IJST, Transactions of Civil Engineering, Vol. 39, No. C2, pp 365-377
Printed in The Islamic Republic of Iran, 2015

CONJUNCTIVE USE OF SURFACE AND GROUND WATER USING FUZZY NEURAL NETWORK AND GENETIC ALGORITHM*

H. R. SAFAVI** AND F. REZAEI

Dept. of Civil Engineering, Isfahan University of Technology, Isfahan, I. R. of Iran
Email: hasafavi@cc.iut.ac.ir

Abstract– Semiarid regions with their exceptional weather conditions, low precipitation, and high evapotranspiration pose a great challenge to water resources managers. One possible way to face this challenge is the conjunctive use of both surface water and groundwater resources in these regions. This paper proposes a conjunctive use model which has been implemented in Najafabad plain in central Iran. The model is one of simulation-optimization in which the simulation portion combines the Fuzzy inference system and Neural Networks (FNN) in order to take the climate conditions and the uncertainty in the relevant data into consideration while the optimization portion consists of a multi-objective Genetic Algorithm (GA). The objectives of the optimization model include not only minimizing water shortages in meeting the irrigation demands by the three irrigation systems operating in the region but also minimizing groundwater drawdown in order to control groundwater extraction in the aquifer. These objectives are subject to constraints on the maximum amount of surface and groundwater allocated to the irrigation zones and the maximum capacity of surface irrigation systems and also maximum and minimum allowable cumulative drawdown in the planning horizon. The results of the proposed FNN-GA model demonstrate the importance of the interactions between surface water and groundwater resources considered in a conjunctive use model for the planning and management of water resources in semiarid regions.

Keywords– Conjunctive use, Simulation-optimization, Neural Networks, Fuzzy Inference System, Genetic Algorithms

1. INTRODUCTION

Semiarid regions with low precipitation and high potential of evapotranspiration are abundant in central Iran. Rapid population growth, increasing irrigation demand, and industrial development during the past decades have led to increased pressure on water resources in semiarid regions [1]. In those regions, both sources of water should be managed conjunctively so as to minimize fluctuations in total water demands caused by variations in rainfall patterns. Conjunctive use has been defined in more ways than one, but in general it is defined as the allocation of surface water and groundwater in terms of quantity and/or quality so as to achieve one or more objectives while satisfying certain constraints [2-4]. However, most systems are introducing 'joint use' of surface and groundwater to overcome problems of poor water delivery or quality, rather than systems which actually maximize water utility [5]. The implementation of conjunctive operation of surface water and groundwater can achieve reasonable spatiotemporal allocation of water resources to improve utilization ratio of water resources and water supply guaranteed rate and realize comprehensive treatment of drought, water logging and alkali [6]. The conjunctive use models based on the particular problem under consideration and the associated assumptions may be classified with such models as linear programming, dynamic programming, hierarchical optimization, nonlinear programming,

*Received by the editors December 24, 2013; Accepted November 23, 2014.
**Corresponding author

and simulation-optimization models, or alternatively with evolutionary algorithms [7]. Linear programming has been successfully applied in conjunctive modeling by a large number of authors including [8-10] in the past, and more recently [11, 7]. Dynamic programming has been used for its advantages in sequential decision making process and applicability to nonlinear systems by many researchers including [12, 13] in the past, and recently by [14, 15]. Hierarchical or multilevel optimization models have been successfully applied by [16-18]. As most conjunctive use problems are nonlinear [19, 20] opted for nonlinear programming in their studies. The main disadvantage with most classical optimization techniques is their reliance on gradient search techniques in which the gradients are usually calculated numerically. The numerical estimation of gradients is the most expensive part of optimization-based management models and may lead to large errors. Evolutionary techniques such as Genetic Algorithm (GA) are designed to cope with these problems. These techniques have been used in nonlinear non-convex problems [21-24]. Furthermore, simulation techniques such as neural networks are based on numerical optimization techniques. Hence, they suffer from a similar drawbacks and need to compute the gradient and sometimes the Hessian matrix which is a complicated and expensive process. New techniques such as back propagation neural networks based on conjugate gradient technique or an improved Newton method (Levenberg-Marquardt algorithm) have, however, been proposed for coping with this problem that not only rapidly converge but also seem to be more practical [25].

In conjunctive use, simulation techniques are applied to establish a meaningful relationship between groundwater drawdown and aquifer depletion, but incorporating the simulation model into an optimization-based management model is a complex and difficult process. Embedding techniques and response matrix approach are the two methods generally used for this purpose [26]. In a coupled simulation-optimization model, the simulation model accounts for the physical behavior of surface water-groundwater systems, whereas the optimization model accounts for the conjunctive management aspects of the system [27]. If conjunctive use is to be implemented in the study area for a rather long period of time, then the effect of climate change and the resulting uncertainty in data must also be taken into consideration for irrigation planning and management. One method commonly used is the Fuzzy Inference System (FIS) which uses farmers' experience and knowledge as well as expert judgments in developing an optimal crop planning and predicting a reliable demand for irrigation on the basis of climate conditions [28]. Leung used fuzzy linear programming (FLP) to study water allocation to three farming areas. The goal was to program water consumption for enhanced profitability [29]. Özger used a genetic algorithm (GA) for training the fuzzy rules and developed if-then rules with linguistic expressions [30]. He also developed two different FIS models to predict the discharge of the Euphrates River in Turkey. In the case of conjunctive use of surface water and groundwater, the major concern is groundwater level variation which can lead to a high shortage in groundwater reservoir storage or cause water level to be uplifted which leads to the need for draining the uplifted water to hinder damaging crops. So groundwater drawdown is required to be controlled and this parameter is usually predicted by a simulating model. A common model used in groundwater level forecasting is neural network and if it is decided to consider uncertainty resulted from the effect of the climate change, it is also necessary for a FIS model to be coupled with the neural network. This linkage can be done with a single framework of Adaptive Neuro-Fuzzy Inference System (ANFIS) [31, 32]

In this paper, the Levenberg-Marquardt Back Propagation (LMBP) neural network is applied to simulate and determine the relationship between groundwater drawdown and extraction from the Najafabad aquifer. Moreover, a multi-objective genetic algorithm is implemented to achieve the management objectives in the optimization model. The objectives consist of minimizing shortages in meeting irrigation demands and simultaneously minimizing monthly groundwater drawdown over one year as the management period for three irrigation systems located in Najafabad plain. Also, a fuzzy inference system is employed that takes into account the variations in weather condition and the uncertainty resulting from climate conditions within a twenty-year period and as a result of relying on expert judgments in developing the FIS rules and also impeding formation the redundant rules which may enhance computational burden and cause computer to make error, the application of a single framework of ANFIS is impeded. On the other hand, the process involves simulating and computing groundwater drawdown by means of the neural network followed by the formation of FIS rules with the fuzzificable parameters as the premises and the calculated drawdown by neural network as a consequence of the rules. Finally, the numerical parameters are fed into the FIS and the drawdown is calculated based on uncertainty as the ultimate output of the simulation model which is used as the one of inputs for the optimization model.

2. STUDY AREA

The study area is Najafabad plain, a part of the Zayandehrood River Basin located in west-central Iran as shown in Fig. 1. In recent years, water has become increasingly scarce in the region and the Zayandehrood Basin has shown signs of salinization of agricultural land and increased pollution in the lower reaches of the river. The Najafabad plain occupies an area of approximately 1,720 km^2 while the Najafabad aquifer has an area of about 1,142 km^2, with geographical coordinates between 50º 57' to 51º 44' north longitudes and 32º 20' to 32º 49' east latitudes. The Najafabad aquifer is recharged by irrigation percolation, canal and river seepages, as well as direct precipitation on the plain. The total number of pumping wells in the aquifer amounts to around 10,160 wells with depths ranging between 17 and 120 m and discharge rates ranging from 2 to 110 l/s [33].

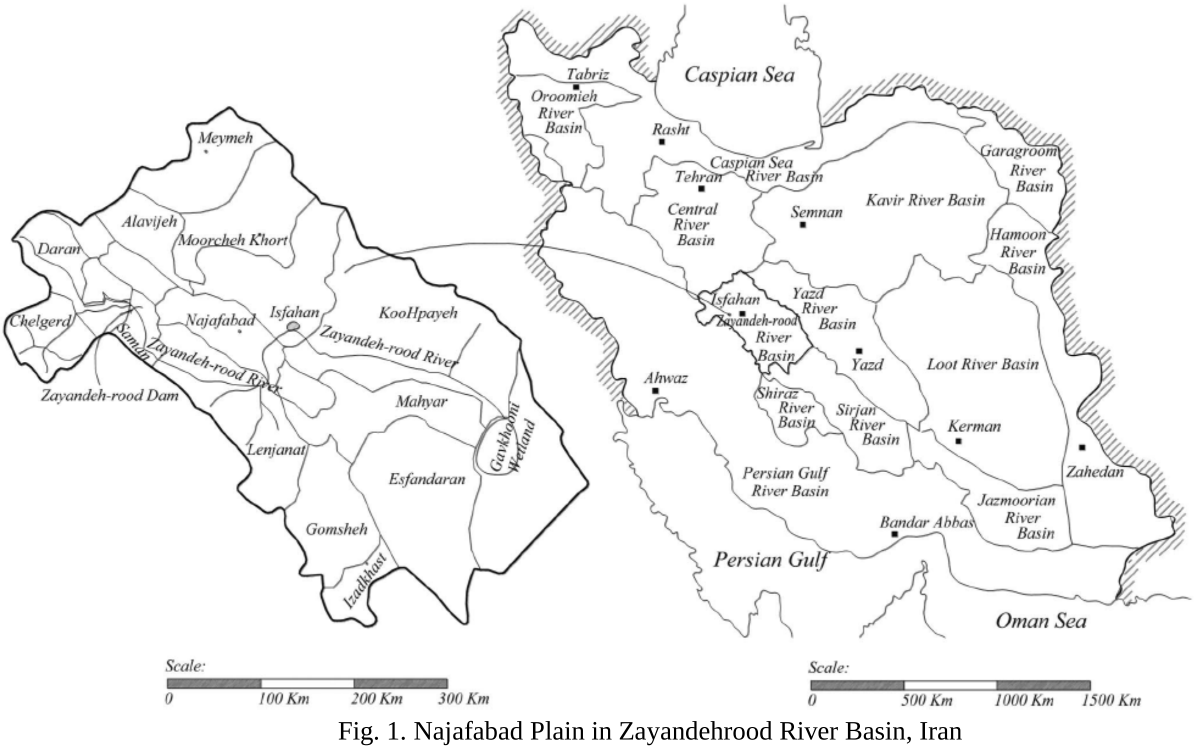

Fig. 1. Najafabad Plain in Zayandehrood River Basin, Iran

The Najafabad sub-basin has a predominantly semi-arid climate. Average annual rainfall is only 150 mm, most of which falls in the winter months from December to April. Annual potential evapotranspiration is about 1,950 mm [34]. Modern surface irrigation started some 42 years ago with the construction of the Nekouabad diversion weir. The weir controls the main channels on both the left and right banks. Khamiran surface irrigation system also started operation when Khamiran Dam was constructed 20 years ago (Fig. 2). Over the past decade, a historical low rainfall occurred at the head of the Zayandehrood Basin, which was further complicated by the growing demand for water. To combat the consequences, farmers have been forced to look for strategies that can help them cope with water scarcity at field level. However, the strategies adopted mainly involve increased groundwater use, adapted production strategies, or adopting other activities for their livelihood. In a conjunctive use system, surface water is replaced by increasing groundwater extraction in drought situations and/or groundwater table is replenished by surface water when surface water is abundant, whereby shortages are somehow compensated for by appropriate utilization and proper management of both surface and ground water resources [35].

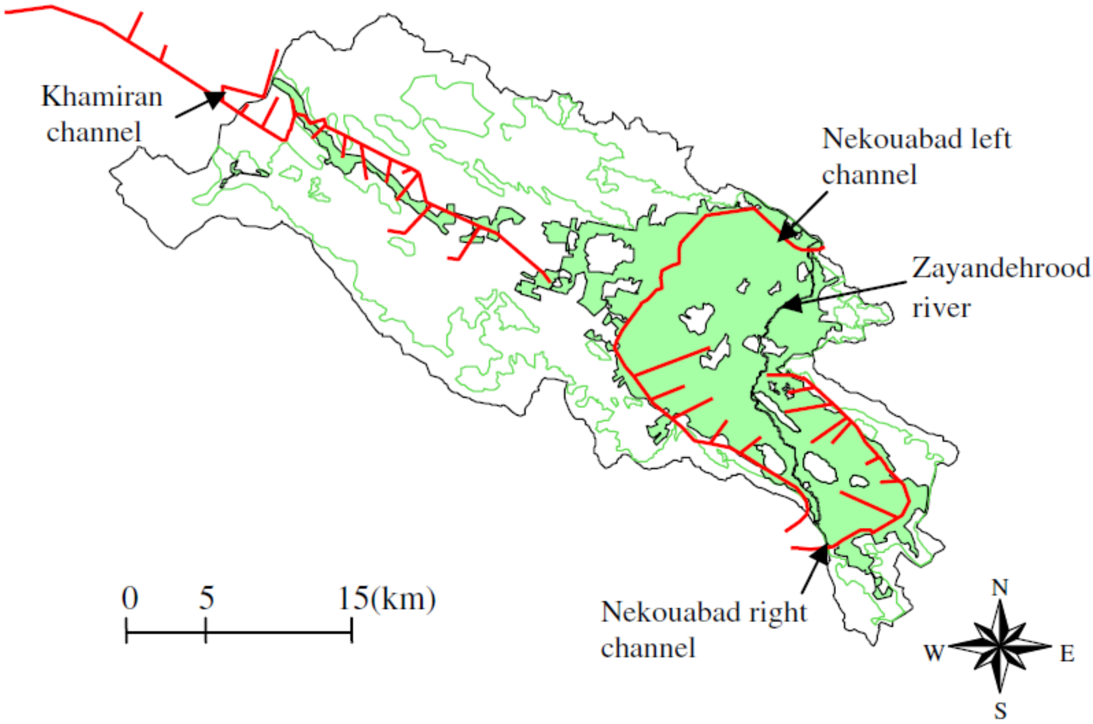

Fig. 2. Nekouabad and Khamiran irrigation channels

3. METHODOLOGY

a) Neural networks

In this study, simulation is accomplished by a two-stepped model the first step of which is performed by a neural network model. The model employed in this study is a network based on the Levenberg-Marquardt Back Propagation (LMBP) algorithm as a special type of the Newton method. In the Newton method, second order derivatives need to be calculated in a template of a matrix named 'the Hessian matrix'. The purpose of the LMBP algorithm, however, is to eliminate the requirement for computing this matrix. One advantage of this algorithm is the good balance it keeps between the speed of the Newton method and the convergence guaranteed by the Steepest Descent method. Convergence is assumed to be fulfilled when the gradient norm becomes less than a default value or when the sum of squared errors falls below a specific limit. The LMBP neural network has the three inputs, hidden, and output layers as shown in Fig. 3. The *tansig* and the *purlin* transfer functions are employed in the hidden and output layers, respectively. It must be mentioned that LMBP goes from one iteration to the next only if the performance index (i.e., the sum of the squared errors) in each iteration is less than that in the previous iteration; hence, the performance index is minimized [25].

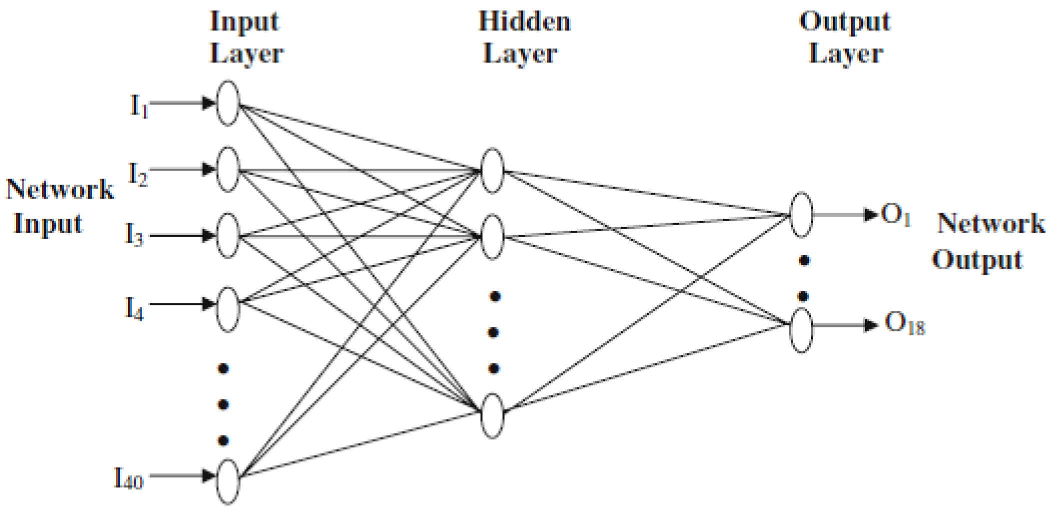

Fig. 3. Three-layer LMBP neural network architecture

b) Fuzzy inference system

The Fuzzy Inference System (FIS) is implemented as the second step of the simulation model. Fuzzy logic is a generalization of the classic logic developed to deal with transitional concepts exemplified by the one between completely true and completely false. The fuzzy set theory which is used to cope with uncertain concepts in natural language contributes a membership degree to each element through a membership function. For classic sets, the membership degree only takes the two values of 0, as non-membership, and 1, as membership, whereas in fuzzy sets, the membership degree could obtain each value from [0,1]. The intermediate values represent partial membership in a specific set [36]. In this paper, a singleton fuzzy membership function is attributed to the consequence of the FIS rules. This function is a constant number and the premises of the rules are input fuzzificable parameters in the form of Gaussian membership functions. So this FIS would be a zero order Sugeno Inference System. In this study, the FIS is used in order to estimate drawdown in groundwater table level. The mean drawdown resulting from different premises is the fuzzy system output in each rule. Once the maximum number of possible rules is formed, input parameters are fed as observations into the rules, and the weighted average defuzzification method is used, the drawdown related to the relevant month is computed and employed as the final simulation result.

c) Genetic algorithm

Genetic Algorithm used in the optimization model is a smart structure for searching randomly for optimum solutions in the likely zones. The main advantages of GA may be summarized as follows:

1- Capability to search simultaneously in more than one zone so as to not become trapped in local optima, capability to cope with each type of objective function and each type of search space,

2- Accurate computation of optimum points without any need for approximation in the objective function, and

3- Application of general probability laws rather than deterministic laws.

The algorithm utilizes certain useful operators such as selection, crossover, and mutation. The best selection method is the tournament method which finally selects the chromosome with the best fitness among other random ones. The crossover probability, P_c, usually lies in the scope of 0.5-1 and is one of the input parameters to GA. If the random number produced for each couple of the population is less than P_c, the crossover is applied over those chromosomes. The final GA operator, i.e. mutation, involves the creation of a random change in a gene's information. The probability for changing a decision variable in each evolutionary step is considered as P_{mut}. If the random number produced for each gene is less than P_{mut}, the mutation takes place. Mutation gives rise to diversity in the population in order to impede the premature convergence and to reach non-optimum solutions. The convergence criteria are twofold: 1) Passing a specific number of generations while GA is running, 2) Determining a condition such that the fitness of the best member of the population is not improved within a number of generations [37].

4. SIMULATION MODEL

In this paper, the simulation model was initially designed before it was linked to the optimization model. As mentioned earlier, the simulation model consists of the two models of neural network (NN) and fuzzy inference system (FIS). The former, a LMBP neural network was designed with input, hidden, and output layers. The input layer includes five parameters: 1) groundwater extraction, 2) precipitation, 3) evaporation, 4) surface water allocation, and 5) groundwater level. The NN output is drawdown of the groundwater level. All the data are reported as monthly records and the output will, therefore, be generated as monthly figures, too. The planning horizon is the 2005-2006 water year as a normal water year beginning in October of the previous year and ending in September of the following year. The NN is a 5-30-1 network consisting of 30 neurons in the hidden layer. The number of hidden layer neurons is determined after a number of trial and errors in running the network until the maximum correlation coefficient and/or the minimum sum of squared errors is reached. For each of the three study areas, the NN model was independently designed and performed. All data series were divided into three parts (65% for Training, 25% for Testing and 10% for Validation) and the NN performance was evaluated based on the criterions R^2 as the Determination Coefficient and ρ as the Correlation Coefficient [38, 39]. The calculated coefficients are shown in Table 1. These figures indicate a plausible precision in NN's learning and also according to the figures attained for Testing and Training stages, overtraining hasn't occurred.

Table 1. Values of Correlation Coefficient (R) and Determination Coefficient (R^2) resulted from NN model

Subarea	Training (R)	Testing (R)	Overall (R)	Overall (R^2)
Khamiran	0.80	0.72	0.68	0.39
Nekouabad right	0.89	0.67	0.68	0.31
Nekouabad left	0.79	0.69	0.71	0.32

The NN model thus designed was employed to predict drawdown as a consequence of the FIS rules. For preparing the FIS model, all the available data consisting of 228 series of five data were divided into three categories each containing 76 series of data and named as high, moderate, and low, respectively, with respect to the magnitude of the values in each category. The categories were subsequently inserted into the NN model in order to calculate the mean drawdown for each rule in the FIS model. The Gaussian membership functions were considered as membership functions of input parameters. Fuzzy singleton membership functions were used to indicate mean drawdown in the consequence of each rule. The Gaussian membership function is defined as follows:

$$\textit{Membership Function} = \exp\left(-(x-c)^2/(2\sigma^2)\right) \tag{1}$$

These parameters were calculated numerically and shown in Tables 2 to 5 in terms of the input parameters.

Table 2. Characteristics of Gaussian membership functions for groundwater extraction parameter

Subarea	Khamiran			Nekouabad right			Nekouabad left		
Class	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
c(MCM)	5.6	2.76	0.26	36.77	18.9	2.51	49.1	26.12	3.58
σ(MCM)	0.88	0.69	0.0087	6.83	3.4	4.39	9.25	5.07	6.3

Table 3. Characteristics of Gaussian membership functions for precipitation parameter

Subarea	Khamiran			Nekouabad right			Nekouabad left		
Class	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
c(mm)	37.32	4.2	0	32.67	2.07	0	32.67	3.07	0
σ(mm)	16.42	4.24	0	18.45	3.86	0	18.45	3.86	0

Table 4. Characteristics of Gaussian membership functions for surface water network allocation parameter

Subarea	Khamiran			Nekouabad right			Nekouabad left		
Class	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
c(MCM)	1.52	0	0	15.3	4.23	0	45.87	12.7	0
σ(MCM)	1.15	0	0	3.55	3.19	0	10.65	9.57	0

Table 5. Characteristics of Gaussian membership functions for groundwater level parameter

Subarea	Khamiran			Nekouabad right			Nekouabad left		
Class	High	Moderate	Low	High	Moderate	Low	High	Moderate	Low
c(m)	31.45	27.71	23.55	28.05	22.7	17.88	32.7	24.35	15.74
σ(m)	1.3	0.68	1.43	2.43	1.3	0.77	2.95	3.25	1.03

Among the input parameters inserted into the FIS, the variable parameters consisted of groundwater extraction and surface water allocation. Precipitation and groundwater level were considered to be equal to the monthly means of a year with the planning horizon taken to be 20 years starting from the 1991-1992 water year to 2009-2010 water year. Furthermore, evaporation was not inserted into FIS model due to its non-fuzzificability. Table 6 shows the relationships among the different classifications of the FIS model for forming the 43 rules.

Table 6. Relationship among different classes of fuzzificable parameters in FIS rules

Groundwater extraction	Precipitation	Surface water allocated	Groundwater level
Low	Moderate/High	Moderate/High	Moderate/High
Moderate	Moderate/High/Low	Moderate/High/Low	Moderate/High/Low
High	Moderate/Low	Moderate/Low	Moderate/Low

5. OPTIMIZATION MODEL

The objectives of the optimization model were minimizing shortages in meeting irrigation demands in each subarea and also minimizing groundwater level drawdown in order to control groundwater extraction subject to certain constraints such as maximum and minimum allowable cumulative drawdown and maximum capacity of surface irrigation systems,

$$\text{Minimize} \quad Z_1 = \sum_{i=1}^{12}(D_{i,z} - Sup_{i,z})^2 \qquad \text{for } z = 1, 2, 3 \tag{2}$$

$$\text{Minimize} \quad Z_2 = \sum_{i=1}^{12}(\Delta H_{i,z} - \Delta H_{opt})^2 \qquad \text{for } z = 1, 2, 3 \tag{3}$$

$$D_{i,z} = \sum_{m=1}^{M} crop_{i,m} A_{i,m} \qquad \text{for } i = 1, 2, \ldots, 12 \tag{4}$$

$$A_{i,z} = \sum_{m=1}^{M} A_{i,m} \qquad \text{for } i = 1, 2, \ldots, 12 \text{ and } z = 1, 2, 3 \tag{5}$$

$$Sup_{i,z} = a_z.GW_{i,z} + a_z.b_z.c_z.SW_{i,z} \tag{6}$$

Subject to:

$$\Delta H_{min} \le \sum_{i=1}^{12} \Delta H_{i,z} \le \Delta H_{max} \qquad \text{for } z = 1, 2, 3 \tag{7}$$

$$SW_{i,z} \le CC_{i,z} \times \alpha_z \qquad \text{for } i = 1, 2, \ldots, 12 \text{ and } z = 1, 2, 3 \tag{8}$$

In this model, the probability of groundwater level to be uplifted and negative drawdown values is met by assigning a negative value to the minimum allowable cumulative drawdown. Among the points suggested by the Pareto curve, the one ultimately selected is that which has relatively lower values of Z_1 and Z_2 compared with other points of the curve by a simple discrete compromise programming. It must also be mentioned here that the sum of the squared drawdown in the second objective function cannot be replaced by the sum of the drawdown values. This is because the optimization model would then tend to reduce the second objective function down as much as possible and reduce each monthly drawdown down to a big negative value. Apparently, this trend is not logical and can never be expected to happen in reality.

In the optimization model, P_c is equal to 0.7 and the number of chromosomes is equal to 190. Also, considering surface water allocation, groundwater extraction, and the summation of them as the gross supply, the number of genes will be equal to the total number of decision variables, i.e., 36 in each chromosome. The genetic algorithm stops when the number of generations exceeds a specific value inserted as the input parameter into the model. Meanwhile, the error of the objective function between two successive iterations must be lower than a default value which is taken to be 10^{-4}. Figure 4 illustrates the structure of the simulation-optimization model.

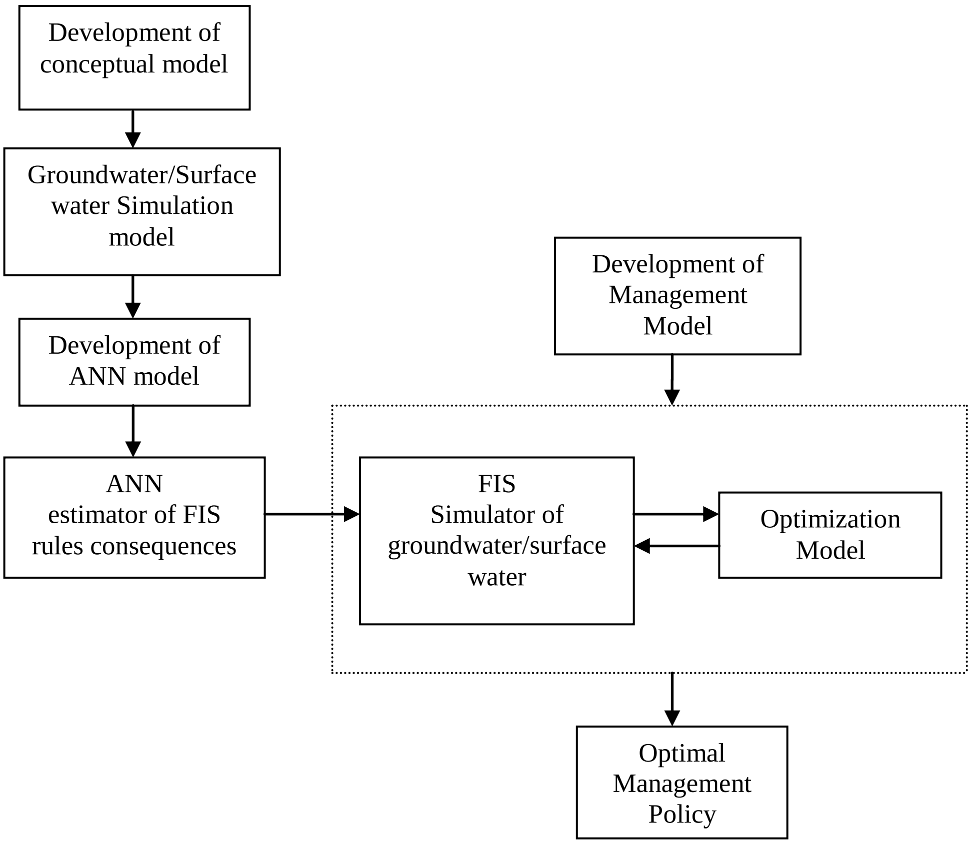

Fig. 4. Schematic representation of the linked simulation-optimization model

6. RESULTS AND DISCUSSION

Considering the fact that the present simulation-optimization model only involves one of the sub-basins and based on the policy adopted for operating the irrigation systems, the maximum volume of surface water available in each period is computed based on the average volume of water available in each irrigation system [35]. The results of the management model implemented in the three zones of Khamiran, Nekouabad right bank, and Nekouabad left bank are presented in Figs. 5 to7.

Clearly, a rather small portion of the water demand during the winter (months 4, 5, and 6) was met in Khamiran. However, the water demand in this season was also negligible compared to those in other seasons. In the summer (months 10, 11, and 12) when the water demand for irrigation was at its maximum, 26%, 27%, and 16% of the water demand was met in July, August, and September, respectively. This indicates that the conjunctive use policy was capable of efficiently managing the water resources systems in this region while drawdown was also at its minimum level or close to zero. For example, the values for drawdown during the final three months of the water year were 0.0925, 0.0928, and 0.0924 meters, indicating that groundwater extraction was appropriately implemented to meet the demands satisfactorily in spite of the negligible drawdown. In the Khamiran irrigation zone, the maximum water demand met was 80.18% which belonged to the month of December while the minimum was about 1.49% and belonged to the month of March.

A trend similar to the one in Khamiran is observed in the Nekouabad right bank irrigation zone, but only with some differences. For example, the maximum value for the demand met in this zone occurred in the spring rather than in the summer. However, the low winter demands were not met, similar to the situation in Khamiran. The maximum value for drawdown in this zone was 0.174 meters which occurred in April and June when 63% and 58% of the demand were met respectively, despite such a small level of drawdown. In fact, the small amount of drawdown couldn't indicate the small groundwater extraction. Because in these months the irrigation demands are rather high and considerably met, so the groundwater extraction must be high and consequently the small drawdown may be sought in the initially high groundwater level caused by a number of consecutive negative drawdown in previous months which affects the aquifer's response. In the Nekouabad left bank irrigation zone, like in Khamiran, the maximum amount of water demand meeting occurred in the spring with a mean value of 42% but its minimum occurred in winter. Drawdown in this zone is always positive and negligible while the maximum demand meeting usually occurs in July which is about 76% and may be the cause of a drawdown of 1.27 meters taking place in this month which is about highest among all drawdowns of the water year.

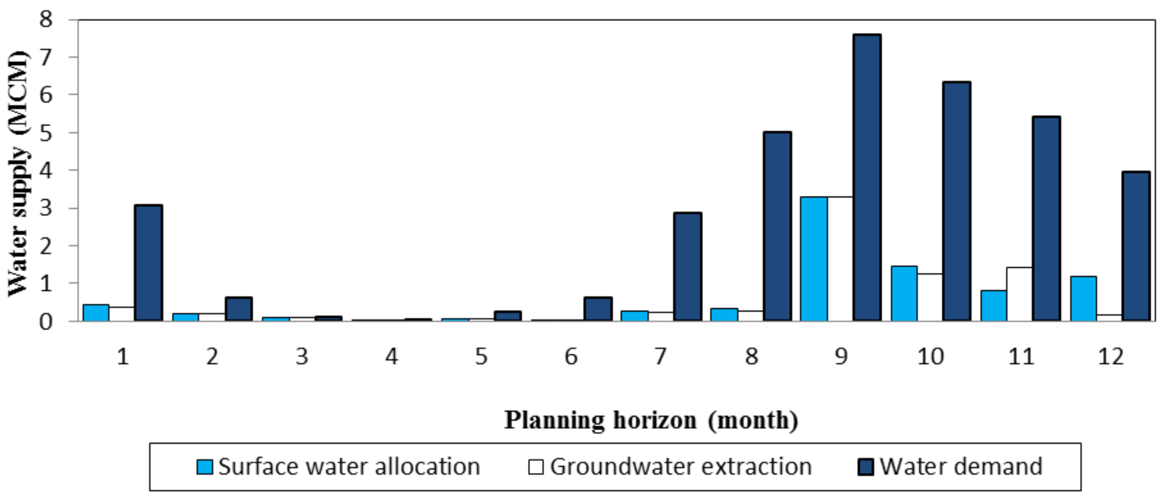

Fig. 5**.** The water demand and monthly allocated surface water and groundwater to Khamiran zone

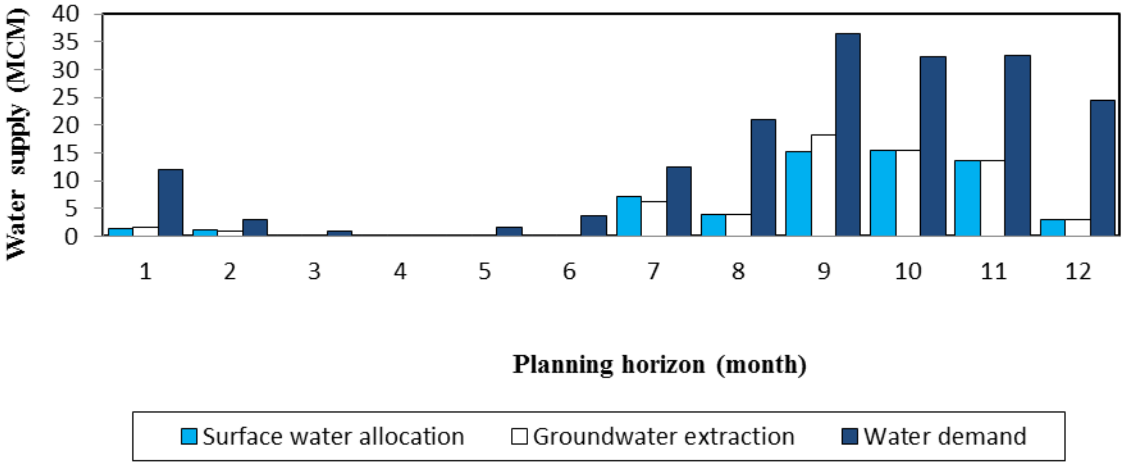

Fig. 6. The water demand and monthly allocated surface water and groundwater to Nekouabad right zone

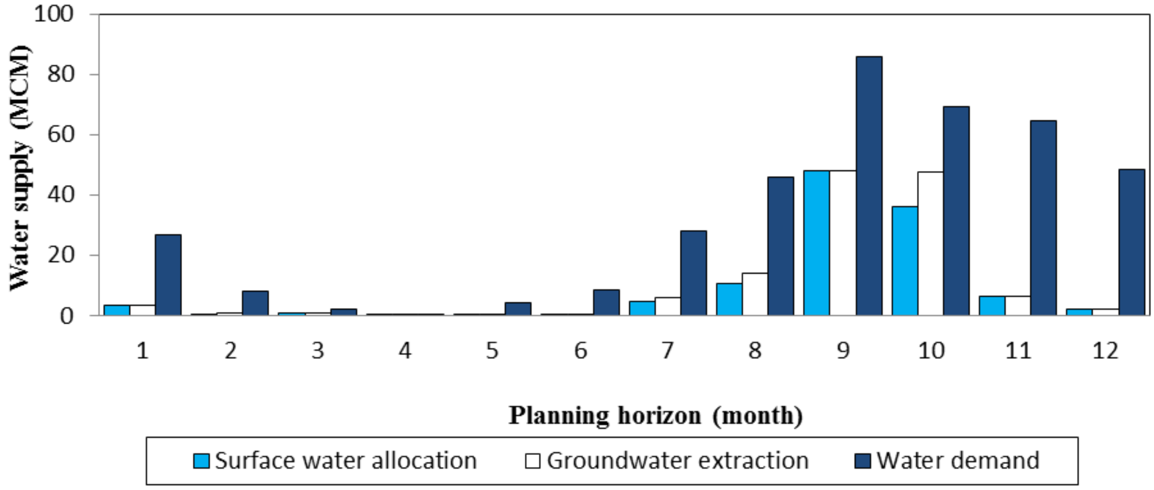

Fig. 7. The water demand and monthly allocated surface water and groundwater to Nekouabad left zone

7. CONCLUSION

A simulation-optimization linked model was developed in this paper for the conjunctive use of surface water and groundwater resources. In this model, neural networks combined with the fuzzy inference system were executed in a simulation model in which the neural network was linked to the fuzzy system. The former predicts an estimated value for the groundwater drawdown while the latter uses the predicted drawdown value as the consequence in its rules. Thus, a surface water and groundwater interaction simulation model was formed in which the Fuzzy-Neural Network (FNN) model is capable of considering uncertainty in the data due to climate conditions. An optimization model based on the multi-objective genetic algorithm (GA) was created and linked to the simulation model in order to minimize shortages in meeting net water demands and also to minimize groundwater drawdown. The FNN-GA model was then applied to investigate the situation in Najafabad plain in Iran. Results indicate that the use of this conjunctive use model does not lead to meeting all the demand completely. Specifically, a large gap is found between water supply and water demand in autumn and winter seasons. However, given the low water demand in these two seasons and the satisfactory meeting of the demands in the summer, the good performance of the proposed conjunctive use model can be concluded.

Anyway, a simulation-optimization model is not a completely accurate model due to some simplifications in both simulation and optimization sectors. The evolutionary algorithms such as Genetic algorithm are the best choices compared with other methods like non-linear programming for solving the multi-objective optimization problems like the model of this paper and the similar models with discontinuous, multi-modal, combinatorial and severely nonlinear objective functions or non-differentiable and non-convex design spaces. In spite of these superiorities, Genetic algorithm can be improved in terms of its capability in global search. The Back Propagation Neural Network (BPNN) used in this paper as simulation model can be also improved in terms of architecture, generalization and convergence to optimal weights and biases. It is strongly suggested that these improvements be carried out, thereby the capabilities of the model and then the model's reliability will be enhanced. Imposing these improvements gives BPNN outperformance and hinders the application of complex, time-consuming and hard-to-handle process-oriented, physical-based models.

Legends

$D_{i,z}$	volume of water demand in zone z in month i (MCM),
$Sup_{i,z}$	volume of water supply in zone z in month i (MCM),
$\Delta H_{i,z}$	drawdown in zone z in month i (m),
ΔH_{opt}	the optimum drawdown which is considered zero (m) in this paper,
$crop_{i,}$	volume of water needed for harvest m in month i (MCM/m^2),
$A_{i,m}$	cropping area of the harvest m in month i,
$A_{i,z}$	the potential cultivable area of zone z in month i (ha),
a_z	efficiency of water use in the farm in zone z,
b_z	efficiency of water use in the main channels in zone z,
c_z	efficiency of water use in the secondary channels in zone z,
$GW_{i,z}$	volume of groundwater extracted in zone z in month i (MCM),
$SW_{i,z}$	volume of water supplied from surface water to zone z in month i (MCM),
ΔH_{min}	minimum allowable cumulative drawdown in a year,
ΔH_{max}	maximum allowable cumulative drawdown in a year,
$CC_{i,z}$	maximum volume of water available for surface water network in zone z in month i (MCM),
α_z	efficiency of surface water network for zone z,
i	number of months,
z	number of zones,
m	number of harvests.

REFERENCES

1. Safavi, H. R. & Bahreini, G. R. (2009). Conjunctive simulation of surface water and groundwater resources under uncertainty. *Iranian Journal of Science and Technology, Transaction B*, Vol. 33, No. B1, pp. 79-94.
2. Paudyal, G. N. & Gupta, A. D. (1987). Operation of groundwater reservoir in conjunction with surface water. *International Journal of Water Resources Development*, Vol. 3, No. 1, pp. 31-43.
3. Mariño, M. A. (2001). Conjunctive management of surface water and groundwater. In: Schumann AH et al (Eds) Regional Management of Water Resources. IAHS Publ. 268. IAHS, Wallingford, UK, pp. 165-173.
4. Afshar, A., Zahraei, S. A. & Mariño, M. A. (2008). Cyclic storage design and operation optimization: Hybrid GA decomposition approach. *International Journal of Civil Engineering*, Vol. 6, No. 1, pp. 34-47.
5. Vincent, L. & Dempsey, P. (1993). Conjunctive water use for irrigation: Good theory, poor practice. *International Journal of Water Resources Development*, Vol. 9, No. 3, pp. 227-245.
6. Zhang, L., Zhang, J. & Wu, Zh. (2013). Advance on conjunctive operation of surface water and groundwater. *Desalination and Water Treatment*, 1-9, 10.1080/19443994.2013.822646. 2013.

7. Vedula, S., Mujumdar, P. P. & Chandra Sekhar, G. (2005). Conjunctive use modeling for multicrop irrigation. *Agricultural Water Management*, Vol. 73, pp.193-221.
8. Rogers, P. & Smith, D. V. (1970). The integrated use of ground and surface water in irrigation project planning. *American Journal of Agricultural* Economics, Vol. 52, No. 1, pp. 13-24.
9. Louie, P. W. F., Yeh, W. W. G. & Hsu, N. S. (1984). Multiobjective water resources management planning. *Journal of Water Resources Planning and Management*, Vol. 110, No. 1, pp. 39-56.
10. Kumar, R. & Pathak, S. K. (1989). Optimal crop planning for a region in India by conjunctive use of surface and groundwater. *International Journal of Water Resources Development*, Vol. 5, No. 2, pp. 99-105.
11. Sethi, L. N., Kumar, D. N., Panda, S. N. & Chandramal, B. (2002). Optimal crop planning and conjunctive use of water resources in a costal river. *Water Resources Management*, Vol. 16, pp. 145-169.
12. Buras, N. (1963). Conjunctive operation of dams and aquifers. *Journal of Hydraulics*, Vol. 89, No. 6, pp. 111-131.
13. Aron, G. (1969). Optimization of conjunctively managed surface and groundwater resources by dynamic programming. Contribution No. 129, Water Resources Center, University of California, California, USA.
14. Provencher, B. & Burt, O. (1994). Approximating the optimal groundwater pumping policy in a multi-aquifer stochastic conjunctive use setting. *Water Resources Research*, Vol. 30, No. 3, pp. 833-843.
15. Barlow, P. M. (1997). Dynamic models for conjunctive management of stream-aquifer systems of glaciated Northeast. PhD Dissertation, Univ. of Connecticut, Storrs, CT, USA.
16. Maddock, T. III. (1972). Algebraic technological function from a simulation model. *Water Resource Research*, Vol. 8, No. 1, pp. 129-134.
17. Maddock, T. III. (1973). Management model as a tool for studying the worth of data. *Water Resources Research*, Vol. 9, No. 2, pp. 270-280.
18. Paudyal, G. N. & Gupta, A. D. (1990). Irrigation planning by multilevel optimization. *Journal of Irrigation and Drainage Engineering ASCE*, Vol. 116, No. 2, pp. 273-291.
19. Willis, R., Finney, B. A. & Zhang, D. (1989). Water resources management in north China plain. *Journal of Water Resources Planning and Management*, Vol. 115, No. 5, pp. 598-615.
20. Matsukawa, J., Finney, B. A. & Willis, R. (1992). Conjunctive use planning in Mad river basin. *Journal of Water Resources Planning and Management*, Vol. 118, No. 2, pp. 115-132.
21. Wang, M. & Zheng, M. (1998). Groundwater management optimization using genetic algorithms and simulated annealing: formulation and comparison. *Journal of the American Water Resources Association*, Vol. 34, No. 3, pp. 519-530.
22. Karamouz, M., Kerachian, R. & Zahraie, B. (2002). Conjunctive use of surface water and groundwater resources. *Proceeding of ASCE Environmental and Water Resources* (CD-Rom). Reston, VA, USA.
23. Karamouz, M., Mohammad Rezapour Tabari, M. & Kerachian, R. (2007). Application of genetic algorithms and artificial neural networks in conjunctive use of surface and groundwater resources. *Water International*, Vol. 32, No. 1, pp. 163-176.
24. Geng, G., Wardlaw, R, Hu, L. & Wang, Zh., (2011). Optimisation to assist IWRM and conjunctive water use. *Proceedings of the Institution of Civil Engineers - Water Management*, Vol. 164, No. 9, pp. 477 –491.
25. Hagan, M. T., Demuth, H. & Beale, M. (1996). *Neural Network Design*, PWS Publishing Co., USA.
26. Gorelick, S. M. (1983). A review of distributed parameter groundwater management modeling methods. *Water Resources Research*, Vol. 13, No. 1, pp. 78-86.
27. Basagaoglu, H. & Mariño. M. A. (1999). Joint management of surface and ground water supplies. *Ground Water*, Vol. 37, No. 2, pp. 214-222.
28. Safavi, H. R. & Alijanian, M. A. (2011). Optimal crop planning and conjunctive use of surface water and groundwater resources using fuzzy dynamic programming. *Journal of Irrigation and Drainage Engineering*, Vol. 137, No. 6, pp. 383-397.

29. Leung, Y. (1988). International equilibrium and fuzzy linear programming. *Journal of Environment and Planning, A.*20, pp. 25-40.
30. Özger, M. (2009). Comparison of fuzzy-inference systems for streamflow prediction. *Hydrological Sciences Journal*, Vol. 54, No. 2, pp. 261-273.
31. Nourani, V., Abolvaset, N. & Salehi, K. (2013). A hybrid goal programming method and ANFIS for optimal operation of a multi-objective two-reservoir systems. *Iran Water Resources Research Journal*, Vol. 8, No. 2, pp. 1-11 (in Persian).
32. Nourani, V. & Komasi, M. (2013). A geomorphology-based ANFIS model for multi-station modeling of rainfall-runoff processes. *Journal of Hydrology*, Vol. 490, pp. 41-55.
33. Isfahan Regional Water Authority, (2005). Zayandehrood river basin report. IRWA, Isfahan, Iran (in Persian).
34. Jamab Consulting Engineers, (2002). Water resources planning in Zayandehrood river basin. JCE, Tehran, Iran (in Persian).
35. Safavi, H. R., Darzi, F. & Mariño, M. A. (2010). Simulation-optimization modeling of conjunctive use of surface water and groundwater. *Water Resources Management*, Vol. 24, pp. 1965-1988.
36. Rezaei, F., Safavi, H. R. & Ahmadi, A. (2013). Groundwater vulnerability assessment using fuzzy logic: A case study in the Zayandehrood aquifers, Iran. *Environmental Management*, Vol. 51, No. 1, pp. 267-277.
37. Darzi, F. (2007). Conjunctive Management of surface water and groundwater under water scarcity. MSc Thesis, Isfahan University of Technology, Isfahan, Iran (in Persian).
38. Nourani, V., Mogaddam A.A. & Nadiri, A.O. (2008). An ANN-based model for spatiotemporal groundwater level forecasting. *Hydrological Processes*, Vol. 22, 26, pp. 5054-5066.
39. Nourani, V. (2010). Reply to comment on, Nourani, V., Mogaddam, A.A. and Nadiri, A.O., (2008) An ANN-based model for spatiotemporal groundwater level forecasting. *Hydrological Processes*, Vol. 24, No. 3, pp. 370-371.