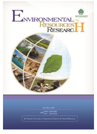

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Derivation of conflict resolution rule-curves in multi-purpose multi-reservoir system for inter-basin water transfer during drought

S. Alahdin*[1], H.R. Ghafouri[2], A. Haghighi[3]

[1]Ph.D. candidate, Department of Civil Engineering, Engineering Faculty, Shahid Chamran University of Ahvaz, Iran.
[2]Professor, Department of Civil Engineering, Engineering Faculty, Shahid Chamran University of Ahvaz, Iran.
[3]Associate Professor, Department of Civil Engineering, Engineering Faculty, Shahid Chamran University of Ahvaz, Iran.

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Abstract

Allocation is the number-one cause of conflict in water resources, whether between sovereign nations, different user groups or neighboring basins. The inter-basin water transfer is a remedy to the negative issues of water shortage in drought-stricken regions. In a water transfer project, the receiving basin always benefits while the donor basin may suffer. In this work, to define an operating policy, a multi-reservoir multi-purpose system is simulated and optimized for a set of long-term historical records. A multi-objective optimization model is developed based on Non-Dominated Sorting Genetic Algorithm (NSGA-II). The optimization results define the best possible performance set for a two-basin system with the objectives of supplied water shortage minimization during droughts. In a multi-objective optimization problem, there is not a single solution that simultaneously optimizes all objectives. However, decision makers are concerned with finding a unique compromise solution that balances conflicting objectives in a socially acceptable manner. The game theory can identify and interpret the behaviors of parties in water resource problems and describe interactions of different parties who give priority to their own objectives, rather than system's objective. Using the strategic form description for different moves or actions available in the optimum trade-off front, Nash equilibrium outcomes predicted by game theory narrow the results suggested by optimization method. In this study, the inter-basin water transfer project from Zohreh multi-reservoir multi-purpose system in southwestern Iran to the Persian Gulf coastal district is investigated using the proposed methodology.

Keywords: Inter-Basin Water Transfer, Conflict Resolution, Rule-Curve, Multi-Objective Optimization, Nash Equilibrium, Quantal Response Equilibrium

*Corresponding author; s-alahdin@phdstu.scu.ac.ir

Introduction

Inter-basin water transfer/diversion, trans-basin diversion of water, inter-river transfer, inter-catchment water transfer, large-scale water transfer and long-distance water transfer are all terms used to describe the man-made conveyance of water from one area to another where the water demand has exceeded, or soon will exceed supply (Zhang et al. 2015). The concept of inter-basin water transfer is not new, strange, or illogical. Historically, water rights have been significant in determining human settlement patterns. The availability of water has always placed a natural constraint on the sustainability of society. Over time, where traditional rain dances, prayer for rain, chants, and cloud seeding have been insufficient to meet accelerated water demand, resource-constrained regions looked to adjacent drainage basins and beyond for water supply needs. The transfer may constrain future development opportunity or inflict environmental damage on the donor basin. Within this context, in this study, a conflict resolution approach between donor and recipient basins is suggested.

Once a conflict has arisen, different individuals and groups have different ways of handling the problem. Some handling styles actually worsen the problem. Seeking to avoid the problem by ignoring it may lead to the conflict becoming more serious and more intractable over time. Choosing to press for victory, may yield short-term gains but is likely to result in long term problems.

A methodology which would fruitfully address the issues and complexities consists of three principal steps, logically executed in the following sequence. Those steps are (Ridgley et al. 1997):

1. Identify stakeholders and structure their concerns into an integrated, criterion hierarchy (here inter and intra-basin water demands);
2. Use these criteria in a multi-criterion optimization model to formulate alternative land and water allocations (in this study simulation-optimization model);
3. Evaluate these alternatives with respect to the integrated, criterion hierarchy (here game theory).

In this paper, different beneficiaries, parties, and sides of the problem are identified and grouped together. Their relevant sources and reasons of benefits and losses due to the inter-basin water transfer problem are determined. After problem description, the multi-purpose multi-reservoir system is simulated, and the multi-objective optimization (NSGA-II) is applied interactively. The derived Pareto front provides a helpful tool for the water resources associations and managers to more carefully and realistically make a decision on the development and operation of inter-basin water transfer projects. Many researchers e.g. Ahmadianfar et al. (2016), Ahmadi najl et al. (2016), Ashofteh et al. (2015), Chu et al. (2015) and Mendes et al. (2015), emphasized on serious trade-off among the water resources management objectives. Now, the big question arises. With all these trade-off solutions in mind, can one say which solution is the best with respect to both objectives? The irony is that none of these trade-off solutions is the best on both objectives (Deb 2001). Pareto efficiency, or Pareto optimality, is a state of allocation of resources in which it is impossible to make any one individual better off without making at least one individual worse off (Wikipedia contributors 2018).

Systems optimality methods that select the Pareto-optimal decision as the solution may not result in the most stable decision because cooperation (group rationality) is not necessarily a stronger driving force than individual benefits (individual rationality). Stability analysis in water allocation negotiations leads to a different rule selection than optimization, and both are important for assessing possible allocation solutions (Read et al. 2014). Therefore, the final stage would be the selection of the best among all Pareto optimal solutions. Kerachian et al. (2007), Shirangi et al. (2007) and Bazargan-Lari et al. (2009) used a variety of game theory (Young Conflict Resolution Theory) to select the best solution among a selection of points on the optimal curve trade-off set with the addition and assumption of utility functions for each objective.

Recent theoretical advances have dramatically increased the relevance of game theory for predicting human behavior in interactive situations. The Quantal Response Equilibrium (QRE) introduced by McKelvey and Palfrey (1995), provides a general framework to extend the probabilistic choice approach to the case of multiple decision-makers. The basic idea behind QRE is that players are "better responders" rather than best responders, and they are aware that others are better responders. In other words, QRE imposes a consistency condition on players' beliefs about others' noisy behavior. That is, individuals are more likely to select better choices than worse choices (Goeree et al. 2005). The logistic Quantal Response Function has one free parameter λ, whose inverse 1/λ has been interpreted as the temperature, or the intensity of noise. At λ = 0, players have no information about the game and each strategy is chosen with equal probability. As λ approaches infinity, players achieve full information about the game and play the best response. McKelvey and Palfrey then defined an equilibrium selection by "tracing" the branch of the logit equilibrium correspondence starting at the centroid. For almost all games, this branch limits to a unique Nash equilibrium as λ goes to infinity (Zhang et al. 2012). Neri (2014), Jessie et al. (2015), Zhang et al. (2016) and Zhang (2016) tested and confirmed capabilities of Quantal Response Equilibrium (QRE) in finding unique preferred Nash equilibrium in different games. In fact, QRE is a generalization of Nash equilibrium, which converges to the Nash equilibrium as the quantal response functions become very steep, and approximate best response functions. This approach provides a useful theoretical framework for looking at comparative statics effects of parameter changes that may not alter Nash predictions (Goeree et al. 2005). Therefore, a novel Quantal Response Equilibrium method is used in this study for water resources management to derive a stable Nash solution among all Pareto-optimal solutions with no more introduction of information.

Case study and problem

In the social sciences, a group has been defined as two or more players who interact with one another, share similar characteristics, collectively have a sense of unity and stress the importance of interdependence or objective similarity. Early water management focused on supply-side management through the expansion of water infrastructure systems and acquisition of new sources to meet needs. Due to population growth, urbanization, and climate change, water supplies have become increasingly stressed, and water utilities have turned to demand-side management through implementation of water conservation activities. Since this approach leads to more pressure on donor group resources, water transfer problem here and more generally water management problems must be integrated with both supply-side and demand-side management approaches. In this section, these two sides are distinctively grouped.

As a case study, an inter-basin water transfer from drought-stricken Zohreh river system in south-western Iran with an area of 15460 km^2 to Persian Gulf coastal provinces is used. The schematic configuration is shown in Figure 1. The system comprises three reservoirs, eight input stream flows, thirteen irrigation networks, three public demands, two minimum flows and two hydropower plants. The conservation storage volumes for Kosar, Chamshir, and Kheirabad reservoirs are 418, 1862, and 105 million cubic meters, respectively (Table 1).

Table 1. Properties of hydropower plants

Properties of dam	Chamshir	Kosar	Kheirabad
Normal level (meter above sea level)	598	625	259.6
Minimum level of operation (meter above sea level)	543.7	580	238
Volume storage in min. level (mcm)	454.5	74.2	0.93
Volume storage in normal level (mcm)	2316.7	492.8	106.3
Installed capacity (Mega Watt)	165	-	2.5
Plant factor (%)	25	-	-
Plant efficiency (%)	91	-	85
Maximum turbine flow (cms)	144.4	-	7.26
Hydropower operation head (m)	128	-	41.3

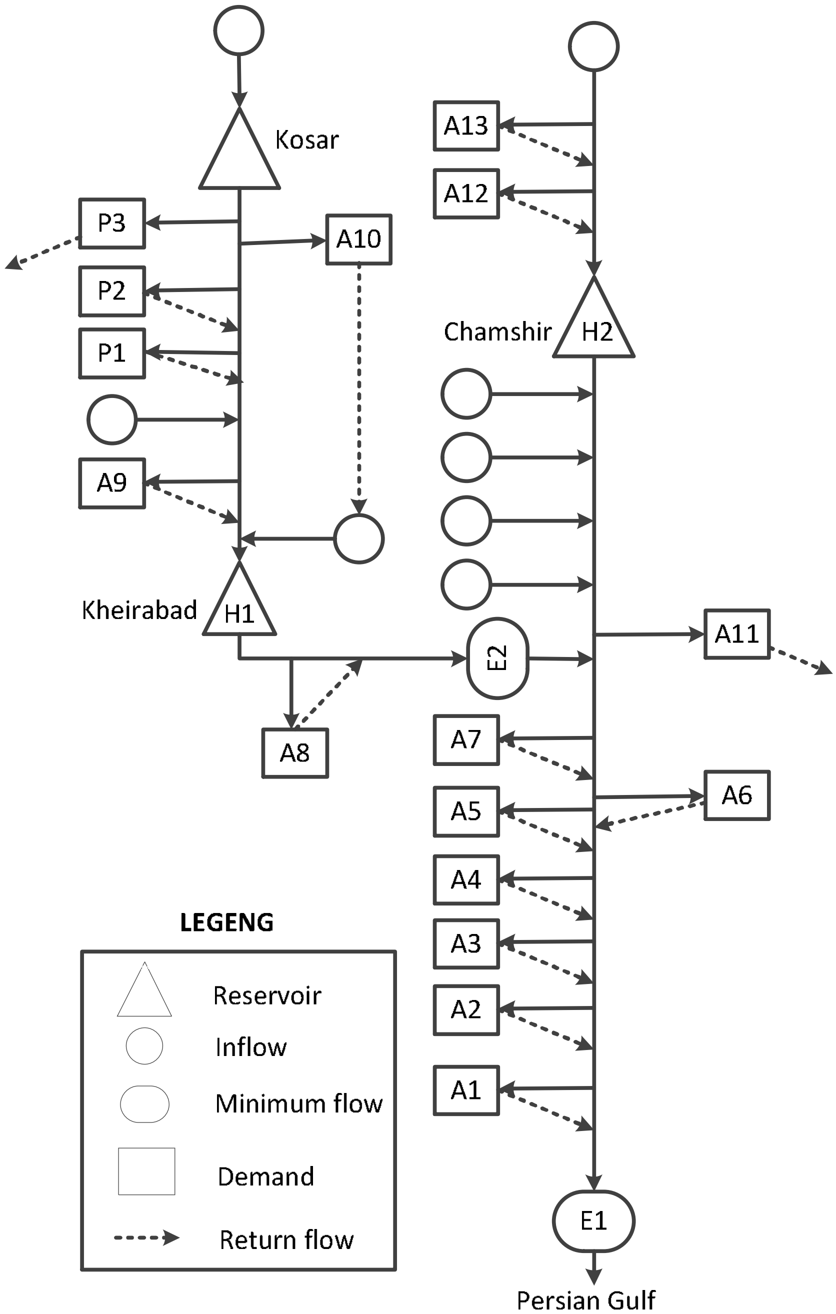

Figure 1. Schematic configuration of the water supply system

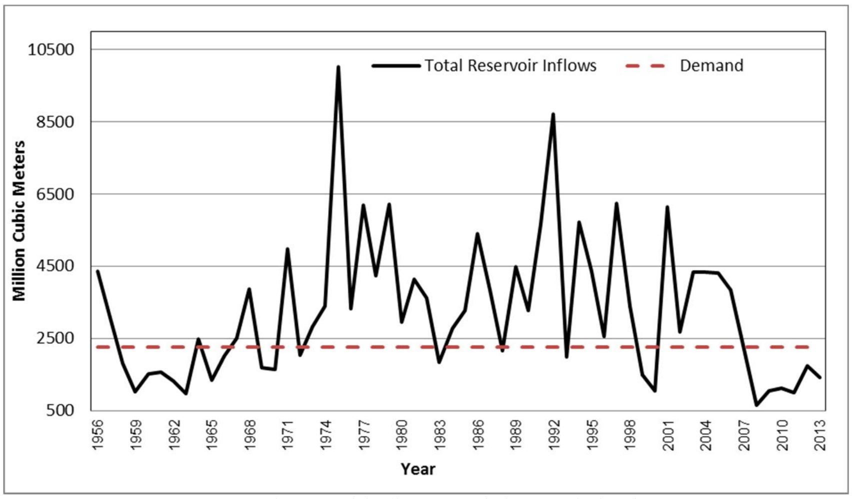

Figure 2. Total annual inflows and demands in the system

The total annual inflow to the reservoirs (sum of all reservoirs' inflows) and the total system demand are depicted in Figure 2. The average value for total annual inflow time-series is 3247 mcm and the average value for the last 7-year (2007-2013) is 1330 mcm. Comparison of this parameter with the total demand reveals two long periods of droughts in the initial and the last stages of the time-series. Because of the importance, the discussion and the focus of this study would be on the current event.

Target values for demands are given based on the planned water demand for the future horizon (2259 million cubic meters), distributed as 73% for agriculture, 16% for the minimum flow, and 11% for public demands as a whole. These demands are grouped by two intra- and inter-basin classes (Tables 2 and 3).

Table 2. Characteristics of intra-basin demands

Demand title	Type	Annual demand (mcm)
A1	Agriculture	20
A2	Agriculture	480
A3	Agriculture	60
A4	Agriculture	77
A5	Agriculture	49
A6	Agriculture	138
A7	Agriculture	114
A8	Agriculture	28
A9	Agriculture	38
A10	Agriculture	48
A12	Agriculture	101
A13	Agriculture	132
P1	Public	32
P2	Public	10
E1	Minimum flow	315
E2	Minimum flow	41
H1	Hydropower	-
H2	Hydropower	-
SUM		1683

Table 3. Characteristics of inter-basin demands

Demand title	Type	Annual demand (mcm)
A11	Agriculture	365
P3	Public	210
SUM		575

In addition to optimizing water allocation in an inter-basin water transfer problem, this work aims specifically at mitigating the drought consequences in reservoir systems. The objective is to alleviate the effects of shortage in supply by rationally distributing it in a longer horizon. There are 76 decision variables including rule curves and hedging factors. The objective functions are the minimization of modified shortage indices for both groups. The performance constraints e.g. rationing rule-curve attributes are added in the constraint handling procedure of optimization algorithm. Physical constraints, mass balance, performance constraints and hedging rules are the main components that are included. Since these variables are to be optimized, the problem is quite complex and requires a proper statement to be described and procedure to be solved. To this end, a multi-objective optimization algorithm is coupled with a standard simulation model (Figure 3). All physical constraints like the maximum dam release, reservoir storage, and channel capacity are handled in the general simulation model. To evaluate the long-term performance of reservoir system operation, 58-year (from 1955 to 2013) time-series of monthly inflows are used, resulting in a total of 696 months. Since the multi-objective optimization results in a set of optimum outcomes, another procedure is adopted to prescribe the final rule curves and hedging factors. Negotiation and conflict resolution between two groups were modeled with Game theory.

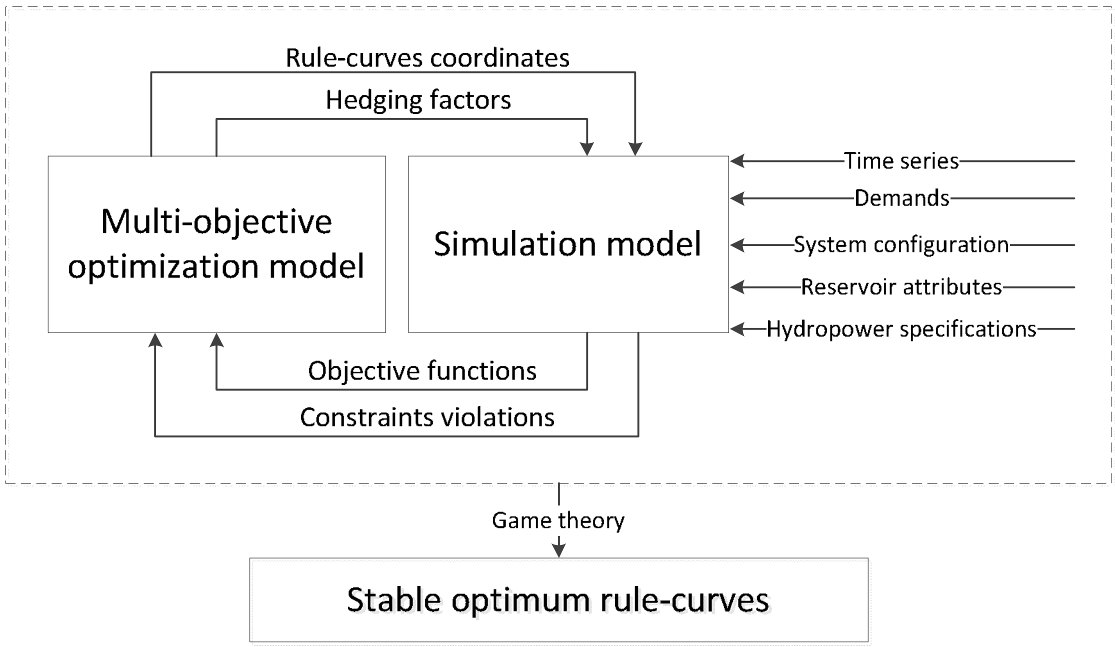

Figure 3. Conceptual model of the study

The simulation-optimization model

After construction of large-scale water storage projects, attention must be on improving the operational effectiveness and their efficiency for maximizing the beneficial uses. Optimal coordination of the many facets of reservoir systems requires the assistance of computer modeling tools to provide information for rational management and operational decisions. A simulation-optimization model was developed in this study as the framework for drought management in the multi-purpose multi-reservoir system (Figure 4). WEAP is linked to the multi-objective genetic algorithm, and the hedging rule is included.

Since the computation time of each simulation run plus data exchange with optimization model takes about 35 seconds, the whole hybrid model composed of 76 parameters including 2 rule curves for each of 3 dams plus 2 hedging coefficients for each basin takes about 2 weeks to reach the optimum decision variables set (the population size is set to 104).

This section describes the theoretical foundation of simulation and optimization models, the objective function, constraints and trigger values. To verify the effectiveness of the optimization model, the simulation results are provided in the result section.

Simulation Model (WEAP)

Reservoir simulation model is based on the continuity of reservoir water release to meet the needs of water users as well as hydropower. WEAP calculates water mass balance for every node and link in the system on a monthly time step. Water is dispatched to meet instream, consumptive and hydropower requirements subjected to demand priorities, supply preferences, mass balance and other constraints. A linear program is used to maximize the satisfaction of needs for demand sites; user specified instream flows and hydropower generation in each time step. Every link and node in WEAP has a mass balance equation, and some have additional equations which constrain their flows like minimum environmental flow (Sieber et al. 2011).

Implementing hedging rules in the simulation model adds three constraints (the following logics and mathematical formulations 1, 2 and 3). When drought occurs, the inflow may not be sufficient to keep the storage level (level and storage in the reservoir could be used interchangeably) above the target storage curve if the target delivery is met at 100%. Releasing currently available water from the reservoir to fully supply the target delivery may jeopardize future water supply. Thus, hedging is introduced to reduce the current reservoir release, and retain an adequate amount of water in storage for future use. When the beginning reservoir storage level is above the firm storage and below the target storage (in the first hedging zone), the reservoir releases water to meet the first phase of hedging ($\alpha_1 Demand$). For severe droughts, when the beginning reservoir storage is below the firm storage curve (in the second hedging zone), less water is released from the reservoir to meet the second phase of hedging ($\alpha_2 Demand$).

$$\text{if } S_t \notin (\text{Zone}_1 \text{ And Zone}_2) \text{ Then Demand} = \text{Demand} \times 100\% \quad (1)$$

$$\text{if } S_t \in \text{Zone}_1 \text{ Then Demand} = \text{Demand} \times \alpha_1 \quad (2)$$

$$\text{if } S_t \in \text{Zone}_2 \text{ Then Demand} = \text{Demand} \times \alpha_2 \quad (3)$$

Multi-Objective Optimization Model

The flowchart in Figure 4 provides a "big picture" overview of the simulation-optimization model. In this paper, we have utilized the industry standard and computationally fast elitist multi-objective evolutionary algorithm based on non-dominated sorting approach or NSGA-II.

The Non-dominated Sorting Genetic Algorithm (NSGA-II) was developed by Deb (2002). It is a popular method for multi-objective optimization based on non-dominated sorting and elitist selection. The NSGA-II starts with the generation of a random parent population, and the objective functions are calculated for this population.

Next, the children population is created based on two operators, namely, crossover and mutation, and the objective functions are calculated for the children population. Then, the combined population that includes parents and children is classified into fronts (Front 1 is the best) based on a ranking process called non-dominated sorting. Afterwards, the crowding distance is computed for the members of each front and these members are sorted based on the crowding distance. Finally, after the classifying and sorting process, the combined population is truncated in the same manner as the parent population, and the new population is ready to generate a children population for the next iteration.

Objective Functions

In the past, many objective functions have been proposed and used, but the most used indices are Shortage Index (SI) and Modified Shortage Index (MSI). The shortage index (SI) was introduced by the U.S. Army Hydrologic Engineering Center (HEC 1966, 1975). Because the SI index is the average of the annual deficit rate squared, the deficit frequency and intensity are incorporated in the index. This point also makes the optimization problem convex and much easier to spot the global minima in the search space topology. To characterize the extremely uneven distribution of the hydrologic conditions, a modified shortage index (MSI) is defined as the following for both basins:

$$MSI_{intra-basin} = \frac{100}{n}\sum_{t=1}^{n}\left(\frac{TS_t}{TD_t}\right)^2 \quad (4)$$

$$MSI_{inter-basin} = \frac{100}{n}\sum_{t=1}^{n}\left(\frac{TS_t}{TD_t}\right)^2 \quad (5)$$

where TS_t is shortage in *t*th period; TD_t is demand in *t*th period; and n is the number of periods (Hsu 1995).

For energy production, the success or failure in each time step is evaluated based on the installed capacity of the hydropower plant. When the generated energy or the equivalent minimum volume of water discharge considering plant factor and minimum operation head, in that period is less than the installed capacity, a failure is counted. Then the deficit would be the difference between the turbine flow and the flow requirement to generate energy up to the installed capacity standard (Ahmadi najl et al. 2016).

Constraints

To make the derived rule-curves meet the operational and real situation standards, two points must be noticed. First of all, the maximum difference between two consecutive operating reservoir storage targets (rule-curve coordinates) must not be more than a defined value (Suen et al. 2006). This is because refilling and emptying a reservoir and fluctuations in reservoirs in the real world follow a supply-demand pattern and its configuration could not be scattered. In mathematical expression, this could be written as,

$$|S_t - S_{t-1}| \leq S_{allowed} \quad (6)$$

where S_t and S_{t-1} are two consecutive operation rule-curve components (storage or trigger value here), and $S_{allowed}$ is the maximum allowable difference. Second, because at the end of the water year and the start of the new one, no significant hydrologic and demand changes are expected to take place in the basin, it is not logical that the difference between the first and the last components of a rule-curve be noticeable. Therefore, the second constraint would be written as follows:

$$(1 - small\ number) \times S_{first} \leq S_{last} \leq (1 + small\ number) \times S_{first} \quad (7)$$

Also, two other points are considered in the algorithm. First, since no project can survive with less than 20% of its demand supplied and on the other side, there is no point in rationing with supply more than 80% of the demand, practical and operational view tells that the hedging coefficient cannot be less than 20 or greater than 80 percent. Although in theory allocation outside this range is possible. Second, lots of trial and errors with the simulation-optimization model have shown that two rule curves for each dam reservoir may cross each other. Therefore a mechanism must be devised to solve this issue. To do this in the optimization routine after mutation process, the values of the second hedging rule-curve were checked and forced to be less than the first phase (Figure 4).

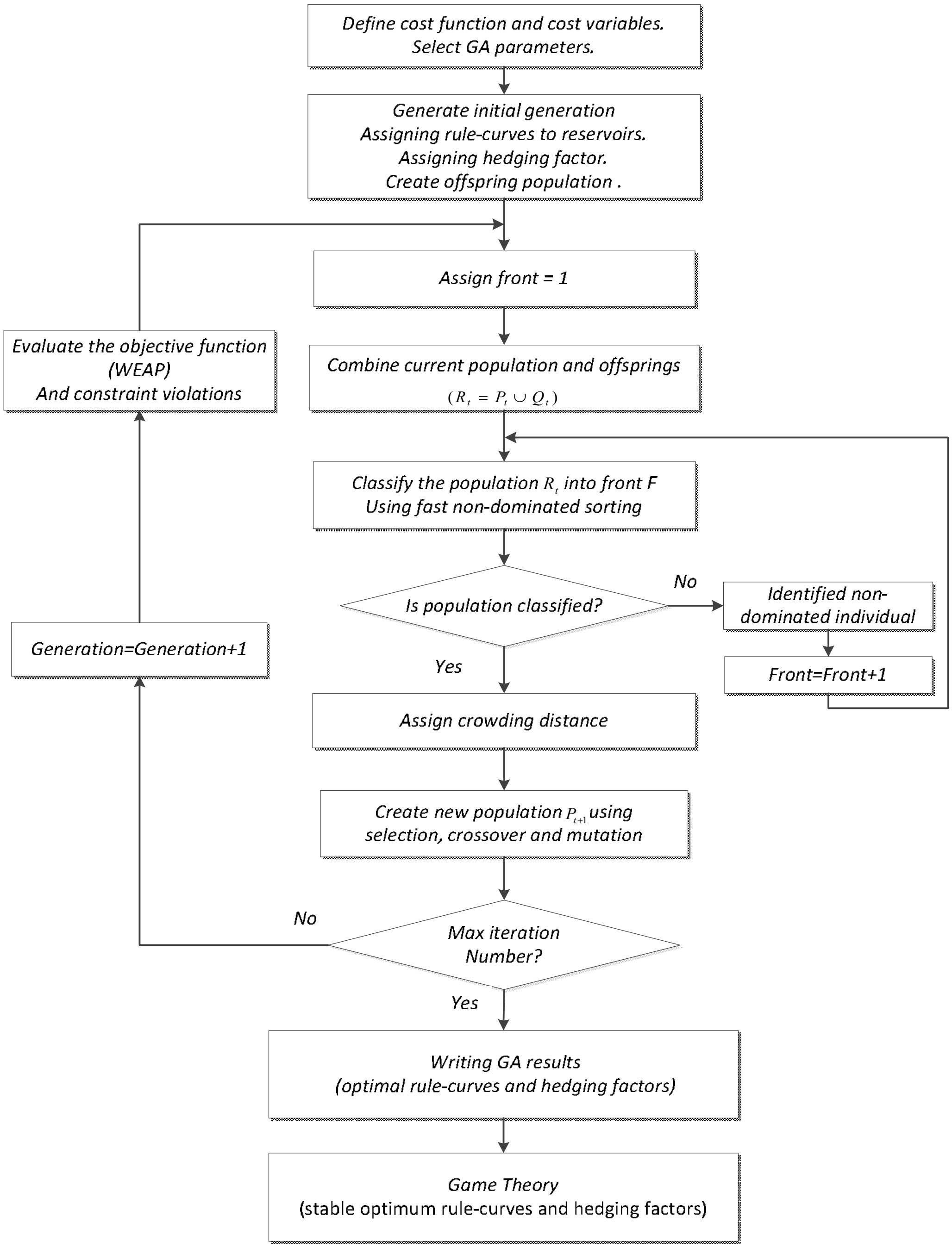

Figure 4. Flowchart of the proposed model

Game theory

Managing water resources systems usually involves conflicts. Behaviors of stakeholders, who might not be willing to share result in worse conditions for all parties. Outcomes predicted by game theory often differ from results suggested by optimization methods which assume all parties are willing to act towards the best system-wide outcome. The former is about what is good for an individual without considering what is good for the whole system and the latter is about what is good for the system without considering the interests of the individuals within the system. Game theory is the formal study of conflict and cooperation. Game theoretical concepts apply whenever the actions of several agents are interdependent. These agents may be individuals, groups, firms, or any combination of these. The concepts of game theory provide a language to formulate, structure, analyze, and understand strategic scenarios. In a game in strategic form, a strategy is one of the given possible actions of a player. A payoff is a number, also called the utility, that reflects the desirability of an outcome to a player, for whatever reason. A Nash equilibrium, also called strategic equilibrium, is a list of strategies, one for each player, which has the property that no player can unilaterally change his strategy and get a better payoff.

So far in this study, the multi-objective optimization leads to a set of Pareto-optimal results (the Pareto-optimal number of results is equal to the population). However, the most challenging and important question, which one of these is the expected and stable final result?, remains unanswered. Application of usual and conventional methods revealed that all of these nodes are also Nash equilibriums. Therefore in this study, a novel (in water resources management) and probabilistic Quantal Response Equilibrium (QRE) method to predict the expected "move" or action of players is adopted.

Probabilistic choice models (e.g., logit, probit) have long been used to incorporate stochastic elements into the analysis of individual decisions, and the Quantal Response Equilibrium (QRE) is the similar way to model games with noisy players. These probabilistic choice models are based on Quantal Response Functions, which have the intuitive feature that deviations from optimal decisions are negatively correlated with the associated costs. That is, individuals are more likely to select better choices than worse choices but do not necessarily succeed in choosing the very best option.

Quantal Response Equilibrium

The term "learning" means different things to different people. The learning process in QRE is close to what some economists call "learning by doing." However, this procedure does not model the detailed mechanics of learning. Player i calculates the expected payoff but makes calculation errors according to some random process. An alternative interpretation is that players calculate expected payoffs correctly but have an additive payoff disturbance associated with each available pure strategy.

The original definition of QRE (McKelvey and Palfrey 1995) adopts an approach in the spirit of Harsanyi (1973) and McFadden (1976) whereby the choice probabilities are rationalized by privately observed, mean zero random disturbances to the expected payoffs. These disturbances are assumed to be private information to the players, thereby converting the original game into special kind of game of incomplete information. Any Bayesian equilibrium of this disturbing game is a QRE of the underlying game. The quantal response function generating the QRE is determined by the probability distribution of the random payoff disturbances. In an individual choice problem, the addition of "noise" spreads out the distribution of decisions around the expected-payoff-maximizing decision. In contrast, expected payoffs in a game depend on other players' choice probabilities, and this interactive element can magnify the effects of noise via feedback effects.

Gambit model computes a branch of the logistic quantal response equilibrium correspondence for n-person normal form games as described in McKelvey *et al.,* 1995. The notations in the following are adopted from McKelvey and Palfrey (1995). Consider an n-person normal (strategic) form game $\Gamma = (N, S, u)$, where $N = \{1, \dots, n\}$ is the set of players. For each player $i \in N$, there is a strategy set $S_{i=}\{s_{i1}, \dots, s_{i1J_i}\}$ consisting of J_i pure strategies and a payoff function, $u_i: S_i \to \mathbb{R}$, where $S = \prod_{i \in N} S_i$ is the set of strategy profiles.

For any given $\lambda \geq 0$, the logistic quantal response function is defined, for $x_i \in \mathbb{R}^{J_i}$, by:

$$\sigma_{ij}(x_i) = \frac{e^{\lambda x_{ij}}}{\sum_{k=1}^{J_i} e^{\lambda x_{ik}}} \quad (8)$$

where j is action or strategy, i player, ε error vector, u payoff function, and σ is statistical reaction function or quantal response function.

Moreover, the formula regards the optimal choice behavior if f_i (density function) has an extreme value distribution, with cumulative density function $F_i(\varepsilon_{ij}) =$

$e^{-e^{-\lambda\varepsilon_{ij}-\gamma}}$ (where γ is Euler's constant) and ε_{ij}'s are independent. Therefore, if each player uses a logistic quantal response function, the corresponding QRE or Logit equilibrium requires, for each i, j to be:

$$\pi_{ij} = \frac{e^{\lambda x_{ij}}}{\sum_{k=1}^{J_i} e^{\lambda x_{ik}}} \quad (9)$$

where $x_{ij} = \bar{u}_{ij}(\pi)$.

For the logistic response function, we can parameterize the set of possible response functions σ with the parameter λ, which is inversely related to the level of error: $\lambda = 0$ means that actions consist of all errors, and $\lambda = \infty$ means that there is no error (λ increases with learning). We can then consider the set of Logit equlibria as a function of λ. It is obvious that when $\lambda = 0$, there is a unique equilibrium at the centroid of the simplex. In other words, $\pi_{ik} = 1/J_i$ for all i, k. On the other hand, when $\lambda \to \infty$, the following result shows that the Logit equilibria approach Nash equilibria of the underlying game. In Table 4, the configuration of a game of two basins as players and the pareto-optimal set as their payoffs is illustrated.

Table 4. Normal description of game (player 1= donor basin, player 2= receiving basin, payoff= objective value of MSI from simulation-optimization model, matrix dimension= Actions available for Player 1× Actions available for Player 1)

Strategic game		Player 1 (intra-basin)						
		Action 1		Action 2		Action 3		…
Player 2 (inter-basin)	Action 1	Payoff 1	payoff 2	×	×	×	×	…
	Action 2	×	×	Payoff 1	payoff 2	×	×	…
	Action 3	×	×	×	×	Payoff 1	payoff 2	…
	…	…	…	…	…	…	…	…

Results

The Quantal Response Equilibrium notion can be viewed as an extension of standard random utility models of discrete choice, or as a generalization of Nash equilibrium that allows noisy optimizing behavior while maintaining the internal consistency of rational expectations (Haile *et al.,* 2008). Application of this procedure to the normal game is presented in Table 4. As λ approaches infinity, players choose the best responses and the correspondence converges to a subset of the Nash equilibria. It is revealed that the 23rd action (for both players) among all of the trade-off set points is the expected and the stable equilibrium (Figures 5 and 6).

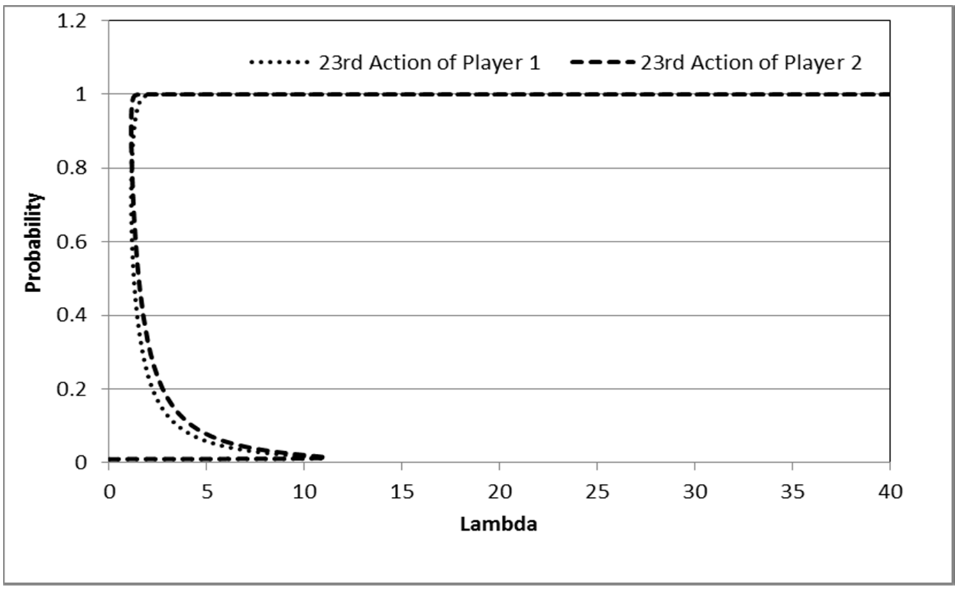

Figure 5. Learning process in QRE

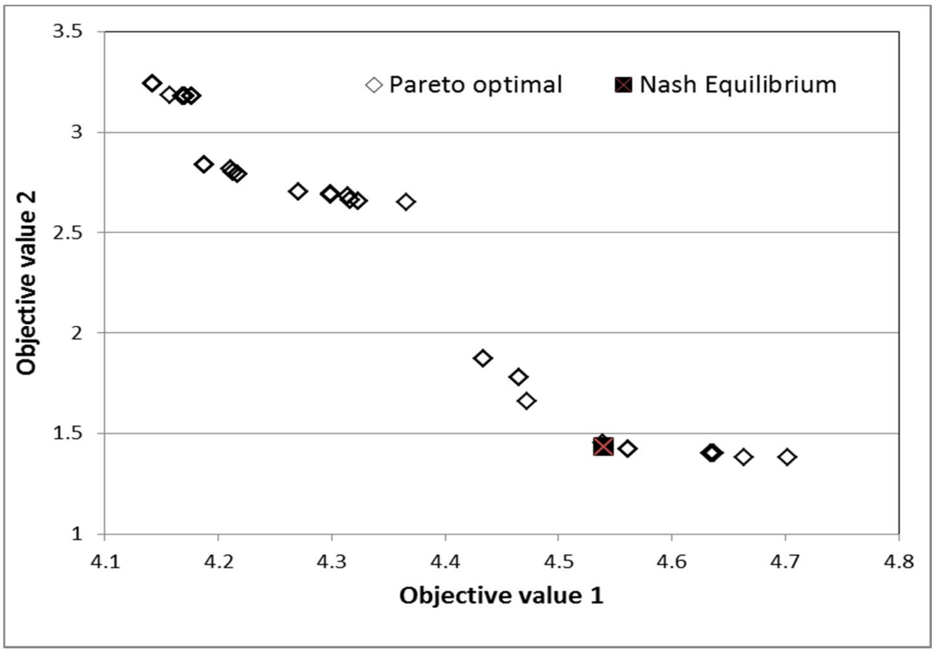

Figure 6. The stable optimum rule-curve

Table 5. Long-Term System Performance during the Period 1955–2013

Index	donor	receiving
SOP (MSI)	6.21	2.31
Optimum (MSI)	4.54	1.43
Hedging factor 1	77.4	44.9
Hedging factor 2	38.9	44.9

SOP and the selected rule system operation performances for the donor and receiving basins are compared in the following Tables (5 and 6) and Figures (7 and 8); which display the long-term system performance and the annual system performance during recent failure years.

The optimum rationing factors are shown in Table 5. According to the planned policy in the studied area, the rationing factors for all types of demands are considered the same. Comparing the two scenarios, it is indicated that total MSI values are improved respectively by 36% and 61% for donor and receiving basins by the proposed method.

The objective function values for the recent drought (Table 6) show that the maximum value of MSI is reduced in two groups of users. This point means that the proposed drought management is working well.

Table 6. Objective function value for two basins in recent drought

Year	Optimum		SOP	
	Intra	Inter	intra	inter
2007	0.19	2.54	1.02	0.67
2008	4.71	18.43	3.39	2.57
2009	34.79	9.11	39.07	18.29
2010	14.01	21.781	38.65	12.70
2011	29.71	2.20	44.09	23.85
2012	7.98	4.47	17.28	3.47
2013	8.22	2.54	26.86	6.02
Max	34.79	21.78	44.09	23.85

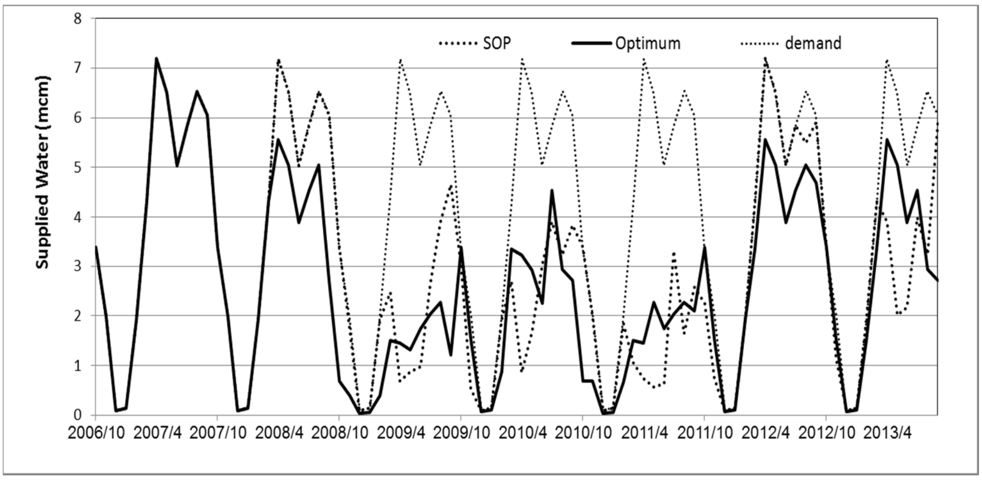

Figure 7. Supplied water for the A5 project (intra-basin)

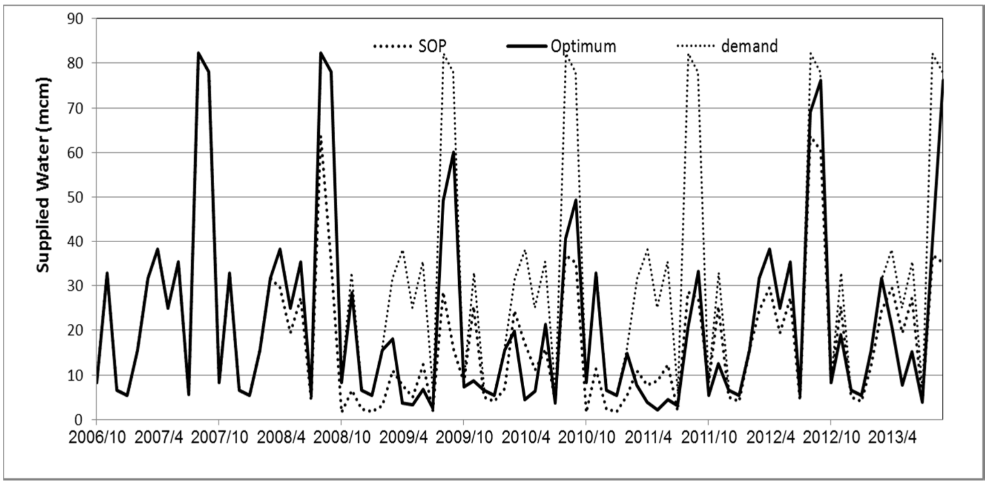

Figure 8. Supplied water for the A11 project (inter-basin)

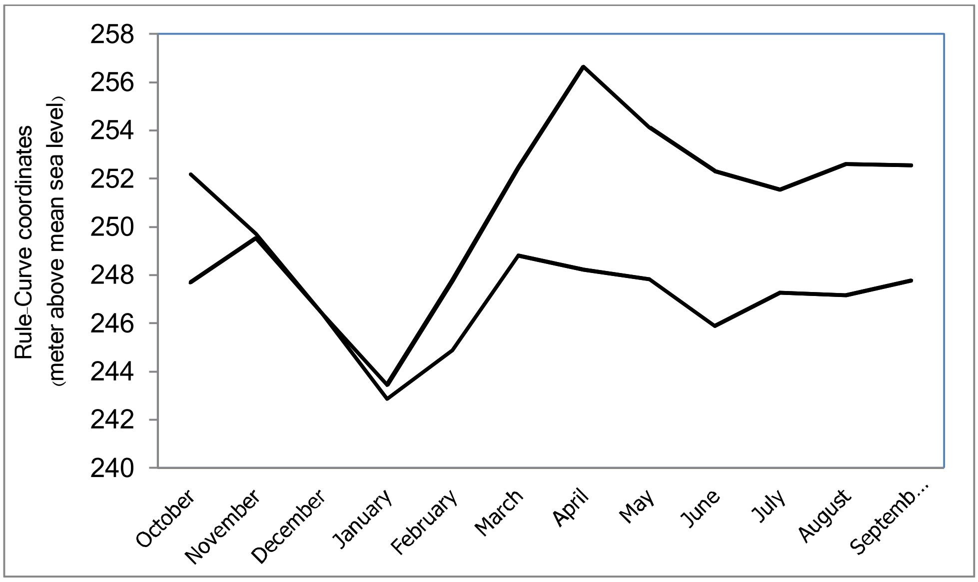

Figure 9. Optimal rule-curves for Kheirabad Reservoir

For A5 and A11 projects which are located respectively in Zohreh system downstream and neighboring basin, the details of operation performance (water supplied) are illustrated for SOP and optimal rule curves. Figures 7 and 8 depict the monthly time series of the supplied water to the A5 and A11 projects. These figures graphically show the superiority of the new routine.

Optimal rule-curves coupling to hedging rules for Kheirabad, Kosar, and Chamshir reservoirs are shown in Figs. 9–11. Trigger levels of the reservoir are optimized for management during droughts.

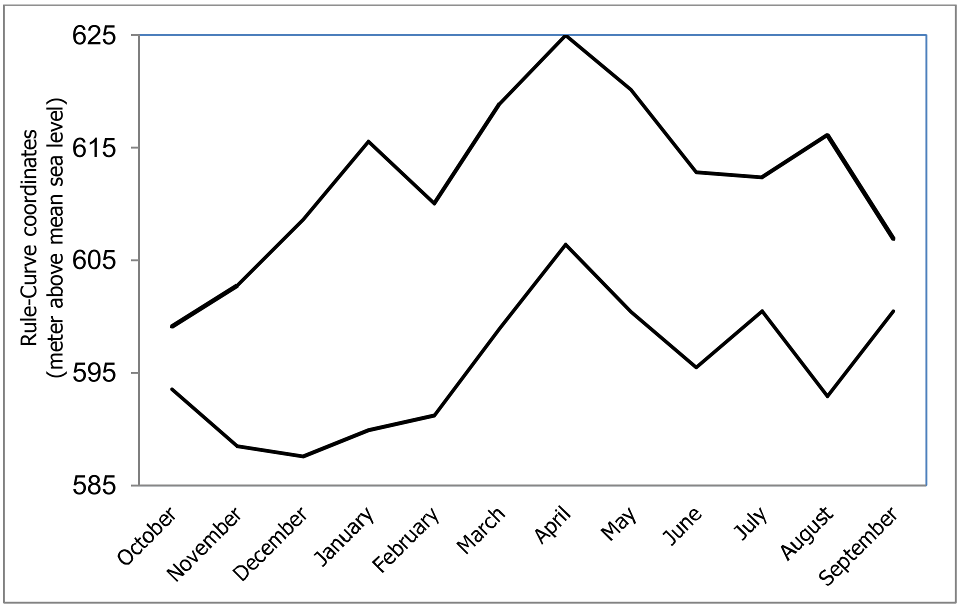

Figure 10. Optimal rule-curves for Kosar Reservoir

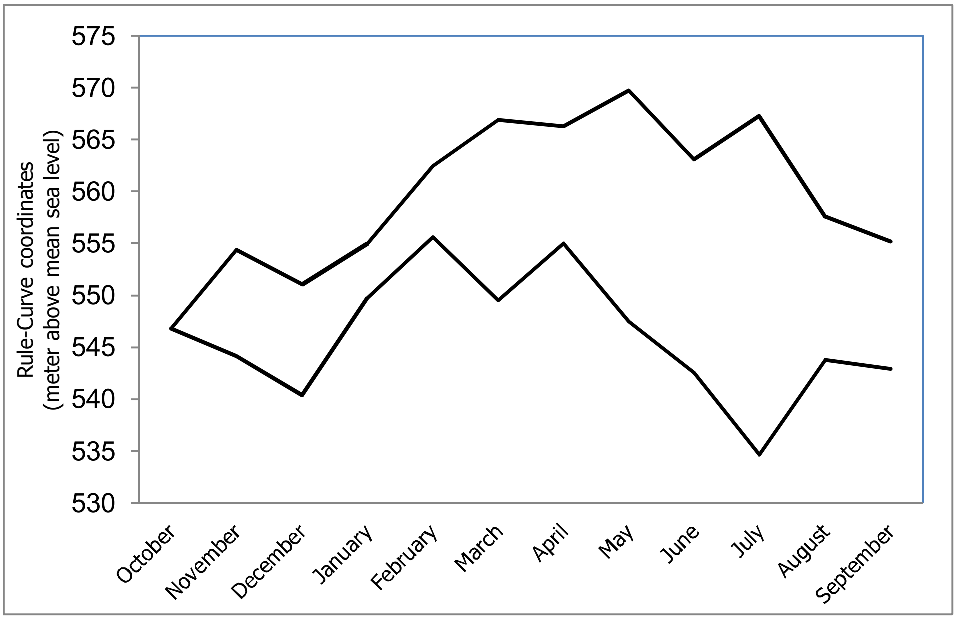

Figure 11. Optimal rule-curves for Chamshir Reservoir

Conclusion

Conflict is a process that begins when an individual or group perceives differences and opposition between oneself and another individual or group about interests and resources, beliefs, values or practices that matter to them. It is generally acknowledged that water resources of all types are under increasing pressures from some actors, forces and factors manifest in the early 21st Century world (WWDR, 2006). In this study, a set of conflict resolution rule-curves in the multi-purpose multi-reservoir system for inter-basin water transfer during drought is derived using simulation-multiobjective optimization model. In this set, there exists a serious trade-off between two objectives. Cooperation and negotiation, emphasizing the similarities and reducing dissimilarities will help to solve decision problems. Compromising is necessary when goals are clearly incompatible and mutually exclusive, decision makers have equal power, and partial satisfaction may be better and feasible. In negotiations, the parties realize the potential of a compromise and can assess main features of the agreement established by mutual concessions (Serafim Opricovic 2009). The intention of this study was to provide the general and specific tools in a user-friendly way so that any water resource researcher may be able to resolve existing or impending disputes over inter-basin water transfer in a way agreeable to all parties. Therefore, the Game theory was applied to the optimal set resulted from the hybrid WEAP-NAGA II model as input data for two players. In a strategic game environment, a player's expected payoffs from different strategies are determined by beliefs about other players' actions, so beliefs determine expected payoffs, which in turn, generate choice probabilities according to some quantal response function. Quantal response equilibrium (QRE) imposes the requirement that the beliefs match the equilibrium choice probabilities. Thus, QRE requires solving for a fixed point in the choice probabilities, analogous to the Nash equilibrium. To determine the expected payoffs for all the available 104 actions of two players or basins, the system simulation model is developed according to the aforementioned operating conditions. As explained through the methodology, two rule curves were introduced to each reservoir resulting in three operating zones for each month of the year. As a consequence, there were totally 76 decision variables consisting of 72 rule curves coordinates and 4 hedging coefficients for two-basin and three-reservoir system.

The graph of QRE (Figure 5) generically includes a unique branch that starts at the centroid of the strategy simplex and converges to a unique Nash equilibrium as noises vanish (Boyu Zhang 2016).

This paper used the establishment of existence and uniqueness of Quantal Response Equilibrium (QRE) in a double auction introduced by Neri (2014). To review, each agent attempts to optimize personal payoffs, where the set of options available to an agent is determined by the other players' choices. A Nash point is where each player's decision (which affects what other players can do) defines an optimal personal value. This ''personally optimal'' property creates a sense of stability because it is to a player's disadvantage to unilaterally change strategy (D.T. Jessie, D.G. Saari, 2015).

The resulted stable optimum rule-curve comparison with SOP showed good performance for the whole proposed procedure.

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