The type of mutation described above is referred to as jump mutation [10]. Another type of mutation, called creep mutation, can be performed in addition to jump mutation. The creep mutation operates on actual parameters, rather than their binary representations, as illustrated below,

$$Q_i^* = Q_i \pm dQ_i \tag{10}$$

Where:

Q_i and Q_i^* are the parameter values prior to and after creep mutation, and

dQ_i is the parameter increment as defined in equation (7).

The creep mutation is controlled by a creep mutation probability. It works by selecting one parameter at a time and generating a corresponding random number. If the random number is smaller than the creep mutation probability, equation (10) is applied to the selected parameter; whether the positive or negative sign is used depending on another random number. If the random number is greater than the creep mutation probability, no creep mutation is performed. According to Carroll (1996) [10], it is usually adequate to set the creep mutation probability equivalent to the jump mutation probability through the following relationship,

$$\mathrm{pcreep} = (l/\mathrm{nparam})\mathrm{pmutate} \tag{11}$$

Where:

pcreep is the creep mutation probability, nparam is the number of parameters, and l is the string length as defined previously.

IV. Application of Management Model

The work presented herein demonstrates the use of groundwater simulation and optimization to construct a two-dimensional management flow model to carry out resources management predictions for specified hydraulic constraints only. Three management cases were undertaken by running the model with adopted calibrated parameters.

Case 1- Fixed Well Location

In the first case, the objectives function for this case presented in equation (12). There is a thirty five pumping wells (actual number of wells in the study area), whose locations are shown in Fig. 2. Thus, the case problem can be formulated as an optimization problem with following objective function and constraints,

$$\text{Maximize } J = \Delta t \sum_{i=1}^{35} |Q_i| \tag{12}$$

Subject to

$$h_{min} \le h_m \le h_{max} \tag{13}$$

$$0 \le |Q_i| \le 4000 \tag{14}$$

Where:

Equation (12), the objective function J is expressed in terms of the absolute pumping rates multiplied by Δt, the length of stress period in the flow model, the number of stress period is equal to (7), Δt is equal to 30 day.

Equation (13), is head limited constraint requiring that the hydraulic head at any monitoring well location, h_m, must be above h_{min} and below h_{max}, where:

$$h_{min} = h_i - 0.5 \tag{13a}$$

And

$$h_{max} = h_i + 0.5 \tag{13b}$$

Where

h_i is the initial hydraulic head, the location of monitoring wells with those hydraulic heads presented in table (1). Nine monitoring wells are taken in the present model to observe the hydraulic heads of groundwater as uniformly over the study area (see Fig. 3).

In equations (13a) and (13b), set the value of 0.5m based on the groundwater levels change in the study area for the observation period (one year), there is no significant change in the hydraulic heads of groundwater during the period of observation, and to take a value is more realistic correspond with the changing reality of these hydraulic heads and away from excess of the water.

Equation (14) specified zero as the minimum and 4000 m^3/day as the maximum for the magnitude of each pumping

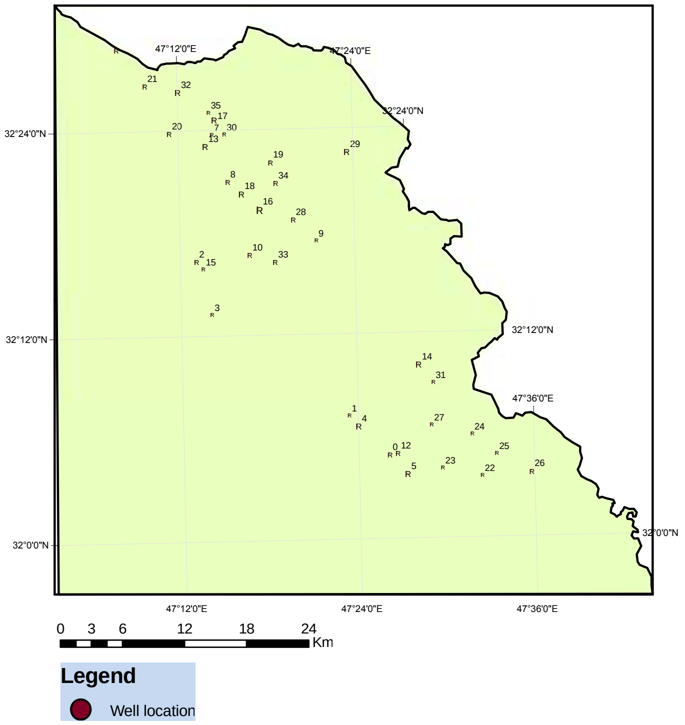

Figure 2. Spatial distribution of existing wells in the study area.

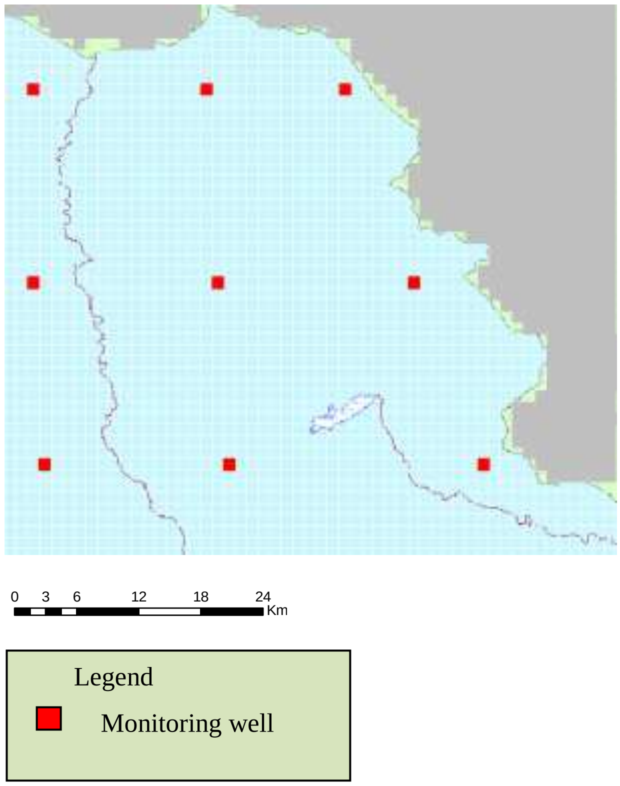

Figure 3. Distribution of monitoring well location in the study area.

TABLE 1 MONITORING WELLS WITH THOSE HYDRAULIC HEADS.

Well No.	Well location		Initial head (m)
	raw no.(I)	column no.(J)	
1	8	3	34.15
2	8	18	69.81
3	8	30	74.38
4	25	3	24.22
5	25	19	40.20
6	25	36	65.52
7	41	4	18.22
8	41	20	30.11
9	41	42	56.39

rate to be optimized. Generally, several test runs are needed to select an appropriate value for use as the maximum pumping rate. If it is set too high, the optimization solution may be inefficient.

The number of discretization intervals (NPStep) for each pumping rate parameter is chosen to be 26. Since the minimum and maximum values for each parameter have been specified as 0 and 4000 m^3/day, respectively, the precision (or resolution) of the identified pumping rates is (4000-0)/ (26-1), or 160 m^3/day. In other words, the final pumping rates obtained by the GA solution may differ from the actual optimal values by as much as (but not to exceed)

160 m^3/day. The number of simulation per optimization iteration (NSimPerIter), or population size (npopsiz), in GA is set at 100. The uniform crossover method is used with a crossover probability set at 0.5. The jump mutation probability is set equal to 1/ NSimPerIter or 0.01. The creep mutation option is used by default.

The objective function converges to a maximum value of (0.32947E+08 m^3/year) after a total of 14 generations satisfying all the constraints. The final solution has only thirty three active wells. The distribution of hydraulic head based on the optimized pumping rates for first stress period is shown in table (2). The distribution of the optimized pumping rates is shown in table (3) under case 1.

TABLE 2 THE DISTRIBUTION OF HYDRAULIC HEAD OF MONITORING WELLS BASED ON THE OPTIMIZED PUMPING RATES

Stress Period	Lower Bound (m)	Upper Bound (m)	Head Value (m)
1	73.8800	74.8800	74.3781
1	69.3100	70.3100	69.7582
1	33.6500	34.6470	34.1400
1	65.0000	66.0000	65.5205
1	39.7000	40.7000	40.2164
1	23.7000	24.7000	24.2244
1	55.8900	56.8900	56.3907
1	29.6100	30.6100	30.1040
1	17.7000	18.7000	18.2235

Case 2- Fixed Well Locations with the on/off Option

To demonstrate the impact of well locations on the optimized pumping rates, a second case is carried out in which a thirty five wells (actual number of wells in the study area) are selected to obtain the optimum pumping rate. Furthermore, the "on/off" status associated with each well is also optimized. The objective function and constraints are similar to case 1 except for the binary variable, yi, representing the "on/off" status of a well, so the formulated of objective function as follow,

$$J = \Delta t \sum_{i=1}^{35} y_i |Q_i| \quad (15)$$

Where,

y_i=1 for active wells (on) and y_i=0 for inactive wells (off).

Also a new constraint is added which requires that the number of wells allowed to be active must not exceed thirty five, i.e.,

$$\sum_{i=1}^{35} y_i \leq 35 \quad (16)$$

The objective function converges to a maximum value of (0.23616E+08 m^3/year) after a total of 15 generations satisfying all the constraints. The final solution has only twenty six active wells.). The distribution of the optimized pumping rates is shown in table (4) under case 2. The distribution of active and inactive wells in the study area is shown in Fig. 4.

Case 3- Flexible Well Location with the Moving Well Option

The simultaneous optimization of pumping rates and well locations can also be handled through the moving well option. The location of a well in this option may not have a fixed location. It is allowed to move anywhere within a user defined region of the model grid until the optimal location is reached. The formulation of the objective function is identical to the case 1. In addition to the constraints specified in case 1, a new constraint is added which requires that each of the wells to be optimized must be located within the patterned area (can be specified by the layer, row, column indices of a model cell representing the upper left and the lower right corner of a rectangular area). i.e.,

$$11 \leq I_w \leq 48 \quad (17)$$

$$2 \leq J_w \leq 34 \quad (18)$$

Where:

I_w and J_w are the row and column indices of the moving well to be optimized.

The number of pumping parameter for case 3 is still as thirty five to compare with the results of case 1. The objective function converges to a maximum value of (0.33754E+08 m^3/year) after a total of 18 generations satisfying all the constraints. To reflect the increase of the higher possibilities as defined in inequalities (17) and (18), the population size is increased from 100 for case 1and case 2 to 200 for case 3. The jump mutation probability is reset to 1/200 or 0.005. After changing these values, the maximum value of the objective function is (0.35539E+08 m^3/year). Compared with the total pumping of (0.32947E+08 m^3/year) for case 1, it can be seen that for this particular example the selection of optimum location of wells results in approximately eight percent of increasing in the total pumping rates. The distribution of the optimized pumping rates is shown in table (5). The distribution of optimized location of wells in the study area is shown in Fig. 5.

TABLE 3 OPTIMIZED PUMPING RATE. (CASE 1)

Well No.	Pumping rate (m^3/day)	Well No.	Pumping rate (m^3/day)
1	-3200	19	-3520
2	-3520	20	-3680
3	-3520	21	-2560
4	-2720	22	-3680
5	-3200	23	-3200
6	0.000	24	-2720
7	-3040	25	-3360
8	-1440	26	-2720
9	-3840	27	-3680
10	-3680	28	-3360
11	-3680	29	-1280
12	-800	30	-2560
13	-3520	31	-1920
14	-1760	32	-3040
15	-2560	33	-3520
16	0.000	34	-160
17	-2720	35	-3200
18	-160		

TABLE 4 OPTIMIZED PUMPING RATES (CASE 2).

Well No.	Pumping rate (m^3/day)	Well No.	Pumping rate (m^3/day)
1	-3520	19	-2880
2	-3520	20	-2880
3	-2240	21	-3680
4	0.000	22	-2720
5	-480	23	-160
6	-1920	24	-3040
7	0.000	25	-2400
8	-3360	26	-1120
9	-2240	27	-3680
10	0.000	28	-320
11	0.000	29	0.000
12	-3200	30	-1920
13	-2560	31	0.000
14	0.000	32	-1600
15	0.000	33	-2880
16	0.000	34	-3360
17	-3680	35	-3040
18	-3200		

TABLE 5 OPTIMIZED PUMPING RATES (CASE 3).

Well No.	Pumping rate (m^3/day)	Well No.	Pumping rate (m^3/day)
1	-3360	19	-3520
2	-3360	20	-3200
3	-3200	21	-2560
4	-3040	22	-2560
5	-2720	23	-3680
6	-3040	24	-3840
7	-320	25	-4000
8	-3040	26	-320
9	-4000	27	-3360
10	-1600	28	-2720
11	-1600	29	-3200
12	-3360	30	-3040
13	-3040	31	-3040
14	-1600	32	-1440
15	-3360	33	-2560
16	-320	34	-3200
17	-3840	35	-4000
18	-3680		

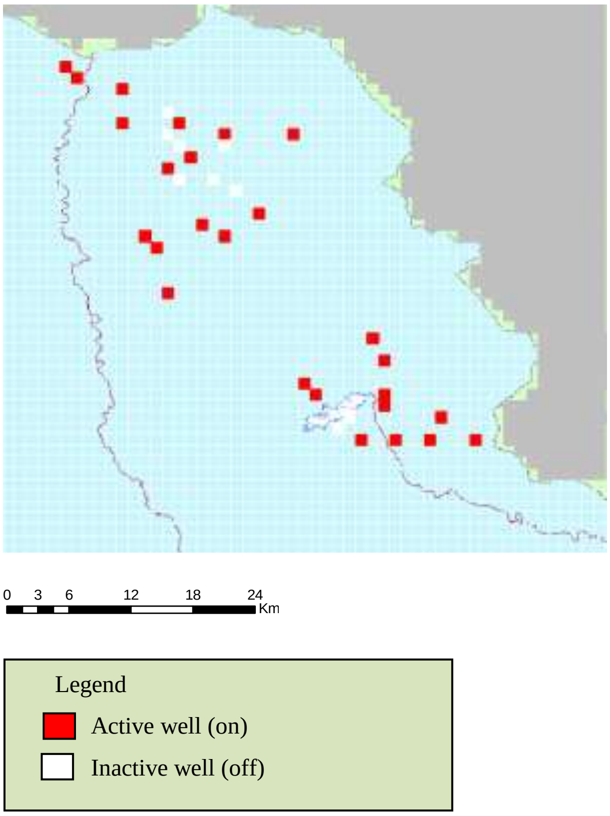

Figure 4. Distribution of active and inactive wells in the study area.

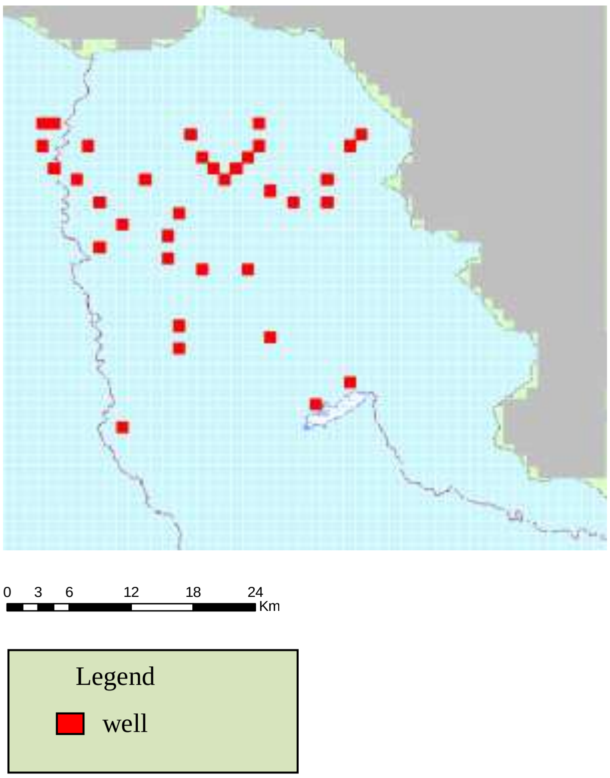

Figure 5. Distribution of optimized location of wells in the study area.

V. Conclusions

As previously mentioned three cases of different optimization process conducted in the study area. In the first case found the optimum value of the objective function is (0.32947E+08 m^3/year), where the maximum value of pumping rate is 3840 m^3/day and the minimum value is 0 m^3/day, this well has an impact on the specified hydraulic head constraints. Hydraulic heads stabilized during the simulation period in this case, which encourages the use of optimal pumping rate values. The highest decline in the hydraulic heads of groundwater compared with initial hydraulic heads about 6 cm. In other words, we can raise the pumping rates to nine times the current pumping rates. Also in this case, a reduction in the hydraulic head constraints from 0.5 to 0.25 for the upper and lower constraints is carried out, there is no a significant change in the results of the program, this is due to the lack of a significant change in groundwater levels. The "on/off" status associated with each well is optimized in case 2 to demonstrate the impact of well locations on the optimized pumping rates. Twenty six wells can be operating to obtain the maximum value of pumping rate. The third case included the moving well option; the location of a well in this option may not have a fixed location. It is allowed to move anywhere within a user defined region of the model grid until the optimal location is reached. The optimum value of objective function is 0.35539E+08 m^3/year with eight percent increasing of the pumping rates compared with the first case. It can be seen from figure (5), the majority of wells located in the northern part of the study area where a good hydraulic characteristics (specific yield and hydraulic conductivity).

References

[1] D.L, Galloway, W.M. Alley, P.M Barlow., T.E. Reilly., P. Tucci, Evolving issues and practices in managing groundwater resources: survey circular, 1247, 2003.

[2] R. Willis, B. Finney, , Optimal control of nonlinear groundwater hydraulics : Theoretical development and numerical experiments,Water Resour. Res., 21 (10) : 1476, 1985.

[3] B . J. Ritzal, J . W . Eheart , S. Ranjithan, Using genetic algorithms to solve a multiple objective groundwater pollution containment problem, Water Resour. Res ., 30(5) : 1589, 1994.

[4] S. M.Gorelick, A review of distributed parameter groundwater management modeling methods, Water Resour. Res., 19(2), 305-319. 1983.

[5] D. P. Ahlfeld, , J. M. Mulvey, G. F. Pinder and E. F. Wood , Contaminated groundwater remediation design using simulation, optimization, and sensitivity theory, 1. Model development, Water Resour. Res., 24(5), 431-441, 1988.

[6] B. J.Wagner, and S. M. Gorelick. Reliable aquifer remediation in the presence of spatially variable hydraulic conductivity: from data to design, Water Resour. Res., 25(10), 2211-2225, 1989.

[7] T. B. Culver, and C. A. Shoemaker, Dynamic optimal control for groundwater remediation with flexible management periods, Water Resour. Res., 28(3), 629-641, 1992.

[8] D.M., Rizzo, and D.E. Dougherty. Design optimization for multiple management period groundwater remediation, Water Resour. Res., 32(8), 2549-2561, 1996.

[9] C. Zheng, and P.P.Wang, A Modular Groundwater Optimizer Incorporating MODFLOW/MT3DMS. The University of Alabama, documentation and user's guide, 119 p, 2003.

[10] D.L Carroll. Genetic algorithms and optimizing chemical oxygen-iodine lasers, In Developments in Theoretical and Applied Mechanics, Vol. XVIII, eds., School of Engineering, The University of Alabama, 1996.

[11] E. Falkenauer . The worth of uniform crossover. Proceedings of the congress on evolutionary computation, vol. 1, CEC99, USA, p. 782, 1999.

[12]A. E.Eiben, ,. "Genetic algorithms with multi-parent recombination". PPSN III: Proceedings of the International Conference on Evolutionary Computation. The Third Conference on Parallel Problem Solving from Nature: 78–87. ISBN 3-540-58484-6, 1994.