Optimal Groundwater Management in Teeb Area, Missan Province, Using Genetic Algorithm Technique

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Abstract : A linked simulation-optimization model for obtaining the optimum management of groundwater flow is presented in this research. (MODFLOW, 98) packages are used to simulate the flow of the groundwater system. 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 m3/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 m3/year) with 8% increasing of the pumping rates compared with the first case. This is due to the random distribution of existing well locations.

Keywords: Management, Groundwater, Teeb, Genetic Algorithm.

الإدارة المثلى للمياه الجوفية في منطقة الطيب، محافظة ميسان، باستخدام تقنية الخوارزمية الجينية

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الخلاصة

انشأ نموذج محاكاة–الامثلية لإدارة المياه الجوفية في منطقة الطيب. استخدم برنامج MODFLOW, 98 لمحاكاة جريان المياه الجوفية، ثم دمج هذا النموذج مع نموذج الامثلية المستند على تقنية الخوارزمية الجينية (Genetic Algorithm). اقترحت ثلاث حالات إدارة مختلفة لتشغيل النموذج المجهز بالمعاملات المعايرة. عثر في الحالة الأولى على القيمة المثلى لدالة الهدف بمقدار (0.32947E+08) متر مكعب / سنويا ، بعبارة أخرى، يمكن رفع معدل الضخ إلى تسعة أمثال معدل الضخ الحالي للمياه الجوفية، وفقا لأعلى انخفاض في مناسيب المياه الجوفية مقارنة مع تلك المناسيب الابتدائية حوالي ٦ سم. في الحالة الثانية تم تشغيل ٢٦ بئر من أصل ٣٥ بأسلوب (تشغيل/إيقاف) للحصول على القيمة القصوى لمعدل الضخ. تم السماح لتغيير مواقع آبار الضخ في الحالة الثالثة ضمن مواقع يحددها المستخدم على شبكة النموذج حتى الوصول إلى المواقع المثلى لتلك الآبار. القيمة المثلى لدالة الهدف في هذه الحالة هي (0.35539E+08) متر مكعب/ سنويا، أي بزيادة مقداره 8% تقريبا من الضخ في الحالة الأولى، يرجع ذلك إلى التوزيع العشوائي لمواقع الآبار الحالية.

Introduction

Since ancient times water resources have influenced, both rise and fall of human civilizations. The water plays more vital and critical role for both economic growth and prosperity. Groundwater is considered one of the important sources of fresh water in the hydrologic cycle. Any water resource system is to be developed with an approach of integrated use. Optimum utilization of water and better management are the important objectives to be considered in any water resource project.

In semiarid regions like Iraq with low precipitation, high potential of evapotranspiration are abundant and rapid population growth have increased the water demand for domestic and other uses , hence increasing pressure on water resources. In those regions, the sources of water should be well managed so to minimize fluctuations in the total water demands caused by variations in rainfall patterns.

The optimization problem can be solved through manual trial-and-error adjustment. While the trial-and-error method is simple and thus widely used, testing and checking hundreds of trial solutions is tedious and cannot guarantee that the optimal solution has been identified. On the contrary, an optimization technique can be used to identify the optimal solution, and equally important, to prove whether a particular management scenario is feasible in terms of satisfying all the constraints.

The combined use of simulation and optimization techniques have been demonstrated to be powerful and useful methods in determining planning and management strategies for optimal development and operation of groundwater systems. However, an optimization model identifies an optimal management strategy from a set of feasible alternative strategies. In order to ensure that the optimal management strategy is physically acceptable, a simulation model is necessary to simulate the system behavior. The simulation model basically provides solutions that obey the equations governing the relevant processes in the system. Thus the simulation models check for feasibility of a management strategy. The development and application of the coupled simulation-optimization approach has been an active and fruitful research area in recent years [1]

This research proposes a linked simulation-optimization model for obtaining the optimum management of groundwater flow in the Teeb area. Teeb area is located in north and north east of Missan province as shown in figure (1). It occurs along the foot of mountains of the Iraqi-Iranian frontier in south of Iraq, between longitudinal-line (47°06'-47°36') and latitude-line (32°06'-32°30'). The considered area is about 1860 km^2. It extended from Teeb area close to the Iraqi-Iranian border to Shikh Fars area.

The Modular Groundwater Optimizer (MGO)[2] is a general-purpose simulation optimization code developed for field scale applications. This modular is used in this research. In the proposed model, MODFLOW packages are used to simulate the flow in the groundwater system. 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

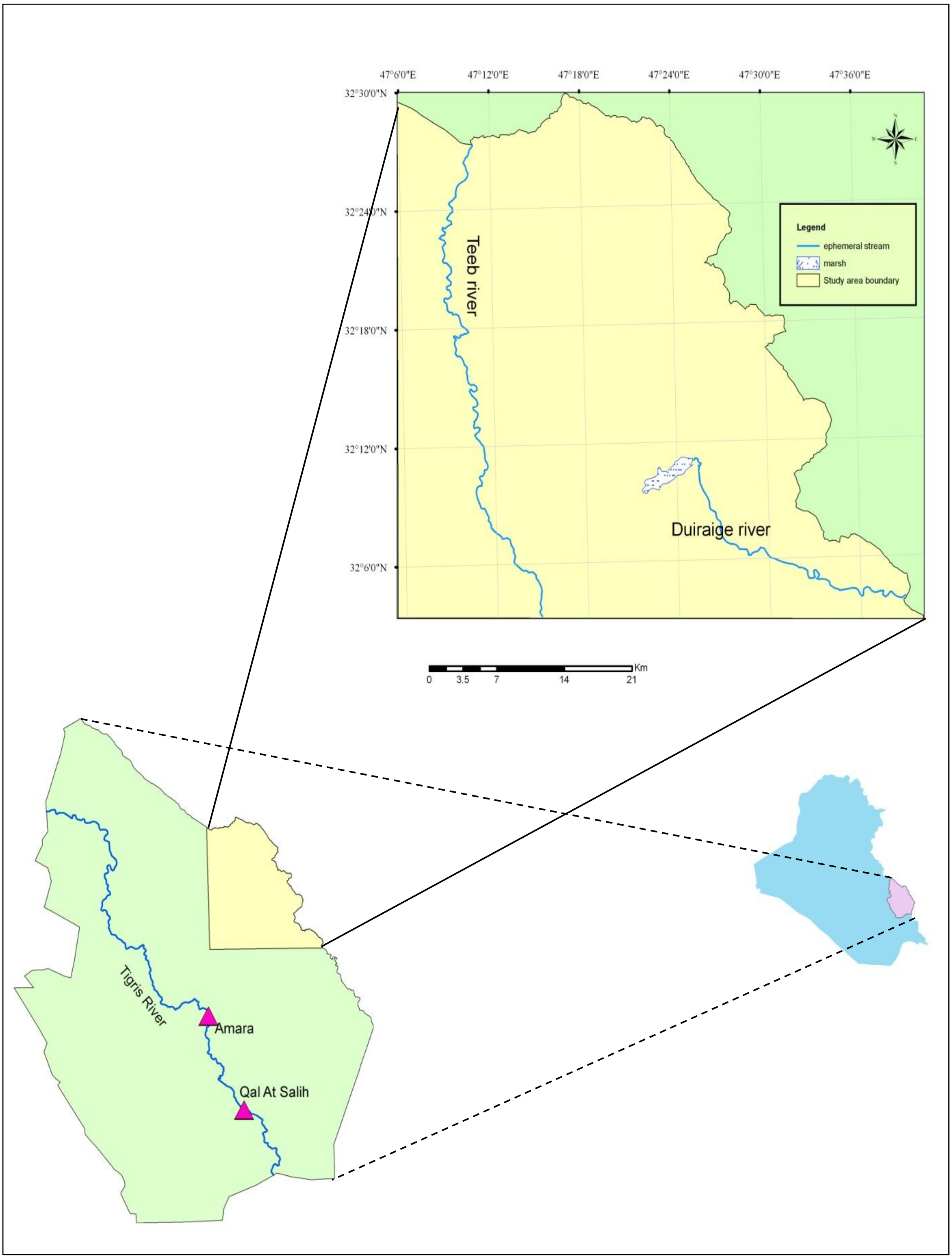

Figure (1) Location of study area in reference to map of Iraq.

Optimization Techniques

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 simulation model update the state variables, and the optimization model determines the optimal values for all decision variables. This process can be carried out in a coupled simulation-optimization model.

The management objectives must be achieved within a set of constraints. The constraints may be decision or state variables. Also they may 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 [2].

Maximize (or minimize)

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

Subject to

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

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

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

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

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

Where, *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.

Q_i is the pumping/injection rate of well represented by parameter *i* (negative for pumping and positive for injection). Note that the term parameter (Q_i) 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* and hydraulic head *h*.

N is the total number of parameters (decision variables) to be optimized.

y_i 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*.

Δt_i is the duration of pumping or injection associated with parameter *i* (or the length of the management period for parameter *i*).

a_1 is the fixed capital cost per well in terms of dollars or other currency units;

a_2 is the installation and drilling cost (dollars or other currency units) per unit depth of well bore (e.g., dollars/m); and,

a_3 is the pumping and/or treatment costs (dollars or other currency units) per unit volume of flow (e.g., dollars/m^3).

a_4 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.

(Q_{min} and Q_{max}) are the minimum and maximum flow rate of a well at any specific management period.

(h_{min} and h_{max}) are the lower and upper bounds of the hydraulic head.

(h_m) is a hydraulic head at any monitoring location.

$(h_m^{out} - h_m^{in})$ is the head difference between an "outside" and an "inside" monitoring wells must be greater than a minimum value, Δh_{min}.

Equation (6) is a constraint stating that the pumping/injection rate of a well at an arbitrary location, Q_m, is proportional to the sum of the optimized flow rates represented by parameters I_1 through I_2 where A and B are proportional constants.

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 of computational systems has 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:

$$\underbrace{0\,0\,1\,1\,0}_{Q_1}\ \underbrace{0\,1\,0\,0\,1}_{Q_2}\ \underbrace{1\,1\,0\,0\,1}_{Q_3}\ \ldots\ldots$$

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, $Q_{min}<Q_i<Q_{max}$, 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.

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

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 [3].

$$npopsiz = order[(l/k)2^k] \qquad (8)$$

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 [4]. 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 [1].

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 [5].

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) [3] suggests a rule of thumb for the mutation probability, pmutate:

$$\text{pmutate} = 1/\text{npopsiz} \qquad (9)$$

Where:
npopsiz is the size of population as defined earlier.

The type of mutation described above is referred to as jump mutation [3]. 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,

$$Q_i^* = Q_i \pm dQ_i \qquad (10)$$

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. It is usually adequate to set the creep mutation probability equivalent to the jump mutation probability through the following relationship [3].

$$\text{pcreep} = (l/\text{nparam})\text{pmutate} \qquad (11)$$

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

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

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

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

Subject to

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

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

Where:

In 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), where the number of stress period is equal to (7). Δt is equal to 30 day.

$$h_{min} = h_i - 0.5 \tag{15}$$

And

$$h_{max} = h_i + 0.5 \tag{16}$$

Where

h_i is the initial hydraulic head. The location of monitoring wells with their hydraulic heads are presented in table (1). Nine monitoring wells is taken in the present model to observed the hydraulic heads of groundwater as uniformly over the study area (see figure 3). In equations (15) and (16), 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 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 the default value of the program.

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 the optimized pumping rates is shown in table (2) under case 1. The distribution of hydraulic head based on the optimized pumping rates for first stress period is shown in table (3).

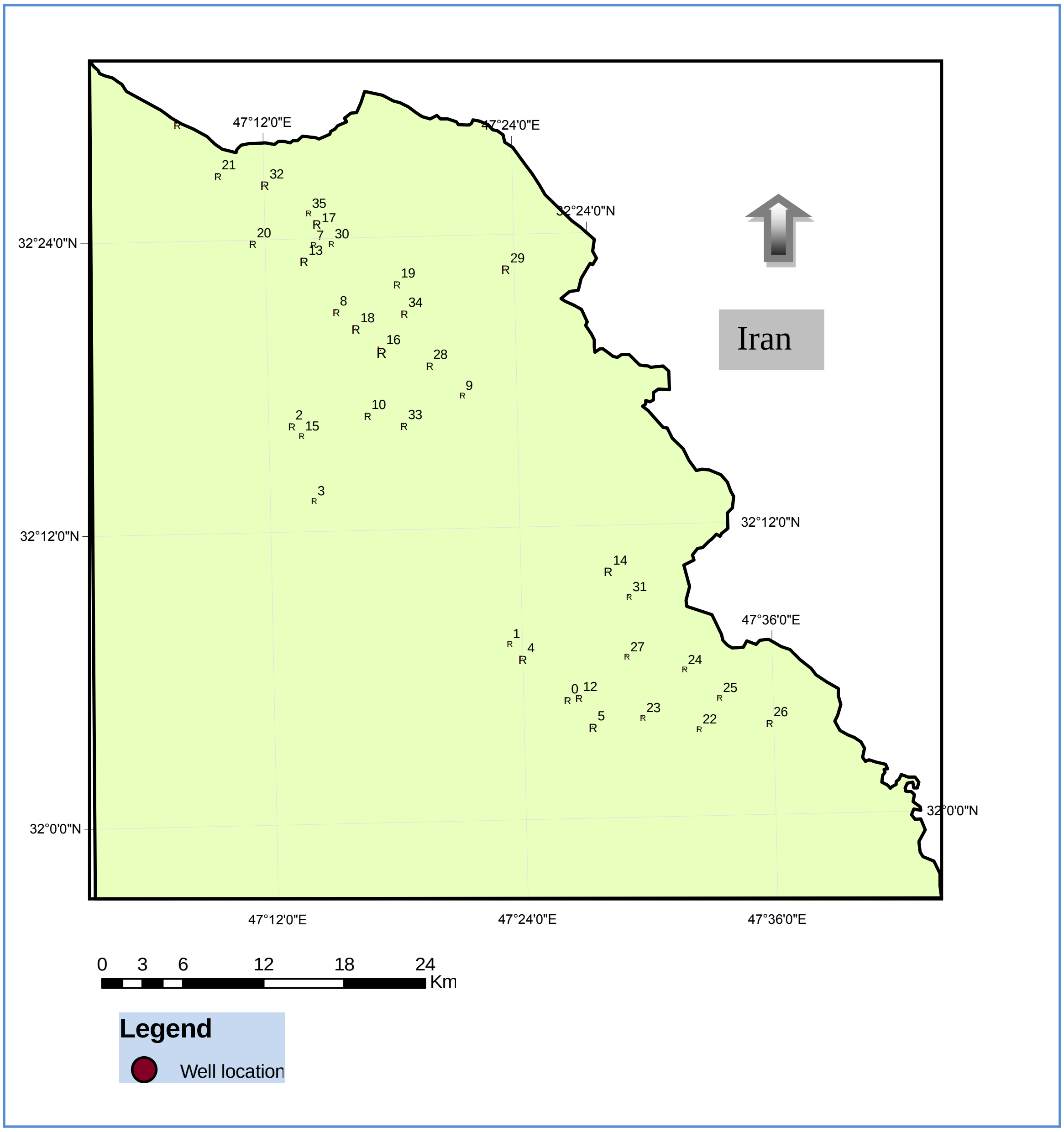

Figure (2) Spatial distribution of existing wells in the study area.

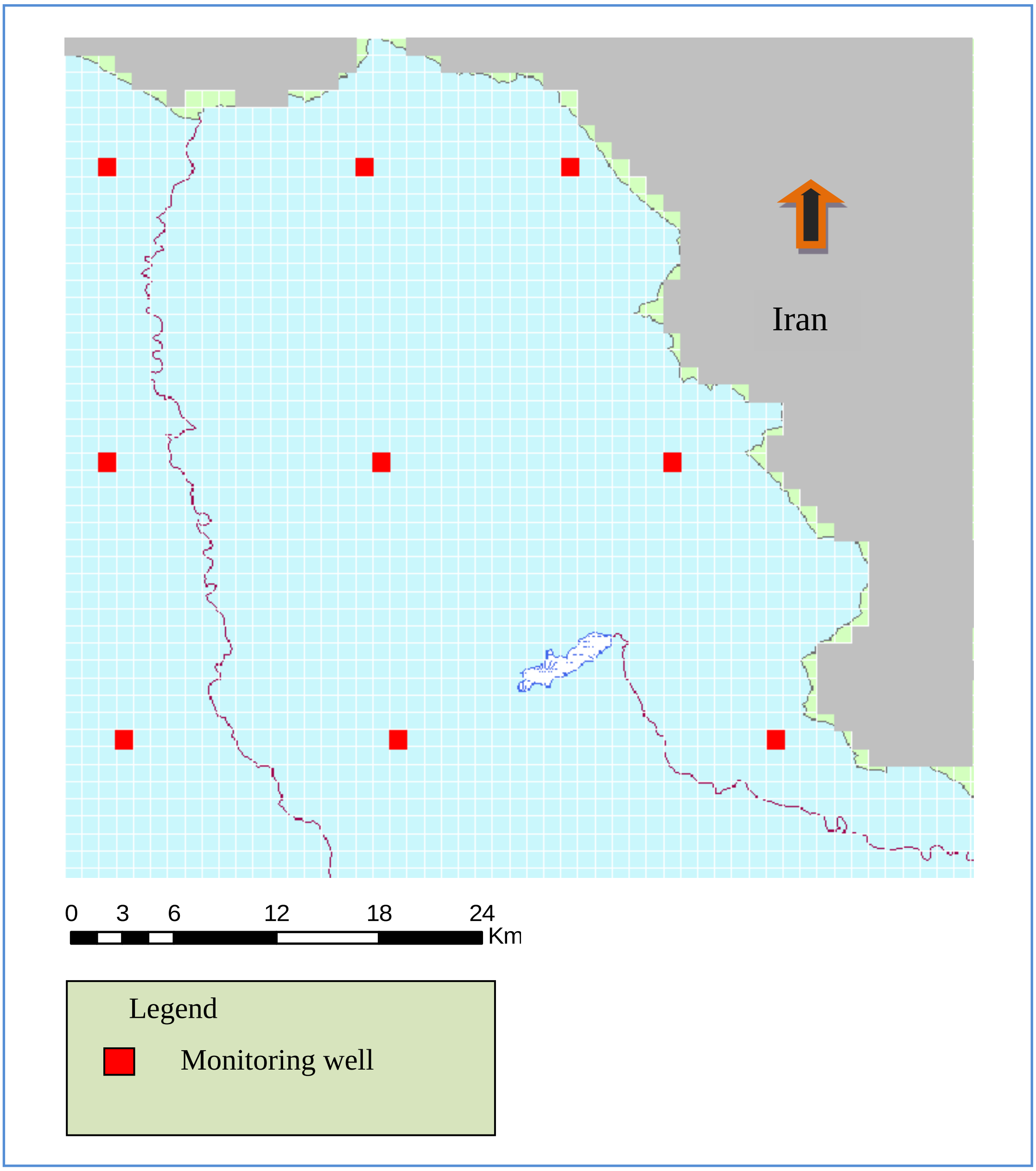

Figure (3) Distribution of monitoring wells in the study area.

Table (1) Monitoring wells with 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

Table (2) Distribution of the optimized pumping rates in the study area.

Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)	Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)
1	6	6	-3200	19	21	13	-3520
2	7	7	-3520	20	21	20	-3680
3	8	11	-3520	21	22	14	-2560
4	10	15	-2720	22	26	15	-3680
5	11	11	-3200	23	30	33	-3200
6	11	16	0.000	24	32	34	-2720
7	12	15	-3040	25	34	27	-3360
8	12	20	-1440	26	35	28	-2720
9	12	26	-3840	27	35	34	-3680
10	13	16	-3680	28	36	34	-3360
11	13	20	-3680	29	37	31	-1280
12	14	17	-800	30	37	39	-2560
13	15	15	-3520	31	38	30	-1920
14	16	16	-1760	32	39	32	-3040
15	16	19	-2560	33	39	35	-3520
16	17	21	0.000	34	39	38	-160
17	19	23	-2720	35	39	42	-3200
18	20	18	-160				
sum							-91520

Table (3) The distribution of hydraulic heads based on the optimized pumping rates.

Stress Period	Location(I,J)	Hydraulic Head (m)		
		Lower Bound	Upper Bound	Head Value
1	8,30	73.8800	74.8800	74.3781
1	8,18	69.3100	70.3100	69.7582
1	8,3	33.6500	34.6470	34.1400
1	25,36	65.0000	66.0000	65.5205
1	25,19	39.7000	40.7000	40.2164
1	25,3	23.7000	24.7000	24.2244
1	41,42	55.8900	56.8900	56.3907
1	41,20	29.6100	30.6100	30.1040
1	41,4	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 was carried out in which thirty five wells 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 those of case 1 except for the binary variable, y_i, representing the "on/off" status of a well, so the formulated of objective function as follow,

$$J = \Delta t \sum_{i=1}^{35} y_i |Q_i| \quad (17)$$

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

$$\sum_{i=1}^{35} y_i \leq 35 \quad (18)$$

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 active and inactive wells in the study area is shown in figure (4). The distribution of the optimized pumping rates for case 2 is shown in table (4).

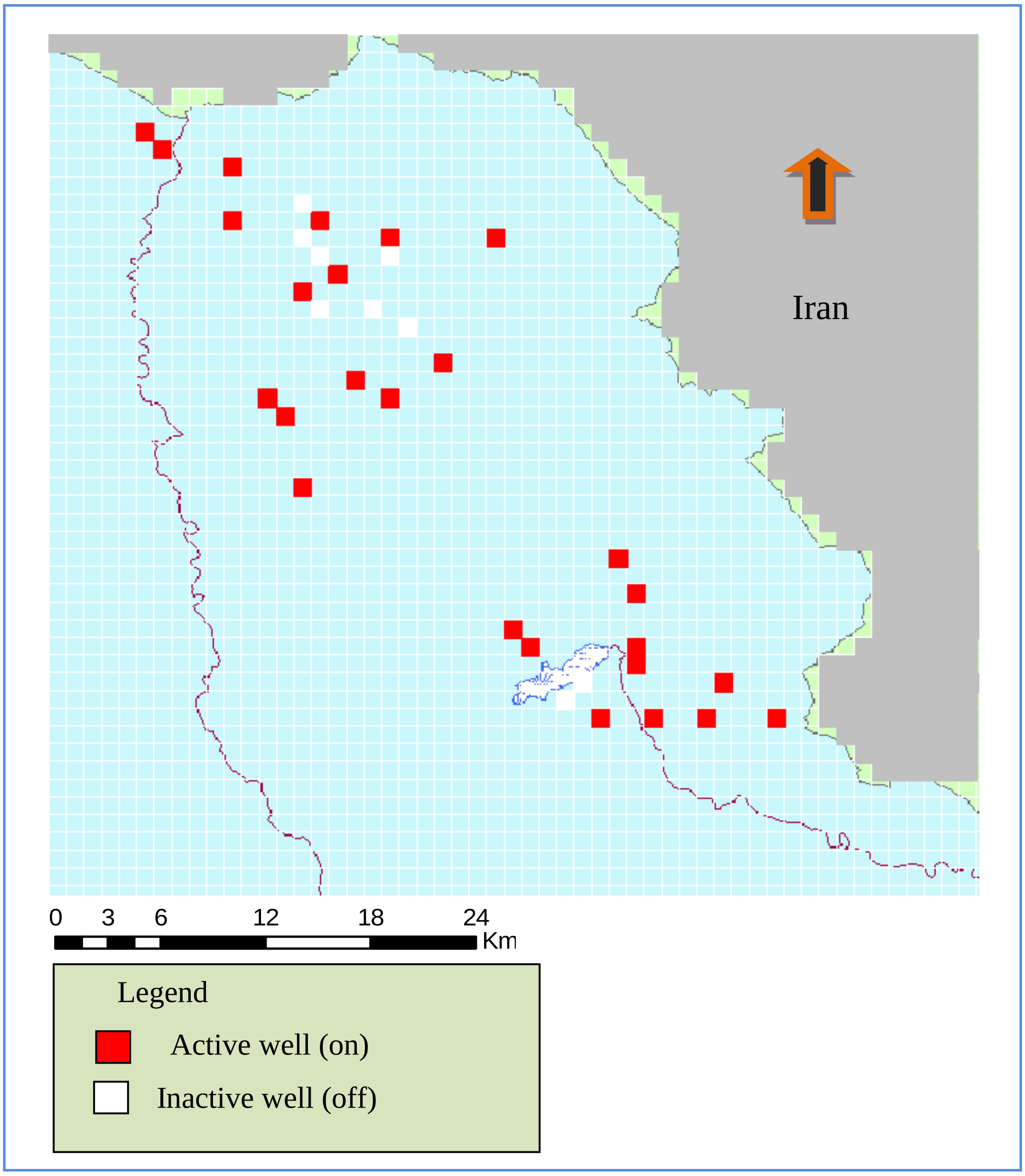

Figure (4) Distribution of active and inactive wells in the study area.

Table (4) Distribution of the optimized pumping rates in the study area.

Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)	Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)
1	6	6	-3520	19	21	13	-2880
2	7	7	-3520	20	21	20	-2880
3	8	11	-2240	21	22	14	-3680
4	10	15	0.000	22	26	15	-2720
5	11	11	-480	23	30	33	-160
6	11	16	-1920	24	32	34	-3040
7	12	15	0.000	25	34	27	-2400
8	12	20	-3360	26	35	28	-1120
9	12	26	-2240	27	35	34	-3680
10	13	16	0.000	28	36	34	-320
11	13	20	0.000	29	37	31	0.000
12	14	17	-3200	30	37	39	-1920
13	15	15	-2560	31	38	30	0.000
14	16	16	0.000	32	39	32	-1600
15	16	19	0.000	33	39	35	-2880
16	17	21	0.000	34	39	38	-3360
17	19	23	-3680	35	39	42	-3040
18	20	18	-3200				
sum						-65600	

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 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 that of 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 (which 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.,

$$11 \le I_w \le 48 \quad (19)$$

$$2 \le J_w \le 34 \quad (20)$$

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 are still as thirty five as compared 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 (19) and (20), the population size was 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 optimized location of wells in the study area is shown in figure (5). The distribution of the optimized pumping rates for case-3 is shown in table (5).

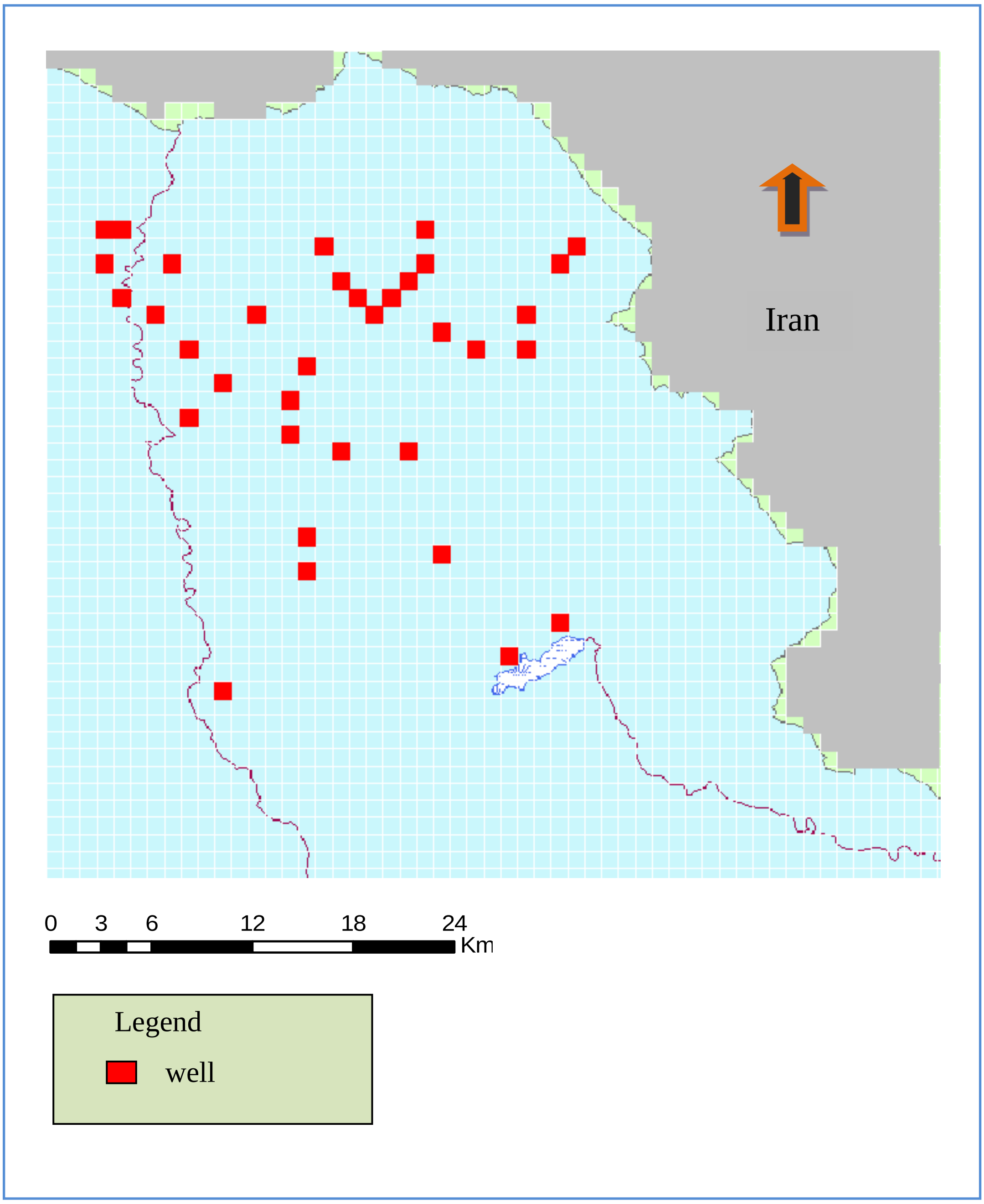

Figure (5). Distribution of optimized location of wells in the study area.

Table (5) Distribution of the optimized pumping rates in the study area.

Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)	Well No.	Raw No. (I)	Column No. (J)	Pumping rate (m^3/day)
1	21	15	-3360	19	16	13	-3520
2	15	19	-3360	20	13	4	-3200
3	16	20	-3200	21	11	4	-2560
4	30	24	-3040	22	13	8	-2560
5	12	17	-2720	23	18	9	-3680
6	34	31	-3040	24	38	11	-3840
7	15	5	-320	25	20	11	-4000
8	24	22	-3040	26	31	16	-320
9	23	15	-4000	27	24	18	-3360
10	36	28	-1600	28	29	16	-2720
11	16	29	-1600	29	16	7	-3200
12	13	23	-3360	30	19	16	-3040
13	17	24	-3040	31	15	21	-3040
14	11	5	-1600	32	13	31	-1440
15	18	29	-3360	33	22	9	-2560
16	14	22	-320	34	14	18	-3200
17	11	23	-3840	35	18	26	-4000
18	12	32	-3680				
sum						-98720	

Conclusions

Three cases of different optimization process were conducted for the study area. In the first case, it was found that the optimum value of the objective function is (0.32947E+08 m^3/year), where the maximum and the minimum value of pumping rate are 3840 m^3/day and 0 m^3/day respectively. The highest decline in the hydraulic heads of groundwater compared with initial hydraulic heads about 6 cm. In other words, the pumping rates can be raised 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 was carried out and it was found that there is no significant change in the results of the program. The "on/off" status associated with each well was optimized in case-2 to demonstrate the impact of well locations on the optimized pumping rates. Twenty six wells can be operated to obtain the maximum value of pumping rate. During case-3 it was found that 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. In this case the majority of wells are located in the northern part of the study area where a good hydraulic characteristics (specific yield and hydraulic conductivity).

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