Multi-objective groundwater management using genetic algorithms in Kerbala desert area, Iraq

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Abstract. Kerbala desert is one of the most important areas in Iraq, due to the large number of groundwater aquifers in the region. Based on this, many agricultural investment projects have been established in this area recently, with multiple new wells being drilled in the desert. All such wells penetrate the Dammam confined aquifer to a depth of 260 to 300 m, and uncontrolled use of these wells, and the additional wells expected as the area develops, is likely to lead to problems with groundwater sources, including depletion of water levels, well interference, and groundwater pollution. This study introduces a multi objectives groundwater management model based on an integrated simulation-optimisation (S/O) model. The simulation of groundwater flow was developed using a finite-difference numerical model, MODFLOW, under GMS software for various conditions, and evaluation of calibration of the transient model was determined by observing the measured and calculated aquifer heads. A multi-objective optimisation model was applied to maximise the pumping rate and minimise pumping costs, and this was solved using a genetic algorithm method supported by two further mechanisms, Pareto optimality ranking and fitness sharing. A set of Pareto optimal solutions as determined in the final generation was thus created for the multi-objective function (maximum pumping rate and minimum pumping cost) to help decision-makers (DM). Based on the Pareto solutions set, a DM or the designer may thus choose a preferred solution, or a compromise solution may be derived by considering the full set of Pareto optimal solutions.

Keywords: Groundwater management, GMS, MOGA, Multi-objective functions, S/O model genetic algorithm, Kerbala, Iraq.

1. Introduction

In the Middle East, groundwater plays an important role in terms of the various water resources available, and it is thus utilised in many fields, including agricultural, industrial, and domestic
applications. The management of groundwater simulation models is thus a high priority in light of increasing water demands. Recently, climate change threats, changes to expected living standards change, and increases in population have all increased requirements for the employment important water resources such as groundwater; however, several related anthropogenic pressures, such industrialisation and urbanisation, have caused the quality and quantity of groundwater resources to be reduced. Accordingly, decision-makers now require more sustainable management strategies to determine the optimum used of groundwater.

There are many differences between multi-objective function optimisation problems and single-objective function optimisation problems. In multi-objective problems, it is not always necessary to find a superior solution for all objectives, as contradictions between numerous objectives may mean that a solution that is optimal for one objective is worse for one or more other objectives. Commonly, there thus exists a set of solutions for each such optimisation problems, and the solutions within each set may be difficult to compare with each other. In contrast, in the case of single-objective function, one optimum solution, which is always superior to all other feasible solutions, is a likely outcome. For some solutions of multi-objective functions, known as Pareto optimum solutions, no refinement in any objective function is potential without negatively affecting at least one of the other objective function [1].

Many researchers, such as [2-10] have studied optimisation problems with multi-objective functions using linear and nonlinear programming with respect to groundwater models. [11] used multi-objective functions to obtain the maximum pumping rates and the best locations for wells in coastal aquifers, seeking decreased saltwater intrusion, while [12 and 13] presented a Progressive Genetic Algorithm (PGA), which utilised a repeated subdomain solution to obtain optimised pumping rates and well locations simultaneously. [14] introduced multi-objective function optimisation for the management of groundwater using genetic algorithms, with the oasis of El-Farafra, Egypt, used as a case study. [15] reported on a new multi-objective optimisation problem by using simulation-optimisation techniques including four objective functions, applying a new probabilistic Pareto genetic algorithm (PPGA) integrated with MODFLOW and MT3DMS codes. [16] presented two multi-algorithm genetic approach methods with a groundwater model, identifying optimum pumping rates with a well-distributed set of Pareto solutions; they also used a three-dimensional finite-difference numerical model (MODFLOW) for groundwater simulation.

In this study, multi-objective functions solved with the Pareto technique were used with respect to groundwater sources in the Kerbala desert area, Iraq. The first objective function was formulated to maximise the pumping rates of the wells, while the second objective function was designed to minimise
pumping costs. A set of Pareto optimal solutions was thus produced to support decision makers (DM) in selecting the optimum solutions from among various alternative feasible solutions.

2. Study Area

Geographically, the study area lies to the west and southwest of Kerbala Governorate, Iraq. The Al-Razzaza lake limits the study area from the south so that it lies between longitudes 43° 46ʹ 47ʺ to 43° 48ʹ 39ʺ E, and latitudes 32° 31ʹ 48ʺ to 32° 29ʹ 28ʺ N, as shown in Figure 1. Its shape is roughly trapezoidal, and it occupies an area of about 134.6 km². The area is comprised of many geological units that exemplify the makeup of the main section of the Kerbala-Najaf plateau. Al-Dammam aquifer is the producing hydrogeological formation of both the western desert and this study region [17, 18], being a karst confined aquifer [19, 20]. In general, the flow direction of groundwater is thus from the west to the east.

Recently, more than 60 new wells for production have been established within the Kerbala desert area [21, 22], with average depths of 250 to 300 m. The main types of soil in the area are sandy soil, sedimentation, and sand-gravel mixtures, with some presence of clay lenses. The slope of the region can be characterised as smooth, and the general elevation ranges from 50 to 95 m.a.s.l., as displayed in Figure 2.

2.1. 2.1 Geological formations

Generally, the study area lies within the plain of the desert, though it also contains a partially expressed hilly region. It may be considered part of the Najaf-Kerbala plateau, which includes the Mesopotamian region covering the middle area of Iraq. The geological formations, in sequence from deepest to highest [23-25] are the Tayarat, Umm Er Radhuma, Dammam, Euphrates, Nfayil, Fatha, Injana, and Dibdibba formations. Some of these geological formations, such as Umm Er-Radhuma, Tayarat, Dammam, Dibdibba, and Euphrates are also considered to be water carrying formations for the Kerbala desert [26 and 27]. Geological profile investigations from many boreholes have confirmed the existence of a rather complex multi-aquifer regime with impervious layers in lens form locally dividing the aquifers. Of the multiple water-bearing formations identified in this manner, the main generating aquifers appear to collect from the Al-Dammam and Umm Er Radhuma formations [28-31]. The average thickness of the Al-Dammam formation is approximately 195m. Figure 3 shows the equipotential contours map for the regional study area, with the main direction of groundwater flow being towards the east and northeast.
Figure 1: Study area and well locations.

Figure 2: Topography of the study area.
3. Materials and Methodology

3.1. Groundwater modelling

The governing equation (Laplace’s equation) for three dimensional heterogeneous and anisotropic groundwater flow modelling as used in the MODFLOW application under groundwater modelling system (GMS) software is as follows:

\[
\frac{\partial}{\partial x} \left( K_x \frac{\partial h}{\partial x} \right) + \frac{\partial}{\partial y} \left( K_y \frac{\partial h}{\partial y} \right) + \frac{\partial}{\partial z} \left( K_z \frac{\partial h}{\partial z} \right) + W = -S_s \frac{\partial h}{\partial t}
\]

where Kx, Ky, and Kz are the permeability coefficients for the x, y, and z directions respectively; h is the total head; W is the flow for one unit volume (sources, sinks), with positive signs for in flux and negative signs for out flux; Ss is the coefficient of specific storage; and t is the time.

3.2. Physical Model

A suitable description of the hydrogeological parameters of the modelled region is required to determine the signs of pertinent flow operations. Where such information is absent, it is difficult to choose a suitable simulation or even to improve a partially calibrated simulation. However only some of the hydrogeologic information was available in certain parts of the study area, sue to the characteristics of the aquifers[32-34]. To assess the information more accurately, the Kriging method was thus applied to obtain the requisite parameters for all study regions. The positions of the 43 wells

Figure 3: Natural piezometric groundwater level contours (m.a.s.l.) for a regional aquifer (Dammam) in Kerbala province (Kriging).
seen in Figure 1 were used to predict aquifer information such as topography, hydraulic conductivity, and rate of recharge. This conceptual model process included the implementation of geographic information system (GIS) tools in the map module to produce a conceptual model of area under simulation. The positions of sinks/sources, simulation boundaries, aquifer properties, and all other information required for modelling was thus identified at this stage of the conceptual model. After the simulation was complete, the grid model was created and the conceptual model transformed into a grid simulation, with cell-by-cell transfers performed automatically. This process of developing a conceptual model was deemed to be the most efficient process, as complicated approaches can undermine the conceptual model. The conceptual model was then applied in this study.

Figure 4 shows the main boundary conditions used in the conceptual model, with the constant head boundary conditions at 65 m acting as a piezometric head in the southwestern area and the 50 m acting similarly for the north-eastern study area. The other sides were represented with wall boundaries or no-flow boundaries on the south-eastern and south-western edges of the simulated area to match the stream lines. The grid selected for the simulation model consisted of two layers, 106 columns, and 87 rows, as shown in Figure 4.

![Flow model boundaries, grid, and pumping wells.](image_url)
3.3. Formulation of the Multi-Objective Optimisation Model

As mention previously, this study applied two objective functions in the optimisation formulation approach:

1. The first objective was to maximise the rate of total pumping \((Z_1)\) in each well \(j\); the decision variable for this objective function was thus the pumping rate of each well, \(Q_j\), and the first objective function was formulated as follows:

\[
Z_1 = \max \left\{ \sum_{j=1}^{N_w} Q_j - \lambda_1 P(h)_j - \lambda_2 P(Q)_j \right\}
\]  

(2a)

where \(N_w\) is the total number of wells pumping; and \(P(Q)\) and \(P(h)\) are penalty expressions related to the total pumping and well piezometric head constraints, respectively, which are set equal to zero where neither the total pumping constraint or hydraulic head constraint are violated, with linear changes according to the value of constraint violation else, such that

\[
P(h) = \begin{cases} r_j - d_j & \text{if } r_j > d_j \\ 0 & \text{if } r_j \leq d_j \end{cases} \quad j = 1, 2, 3, \ldots, N_w
\]  

(2b)

\[
P(Q) = \begin{cases} Q_D - \sum Q_j & \text{if } \sum Q_j < Q_D \\ 0 & \text{if } \sum Q_j \geq Q_D \end{cases} \quad j = 1, 2, 3, \ldots, N_w
\]  

(2c)

where \(r_j\) is the calculated decline in water level at well \(j\) due to the rate of the pumping, \(Q_j\), from well \(j\); \(d_j\) is the allowable decline in water level at pumping well \(j\); and \(Q_D\) is the amount of water required.

2. The second objective \((Z_2)\) is the minimisation of operational cost: This essentially requires the identification of well locations as well as determination of their pumping rates, so that, when operated, the system can satisfy the required water demand at the least possible cost. This objective can be stated as

\[
Z_2 = \min \left\{ \sum_{j=1}^{N_w} C_j e_j Q_j + \lambda_3 P(h)_j + \lambda_4 P(Q)_j \right\}
\]  

(3)

where \(C_j\) is daily pumping rate cost in units of Iraqi Dinar (I.D) per unit lift for cell \(j\); \(Q_j\) is the rate of pumping in cell \(j\) \((j=1, 2, 3, \ldots, N_w)\); \(e_j\) is the lift produced by pumping, as calculated using \((E-h_j)\); \(E\) is the ground elevation; and \(h_j\) is the piezometric head elevation in well \(j\).

The two objective functions (Eq. 2 & Eq. 3) were also subjected to some constraints related to the pumping rates, maximum water drawdown, and water demand in the study area. These constraints were formulated as follows:
First constraint: this was the well pumping rate constraint, which represents the potential pumping rates based on the water demand in the well service areas as a minimum value \( Q^\text{min}_j \), while the permissible pumping rate was set as the maximum values \( Q^\text{max}_j \), as follows:

\[
Q^\text{min}_j \leq Q_j \leq Q^\text{max}_j \quad j = 1,2,3, \ldots, N_w
\]  

Using a genetic algorithm solution method, this constraint can easily be satisfied by limiting the space of the initial population variables to be within these values; thus, no special working was required for this constraint.

Second constraint: this constraint related to the drawdown in each well, representing limitations for uneconomic withdrawals and added environmental protection; this was formulated as follows:

\[
r_j \leq d_j \quad j = 1,2,3, \ldots, N_w
\]  

where \( r_j \) is the value of drawdown in well \( j \) resulting from the pumping rate from the well \( j \), and \( d_j \) is the allowable drawdown in the same well \( j \).

Third constraint: this was related to the quantity of water required to meet the water demand from each well in the study area, formulated as follows:

\[
\sum_{j=1}^{N_w} Q_j \geq Q_D
\]  

where \( Q_D \) is the total water demand.

3.4. Discretisation of the optimisation model

If either of constraints (head bound or water demand) were not satisfied at any location, a penalty, \( P \), proportional to the amount of violation, was calculated as in Equations (2b) and (2c), respectively, and the sum of all penalties was deducted from the objective function. The implementation of this penalty approach was achieved by multiplying the penalty terms with a weighting factor, \( \lambda \), which acted as a penalty coefficient to control the magnitude and unit of each penalty before this was deducted from the objective function. Such a penalty coefficient should be initially assigned a sufficiently large value so that the sum of penalties at all constraint points is less than the objective function value before any penalty is added; however, the penalty coefficient may be subsequently adjusted to speed up the
convergence of the optimisation solution, as the choice of penalty coefficient can significantly affect the performance of the optimisation model.

Where penalty coefficients are not set large enough, the final optimised well rates may end up being zero as the resulting objective function value is optimal despite none of the specified constraints being satisfied. However, if they are set too large, the optimisation model may become less efficient as the objective function becomes dominated by the penalty and is no longer sensitive to the parameters to be optimised. The choice of penalty coefficients must be done empirically, and generally, sufficiently large values should be set initially to ensure that the sum of penalties is less than the anticipated objective function value without any penalty, to avoid the problem of zeros arising for all optimised parameters, as discussed above. However, such penalty coefficients may require subsequent fine-tuning to speed up the convergence of the optimization solution.

Multi-objective optimisation theory develops an optimisation method by applying multiple objectives and solving for these simultaneously. This means that, unlike for the single objective function, there may not be one optimal solution for all objectives in a multi-objective problem. Most commonly, a group of optimum solutions which are preferable to other solutions within the set of feasible solutions emerges; however, no solution in this smaller group will be better than others in more than one aspect. This solutions group is known as the Pareto optimum solution group [35], and many different approaches can be used to produce such a group in a multi-objective function optimisation problem, such as the constraint method, weighting objectives, and target programming. The main concept underlying all these methods is the conversion of the optimisation problem from multi-objective to a single-objective function based on merging the multi-objective functions into a single objective function or by changing objectives in original formulation into constraints.

3.5. Pareto optimality

The optimised Pareto Rating suggested by [36] is an arrangement-based fitness mapping technique that considers each of the various optimisation objectives. To offer an example of this technique, a population of 20 ranked solutions, based on the costs of pumping with the pumping rate set to an average value, is illustrated in Figure 5. The labelling on the x-axis indicates the population group, while the labelling on the y-axis symbolises the rank number. All individual items within the population are compared, with non-controlling items specified and set at Rank 1, which is represents the optimum Pareto group of this population. Such items are separated from the 1st rank, and the remaining items are compared to choose a new non-controlling group, set to the 2nd rank. This procedure is repeated until the population is fully ordered, and a fitness function value is assigned to each item based on rank, per Eq. 7:
\[ fit(i) = \frac{1}{\text{rank}_i} \]  

(7)

where \( fit(i) \): fitness of individual item \( i \) and \( \text{rank}_i \): rank number of item \( i \).

This fitness ranking is then used to split the population into sub-populations as shown in Figure 5. In these types of optimisation problems (multi-objective functions), sharing fitness is beneficial in terms of stabilising the multiple sub-groups that grow alongside the Pareto optimal range and to prevent unnecessary contest between distant populations.

In this paper, the pumping rate, which represents one of the two objective functions, was also divided into different periods such that each solution was also assigned a time interval, thus creating sub-categories of solutions. The function of fitness sharing for solution \( i \) is considered to be the fitness function divided by the number of solutions belonging to its group:

\[ \text{shared fit} \,(i) = \frac{fit(i)}{\text{num}(i)} \]  

(8)

where \( i \) represents any solution in the population, \( \text{shared fit} \,(i) \) represents the function of shared fitness among solutions in that population, and \( \text{num}(i) \) is the solution number within the group to which individual \( i \) belongs. The function of shared fitness of any solution thus displaces its fitness function as a selection criterion.

**Figure 5:** Pareto optimality ranking and shared classes of population individuals.
4. Results and discussion

To determine steady-state calibration, the recharge and hydraulic conductivity for aquifers were required. The calibration process of steady condition was thus done based on 43 wells and the two variables required. GMS has a Parameter Estimation Tools (PEST) function which represents the inverse simulation, and this was used for calibration in this research [37]. Figure 6 shows the scatter diagrams with best fit lines for observed and computed piezometric heads for steady-state and transient simulations in January 2013. The groundwater simulation model matches the field piezometric water level head sufficiently, with $R^2 = 0.9747$ and $R^2 = 0.7818$ for steady-state and transient simulations, respectively. The transient simulation model for the Dammam confined aquifer included ten intervals, from March 2012 to January 2013, discretised over 11 stress periods.

![Computed vs. Observed Values](image)

**Figure 6:** Scatter plot of computed piezometric head versus observed values A) steady-state and B) transient simulation in January 2013.

Figure 7A shows the contour map of observed piezometric heads during 2012, while the results of model calibration are presented in Figure 7B. The components of the calibration target are also illustrated in Figure 7B. The centre of the target corresponds to the observed value, while the top of the target corresponds to the observed value plus the interval (allowable error) and the bottom corresponds to the observed value minus the interval. The length of the bar thus represents the possible error. Where the bar lies entirely within the target, the bar is drawn in green, and the allowable error is assigned as ±0.5m; the confidence in error estimation is thus 95%, showing that the conceptual model of the Dammam aquifer built has good validity and excellent accuracy. Based on the calibration model, the optimal hydraulic conductivity and recharge rate values were extracted, as shown in figure 8.
The resulting multi-objective optimisation model was applied to the Dammam confined aquifer within the study area in the Kerbala desert area of Iraq, with maximum pumping rate and minimum operation cost being the first and second objective functions in the formulation of the optimisation problem. Calculation of the expected future variations in both pumping operation cost and quantity of pumping rate were included. A compromise solution was thus generated, selected from a set of Pareto
optimal solutions designed to help DMs. This use of a set of Pareto solutions also allows DMs to make considered decisions based on awareness of the scope of alternatives by offering all solutions that are optimum from an “overall” viewpoint, while single-objective function solutions may eliminate this broader view.

In this study, the permissible drawdown at well j (d_j) was not permitted to exceed the 60 m depth from ground level of well j, to avoid the process of changing pumps due to a decline in efficiency based on increases in lifting depth. All pumping rates were also required to be in the range of 500 to 3000 m$^3$/day (i.e. $Q_i^{min} = 500$ and $Q_i^{max} = 3000$) to prevent aquifer dewatering. Several test runs were needed to select an appropriate value for use as the maximum pumping rate, as if this were set too high, the optimisation solution may be inefficient. Water demand ($Q_D$) was calculated by multiplying the served area for each well and the water duty of the suggested agriculture plant by the total number of wells.

With regard to groundwater management, the total cost generally consists of well installation costs (fixed costs) and pumping costs (operating costs). As the fixed cost function is discontinuous and all wells are drilled at the government’s expense, fixed costs are frequently neglected in the application of optimisation algorithms. Only operating costs were thus calculated, as based on the use of kerosene and oil and maintenance at current prices in the local market ($C_j = 0.072$ I. D/m$^3$/m lift), taking into account an expected increase in prices (1%) each year.

The following parameters were thus considered across the multi-objective model: number of generations = 200, population size = 200, crossover probability = 0.6 and uniform crossover with a mutation ratio = 0.05. The values of minimum space among the optimal Pareto solutions in a given generation and the corresponding ones in the previous generation divided by the number of optimal Pareto solutions in the current generation were used to create an index of convergence for each generation. These values can thus be pursued depending on the variables in the index of convergence against the number of generations, as displayed in Figure 9. The optimisation model was set to terminate when either value in a generation attained its maximum number or where the index of convergence was equal to or less than a selected value (0.001).
Applying the multi-objective optimization model represented by Eq. 2 and 3 along with the corresponding formulation constraints shown in Eqs. 4 to 6, the model was run for six periods (2018, 2023, 2028, 2043, 2053, and 2063) to produce maps of piezometric groundwater levels and heads and to predict the optimal values for pumping rates corresponding with minimum operation costs.

Figure 10 shows the predicted spatial distribution of piezometric head maps for the Dammam confined aquifer in the Kerbala desert area for the selected periods. From this figure, a cone of depressions around 3.0 km diameter appears in the study area (close to well no.8) at the end of the simulation period, while other portions of the study area show low impact at similar pumping rates. This may be attributed to the influence of aquifer thickness, which is significant, as well to impacts from geologic effects. This suggests weak potentiality of the area near well no.8 for heavy pumping activity. The optimum pumping rate ranged from 115,092 m$^3$/day to 89,323 m$^3$/day, with the corresponding drawdown range being 24.501 to 29.25 m.

The final Pareto optimum solution set is shown in Figure 11. Each point within this figure represents a potential optimum solution for the problem, with values for pumping rate and operation cost. To obtain a compromise solution from this group of Pareto optimal solutions, the method illustrated by [38] was used, with the optimal pumping rate decreased while the optimal pumping cost was increased for specific periods. The values of the compromise solutions are given in Table 1.

As Table 1 shows, when the values for optimal pumping rate decrease, the cost of optimal pumping increases during the relevant periods (including the assumption that costs increase by 5% in every five period). Furthermore, the optimal pumping rate decreases up to the year 2043, stabilising for the period from 2043 to 2063. This behaviour may reflect an increase in the local recharge of groundwater percolation from the surrounding Al-Dammam confined aquifer outside the studied area for the initial
15 years of modelling until a gradual normal equilibrium is obtained at the end of the modelling period (50 years). All optimum pumping rates (compromise solutions) for each well in this scenario were presented in Table 2. Well No.8 demonstrates the minimum pumping rate value during all periods, however, due to its location within an area with minimum recharge and very low hydraulic conductivity, as shown in figure 8.

**Table (1):** Compromise solutions for optimal pumping rate and optimal pumping cost.

| year | No. of Wells (43) | Optimal pumping rate (m³/day) | Optimal pumping cost (I.D) |
|------|-------------------|------------------------------|---------------------------|
| 2018 | 43                | 115092                       | 12842869                  |
| 2023 | 43                | 95987                        | 12156331                  |
| 2028 | 43                | 91950                        | 12669964                  |
| 2043 | 43                | 89772                        | 14938161                  |
| 2053 | 43                | 89426                        | 16076750                  |
| 2063 | 43                | 89323                        | 17221630                  |
Figure (10): Predicted head distribution map for the Dammam confined aquifer study area for (a) 2018, (b) 2023, (c) 2028, (d) 2043, (e) 2053, and (f) 2063.
Figure (11): Final Pareto optimal solutions and compromise solution for (a) 2018, (b) 2023, (c) 2028, (d) 2043, (e) 2053, and (f) 2063.
Table 2: Optimum pumping rate of wells (m$^3$/day) obtained from the multi-objective function model.

| Well No. | 5 year | 10 year | 15 year | 30 year | 40 year | 50 year |
|----------|--------|---------|---------|---------|---------|---------|
| 1.       | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 2.       | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 3.       | 2898.236 | 2223.759 | 2081.730 | 2000.650 | 1994.164 | 1991.211 |
| 4.       | 2856.326 | 2191.602 | 2051.555 | 1971.719 | 1965.328 | 1962.417 |
| 5.       | 2795.236 | 2144.729 | 2008.570 | 1929.549 | 1923.294 | 1920.446 |
| 6.       | 1789.54 | 1373.078 | 1283.469 | 1235.318 | 1231.313 | 1229.490 |
| 7.       | 1334.56 | 1023.981 | 955.883  | 921.246  | 918.259  | 916.899  |
| 8.       | 754.88  | 579.204  | 541.514  | 521.093  | 519.404  | 518.635  |
| 9.       | 2985.236 | 2290.512 | 2145.370 | 2060.706 | 2054.026 | 2050.984 |
| 10.      | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 11.      | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 12.      | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 13.      | 2850   | 2850    | 2850    | 2850    | 2850    | 2850    |
| 14.      | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 15.      | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| Well No. | 5 year | 10 year | 15 year | 30 year | 40 year | 50 year |
|---------|--------|---------|---------|---------|---------|---------|
| 16.     | 3000   | 3000    | 3000    | 3000    | 3000    | 3000    |
| 17.     | 2852.253 | 2188.477 | 2048.622 | 1975.582 | 1962.024 | 1959.619 |
| 18.     | 2758.254 | 2116.353 | 1981.943 | 1910.475 | 1897.364 | 1895.038 |
| 19.     | 2925.263 | 2244.496 | 2101.189 | 2026.152 | 2012.247 | 2009.780 |
| 20.     | 2958.263 | 2269.816 | 2124.949 | 2049.009 | 2034.947 | 2032.452 |
| 21.     | 2653.253 | 2035.788 | 1905.342 | 1837.747 | 1825.135 | 1822.898 |
| 22.     | 2152.5357 | 1651.381 | 1544.622 | 1490.735 | 1480.504 | 1478.689 |

| Well No. | 5 year | 10 year | 15 year | 30 year | 40 year | 50 year |
|---------|--------|---------|---------|---------|---------|---------|
| 23.     | 2658.26 | 2039.630 | 1908.947 | 1841.215 | 1828.579 | 1826.338 |
| 24.     | 2543.289 | 1951.415 | 1828.168 | 1761.581 | 1749.492 | 1747.348 |
| 25.     | 2800.256 | 2148.580 | 2011.184 | 1939.567 | 1926.256 | 1923.895 |
| 26.     | 1485.236 | 1139.592 | 1064.370 | 1028.733 | 1021.673 | 1020.420 |
| 27.     | 2930.256 | 2248.327 | 2105.784 | 2029.610 | 2015.681 | 2013.210 |
| 28.     | 2995.856 | 2298.660 | 2152.016 | 2075.047 | 2060.807 | 2058.280 |
| 29.     | 2952.256 | 2265.207 | 2120.624 | 2044.848 | 2030.815 | 2028.325 |
| 30.     | 2856.256 | 2191.548 | 2027.654 | 1978.355 | 1964.778 | 1962.369 |
| 31.     | 1958.263 | 1503.121 | 1391.343 | 1356.208 | 1347.482 | 1345.580 |
|  | 1985.256 | 1523.247 | 1408.456 | 1375.066 | 1365.629 | 1363.955 |
|---|---|---|---|---|---|---|
| 33. | 2562.236 | 1965.952 | 1820.312 | 1774.705 | 1762.526 | 1760.365 |
| 34. | 2752.263 | 2111.756 | 1954.611 | 1906.325 | 1893.243 | 1890.922 |
| 35. | 2895.365 | 2221.556 | 2061.500 | 2005.443 | 1991.680 | 1989.239 |
| 36. | 2985.658 | 2290.836 | 2121.789 | 2067.984 | 2053.792 | 2051.274 |
| 37. | 2856.253 | 2191.546 | 2033.752 | 1978.353 | 1964.776 | 1962.367 |
| 38. | 2879.36 | 2209.275 | 2050.104 | 1994.357 | 1980.671 | 1978.243 |
| 39. | 2452.263 | 1881.572 | 1746.081 | 1698.533 | 1686.877 | 1684.809 |
| 40. | 2981.2563 | 2295.166 | 2122.664 | 2064.935 | 2050.764 | 2048.250 |
| 41. | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 |
| 42. | 3000 | 3000 | 3000 | 3000 | 3000 | 3000 |
| 43. | 2998.258 | 2326.509 | 2395.606 | 2070.864 | 2062.902 | 2029.099 |

5. **Conclusions**

A multi-objective optimisation model was applied to the Dammam confined aquifer in Kerbala, Iraq with the aim of improving two objective functions: maximum rate of pumping and minimum cost of operations. The prediction of the expected future changes to both objectives was considered (pumping rate and pumping operation cost).

A compromise solution was developed, based on the resulting set of Pareto optimal solutions, to help decision-makers. The MODFLOW model under GMS 10.1.4 was used as a simulation tool to model the groundwater aquifer system in the Kerbala desert area, and the performance of the groundwater model was evaluated under both steady and transient conditions. The results of calibration for both steady and transient models were highly constrained between the field measured and computed.
piezometric heads of the aquifers. Parameter estimation tools (PEST) were used to determine the final calibrated model, and the groundwater simulation model matched the field-observed piezometric water level head effectively, with $R^2=0.9747$ and $R^2=0.7818$ for steady-state and transient simulations, respectively. The transient simulation model for the Dammam confined aquifer was then applied over ten intervals from March 2012 to January 2013, discretised into 11 stress periods. One cone of depressions appeared in the study area (near well no.8, with a diameter of about 3.0 km), which was noted when applying the compromise solution for optimum pumping rates at the end of the simulation time. To increase the overall pumping rates in the modelled area, a reduction in the withdrawal from the wells adjacent to this (especially no.8) or a complete cessation of such flow, is thus required, as this reflects that this well violates the drawdown constraints.

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