International Journal of Water Resources and Environmental Engineering Vol. 3(7), pp. 139-149, August 2011
Available online at http://www.academicjournals.org/ijwree
ISSN 1991-637X ©2011 Academic Journals

Full Length Research Paper

A multi-objective optimization approach to groundwater management using genetic algorithm

T. A. Saafan[1], S. H. Moharram[1], M. I. Gad[2] and S. KhalafAllah[1]*

[1]Department of Irrigation and Hydraulics, Faculty of Engineering, Mansoura University, Egypt.
[2]Hydrology Division, Desert Research Center, Cairo, Egypt.

Accepted 11 July, 2011

Management of groundwater resources is very important for regions where freshwater supply is naturally limited. Long-term planning of groundwater usage requires method-based new decision support tools. These tools must be able to predict the change in the groundwater storage with sufficient accuracy, and must allow exploring management scenarios with respect to different criteria such as sustainability and cost. So, a multi-objective optimization algorithm is used for groundwater management problem. In this paper, a genetic algorithm with two additional techniques, Pareto optimality ranking and fitness sharing, is applied to simultaneously maximize the pumping rate and minimize pumping cost. The methodology proposed has more Pareto optimal solutions. However, it is desirable to get, and to find the ones scattered uniformly over the Pareto frontier in order to provide a variety of compromise solutions to help the decision maker. A groundwater resources management model in which performed through a combined simulation-optimization model is used. This multi-objective genetic algorithm (MOGA) of optimization combines the modular three-dimensional finite-difference (MODFLOW) and genetic algorithm (GA). MOGA model is applied in El-Farafra oasis, Egypt to develop the maximum pumping rate and minimum operation cost as well as the prediction of the future changes in both pumping rate and pumping operation cost. It also makes a feasible solution in groundwater management. Finally, a compromise solution is presented from a set of Pareto optimal solutions.

Key words: Groundwater management, multi-objective optimization, genetic algorithm, Farafra oasis, Egypt.

INTRODUCTION

Multi-objective optimization problems are mostly different from single-objective optimization problems. In the single-objective case, one attempts to obtain the best solution, which is absolutely superior to all other alternatives. While in the case of multiple objectives, it may not be necessary to obtain a best solution with respect to all objectives because of the conflict among multiple objectives. A solution may be the best in one objective but the worst in other objectives. There usually exist a set of solutions for the multiple-objective case which cannot simply be compared with each other. For such solutions called Pareto optimal solutions, no improvement in any objective function is possible without sacrificing at least one of the other objective functions (Cheng and Gen, 1998).

Compromise solution-based fitness assignment has been proposed by Cheng and Gen (1998) as a mean to obtain a compromised solution instead of generating all Pareto optimal solutions. For many problems, a set of Pareto solutions may be very large. Having to evaluate a large set of Pareto solutions in order to select the best one poses a considerable cognitive burden on the decision maker. Groundwater simulation and optimization techniques have been used together to explore management options. Depending on the particular problem under consideration and the assumptions made in solving it, the optimization problem may be deterministic, stochastic, or a combination of both. Shafike et al. (1992) used quadratic programming to study pumping costs with drawdown, when drawdown magnitude exceeds a small fraction of the saturated thickness. Hsiao and Chang (2002) presented optimization

*Corresponding author. E-mail: samykhalaf2005@yahoo.com.

required in a broad range of design problems for fixed costs of installing new wells which may be a relevant component of cost functions in groundwater planning strategies. Hsu and Yeh (1989) studied monitoring network design and several groundwater remediation design projects giving rise to combinatorial problems in which decision variables included location of wells and pumping rates. Ahlfeld and Heidari (1994) studied hydrogeological complex sites in which conditions were obscured an obvious intuitive design. Park and Aral (2003) presented a multi-objective optimization approach to determine pumping rates and well locations to prevent saltwater intrusion, while satisfying desired extraction rates in coastal aquifers. This approach was an iterative sub-domain method, in which the proposed algorithms searched for the optimal solution by disturb the well locations and pumping rates simultaneously. Frind (1982) and Cheng et al. (2000) studied two important objectives that were associated with the management of groundwater extraction in coastal aquifers. Ritzel et al. (1994) applied two variations of the genetic algorithm (GA), a Pareto GA and a vector-evaluated genetic algorithm (VEGA), for a multi-objective, groundwater pollution containment problem. The multi-objective problem was formulated to minimize the containment design cost while maximizing the design's reliability. The Pareto GA based on a ranking scheme that ordered the population according to each containment design's degree of domination. The VEGA searched for multiple solutions for multi-objective problems simultaneously by selecting a fraction of the next population, based on the associated values of each objective function. Richardson et al. (1989) considered the VEGA as a multi-objective optimization method and reported that VEGA tended to favor the extreme of the objective functions, such that only the endpoints of the tradeoff curve were found. Ritzel et al. (1994) also concluded that the Pareto GA was superior to the VEGA in finding the largest portion of the Pareto optimal solutions. Cieniawski et al. (1995) investigated the performance of four GA formulations in solving a multi-objective groundwater monitoring problem where they simultaneously maximized reliability of a monitoring system and minimized the contaminant plume size at time of first detection. They implemented a weighted GA, VEGA, Pareto GA and a VEGA/pareto GA combination and compared them to the results generated by simulated annealing. The VEGA and Pareto GA method was showed to be more computationally efficient and more successful at generating the greatest portion of the tradeoff curve than the other GA formulations. Goldberg (1987) recommended that a form of fitness sharing used to enhance the Pareto GA in this area, where crowding in the Pareto optimal solutions were alleviated by decreasing the fitness of crowded individuals. For multi-objective optimization methods, some modifications to simple GA had been made to produce multi-objective genetic algorithm (MOGA) (Fonseca and Fleming, 1993), VEGA (Schaffer, 1985), niched pareto genetic algorithm (NPGA) (Horn et al., 1994) and non-dominated sorting genetic algorithm (NSGA) (Srinivas and Deb, 1994). In this paper, the main objectives are to develop the MOGA with two additional techniques, pareto optimality ranking and fitness sharing, that simultaneously maximizes the pumping rate and minimizes pumping cost. A compromise solution from a set of Pareto optimal solutions is also achieved to help the decision maker for choosing the best groundwater management scenario for the unique source of fresh water in El-Farafra Oasis, Egypt.

Site description

El-Farafra oasis is a natural depression located in the hyper arid region of the Western Desert, Egypt. It lies between latitudes 26° 00" and 27° 30" N and longitudes 27° 20" and 29° 00" E, 510 km south the Mediterranean shoreline and at 240 km east of the Libyan borders (Figure. 1). It represents one of the morphotectonic depressions of the western desert. It is excavated in the eocene limestone plateau (400 masl). The plateau surface is covered in some parts by sand dunes (Ghard Abu-Mohariq). Dry wadies dissect the plateau surface and drain into the excavated depression. The eocene plateau is bounded by conspicuous escarpment which takes the shape of questa. In addition, the floor of the depression is excavated in the soft carbonate of chalk formation. It is characterized by desert climate with scarce precipitation (3 mm/year).

Geologically, the previous literatures (Hermina, 1990; Abdel-Atti, 2002; Ebraheem et al., 2002; Ali, 2004; Hamad, 2004; El Sabri and El Sheikh, 2009) concluded that the sedimentary succession is not fully penetrated by the recent deep wells. The sedimentary succession, from older to younger, includes the partially penetrated pre cenomanian rocks (188 m). Bahariya formation (lower Cenomanian) with a thickness of about 605 m composes of two sandstone rock units separated by a marker shale rock unit. hafuf formation (campanian- turonian) reaches 18 m thick. It is composed of dolostones, alternating with arenaceous and argillaceous beds. Khoman chalk formation reaches 220 m while the El-Farafra chalk formation reaches 220 m (Maestrichtian Rocks). Dakhla formation (Maestrichtian-Danian) covers the floor of Abu Monqar depression with thickness of 185 m. Tarawan chalk formation forms the low dissected plateau between north Abu Monqar scarps and south El-Quss Abu Said plateau with thickness of about 5.5 m in Gabal Gunna North (Upper Paleocene). Esna shale formation with maximum thickness of 123 m was recorded in El Quss Abu said section (late paleocene-early eocene). Thebes formation (lower eocene limestone) is of thickness 145 m. Radwan formation (Oligocene Rocks) unconformably overlies Bahariya formation. Naqb formation (early middle

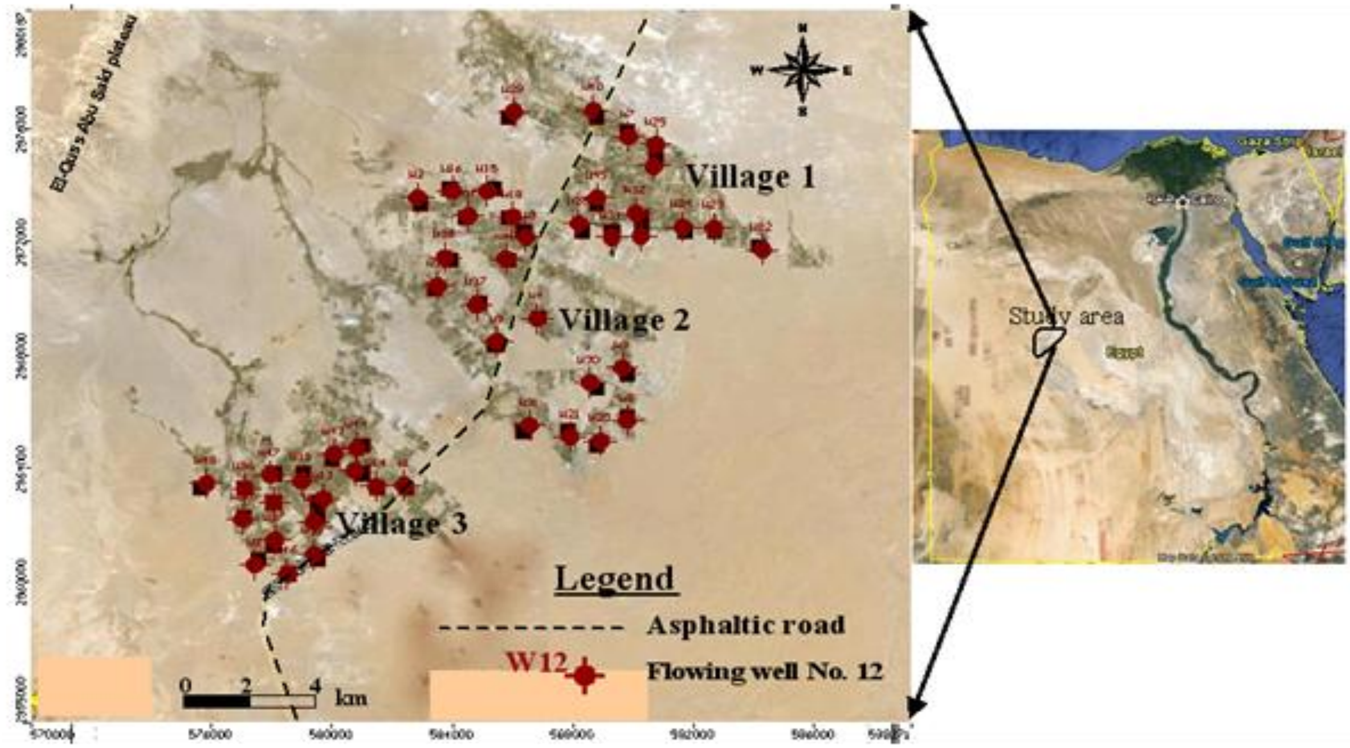

Figure 1. Location map of the study area showing the location of 48 flowing wells.

miocene) unconformably overlies the paleocene tarawan chalk. Monqar el talh formation (post-miocene) unconformably covers Bahariya formation of lower cenomanian age with a thickness of about 158 m. The quaternary deposits are represented by eolian sands, playa, sabkhas and salt deposits.

Hydrogeologically, the present aquifers are considered a part of the well known Nubian sandstone aquifer system. Their large areal extent across the western desert implies serious consideration towards optimizing the utilizations of these most vital natural water resources especially where extreme aridity prevails. Abdel-Atti (2002) and Hamad (2004) differentiate the water-bearing complexes in El-Farafra depression into two distinctive aquifers. The fractured chalky limestone shallow aquifer (171 m) with secondary hydraulic conductivity due to the interconnection between the fractures and faults is underlain by the deep Nubian sandstone aquifer. The deep aquifer is classified into three productive zones. The first productive zone is of thickness 139 m and the second productive zone, acting as the main groundwater resource, is of average thickness of 402 m. The third productive zone is consisting of two distinctive intervals, the low productive interval (145 m) and the productive one (249 m). The bottom level of the Nubian aquifer varies from 1700 m to about 2300 m (Thorweihe, 1990). The number of wells tapping this aquifer increased from 18 wells in 1960s to about 140 wells in the present time. Hence, the pumping from the aquifer was increased in the last decade to reach about 145 million m^3/year. This figure is expected to increase in the near future due to continuous increment in drilling of wells. The transmissivity of the three productive zones recorded 148.6, 1613 and 1642 m^2 per day respectively while the average permeability reached 1.3, 5.7 and 7 m/day respectively. The groundwater flow direction is from South East (SE) to North West (NW) (Figure 2). The equipotential lines reflect the extensive exploitation of groundwater in the northern areas. Southern parts showed small drawdown indicated by regular contour lines. The direction of head decline is from 136 masl at Abu Minqar area to about 88 masl at north Qasr El Farafra area (Moharram et al., 2011).

MATERIALS AND METHODS

The materials used in this paper were collected through carrying out two field trips in El-Farafra depression during the period 2009 to 2010. The two field trips were achieved with the team work of the desert research center. The basic hydrologic data of the present flowing wells were obtained from the groundwater sector, water resources research institute (WRRI) during these field trips. These materials include collection of archival data (well drilling reports, registration of discharge, distribution of wells, proposed operating systems for both groundwater supply and reclaimed area beside recording depth to water for groundwater level changes) were gathered from both groundwater sector- WRRI and GARBAD, 2005.

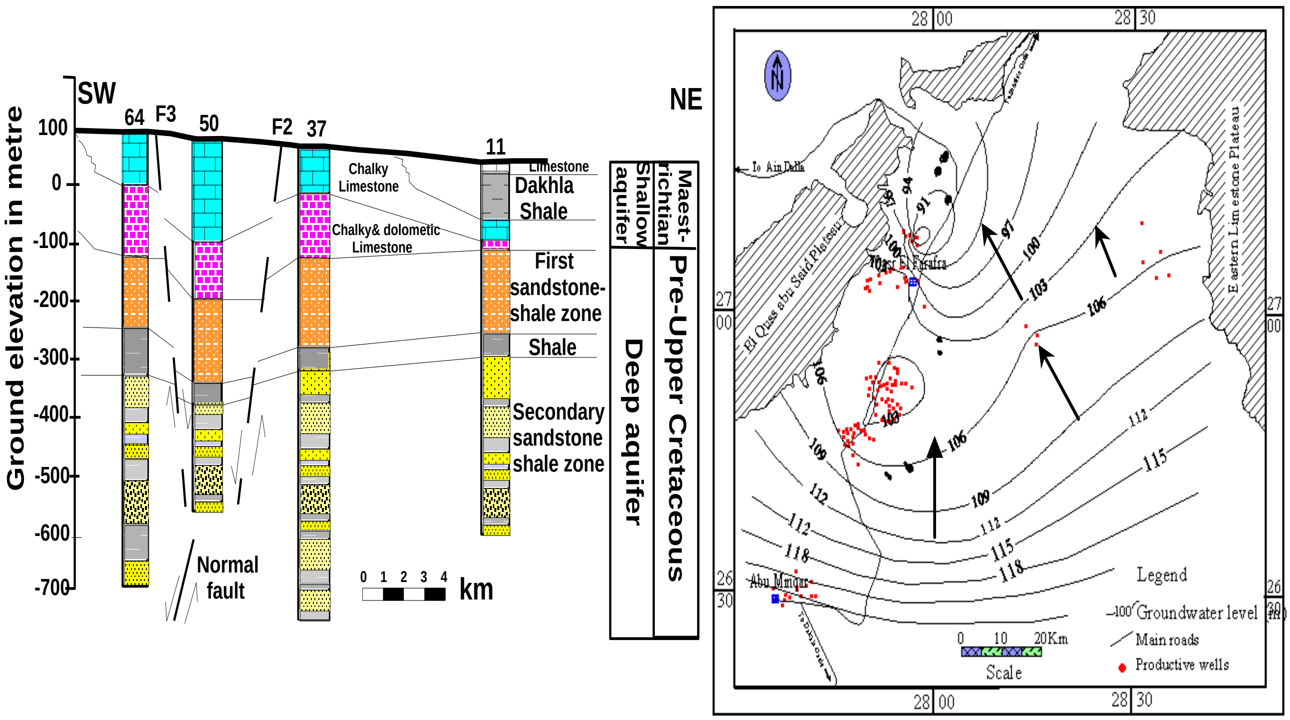

Figure 2. Hydrogeologic cross-section in El-Farafra depression (after Hama, 2004-left graph) and Piezometric head contour map of the Nubian Sandstone aquifer at April 2008 (after El Sabri and El Sheikh, 2009-right map).

In addition, the results of the groundwater flow simulation of El-Farafra depression applying MODFLOW software (Moharram, 2011) were used in this paper. Moreover, the results of the combination between MODFLOW and optimization techniques -optimization procedure of the simulation-optimization (S/O) model- applied by Moharram et al. (2011) were also used as input data for the multi-objective optimization approach in this work.The methodological approach used in this paper is based on the multi-objective optimization with genetic algorithm techniques applying MOGA software. In this technique, two objectives are considered as follows:

(1) First objective, minimization of operation cost (Z_1): The cost objective demands for wells are operated in such a manner as to minimize the total cost. This essentially requires the identification for locations of wells as determination of their pumping rates, which, are satisfying operated the required water demand with the least possible cost. This objective is formulated as:

$$\text{Min} \quad Z_1 = \sum_{j=1}^{N_w} C_j \; r_j \; Q_j \qquad (1)$$

Where, N_w is the number of potential pumping wells, C_j is the daily cost of pumping and transportation in monetary units, per unit volume per unit lift for location j, Q_j is the pumping rate in cell j ($j = 1,\ldots,N_w$) ; r_j is the pumping lift given by ($H-h_j$); H is height of ground surface and h_j is the head in pumping well j.

(2) Second objective, maximization of total pumping rates (Z_2): The studied area is characterized by inadequate water supply for both domestic and irrigation requirements. Then any surplus water from the domestic demand can be used for irrigation. Therefore, this objective seeks to maximize the amount of water which can sustainable be extracted from the groundwater aquifer. The objective function can be written as:

$$\text{Max} \quad Z_2 = \sum_{j=1}^{N_w} Q_j \qquad (2)$$

Equations (1) and (2) are subject to three constraints: pumping constraint, drawdown constraint and water demand constraint.

(a) Pumping constraint (Q_j): The pumping rates at potential pumping wells in the water demand are constrained for values between some minimum (Q_j^{min}) and maximum (Q_j^{max}). The permissible pumping rates are formed as follows:

$$Q_j^{min} \le Q_j \le Q_j^{max} \quad j = 1,\ldots\ldots,N_w \qquad (3)$$

For the GA simulation, this constraint can be easily satisfied by restricting the population space of the design variables within the above limits. Hence no special treatment is needed for this constraint.

(b) Drawdown constraint (r_j): This constraint normally means to protect the ecosystem by avoiding excessive drawdown. In this work, the drawdown constraints are formulated to avoid mining and formulated as follows:

$$\sum_{j=1}^{N_w} r_j \le d_i \qquad (4)$$

Where r_j is the drawdown at control point i caused by a pumping rate from pumping well j, d_i is the permissible drawdown at control point i.

(c) Water demand constraint (Q_D): The Nubia Sandstone aquifer is considered the sole source of water. Therefore, the designed optimal pumping strategy must supply at least the minimum water demand. It is formulated as follows:

$$\sum_{j=1}^{N_w} Q_j \geq Q_D \qquad (5)$$

Where Q_D is water demand.

Discritization of optimization model

Multi-objective optimization extends optimization theory by permitting multiple objectives to be optimized simultaneously. In contrast with single objective optimization problems, there may not exist a single solution that is optimal with respect to all objectives of the multi-objective optimization problem. Instead, there is a set of solutions that is superior to the rest of the solutions in the search space considering all objectives, and no solution in this set is absolutely better than the other solutions. This set is called the Pareto optimal set (Liu and Hammad, 1997). Several methods for generating the Pareto optimal set of a multi-objective optimization problem have been proposed, such as weighting objectives, constraint approach, and goal programming, (Konak et al., 2006). The basis of these methods is the transformation of the multi-objective optimization problem into a single-objective optimization problem by combining multi-objective into a single objective or transforming some objectives into constraints.

The flowchart illustrating the MOGA implemented in the present study is shown in Figure 3. Three modules numbered in this figure are the main processes. These are: (1) production of the initial generation and establishment of an initial Pareto optimal set, (2) application of MOGA techniques of Pareto optimality ranking and fitness sharing, and (3) reproduction by selection, crossover, and mutation operators and revision of the pareto optimal set. For each generation, MOGA firstly determines the fitness function of each population individual of the previous generation and then generates strings by selecting two parents on the basis of their fitness and reproducing them by crossover and mutation until the whole population is recreated. Finally, MOGA decoded and evaluates the strings of this new generation and revises the pareto optimal set of the previous generation. This procedure is repeated many times until one of the following termination criteria is satisfied: (1) the maximum generation number is reached or (2) the convergence index is sufficiently small. Termination criterion (1) is necessary to prevent a run with excessively long time. Termination criterion (2) is an important criterion to check the convergence of the optimization procedure, as will be shown in the numerical example of the next section. In the numerical examples, the convergence of the preceding procedure was checked for several cases with different parametric values using a suggested convergence index.

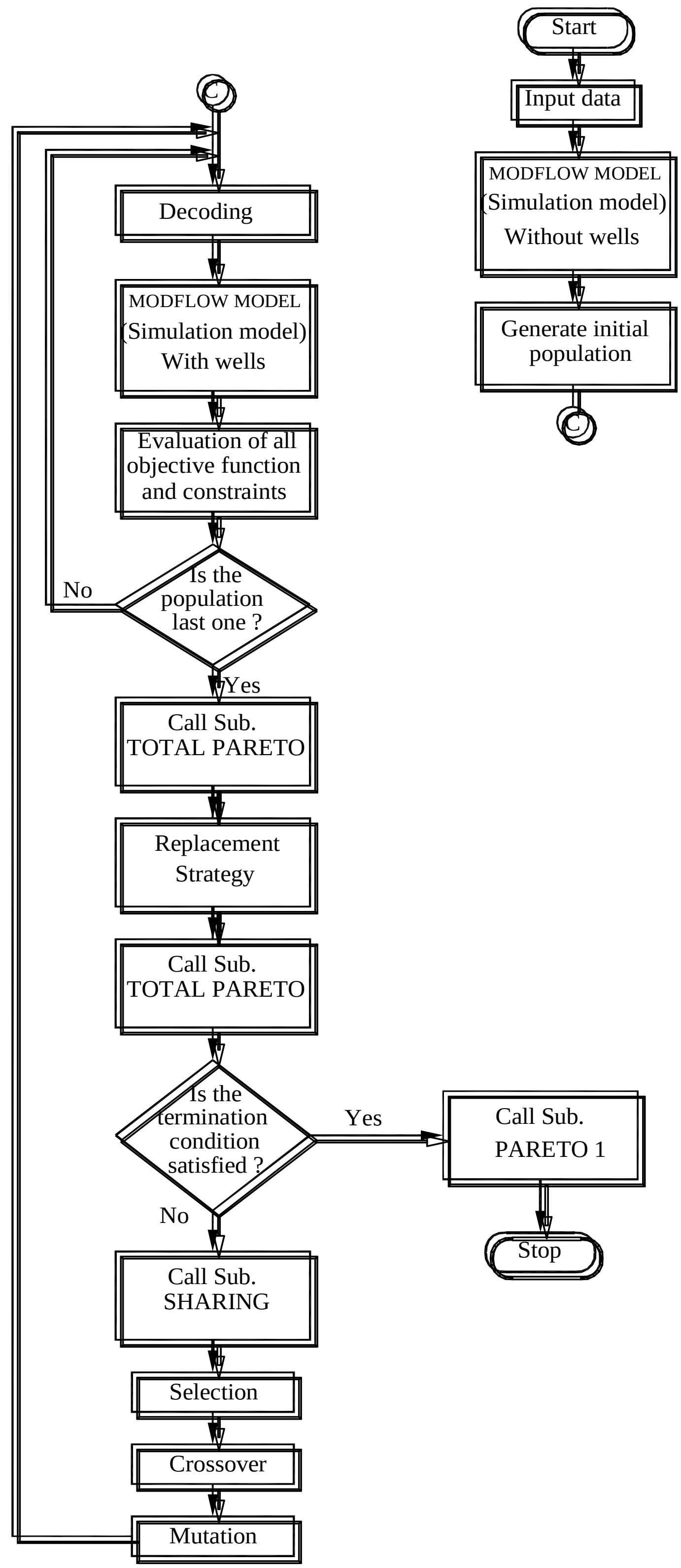

Figure 3. Flowchart describing the MOGA model.

Pareto optimality ranking and fitness sharing

Pareto optimality ranking suggested by Goldberg (1989) is rank based fitness assignment method that takes into consideration each of the different optimization objectives. To illustrate this method, an example of a ranked population of 20 solutions, plotted according to pumping cost versus average pumping rate, is shown in Figure 4. The superscripts of these individuals are the rank number, and their subscripts represent indicates. All individuals in the current population are compared, and the non-dominated individuals are identified and assigned a rank of 1, which is also the

Pareto optimal set of this population. Then, these individuals of rank 1 are set apart, and the remaining individuals are compared to select a new non-dominated set with a rank of 2. This process continues until the entire population is ranked. The fitness function value of each individual is assigned according to its rank, as shown in Equation 6:

$$fit(i) = \frac{1}{rank(i)} \quad (6)$$

Where, fit (i) and rank (i) are the fitness function and the rank number of individual number of individual i, respectively.

In addition, the fitness sharing is used to divide the population into subpopulations of similar individuals as shown in Figure 4. In a multi-objective optimization problem, fitness sharing is useful in stabilizing the multiple subpopulations that arise along with the Pareto optimal set and preventing excessive competition among distant population members. In this study the pumping rate, one of the two objective functions, is divided into several intervals. Each solution is assigned to an interval, thus forming subpopulations classes of solutions. The sharing fitness function of a solution *i* is taken as its fitness function divided by the number of solutions belonging to its class, that is;

$$shared\ fit(i) = \frac{fit(i)}{num(i)} \quad (7)$$

Where, shared fit (i) is the shared fitness function of solution i, and num (i) is the number of solutions in the class to which individual i belongs. The shared fitness function of each solution replaces its fitness function as the selection criterion.

Selection, crossover, and mutation

The fitness proportionate selection is adopted as the selection method by Goldberg (1989). For this method, the pumping rate solutions with shared fitness function values that are equal to or greater than the average shared fitness function in the population will survive and be selected to generate the new population individuals of the next generation, while the pumping rate solutions with smaller values will be eliminated in the selection procedure. As shown in Figure 5, crossover is introduced within every substring corresponding to one point, and the number of the crossover variables is the same as the number of points. The multipoint crossover affects every bridge with the same probability and accelerates the optimization process. Similarly, the bitwise complement mutation operator changes one binary value to the opposite within every substring such as 0 to 1 or 1 to 0. The details of multipoint crossover and multipoint mutation can be found in Liu et al. (1996).

Multi-objective genetic algorithm (MOGA) model

MODFLOW FORTRAN code is used as the simulation of groundwater flow which is linked with genetic algorithm optimization. Figure 3 shows the flowchart for simulation-optimization model where FORTRAN program is used to link between the simulation code and genetic algorithm. To obtain the compromise solution of multi-objective optimization in this paper, the technique based on a theorem proposed by Grierson (2008) is used. This is from a set of Pareto optimal solutions for which the competing criteria/objectives are mutually satisfied in a Pareto optimal sense. This technique is called Multi-Criteria Decision Making (MCDM) strategy. The theorem is called Pareto-Edgeworth-Grierson (PEG). The mathematical formulations used to determine the compromise solution among a set of Pareto–optimal solutions, are programmed in a code by El-Beltagy et al. (2010).

RESULTS AND DISCUSSION

The parameters of GA used as inputs to the applied MOGA model in this study are population size (200); number of generations (200); crossover ratio (0.6); mutation ratio (0.05); and uniform crossover. Convergence index for any generation equals the minimum distance between the current pareto optimal solutions and the corresponding ones at the previous generation dividing by number of current Pareto optimal solutions. The resulted convergence of the optimization process after checking according to the change in a convergence index with the number of generations is shown in Figure 6. The code terminates as stated before either the number of generation reaches to its maximum value or the convergence index is less than or equal 0.001.

By applying the objective functions, equation 1 and 2 and corresponding constraints, equation 3 to 5, MOGA model was run for the chosen time steps (the years 2015, 2020, 2025, 2030, 2035, 2040, 2050 and 2060) to predict the head maps and to estimate the optimal pumping rate with minimum operation pumping cost. The predicted head maps of the Nubian Sandstone aquifer in El-Farafra oasis for specific periods are shown in Figure 7. It is noticed that, from these figures, two cones of depression will appear in the cultivated areas in the model domain in the end of the simulation time with approximate diameter of 1.5 and 3 km respectively under the current pumping rates. This may attribute to the presence of relatively high sand-clay ratio in the aquifer lithology with low groundwater recharge rate characterizing to these aquifer localities. Otherwise, the middle part of the model domain does not affect with this phenomenon due to the effect of the great aquifer thickness and the presence of thin clay layers rather than the geologic structure impact. The resulted optimal pumping rate and the corresponding drawdown range from 190699.34 m^3/day to 179423.32 m^3/day and 6.133 to 8.344 m respectively.

Figure 8 presents results of the final Pareto optimal solutions. Each point in the figure represents a possible solution for the problem, which contains pumping rate versus operation pumping cost. To determine the compromise solution among the set of Pareto optimal solutions shown in this figure, the code given by El-Beltagy et al. (2010) is again used. The values of the compromise solutions are presented in Table 1.

From Table 1, it is noticed that, as the optimal pumping rate decreases the optimal pumping cost increases at specific periods (the cost assumption is increased with

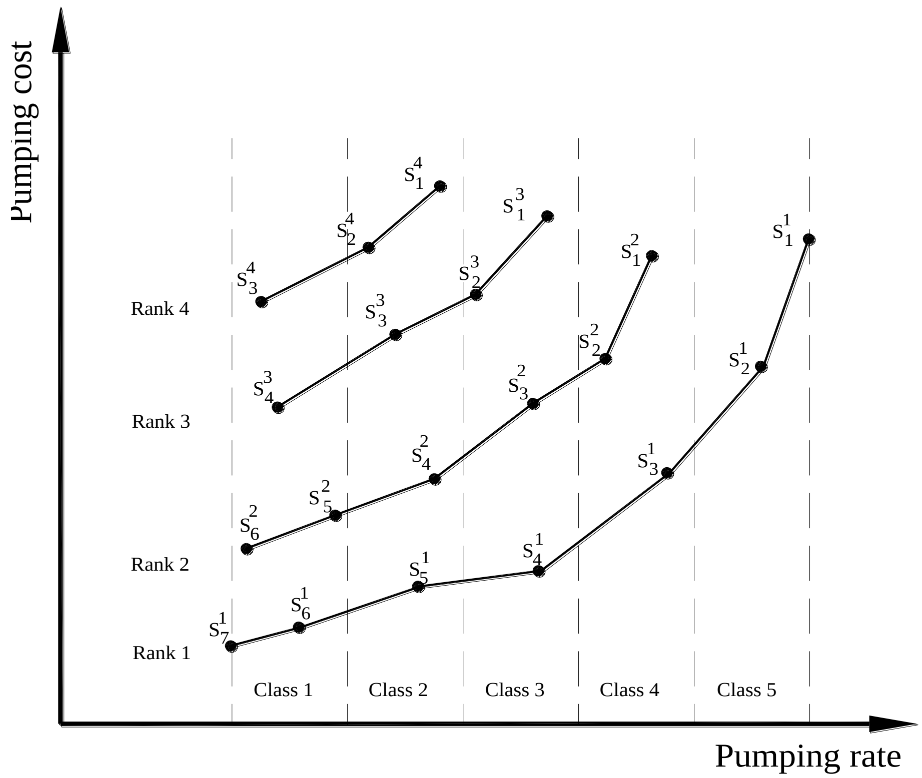

Figure 4. Pareto optimality ranking and shared classes of population individuals.

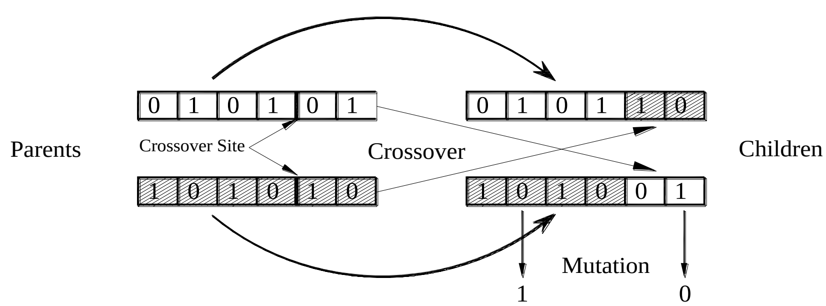

Figure 5. Crossover and mutation operators.

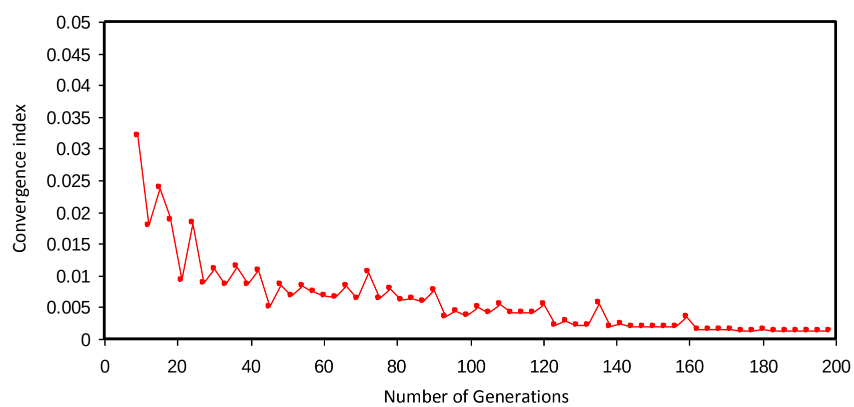

Figure 6. The resulted convergence of MOGA model with fitness sharing.

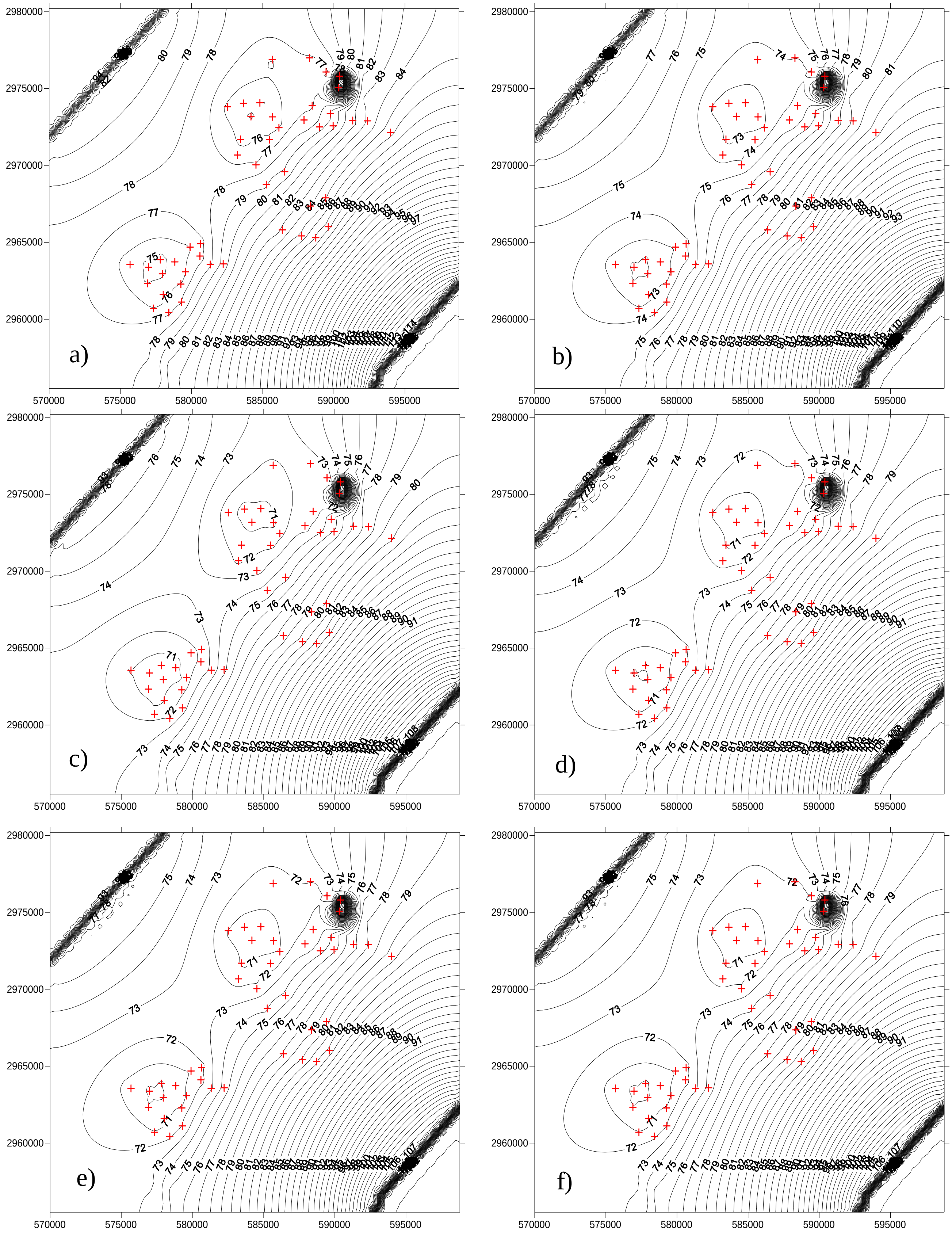

Figure 7. Predicted head distribution map of the Nubian Sandstone Aquifer in El-Farafra Oasis (a) at 2015, (b) at 2020, (c) at 2030, (d) at 2040, (e) at 2050, and (f) 2060 (after Moharram et al., 2011).

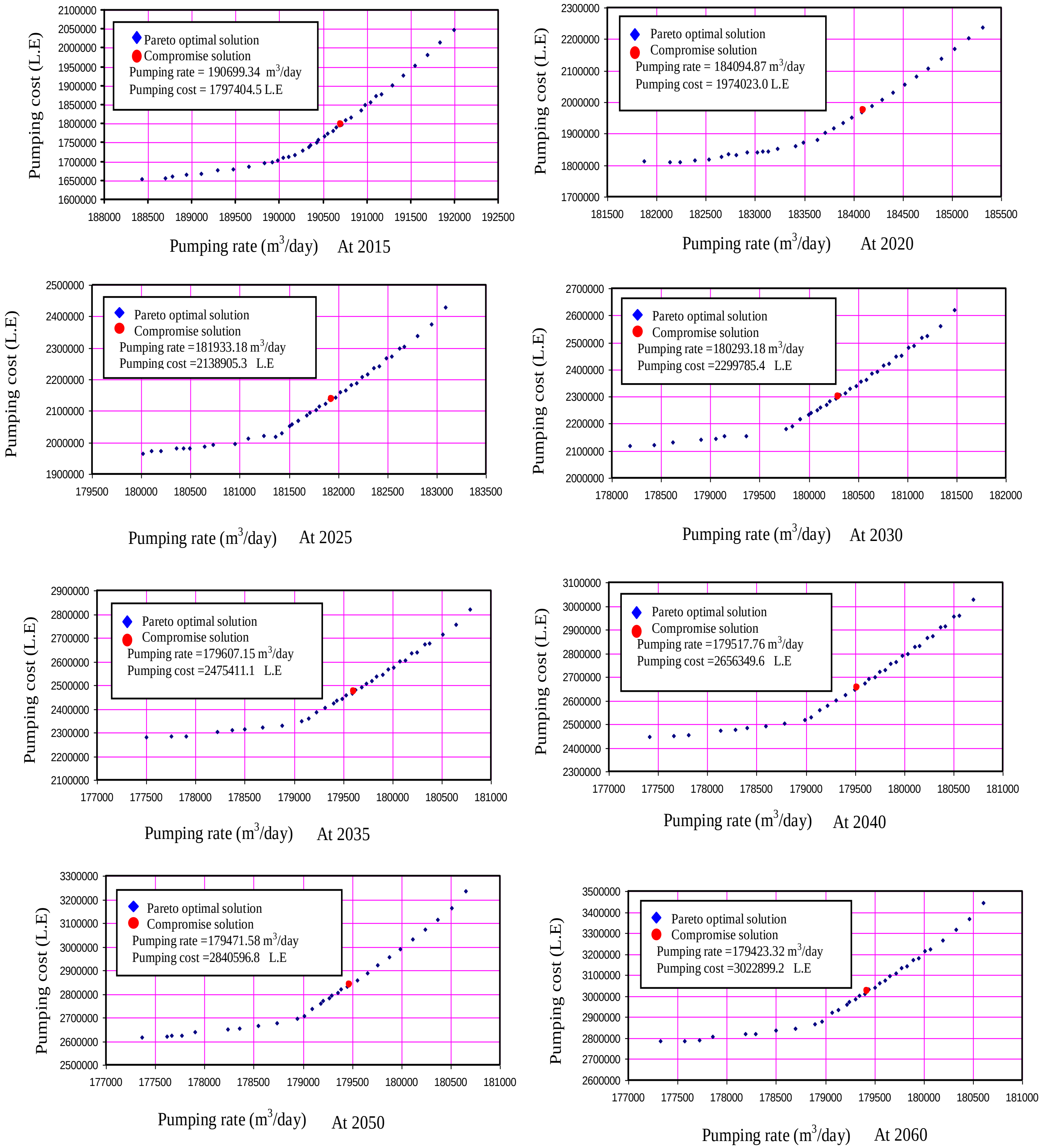

Figure 8. Final Pareto optimal solutions and compromise solution.

10% for each five years). Moreover, it is observed that the optimal pumping rate is decreased up to the year 2030 while it is almost constant during the interval from 2030 up to 2060. This may be attributed to the increase

Table 1. Compromise solution for optimal pumping rate and optimal pumping cost.

Year	Optimal pumping rate (m^3/day)	Optimal pumping cost (L.E)
2015	190699.34	1797404.5
2020	184094.87	1974023.0
2025	181933.18	2138905.3
2030	180293.18	2475411.1
2035	179607.15	2656349.6
2040	179517.76	2656349.6
2050	179471.58	2840596.8
2060	179423.32	3022899.2

in the local groundwater recharge from the surrounded Nubian Sandstone Aquifer System outside the oasis after the first 15 years of the simulation period till it reaches gradually to the natural balance by the end of the simulation period (50 years).

Conclusions

A computer programming with FORTRAN language has been originally established to apply the principles of the Multi-Objectives Genetic Algorithm (MOGA) for studying the groundwater resources management. In MOGA model, MODFLOW is linked with Genetic Algorithm (GA) technique to establish a simulation optimization groundwater model. MOGA model is applied for Nubia Sandstone aquifer in El-Farafra oasis to develop maximum pumping rate and minimum operation cost.

Also the prediction of the future changes in both pumping rate and pumping operation cost are developed. Pareto optimality ranking and fitness sharing are the two necessary techniques to modify the fitness function of each population solution, by which a uniform distribution of the population solutions evolved with increase in the generation number. The Pareto optimal set at the final generation illustrates the relationship between the pumping rate and pumping operation cost. This relationship provides the decision makers with several candidate solutions. According to this relationship, the decision maker can work out the groundwater management considering both pumping rate and pumping cost.

Finally, the compromise solution has been chosen from a set of Pareto optimal solutions to help the decision maker. The performance of the proposed MOGA model, when applied to El-Farafra Nubia Sandstone aquifer, under the available data, establishes its potential applicability to solve the complex groundwater management problems. The main advantage of the MOGA model is the possibility of linkage the GA based optimization model with an external flow simulation model. The relative ease and efficiency of this linkage, compared to the linkage using a classical nonlinear optimization technique, shall facilitate a solution to large scale and complex groundwater management problems.

REFERENCES

Abdel-Atti AAA (2002). “Hydrogeological studies on the Nubia Sandstone aquifer in Bahariya and Farafra depressions, Western Desert, Egypt” Ph. D. Thesis. Faculty of Science, Ain Shams University.
Ahlfeld DP, Heidari M (1994). “Applications of optimal hydraulic control to groundwater systems” J. Water Resour. Plan. Manage., 120(3): 350–365.
Ali MT (2004). "Evaluation of groundwater resources of El Sheikh Marzouq area at Farafra Oasis in the Desert of Egypt." Ph. D. Thesis, Geol. Dept. Fac. Sci. Menoufiya Univ., Egypt, p. 238.
Cheng R, Gen M (1998). "Compromise approach-based genetic algorithms for bicriterion shortest path problems." Technical report, Ashikaga Institute of Technology.
Cieniawski SE, Eheart JW, Ranjithan S (1995). "Using genetic algorithms to solve a multi-objective groundwater monitoring problem." Water Resour. Res., 31(2): 399–409.
Ebraheem AM, Riad S, Wycisk P, Seif El-Nasr AM (2002). “A local-scale groundwater flow model for modeling groundwater resources management options in Dakhla Oasis, SW Egypt”. Arab Workshop on Application of Math. Modeling Techniques for Management and Planning of Water Resource Proceedings, 10-14 March Egypt, Cairo. pp. 25-55
El Sabri MA, El Sheikh A (2009). "Groundwater Sustainability of The Post Nubian Sandstone Aquifer In Farafra Oasis, Western Desert, Egypt", J. Sci. Fac. Sci. Assut Univ., 3: 64-72.
El-Beltagy E, Hegazy T, Grierson D (2010). "A New Evolutionary Strategy for Pareto Multi – Objective Optimization." Proceedings of the Seventh International Conference on Engineering Computational Technology, Civil-Comp Press, Stirlingshire, Scotland.
Fonseca C, Fleming PJ (1993). “Genetic Algorithms for Multi-objective Optimization: Formulation, Discussion and Generalization.” Proceedings of the 5th International Conference on Genetic Algorithms, pp. 416-423.
Frind EO (1982). "Saltwater intrusion in continuous coastal aquifer–aquitard systems." Adv. Water Resour., 5: 89–97.
Goldberg DE (1989). "Genetic Algorithms in Search, Optimization, and Machine Learing." Addison-Wesley, Reading, MA.
Goldberg DE, Richardson J (1987). "Genetic algorithms with sharing for multimodal function optimization." In: Grefenstette JJ, editor. Genetic algorithms and their applications: Proceedings of the Second International Conference on Genetic Algorithms. San Mateo, CA: Morgan Kaufmann, p. 41–49.
Grierson DE (2008). "Pareto Multi-Criteria Decision Making." J. Adv. Eng. Inf., 22: 371–384.
Hamad MH (2004). "Subsurface Geological, Hydrogeological and Hydrogeochemical Studies on the Inter-stratal Water in Farafra oasis,

western Desert, A. r. Egypt", M. Sc. Thesis submitted to Geology Department, Faculty of Science, Cairo University.

Hermina MH (1990). “Geology of the selected areas, the surroundings of Kharga, Dakhla and Farafra Oases. The Geology of Egypt, Part 3, Chapter 14, pp. 259-292, Book edited by Said, R. 1990, Balkama, Rotterdam, Brook field.

Horn J, Nafpliotis N, Goldberg DE (1994). “A Niched Pareto Genetic Algorithm for Multi-Objective Optimization.” Proceedings of the 1st IEEE Conference on Evolutionary Computation, IEEE World Congress on Computational Intelligence, Orlando, FL, USA., 1: 82–87.

Hsiao CT, Chang LC (2002). “Dynamic optimal groundwater management with inclusion of fixed costs.” J. Water Resour. Plan. Manage., 128(1): 57–65.

Hsu NS, Yeh WWG (1989). “Optimum experimental design for parameter identification in groundwater hydrology.” Water Resour. Res., 25(5): 1025–1040.

Konak A, Coit DW, Smith AE (2006). "Multi-objective optimization using genetic algorithms: A tutorial", Reliab. Eng. Syst. Saf., 91: 992–1007.

Liu C, Hammad A (1997). "Multiobjective Optimization of Bridge Deck Rehabilitation Using a Genetic Algorithm." Microcomput. Civ. Eng., 12: 431–443.

Liu C, Hammad A, Itoh Y (1996). "Cost optimization of bridge maintenance using genetic algorithm." In Proceedings of the 15th IABSE Congress, Copenhagen, Denmark, pp. 457-462.

Moharram SH (2011). "Applying MODFLOW to Simulate Groundwater Flow in El-Farafra Depression, Western Desert, Egypt.” Int. J. Water Resour. Environ. Manage., June-December issue, 2011 (in press).

Moharram SH, Gad MI, Saafan TA, Khalaf S (2011). “Optimal Groundwater Management Using Genetic Algorithm in El-Farafra Oasis, Western Desert, Egypt.” Water Resour. Manage., DOI 10.1007/s11269-011-9865-3.

Park CH, Aral MM (2003). "Multi-objective optimization of pumping rates and well placement in coastal aquifers." J. Hydrol., 290: 80–99.

Richardson JT, Palmer MR, Liepins G, Hilliard M (1989). "Some guidelines for genetic algorithms with penalty functions." In Proceedings of the Third International Conference on Genetic Algorithms. San Mateo, CA: Morgan Kaufman, pp. 191–197.

Ritzel BJ, Eheart JW, Ranjithan S (1994). "Using genetic algorithms to solve a multiple objective groundwater pollution containment problem." Water Resour. Res., 30(5): 1589–603.

Schaffer JD (1985). “Multiple Objective Optimization with Vector Evaluated Genetic Algorithms.” Proceedings of the First International Conference of Genetic Algorithms, Pittsburgh, PA, USA., pp. 93-100.

Shafike NG, Duckstein L, Maddock T (1992). “Multicriterion analysis of groundwater contamination management.” Water Resour. Bull., 28(1): 33–43.

Srinivas N, Deb K (1994). “Multi-Objective Function Optimization Using Nondominated Sorting Genetic Algorithms.” Evol. Comput., 2(3): 221–248.

Thorweihe U (1990). Nubian aquifer system. In: Said, R. (ed): The geology of Egypt, 2nd edition (1990), Balkema, Rotterdam.