Multiple-Use Water Resources Management By Using Fuzzy Multi-Objective Heuristic Optimization Methods: An Overview

André A. Keller

Abstract— Environmental management and planning problems cover important real life areas. These problems may include the scarcity of groundwater resources, the optimality of a multi-reservoir system, the management of forest resources, the air quality monitoring networks, the municipal solid waste policies. Management and planning targets by authorities consist in allocations at appropriate places and times, protection from disasters, maintenance of quality (e.g., water quality, water pollution control, nitrate concentration diminishing), sustainable development of the groundwater resources. The formalization of such optimization problems includes multiple objectives and constraints. The multiple objectives consist in maximizing/minimizing of various aspects of environmental management (e.g., maximizing irrigation releases, maximizing the hydropower production, maximizing net returns, minimizing costs, minimizing the investment in water development, minimizing groundwater quality deterioration.) [1]. Physical, biological, economic and environmental constraints are notably the constraint of surface water balance, water supply constraints, water quality constraints, economic constraints (e.g., demand, resource costs), reservoir storage constraints. The eco-environmental objectives are often conflicting (e.g., the optimum use of water resources under conflicting demands). The use of multi-objective optimization allows a simultaneous treatment of all the objectives and constraints. The solutions take the form of non-dominated Pareto solutions, which enable the decision makers to study the tradeoffs between the objectives (e.g., between profitability and risk). Most of the environmental domains are faced to uncertainties due to variabilities (e.g., climate, rainfalls, hydrologic variability, environmental policy, markets), imprecisions and lack of data, vagueness of judgments by decision makers. These uncertainties lead to extending the analysis to fuzzy environments. This presentation introduces to the multiple-use water resources management by using heuristic optimization methods in a fuzzy environment where the decision makers have vague objectives. Most of the case studies are on river basins and dams in China.

Keywords— *multi-objective optimization, niched Pareto genetic algorithm, fuzzy objectives, water resources planning, river basins in China.*

A. A. Keller is with the Laboratoire d'Informatique Fondamentale de Lille (LIFL)/ Section SMAC (UMR8022:CNRS) of the Université de Lille 1 Sciences et Technologies, Cité Scientifique, 59100 Lille, FRANCE; e-mail : andre.keller@ univ-lille1.fr.

I. Introduction

THIS paper introduces to the environmental management and planning problems by using evolutionary[1] multi-objective optimization algorithms[2]. Natural genetic and natural selection based algorithms (GA's) belong to this class of methods and consist in search procedures[3]. GA's are flexible and effective methods for solving complex real life optimization problems. GA's have been adapted to multi-objective optimization problems where all objectives are optimized simultaneously and where a Pareto front of optimal solutions is approximated (e.g., the tradeoff between the sustainability of groundwater use and economic development [4]).

Evolutionary methods have been used to solve large scale real world eco-environmental problems. Such problems are, for example, the irrigation management of water resource (i.e., determining optimal crop patterns and allocating irrigation water resources). Other problems were analyzed in the literature such as the optimization of multi-reservoir systems for hydropower and irrigation purposes (e.g., in Reddy and Kumar, 2006 [5]), for water quality management, for forest planning. This study is focused on water resources management[4], with applications using mostly GA's. An example problem is drawn from Xevi and Khan, 2005 [8] to illustrate the technical pattern of such formulation. The case studies in this paper focus on water resources management

[1] Evolutionary approaches refer to search optimization algorithms inspired by the process of natural evolution. They include evolutionary programming, evolution strategies, genetic algorithms and genetic programming.

[2] This paper is an extended version of the Conference Paper 70901-133 presented by Keller [1] at the WSEAS/NAUN World Congress in Nanjing, China, November 17-19, 2013.

[3] A bees algorithm has been also proposed by Tapkan *et al.*, 2013 [2] for solving multiple objective problems. It is a swarm based optimization algorithm inspired by the foraging behavior of honey bees. An ant colony algorithm (ACO) was proposed by Jalali and Afshar, 2005 [3] for engineering optimization.

[4] In the literature, other multi-objective environmental applications are with energy problems, solid waste management, air quality, fisheries management, agricultural land use, etc. The book by Loucks and Van Beek [6] is devoted to the simulation and optimization models for water resources systems planning and management. The authors show how the fuzzy optimization can be applied to water allocation, reservoir operation and pollution control problems. Kindler [7] formulates an extended fuzzy allocation model for water resources planning.

problems, such as with Shiyang River and Hai River basin in China, and groundwater management in the arid countries of the Arabian Peninsula[5].

Uncertainties are notably in water resources data and planning decisions. They are due to numerous factors, such as, lack of information, inexact or imperfect data, statistical estimation errors, imprecisions, vagueness of qualitative judgments by the decision makers (DM's). For this context, fuzzy optimization techniques have been developed in water resources [14]-[15]. Fuzziness in multi-objective optimization problems may be aspiration values of the objectives, limit values for resources in the constraints with tolerance threshold, fuzzy coefficients in the objectives and constraints.

II. MULTI-OBJECTIVE OPTIMIZATION

A. Nonfuzzy Multi-Objective Optimization

The classical maximizing linear programming (LP) problem states

$$\text{maximize} \;\; z = \mathbf{c}^T \mathbf{x}, \;\; \left(\mathbf{c}, \mathbf{x} \in \mathbb{R}^n\right) \text{ s.t. } \mathbf{x} \in X$$

where the feasible region $X = \left\{ \mathbf{x} \in \mathbb{R}^n \,\middle|\, \mathbf{A}\mathbf{x} \le \mathbf{b}, \, \mathbf{x} \ge \mathbf{0} \right\}$ with $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$, $\mathbf{x} \in \mathbb{R}^n$ is defined by all the constraints. The method consists in three main aspects. The first aspect is the formulation and the solution of multiple objective programming problems. The second aspect is the determination of the so-called Pareto solution by using the basic principles of genetic algorithms (GAs). In the third aspect, two additional genetic operators are introduced to preserve the diversity of the optimal solutions.

1) *Multiple objective problem formulation and solution*. In practice, the DM's are confronted with multiple objectives. The multi-objective linear problem (MOLP) is

$$\text{maximize} \;\; \mathbf{Z}(\mathbf{x}) = \mathbf{C}_{k \times n} \mathbf{x} \text{ s.t. } \mathbf{x} \in X,$$

where $\mathbf{Z}(\mathbf{x})$ states a k-vector valued objective function

$$\mathbf{Z}(\mathbf{x}) \triangleq \left(z_1(\mathbf{x}), z_2(\mathbf{x}), \ldots, z_k(\mathbf{x}) \right)^T .$$

Definition 1. *Let* $\left\{ \text{maximize } \mathbf{Z}(\mathbf{x}) \,\middle|\, \mathbf{x} \in X \right\}$ *be a vector-maximum problem,* $\hat{\mathbf{x}} \in X$ *is an efficient Pareto optimal solution, if and only if, there is no* $\mathbf{x} \in X$ *such that* $z_i(\mathbf{x}) \ge z_i(\hat{\mathbf{x}})$, $\left(i \in \mathbb{N}_k\right)$ *and* $z_i(\mathbf{x}) > z_i(\hat{\mathbf{x}})$ *for at least one* i.

2) *Pareto optimal solution search using genetic principles.* Genetic algorithms are stochastic search techniques. Their procedures are inspired from the genetic processes of biological organisms by using encodings and reproduction mechanisms [16]-[17]. These principles may be well adapted to more complex real-world optimization problems. Let $P(t)$ be a population of potential solutions at generation t, and new individuals (or offspring) $C(t)$, the pseudo-code of a simple algorithm is the following:

```
begin                          /* initial random population */
t:=0
generate initial P(t)
evaluate fitness of P(t)
  while (NOT finished) do
  begin                        /* new generation */
    for population Size/2 do
    begin                      /* reproduction cycle */
      select two individuals for mating;
      recombine P(t) to yield offspring C(t);
      evaluate P(t+1) from P(t) and C(t);
      t:=t+1;
    end if population has converged then
        finished:=TRUE
  end
end
```

An initial population of individuals (chromosomes) is generated at random and will evolve successive improved generations towards the global optimum. Usually, a gene has converged when 95% of the population has the same value, and the population has converged when all the genes have converged. There are three types of operators for the reproduction phase: the selection operator for more fitted individuals, the crossover operator that creates new individuals by combining parts of strings of two individuals and the mutation that makes one or more changes in a single individual string.

Real optimization problems often require the identification of multiple optima due to multivariate objective functions and multiple objective functions. In this study, the evolutionary GA's are used to approximate the Pareto-optimal set in the objective function space.

3) *Niched Pareto genetic algorithm*. Sampling non-dominated solutions from the Pareto-optimal set, requires a diversity of solutions. This problem is due to the stochastic selection process of a simple GA procedure. Niching methods have been introduced to reduce the effect of the "random genetic drift" and to preserve the genetic diversity of the optimal solutions. Niching is based on the mechanics of natural ecosystems[6]. Goldberg and Richardson [19] suggested the use of a sharing function to estimate the number of solutions belonging to each optimum, such as

$$\text{sh}\left(d_{ij}\right) = \begin{cases} 1 - \left(d_{ij} / \sigma_{share}\right)^{\alpha}, & \text{if } d_{ij} < \sigma_{share} \\ 0, & \text{otherwise} \end{cases}$$

[5] Other case studies are notably the Fengman reservoir (Sonhua River) in China by Chuntian and Chau , 2002 [9], the Xingkaihu Lake Irrigation District in China by Zhou *et al.* , 2007 [10], the Bhadra reservoir system in India by Reddy and Kumar [5], the multi-reservoir system in Goldvari River sub basin in India by Regular and Raj , 2008 [11], the Bagmati River basin in Nepal by Onta *et al.* , 1991 [12], the Rio Colorado River in Argentina ([13], pp. 243-280).

[6] A niche can be viewed as a subspace in the environment that can support different types of life [18].

where d_{ij} is a similarity metric between individuals i and j, σ_{share} the threshold of dissimilarity and α, a constant that regulates the shape of the function. The niche count m_i approximates the number of individuals that share the fitness f_i is $m_i = \sum_{j=1}^{N} \mathrm{sh}\left(d_{ij}\right)$, where N is the population size.

The Niched Pareto Genetic Algorithm (NPGA) extends the basic GA to multiple objective optimization problems with two additional genetic operators: the Pareto domination ranking[7] and fitness sharing [19]-[21]. Tournament competitions help for deciding which candidates should go to the next generation. The fitness sharing operator contributes to maintain diversity in the population of solutions. Fig. 1 shows a modified flowchart corresponding to the NPGA. This flowchart is adapted from Erickson *et al*., 2002 [20]. Three main steps are: (**I**) ranking the population of designs, (**II**) choosing designs for reproduction, and (**III**) using the genetic operators.

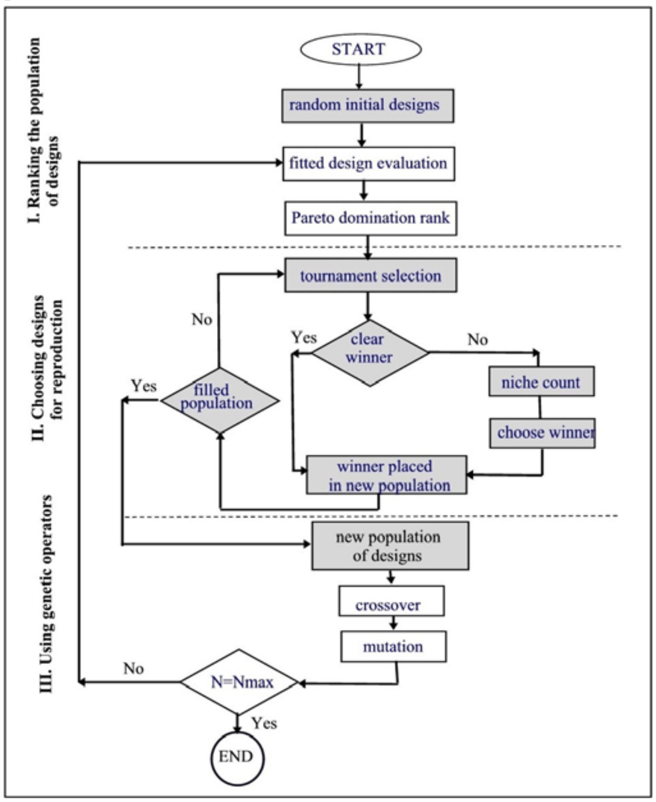

Fig. 1 NPGA flowchart showing the basic steps

B. *Fuzzy Multiobjective Optimization*

A fuzzy linear programming (FLP) multiobjective problem is first presented. Then, a crisp equivalent model is determined and solved. Thereafter, the direct solutions are searched via meta-heuristic algorithms.

1) *Fuzzy LP problem*. A fuzzy single objective FLP may be

$$\widetilde{\text{maximize}}\ \mathbf{c}^T\mathbf{x} \ \text{ s.t. } \ \mathbf{A}_i\mathbf{x}\ \mathrm{d}\ b_i,\left(i \in \mathbb{N}_m\right),\ \mathbf{x} \geq \mathbf{0},$$

where $\widetilde{\text{maximize}}$ means "improve reaching some aspiration level" and where the fuzzy inequality d means "roughly smaller than''. More generally, we may introduce fuzzy $\tilde{b}_i$'s coefficients, such that we may write

$$\widetilde{\text{maximize}}\ \mathbf{c}^T\mathbf{x} \ \text{ s.t. } \ \mathbf{A}\,\mathbf{x}\ \mathrm{d}\ \tilde{\mathbf{b}},\ \mathbf{x} \geq \mathbf{0}.$$

2) *Fuzzy multiobjective LP solution by using crisp equivalents.* Given the following fuzzy multi-objective problem with fuzzy objectives and crisp constraints

$$\text{maximize } \mathbf{C}\,\mathbf{x}\ \mathrm{t}\ \mathbf{Z} \ \text{ s.t. } \ \mathbf{A}\,\mathbf{x} \leq \mathbf{b},\ \mathbf{x} \geq \mathbf{0}$$

The k linear objective functions are maximized simultaneously, subject to m linear constraints for the n decision variables. The coefficients are the $k \times n$ matrix $\mathbf{C}$, the $m \times n$ matrix $\mathbf{A}$ and the $m \times 1$ vector $\mathbf{b}$. The $1 \times m$ vector $\mathbf{C}_1$ will denote the first line of the matrix $\mathbf{C}$.

The resolution process consists in solving successive single objective LP's by using each objective, such as

$$\text{maximize } \mathbf{C}_i\mathbf{x}\ \left(i \in \mathbb{N}_k\right).$$

Using the payoff data in Table 1, we can obtain lower and upper bounds L_i's and U_i's such that

$$L_i = \min\left\{z_1\left(\hat{\mathbf{x}}^i\right), z_2\left(\hat{\mathbf{x}}^i\right), \ldots, z_k\left(\hat{\mathbf{x}}^i\right)\right\},$$
$$U_i = \max\left\{z_1\left(\hat{\mathbf{x}}^i\right), z_2\left(\hat{\mathbf{x}}^i\right), \ldots, z_k\left(\hat{\mathbf{x}}^i\right)\right\}.$$

Table 1 payoff table with *k* objectives

Solution	Objective value			
	$z_1(\mathbf{x})$	$z_2(\mathbf{x})$	$\cdots$	$z_k(\mathbf{x})$
$\hat{\mathbf{x}}^1$	$z_1\left(\hat{\mathbf{x}}^1\right)$	$z_2\left(\hat{\mathbf{x}}^1\right)$	$\cdots$	$z_k\left(\hat{\mathbf{x}}^1\right)$
$\hat{\mathbf{x}}^2$	$z_1\left(\hat{\mathbf{x}}^2\right)$	$z_2\left(\hat{\mathbf{x}}^2\right)$	$\cdots$	$z_k\left(\hat{\mathbf{x}}^2\right)$
$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
$\hat{\mathbf{x}}^k$	$z_1\left(\hat{\mathbf{x}}^k\right)$	$z_2\left(\hat{\mathbf{x}}^k\right)$	$\cdots$	$z_k\left(\hat{\mathbf{x}}^k\right)$

The linear membership functions (MF's) $\mu_{\tilde{G}_i}\ \left(i \in \mathbb{N}_k\right)$ are expressed by

$$\mu_{\tilde{G}_i}\left(\mathbf{x}\right) = \begin{cases} 1, & \mathbf{C}_i\mathbf{x} \geq U_i \\ \left(\mathbf{C}_i\mathbf{x} - L_i\right)/\left(U_i - L_i\right), & \mathbf{C}_i\mathbf{x} \in \left(L_i, U_i\right) \\ 0, & \mathbf{C}_i\mathbf{x} \leq L_i \end{cases}$$

The fuzzy set of the objectives[8] is $G = \bigcap_{i=1}^{k} G_i$ and $\mu_G\left(\mathbf{x}\right) = \wedge_{i=1}^{k} \mu_{G_i}\left(\mathbf{x}\right)$. The decision set is defined by

[7] A design dominates another design if it is at least equal in all the objectives and better than one another in at least one objective. The Pareto domination rank of an individual design is the number of designs that dominate it [20].

[8] Other real-valued functions have been proposed in the literature : a weighted sum of objectives $\sum_{i=1}^{k} \alpha_i\left(z_i\left(\mathbf{x}\right)^{\beta_i}\right), \alpha_i, \beta_i > 0$ or a

$D = G \bigcap X$. The optimal solution is an efficient solution, which is obtained for the greatest degree α of satisfaction for which the program is

$$\text{maximize } \lambda \text{ s.t. } \left(C_i\mathbf{x} - L_i\right) / \left(U_i - L_i\right) \geq \lambda,$$

with $i \in \mathbb{N}_k$, $\mathbf{x} \in X$, $\lambda \in \left(0,1\right]$.

In the constrained method, the problem is transformed to a partially FLP problem with only one of the k objective functions, the remaining $k-1$ fuzzy objectives being placed into the set of constraints. Choosing the first objective and transferring the other objectives yields

$$\begin{aligned} &\widetilde{\text{maximize}} \quad z_1\left(\mathbf{x}\right) = \mathbf{C}_1\mathbf{x} \\ &\text{s.t.} \qquad \mathbf{C}_j\mathbf{x} \text{ t } z_j^U, \ \left(j \in \mathbb{N}_k \setminus \{1\}\right), \\ &\qquad\qquad \mathbf{A}\,\mathbf{x} \leq \mathbf{b}, \\ &\qquad\qquad \mathbf{x} \geq \mathbf{0}, \end{aligned}$$

The aspiration level equals the upper value of z_1^U with a tolerance of $z_1^U - z_1^L$. The MF's of the objectives are

$$\mu_{\tilde{G}_i}\left(\mathbf{C}_i\mathbf{x}\right) = \begin{cases} 1, & \mathbf{C}_i\mathbf{x} \geq z_i \\ \dfrac{\mathbf{C}_i\mathbf{x} - z_i^L}{z_i^U - z_i^L}, & \mathbf{C}_i\mathbf{x} \in \left(z_i^L, z_i^U\right) \\ 0, & \mathbf{C}_i\mathbf{x} \leq z_i^L \end{cases}$$

Then, we have to solve the parametric programming problem

$$\begin{aligned} &\text{maximize } z_1\left(\mathbf{x}\right) = \mathbf{C}_1\mathbf{x} \\ &\text{s.t.} \qquad \mathbf{C}_j\mathbf{x} \geq z_j^U - \lambda\left(z_j^U - z_j^L\right), \ \left(j \in \mathbb{N}_k \setminus \{1\}\right) \\ &\qquad\qquad \mathbf{A}\,\mathbf{x} \leq \mathbf{b}, \ \ \mathbf{x} \geq \mathbf{0}. \end{aligned}$$

This programming technique will provide a fuzzy decision depending on the preference parameter λ.

3) *Direct solution method via meta-heuristic algorithms*. Baykasoglu and Göçken [22]-[23] proposed a direct solution method (DSM) for solving fuzzy multi-objective optimization problems to avoid the inconveniences of a transformation into equivalent crisp programs. A ranking method is used for fuzzy numbers to rank the objective values and to determine the feasibility of the constraints. Thereafter, a meta-heuristic algorithm is carried out for searching efficient solutions [2].

C. *Multi-Objective Water Resources Example Problem*

The example problem is a two objectives multipurpose reservoir for irrigation and hydropower production. The following model for water resources management is drawn from Reddy and Kumar, 2006 [5][9]. This model is for the Badra dam, in Chimagalur district of Karnataka State, India. The reservoir is multipurpose, providing for irrigation and hydropower production. The two irrigation areas are of 87,512 ha and 6,367 ha, respectively. There are three hydropower turbines. One turbine is at the bed of the dam. Fig. 2 shows the flowchart of the reservoir system.

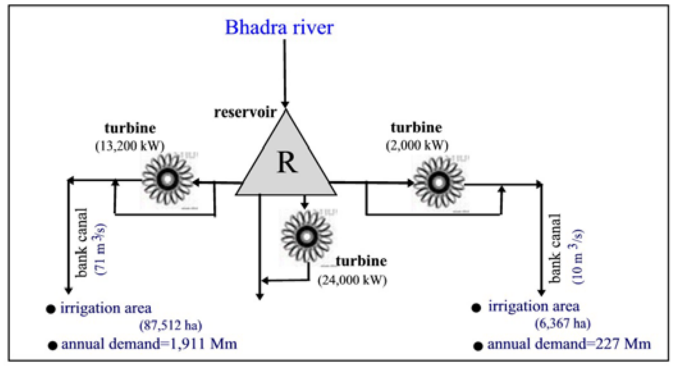

Fig. 2 the Badra multipurpose reservoir in India

The model formulation consists in two objectives and six constraints [5] in Table 2. There are two conflicting objectives which consist in minimizing the deviation of releases from demands and in maximizing the total production of energy. Physical and environmental constraints are imposed on the system: i.e., a storage continuity equation, the storage limits, the maximum power production limits, the canal capacity limits, the irrigation demand limitations and the water quality requirements.

The non-dominated sorting genetic algorithm (NSGA II) is used in [5] to derive operating policies for the reservoir operation problem. The selected parameters proceed from a sensitivity analysis. The population size is of 200 individuals, and the maximum generation number is of 1,000. The trade-off between irrigation and hydropower in the objective space is shown in [5]. At this Pareto front, the DM may choose a solution corresponding to some preferences.

product of objectives $\prod_{i=1}^{k} \alpha_i\left(z_i\right)$. This aggregation may also be based on the DM's preferences with utility functions.

[9] The formulation of a water pollution control problem was presented by Sakawa and Seo, 1980 [24], with application to Osaka City, Japan (See also, Lai and Huang, 1994 [25], pp. 119-123).

Table 2 water resource management example problem

Objectives:

- minimize $\sum_{t=1}^{12}\left(D_{1,t}-R_{1,t}\right)^2+\sum_{t=1}^{12}\left(D_{2,t}-R_{2,t}\right)^2$
- maximize $\sum_{t=1}^{12} p\left(R_{1,t}H_{1,t}+R_{2,t}H_{2,t}+R_{3,t}H_{3,t}\right)$

Constraints:

- $S_{t+1}=S_t+I_t-\left(R_{1,t}+R_{2,t}+R_{3,t}+E_t+O_t\right)$
- $S_t\in\left[S^{\min},S^{\max}\right]$
- $p\,R_{j,t}H_{j,t}\le E_j^{\max},\ j=1,2,3$
- $R_{j,t}\le C_j^{\max},\ j=1,2$
- $R_{j,t}\in\left[D_j^{\min},D_j^{\max}\right],\ j=1,2$
- $R_{3,t}\ge MDT_t$ for t = 1,…,12

$C^{\max}$ ……..	= canal carrying maximum capacity
D_1, D_2 …..	= irrigation demand
$D^{\min}, D^{\max}$.	= minimum and maximum demands
E …………	= evaporation losses
$E^{\max}$ ……..	= turbine capacity
H_1, H_2, H_3	= net heads available
I ……………	= inflow to the reservoir;
MDT ……..	= minimum release to meet downstream water quality
O …………..	= overflow from the reservoir;
p …………..	= power production coefficient
R_1, R_2, R_3 …	= releases into bank canals
S …………	= active reservoir storage.

III. MODELING ENVIRONMENTAL MANAGEMENT PROBLEMS

In this study, the management and planning problems are illustrated for water resources environmental areas [26]- [28].

A. Model Formulation

The standard formulation of the model concerns the variables (or parameters), the multiple objectives and the constraints. The parameters consist of state and decision variables. The set of the state variables (state vector) for a given system aims at describing the system and all its elements (e.g., labor force, budget). The variable decisions are under the control of the DM’s and can influence the system. This set of feasible parameters is notably constrained by budget limits, available labor force. The multiple objectives for water resources are in Table 3. The different types of objectives are economic objectives (e.g., output of groundwater, benefits and costs, labor employment, hydropower production in water resources), physical objectives (e.g., irrigation releases); environmental and ecological objectives (e.g., aquifer yield, BOD discharge, TDS concentration, groundwater salinity in water resources, wildlife habitat condition). Social health and education are other important objectives (e.g., food production, employment possibilities, health risk, environmental awareness). The constraints are inequalities and equalities that determine the set of the admissible decisions. They can be divided into physical, economic and environmental constraints as in Table 3. Thus, the physical constraints are limitations such as the water level, and turbine releases for multi-reservoir systems.

Table 3 objectives and constraints in water resources management problems

Literature	Objective functions	Constraints
Surface water resources management problem		
Haimes *et al.*, **1975** [26]; Onta *et al.*, **1991** [12]; Makowski & Somlyody **2000** [29]; Cohon **2003** [13]; Weng, **2005** [30]	●**Economic objectives** : **1)** maximize economic output of industries; **2)** maximize Gross Domestic Product (GDP); **3)** maximize net benefits from agricultural; **4)** maximize the ratio benefits to costs; **5)** maximize employment of labor; **6)** minimize cost; **7)** minimize investment in water development; ●**Environmental objectives**: **1)** maximize cleanup time; **2)** minimize BOD (biological oxygen demand) discharge; **3)** minimize the water pollution (dissolved oxygen (DO) and ammonia (NH_4) concentrations); ●**Social, health and educational objectives**: **1)** maximize food production; **2)** maximize food grain production; **3)** minimize the health risk.	●**Physical constraints**: **1)** water level; **2)** water resources; **3)** maximum surface availability; **4)** crop water requirement; **5)** maximum area availability; **6)** crop area continuity; **7)** forestry; **8)** surface water balance; ●**Economic constraints**: **1)** water demand; **2)** microeconomic constraints; **3)** expenditures; **4)** agricultural production requirement. ●**Environmental constraints**: **1)** animal husbandry and fishery; **2)** BOD discharge; **3)** water quality.
Reservoir and multi-reservoir operations		
Raju & Duckstein **2003** [15]; Reddy & Kumar **2006** [5]; Zahraie & Hosseini **2007** [31]; Chang **2008** [32]; Haghiabi *et al.*, **2009** [33]; Adeyemo, **2011** [34]; Li *et al.*, **2011** [14]; Haghiabi *et al.*, **2012** [35]	●**Economic objectives : 1)** maximize benefits from hydropower generation; **2**) maximize the irrigation water releases; **3**) maximize the irrigated cropped area; **4)** maximize hydropower production; ; **5)** minimize the irrigation deficit; **6)** minimize costs; ●**Physical objectives**: **1)** maximize irrigation releases; **2)** maximize hydropower production; **3)** maximize the irrigated cropped area; **4)** minimize the irrigation deficit; ●**Environmental objectives**: **1)** minimize the flood risk.	●**Physical constraints**: **1)** turbine release (for multi-reservoir system); **2)** irrigation release; **3)** reservoir storage; **4)** hydrologic continuity for all reservoirs; ●**Economic constraints**: **1)** meet various water demands; ●**Environmental constraints**: **1)** downstream ecological requirements; **5)** ensure dam safety.
Groundwater management problems		
Dawoud, **2006** [4]; Yang, *et al.*, **2001** [36]; Erickson, *et al.*, **2002** [20];	●**Economic objectives 1)** maximize economic output of groundwater use; **2)** minimize net value of groundwater depletion mitigation cost; ●**Environmental objectives**: **1)** maximize aquifer yield; **2**) minimize concentration (in total dissolved solids (TDS)) increment in groundwater; **3**) minimize groundwater salinity.	●**Physical constraints**: **1)** maximum groundwater availability.

B. Environmental Water Resources Case Studies

Environmental case studies in water resources illustrate this study. Three case studies are river basins of China. Other case studies are the Rio Colorado River in Argentina, the multireservoir system on the Godavari River in India, and groundwater in the arid Arabian Peninsula.

The map in Fig. 3 shows the geographical situation of the Yangtze River basin, the Hai River basin, and the Shiyang River basin. The characteristics, problems and drawbacks, the policies and programming methods are in Table 4. Appendix C presents some characteristics of the river basins in China: the size (i.e., surface area and population) , the water resources and demand. The other case studies on the Rio Colorado River in Argentina, on the multireservoir Godavari in India and on the groundwater state in the Arabian Peninsula are in Table 5. The characteristics, problems and drawbacks, policies and programming methods describe the case studies.

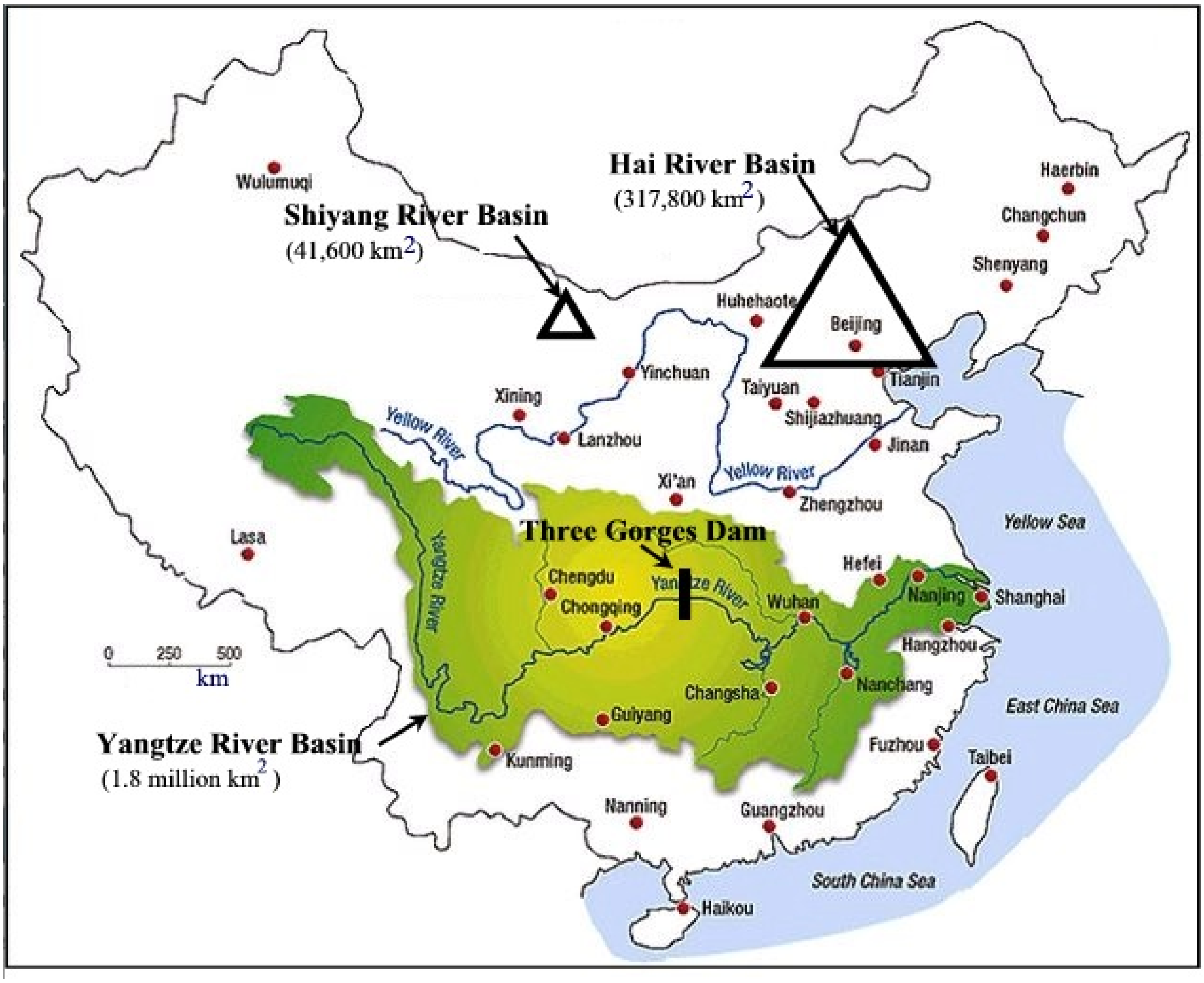

Fig. 3 Yangtze River basin, Hai River basin and Shiyang River basin in China

Table 4 environmental selected water resources management case studies in China

Case study	Location and characteristics	Problems and drawbacks	Policies and programming method
Shiyang River Yang *et al.*, **2001** [36] ; Wang *et al.* **2003** [37]-[38] ; Yizhong **2008** [39]	●**Location**: northwestern China, Hexi Corridor in Gansu province; ●**Characteristics**: **1)** a sediment filled graben of $30,000\ \text{km}^2$ area; **2)** annual average precipitation of 100-250 mm; **3)** potential evaporation of 2000-3000 mm; **4)** about 65% of water coming from the precipitation and 35% from groundwater.	●**Problems**: **1)** Extensive water uses begin in the 1950s; **2)** overexploitation of groundwater; ●**Drawbacks**: **1)** conflicts between water supply and water demand; **2)** continuous drawdown of the groundwater level; **3)** deterioration of water quality; **4)** withering of vegetation; **5)** soil desertification and salinization; **6)** pollution.	●**Policies**: **1)** maintain the current water utilization; **2)** perform a conjunctive management of groundwater and surface water; **3)** minimize the groundwater deterioration; **4)** meet the increasing water demand of human, livestock, industry and forestry users; **5)** achieve economic, best social and ecological values of water uses; ●**Programming method**: multi-objective optimization model.
Hai River Weng, **2005** [30]; Li *et al.* **2011** [14]	●**Location**: northern part of China, east of Tianjin (New Binhai district) close to Bohai Sea; ●**Characteristics**: **1)** basin area of $189,000\,\text{km}^2$; **2)** semi-humid climate with uneven rainfall distribution (average precipitation of about 550 mm); **3)** about 10% of China grain output, the center of various industrial activities, the population of 110 million people in 1994; **4)** New Binhai district with an area of $2,270\times\text{km}^2$ and a population of 2,073,440 in 2009.	●**Problems**: **1)** rapid economic growth wide variety of industries; **2)** industrialization and urbanization in Tianjin; **3)** substantial changes in the water demand; **4)** few water treatment facilities; **5)** conflicts between economic development and environmental protection; ●**Drawbacks**: **1)** water deficit; **2)** scarce of water resources; **3)** increase in the water area; **4)** competition of other uses; **5)** water pollution (urban population growth and industry); **6)** wastewater discharged to the river; **7)** large amounts of pollutants into the river.	●**Policies**: **1)** water saving policy (controlling, leakage, promoting re-use of water, etc.); **2)** protection of water resources (reducing water pollution, building waste water infrastructure, charging rational prices); **3)** South-north water transfer project; ●**Programming method**: **1)** microeconomic multiobjective water resource model; **2)** multiobjective optimization component; **3)** a stepwise multiobjective programming algorithm; **4)** scenarios.
Three Gorges Reservoir Li *et al.* (**2011**)[40]	●**Location:** reservoir of the Yangtze River; the largest hydro-electric power station in the world, located on the upper reach of the Yangtze River; ●**Characteristics**: **1)** storage capacity of $3.93\times10^{10}\,\text{m}^3$ and dead storage of $1.72\times10^{10}\,\text{m}^3$; **2)** 26 generators with an installed plant capacity of 18,200 MW and a warranted output of 4,990 MW.	●**Problems**: **1)** major floods; ●**Drawbacks**: **1)** erosion in the reservoir and sedimentation changes**; 2)** displaced population**; 3)** significant ecological changes: wildlife impacts of higher temperature on plant species, freshwater fish, etc.	●**Policies**: **1)** control floods; **2)** increase the Yangtze River's shipping capacity; **3)** provide flood storage space; **4)** limit greenhouse gas emissions; ●**Programming method**: **1**) genetic algorithm-based hydropower optimization.

Table 5 environmental selected water resources management case studies in other countries

Table 5 environmental selected water resources management case studies in other countries

Case study	Location and characteristics	Problems and drawbacks	Policies and programming method
Rio Colorado, Argentina Cohon, **2004** [13]	●**Location**: Rio Colorado river flows from the Andes Mountains in the west to Atlantic Ocean in the east. Rio Colorado river flows through 5 provinces: Mendoza, La Pampa, Neuquen, Rio Negro, Buenos Aires; ●**Characteristics: 1)** small river with mean annual flow of $120 \times m^3/s$; **2)** major water resource factor for La Pampa and the southern tip of Buenos Aires; **3)** a critical factor for the existing irrigation in Mendoza; **4)** 8 reservoirs for regulating the river, 13 hydroelectric power plants and 17 irrigation zones.	●**Problems**: **1)** not enough water in the river to pursue all the proposed development (a province allocation problem); **2)** Mendoza is a well-developed and growing province.	●**Policies**: **1)** maximize net economic efficiency benefits; **2)** minimize total deviation from an equal water allocation; ●**Programming method**: one of the first attempts at the multi-objective programming and planning for a large scale real-world public investment problem.
Godavari River, India Regulwar & Raj, **2008** [41], **2009** [11]	●**Location**: Maharashtra State, in India; ●**Characteristics:** the physical water system consists of five reservoirs (one is a barrage): the Jayakwadi project stages *I* and *II*, the Yeldari project, the Siddheshwar project and the Vishnupuri project.	●**Problems**: **1)** scarcity of water for irrigation and hydropower production, industrial requirement and domestic purposes; **2)** increasing water demands; **3)** the complexity of water resources domains, of river basin planning under uncertainty; ●**Drawbacks**: **1)** water quality deterioration; **2)** water deficit; **3)** competition between uses.	●**Policies**: **1)** maximize the irrigation releases; **2)** maximize the hydropower production; **3)** consider other increase alternatives for irrigation and hydropower demands; ●**Programming method**: multi-objective optimization by using genetic algorithms with fuzzified objectives; solution surface covering the whole range of policies for different levels of satisfaction.
GCC Groundwater Dawoud, (**2006**) [4]	●**Location**: Arabian Peninsula of the countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, The United Emirates; ●**Characteristics: 1)** total land area of $2,7\,Mkm^2$, population over 30M.; **2)** arid environment, rare rainfall, high evaporation rates, limited non-renewable groundwater resources; **3)** the agriculture accounts for 85% of all water uses.	●**Problems**: **1)** severe water shortage; **2)** increasing water demands; **3)** water deficit increases; **4)** insufficient available water supplies on renewable basis; ●**Drawbacks**: **1)** water quality deterioration; **2)** saline water intrusion into fresh aquifer systems.	●**Policies**: **1)** minimize the drawdown of the water table at any selected local area; **2)** act over groundwater exploitation patterns, search for alternative sources of water supply; **3)** increase the groundwater aquifer yield; **4)** maximize the outcome from groundwater water use; **5)** minimize the groundwater salinity; ●**Programming method**: multiobjective optimization.

C. Multireservoir Case Study in Maharastra Sub Basin India

The real-world case study by Regulwar and Raj, 2009 [41], 2008 [11] illustrates a multireservoir management problem for irrigation and hydropower production. The multireservoir system in Godavari River sub basin in Maharashtra State India consists of four reservoirs and a barrage. The DM aims at maximizing two objectives simultaneously, the irrigation releases and the hydropower production. These two objectives being fuzzified; a level of satisfaction is maximized in a crisp equivalent version of the program. The presentation of this study describes the following aspects: 1) the multireservoir physical system, 2) the different steps used for solving the fuzzy multiobjective optimization problem, 3) the results and simulations.

1) *Multireservoir physical system*. The physical system in Fig. 4 is adapted from [41]. It consists of four reservoirs and a barrage. Each reservoir is expressed in terms of gross storage, live storage, installed capacity for power generation[10]. The irrigable area is also defined. The monthly irrigation demand and inflow are available for all the reservoirs.

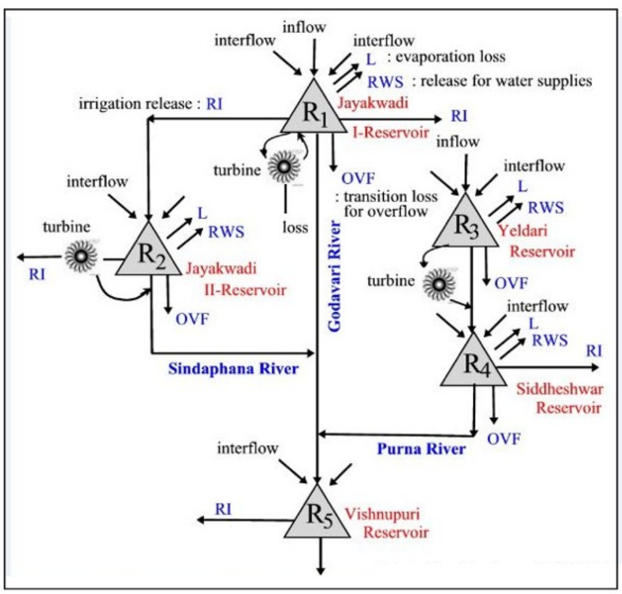

Fig. 4 multireservoir system in Godavari sub basin in Maharastra State, India

2) *Different steps of resolution*. The DM aims at maximizing two objectives: the irrigation releases and the hydropower production. The constraints are due to the turbines for power production, to irrigation releases, to the reservoir storage capacities. There are also hydrologic continuity constraints for all reservoirs [41]. Only the two objectives are supposed to be fuzzy, all other parameters being crisp in nature. The membership functions (MF's) of the two objectives are supposed to have a linear formulation, for which the best and worst values are determined for each MF[11]. The different steps of resolution are the following:

● At *step 1*, the best and worst values for both objectives are determined, by considering one objective at a time, while ignoring the others. Thus, when the objective 1 is maximized, the corresponding value of the objective 2 is considered to be the worst and vice versa. The best and worst values for the objectives are in Table 6.

Table 6 best and worst values for the objectives

Objective function	Existing demand	
	Best value	Worst value
Objective 1: Irrigation releases $(10^6\,\mathrm{m}^3)$	2,218.36	1,807.97
Objective 2: Hydro-power production $(10^4\,\mathrm{kWh})$	11,739.5	8,559.2

●At *step 2*, both irrigation releases and hydropower production objectives are fuzzified by considering linear membership functions. The membership function (or characteristic function, or degree of truth) is an essential component of a fuzzy set. Formally, we have

$$\mu(\mathbf{x}): \mathcal{U} \to [0,1],\ \mathbf{x} \in \mathbb{R}^n,$$

This function yields for any vector element $\mathbf{x}$ of the universum $\mathcal{U}$. The linear MF of the objective 1 uses the corresponding elements of Table 6, and takes the form[12]:

$$\mu_{Z_1} = \begin{cases} 0, & \text{if } \ Z_1 \le 1807.97 \\ \dfrac{Z_1 - 1807.97}{2218.36 - 1807.97}, & \text{if } \ Z_1 \in [1807.97, 2218.36] \\ 1, & \text{if } \ Z_1 \ge 2218.36 \end{cases}$$

The MF of objective 1 is pictured in Fig. 5.

[10] All the data are given in [41]. The reservoir R_1 is the largest reservoir with a gross storage of $2,909 \times 10^6\,\mathrm{m}^3$, an installed capacity for power generation of $12.\,\mathrm{MW}$ and for an irrigable area of $1,416.40\,\mathrm{km}^2$. Considering the gross storage, the reservoir are ranked as $R_5 < R_4 < R_2 < R_3 < R_1$. Monthly historical flow data have been collected over 32 years.

[11] For the irrigation releases first objective the worst and best values are respectively $1,807.97$ and $2,218.36 \times 10^6\,\mathrm{m}^3$ respectively. For the hydropower production second objective the worst and best values are respectively $11,739.5$ and $8,559.5 \times 10^4\,\mathrm{kWh}$ respectively [41].

[12] The MF for objective 2 is similar.

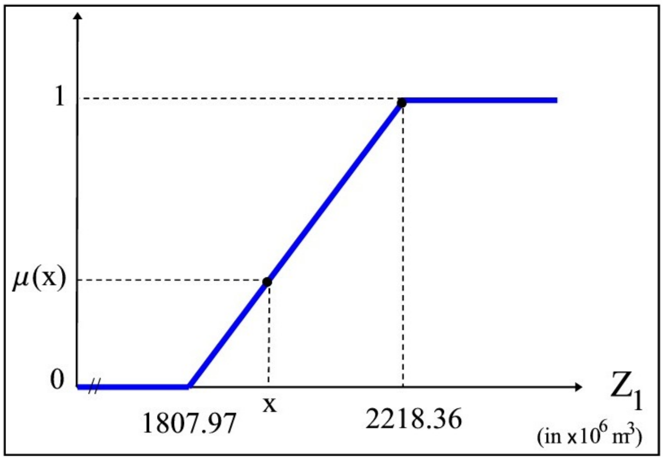

Fig. 5 linear membership function of objective 1

●At *step 3*, a crisp equivalent optimization problem is formulated. The single objective to be maximized is the level of satisfaction (ranged from 0 to 100%). The both initial objectives are placed into the constraints. We have the following programming problem from [11]:

maximize λ

subject to

, fuzzified objectives

$$\frac{Z_1 - 1807.97}{2218.36 - 1807.97} \geq \lambda$$

$$\frac{Z_2 - 8559.2}{11739.5 - 8559.2} \geq \lambda$$

, turbine release - capacity constraints

$$RP_{i,t} \leq TC_i$$

$$RP_{i,t} \geq FP_i$$

, irrigation release - demand constraints

$$RI_{i,t} \leq ID_{i,t}$$

$$RI_{i,t} \geq ID_{i,t}^{\min}$$

, reservoir storage - capacity constraints

$$S_{i,t} \leq SC_i$$

$$S_{i,t} \geq S_i^{\min}$$

, hydrologic continuity constraints (five reservoirs)

$$\begin{aligned}
\left(1 + a_{1,t}\right) S_{1,t+1} &= \left(1 - a_{1,t}\right) S_{1,t} + IN_{1,t} - RP_{1,t} - RI_{1,t} \\
&\quad - OVF_{1,t} - RWS_{1,t} - FCR_{1,t} + \alpha_1 RP_{1,t} - A_0 e_{1,t}, \\
\left(1 + a_{2,t}\right) S_{2,t+1} &= \left(1 - a_{2,t}\right) S_{2,t} + IN_{2,t} - RP_{2,t} - RI_{2,t} \\
&\quad - OVF_{2,t} - RWS_{2,t} + \alpha_2 FCR_{1,t} - A_0 e_{2,t}, \\
\left(1 + a_{3,t}\right) S_{3,t+1} &= \left(1 - a_{3,t}\right) S_{3,t} + IN_{3,t} - RP_{3,t} \\
&\quad - OVF_{3,t} - RWS_{3,t} - A_0 e_{3,t}, \\
\left(1 + a_{4,t}\right) S_{4,t+1} &= \left(1 - a_{4,t}\right) S_{2,t} + IN_{4,t} - RI_{4,t} \\
&\quad - OVF_{4,t} + \alpha_3 OVF_{3,t} - RWS_{4,t} + \alpha_4 RP_{3,t} - A_0 e_{4,t}, \\
DSREQ_t &= C_1 \times OVF_{1,t} + C_2 \times OVF_{2,t} + C_3 \times OVF_{4,t} \\
&\quad + DSIN_t + \alpha_5 RP_{2,t}, \\
S_{i,1} &= S_{i,13}
\end{aligned}$$

where we have $a = 0.5 A_a e$, and where the parameters denote

A_a ……….	= reservoir water spread area per unit value of active storage volume
A_0 ………..	= reservoir water spread area per unit value of dead storage volume
DSIN …….	= downstream inflow
DSREQ …..	= downstream requirement
e ………….	= evaporation rate
FCR ……..	= transition loss for canal feeder release
ID ……….	= irrigation demand
IR ……….	= inflow into reservoirs
OVF …….	= transition loss for overflow
RI ………...	= release into canals for irrigation
RP ………...	= release into canals for irrigation
RWS ………	= release for water supply
S …………...	= storage in the reservoirs
S_{min} ………...	= minimum storage capacity
SC …………	= maximum storage capacity
TC …………	= flow through turbine capacities
λ	= level of satisfaction

●At *step 4*, the resulting crisp equivalent single objective programming problem is solved by using GA. The genetic operators are the stochastic remainder selection, the one point crossover and the binary mutation. The crossover probability is 0.7 for the first objective and 0.9 for the second. In both cases, the mutation probability is set to 0.1. The parameter values are a population of 130 and 500 generations.

3) *Results for different demand evolutions*. The results for an existing demand[13] are the level of satisfaction of 60%, irrigation releases (objective 1) of $2,054.22 \times 10^6 \, \mathrm{m}^3$ and a hydropower production (objective 2) of $10,475 \times 10^4 \, \mathrm{kWh}$ [11]. The results for other demand evolution assumptions are in Table 7.

[13] The results for an increased demand of 10 % are the following [11] : a level of satisfaction of 52%, irrigation re into canals for irrigation, leases (objective 1) of $2,195.34 \times 10^6 \, \mathrm{m}^3$ and a hydropower production of $11,026 \times 10^4 \, \mathrm{kWh}$.

Table 7 results for different demand evolutions

	Existing demand	Other demand variations	
		Increase of 10%	Increase of 20%
Level of satisfaction (in %)	60	52	47
Objective 1: irrigation releases (in $10^6 \, \mathrm{m}^3$)	2,054.22	2,195.34	2,342.94
Objective 2: Hydropower production (in $10^4 \, \mathrm{Kwh}$)	1,47750	11,026	11,625

IV. Conclusion

The importance of water resources and forest management is due to the numerous applications in the environmental literature. DM’s aim at sustainable solutions. They are faced to long term multi-objective planning problems for which data are imprecise, and judgments are vague. Therefore, most decision-making systems are based on fuzzy evolutionary multi-objective optimization methods. This introductory study is using adequate methods and examples with selected case studies in water resources..

APPENDIX A EXAMPLE APPLICATION FOR WATER RESOURCES MANAGEMENT

A.1 Network System

The following model for water resources management is drawn from Xevi and Khan, 2005 [42]. This model is a nodal network that connects supply nodes (e.g., reservoir) to demand nodes (e.g., drink water from urban areas, irrigation for crops). The links connecting the nodes include irrigation canals and rivers. Fig. 6 illustrates a simple 3-nodes example.

The illustrative example by Xevi and Khan [42] is a network of three nodes: node 1 is a reservoir (i.e., supply side), node 2 is for water distribution, node 3 is the irrigation area (i.e., demand side) for six crops (e.g., barley, canola, maize, oats, rice and wheat). Supplementary groundwater pumping are required to meet the crop demand if the surface water supplies are not sufficient. The continuity equations for this example are in Table 9.

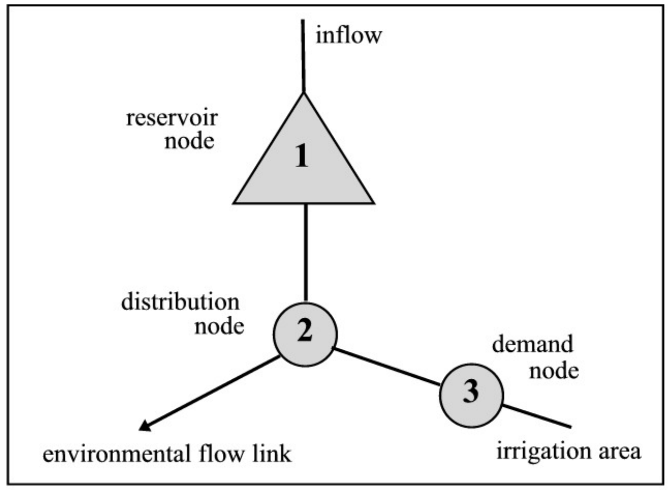

Fig. 6 illustrative water resource network

A.2 Model Formulation

The model formulation in Table 8 consists in three objectives and six constraints. There are two economic objectives (i.e., maximizing net returns and minimizing variable cost) and one environmental objective (i.e., minimizing the supplementary groundwater pumping requirements) to avoid groundwater mining and pollution of aquifers [42]. Physical and environmental constraints are imposed on the system. They consist in a continuity equation (4) for each node (supposing no storage) The total water use for irrigation areas in (5) should not exceed the allocation. Each month; the sum of all crops areas in (6) should not exceed target flows, in each month. Environmental flows in (7) should be greater or equal to the target flows. Total pumping from the irrigation area should be less or equal to the allowable pumping. The auxiliary equations (9) are used to restrict the minimum cropped area.

Table 8 water resource management problem formulation

Objectives:

$$\zeta \text{ maximize } \mathrm{NR} = \sum_c \mathrm{CGM}(c) \times \mathrm{X}(c) - \sum_c \sum_m \mathrm{WREQ}(c,m) \times \mathrm{X}(c) \times \mathrm{C_w} - \mathrm{C_p} \sum_c \sum_m \mathrm{P}(c,m), \quad (1)$$

$$\zeta \text{ minimize } \mathrm{VC} = \sum_c \sum_m \mathrm{X}(c) \times \mathrm{WREQ}(c,m) \times \mathrm{C}_w + \sum_c \mathrm{X}(c) \times \mathrm{Vcost}(c), \quad (2)$$

$$\zeta \text{ minimize } \mathrm{TP} = \sum_c \sum_m \mathrm{P}(c,m) \quad (3)$$

Constraints:

$$, \sum_j \mathrm{Q}(i,j) = \sum_k \mathrm{Q}(k,i) \quad (4)$$

$$, \sum_c \mathrm{X}(c) \times \mathrm{WREQ}(c,m) \le \mathrm{Allocation}(m) \quad (5)$$

Allocation(*m*)…	= water allocation for irrigation area;
CGM(*c*)……...	= gross margin for crop
C_p …………	= cost of groundwater
C_w …………	= total cost of water per unit volume
Env_f(*m*) ……	= environmental flow
Env flow (*m*)…..	= target environmental flow
mArea ……….	= minimum crop area
NR……………..	= net returns
P(*c, m*)…………	= volume of groundwater pumping and delivery
Pump(*m*)……..	= allowable pumping in the irrigated areas
Q(*i,j*) …………	= flow of water from node i to node j
TP………………	= total supplementary groundwater pumping requirements to meet crop demand from the irrigated area

, $\sum_c X(c) = \text{TArea}$ (6) , $\text{Env\_f}(m) \geq \text{Env flow}(m)$ (7) , $\sum_c P(c,m) \leq \text{Pump}(m)$ (8) , - $X(c) + \text{mArea} \leq \text{TArea} \times Y(c)$, $X(c) \leq \text{TArea} \times (1 - Y(c))$ (9) for $m = 1,\ldots,12$	Tarea………… = total irrigable farm area VC…………… = variable cost Vcost(*c*)……… = variable cost (such as fertilizer and pesticides) per ha other than water cost *WREQ(c,m)*…. = requirement for crops X(*c*)………… = area of crop … = binary variable for crops Y(*c*)………… ….

Nota: the arguments *c* and *m* of the functions are for crops and months, respectively.

A.3 Model Results

Rainfall and reference evapo-transpiration data are pictured in Fig. 7 for dry seasons[14]. Using the three objective functions and the constraints of the optimization model, Xevi and Khan [42] determine a payoff matrix and the corresponding crop mix in Table 10. The elements of the payoff matrix are obtained by optimizing each objective individually. Thus, the elements of the first row are obtained by maximizing net returns. The optimal values for each objective are in bold character. The results illustrate the trade-offs between the objectives. Similarities occur between the policies of minimizing cost and minimizing total pumping. Thereafter, a weighted goal programming model is used for this example. The model is defined to minimize undesirable deviations from

defined target values[15] [42].

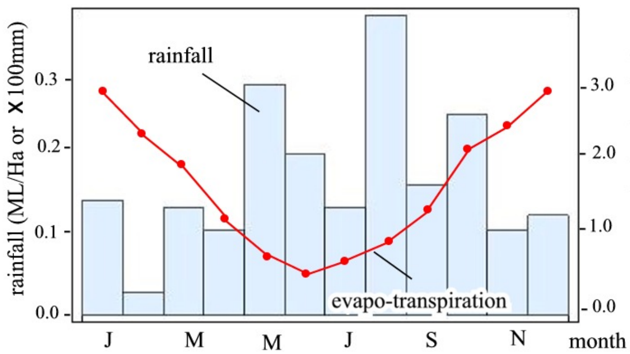

Fig. 7 Rainfall and reference evapo-transpiration for dry seasons

[14] The study by Xevi and Khan [42] also analyzed the consequences of average and wet seasons.

[15] The complete results of the goal programming and sensitivity analysis are presented in [42].

Table 9 continuity equations for the illustrative example

Continuity equations		List of parameters	
ζ $\mathrm{IRR\_3}(m)+\mathrm{Pump}(m)=\sum_c \mathrm{X}(c)\times \mathrm{WREQ}(c,m)$	(10)	Chn_l(*link(.)*)…….	= channel length
		Chn_losses(*link(.)*)	= channel seepage
		Env_f(*m*) ………..	= environmental flow
ζ $\mathrm{w\_2}(m)=\mathrm{S\_1}(m)-\mathrm{Chn\_losses}(\mathrm{link}(1,2))\times \mathrm{Chn\_l}(\mathrm{link}(1,2))$	(11)	IRR_3(*m*) ……….	= surface water available at node 3
		link(*i*,*j*)…………..	= link joining node *i* to node *j*
ζ $\mathrm{w\_2}(m)-\mathrm{Env\_f}(m)=\mathrm{IRR\_3}(m)+\mathrm{Chn\_losses}(\mathrm{link}(2,3))\times \mathrm{Chn\_l}(\mathrm{link}(2,3))$	(12)	Pump(m)…………	= allowable pumping
for $m=1,\ldots,12$		S_1(*m*)……………	= reservoir supply
		w_2(*m*)……………	= surface water available at node 2
		WREQ(*c*,*m*)……….	= water requirements for crops
		X(*c*)……………….	= area of crop.

Nota: the arguments *c* and *m* of the functions are for crops and months, respectively.

Table 10 optimal payoff matrix and crop-mix for dry seasons

	Payoff matrix			Crop-mix (Ha)					
Goal	Net Revenue ($)	Total Cost ($)	Total Pumping (ML)	Barley	Canola	Maize	Oats	Rice	Wheat
Net revenue	**34,348,685**	20,180,526	16632	0	19,518	4693	1,000	4,789	0
Total cost	26,107,450	**14,873,443**	0	0	1,000	4,592	10,605	0	13,803
Total pumping	27,032,049	15,569,178	**0**	1,000	1,000	5,045	10,605	1,000	11,350

APPENDIX B GENETIC IMPLEMENTATION FOR A MULTIRESERVOIR SYSTEM WITH ONE OBJECTIVE

B.1 Introduction to the Problem

This example problem is due to Hinçal *et al*, 2011 [43]. There are four reservoirs in the system[16]. The only optimal operating policy aims the maximum benefit satisfying the flow requirements and demands to the system. The question is: how water is to be released or stored during the time period based on the current state of the system? The decision variables for this problem are the releases from each reservoir at each time interval. The aim is to find the optimum combination of releases that will lead to generating maximum energy. This study from [43] explores the efficiency and effectiveness of genetic in optimization of multireservoirs.

B.2 Multireservoir System

Four reservoirs are used for irrigation (one activity) and hydropower (four activities). There are inflows to the first and second reservoirs only. Water losses due to evaporation and seepage in the ground are neglected. The whole system is shown[17] in Fig. 8.

[16] A four-reservoir problem was formulated and first solved by Larson 1968 [44]. The global optimum for the one-objective four-reservoir problem was already determined by Warlaw and Sharif , 1999 [45].

[17] This representation is adapted from Hinçal , *et al*.[43].

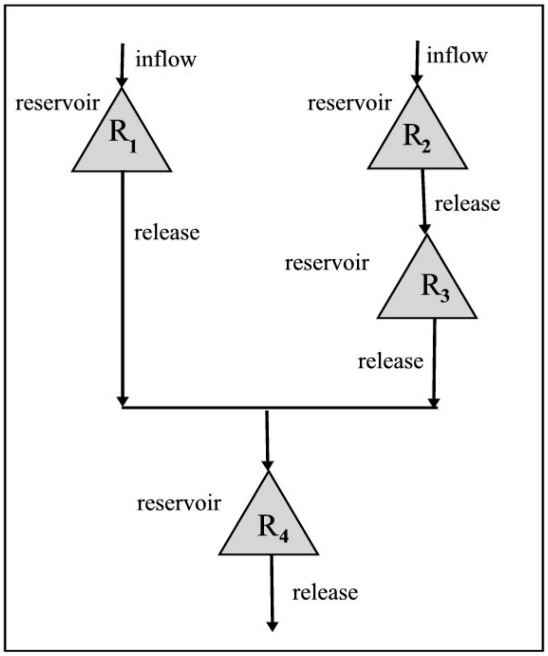

Fig. 8 four reservoir system

The objective function for this programming problem is to maximize the benefits from the system. The main constraints are represented by the continuity equations for each reservoir. Other constraints are on initial storage, on releases for all times, and target ending minimum storages.

B.3 System Formulation

The programming problem for this problem is [43]

θ benefit from the system

maximize $\sum_{i=1}^{4}\sum_{t=1}^{12} b_{i,t}R_{i,t} + \sum_{t=1}^{12} b_{5,t}R_{4,t}$

subject to

, storage continuity

$S_{i,t+1} = S_{i,t} + I_{i,t} - R_{i,t},\ i = 1,\dots,4$

, storage limits

$S_1, S_2, S_3 \in [0,10]$ and $S_4 \in [0,15]$

, constraints on releases

$R_1 \in [0,3], R_2, R_3 \in [0,4]$ and $R_4 \in [0,7]$

, target ending minimum storage

$d_1 = d_2 = d_3 = 5$ and $d_4 = 7$

, penalty function

$$g_i\left(S_{i,12}, d_i\right) = \begin{cases} -40\left(S_{i,12} - d_i\right)^2, & \text{for } S_{i,12} \le d_i \\ 0, & \text{for } S_{i,12} > d_i \end{cases},$$

for $i = 1,\dots,4$

where the parameters are denoted by

I……..	= inflow
R……..	= release
S……..	= storage
b_i ……	= unit return due to activity *i*
d_i ……	= target ending minimum storage
$g_i(.)$ …	= a penalty function

B.4 Implementation of the genetic algorithm

The implementation of the basic genetic algorithm consists in different steps.

● At *step 1*, an initial population is first generated. This population consists of chromosomes (individuals). A chromosome represents all the *N* reservoirs at all the *T* time steps. Each gene within a chromosome represents release (a decision variable) made from a reservoir at a particular time period. The number of genes is $N \times T$. The genes can be arranged, either grouping releases by time steps or grouping them by reservoirs. The initial population is generated randomly within the range of releases for all reservoirs. The objective is to find a gene sequence that yields the best chromosome generating the maximum energy.

● At *step 2*, the storages (state variables) are calculated for each gene by making use of the continuity equality constraints. Penalties are embedded into the objective function in order to satisfy the storage limits. The resulting fitness function is then maximized without constraints.

● At *step 3*, fitness values are calculated for each gene. It conditions the possibility for a chromosome to survive in the next generation. The constraints are embedded in the objective function as penalty terms. At this stage, the genetic operators are implemented onto the population. They consist in the selection, crossover and mutation operators. The roulette wheel selection is mostly chosen: the highest the fitness value, the higher the probability for an individual of being selected, as one of the mates whose children will live in the next generation. The selected parents reproduce the offspring by sharing information between the chromosomes (random crossover). The mutation is also a random process by which genes of the offspring are replaced.

A sensitivity analysis is performed to evaluate the influence of the change in the input parameters on fitness. This study uses the following parameter values [43]: a population size of 5,000, a generation number of 5,000, a crossover probability and mutation probability of 0.70 and 0.02, respectively.

The known global optimum of 401.3 units by Wardlaw and Sharif [45] is achieved. The output storages and releases also fit perfectly in the Hinçal *et al*. study [43].

APPENDIX C ALL RIVER BASINS IN CHINA

All the river basins in China were studied in the report of the International Water Management Institute (IWMI) by Amarasinghe *et al*., 2005 [46]. The study shows that the water availability varies significantly between the northern basins (covering 28 percent of the area with 44 percent of the total population) and the southern basins(covering also 28 percent of the area with 52 percent of the total population). Demand estimates were given for the use of agriculture, industry and domestic demand. These estimates allowed to construct water accounts for China [46].

The following comparison of all the river basins in China retains some essential elements of the report. The map (adapted for this study) in Fig. 9 shows the river basins boundaries with the Chinese Provinces

.

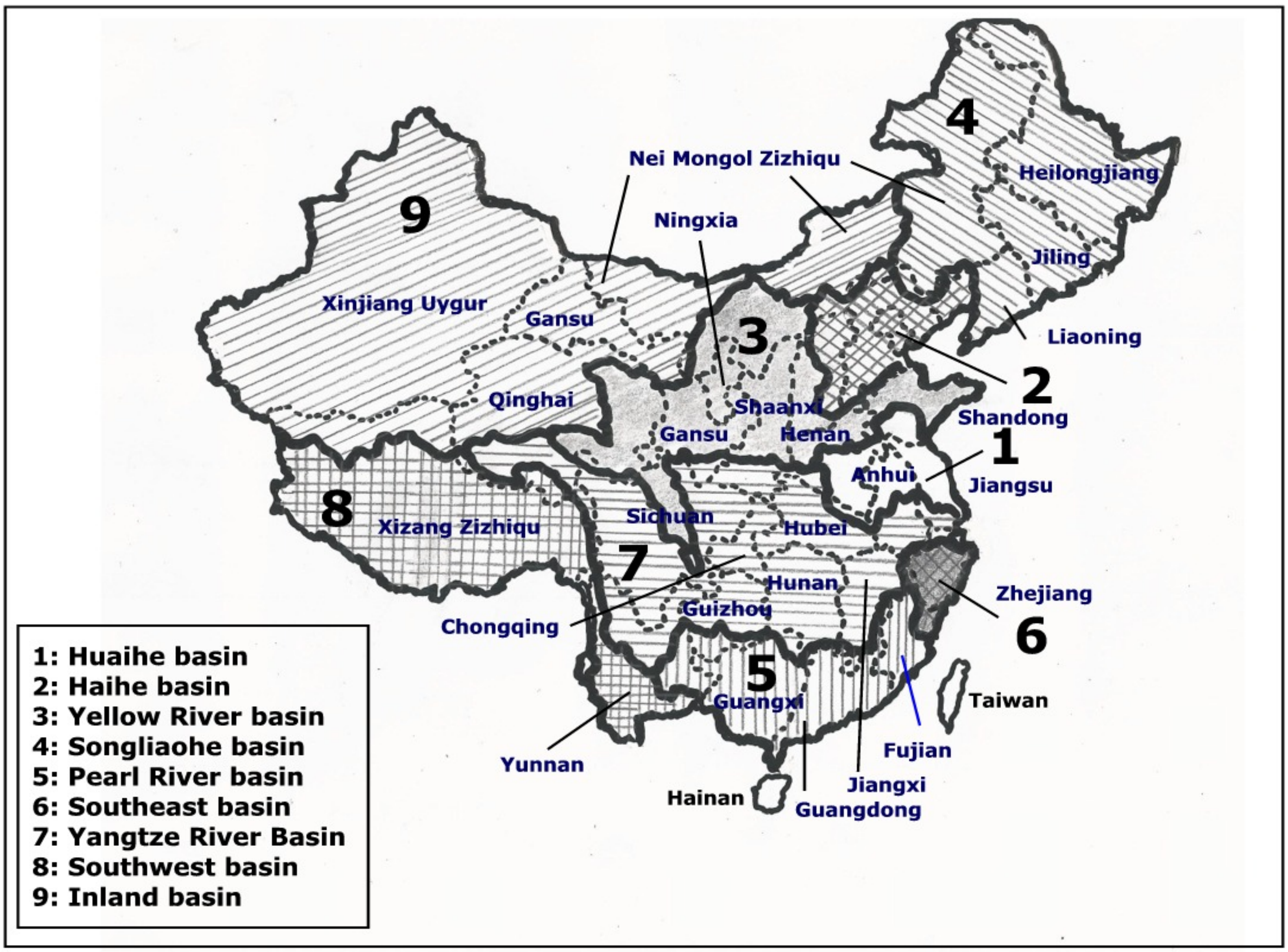

Fig. 9 all the river basins and provincial boundaries in China

Table 11 surface area and population density of river basins in China

No	River basin	Area size		Population	
		$10^3 km^2$ (1)	Rank	10^6 (2)	Density (1)/(2)
1	Huaihe	329	7	200	608
2	Haihe	318	8	130	409
3	Yellow River	795	5	114	143
4	Songliaohe	1,248	3	122	98
5	Pearl River	581	6	152	262
6	Southeast	240	9	72	300
7	Yangtze River	1,809	2	442	244
8	Southwest	851	4	22	26
9	Inland basin	3,374	1	29	9
All river basins		9,545		1,282	134

Table 11gives the main characteristics of all the basins in terms of area size and population. The Inland basin has a maximum area size whereas the Yangtze River basin contains a maximum population size. The maximum density of population is for the Huaihe River basin.

The rainfall, the water resources and total demand are in Table 12. A more detailed analysis is in Amarasinghe *et al.*, 2005 [46].

Table 12 water resources and demand of river basins in China

No	River basin	Rainfall (Mm)	Water supply/demand	
			Resources (Km^3)	Demand (Km^3)
1	Huaihe	860	96	73
2	Haihe	560	42	42
3	Yellow River	464	74	34
4	Songliaohe	511	193	59
5	Pearl River	1543	471	69
6	Southeast	1757	259	34
7	Yangtze River	1070	961	181
8	Southwest	1098	585	10
9	Inland basin	158	130	43
All river basins		648	2,813	545

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André A. Keller (Prof.) is at present research associate in the Laboratoire d’Informatique Fondamentale de Lille (LIFL) UMR 8022/ Lille Fundamental Computer Science Laboratory, a unit of the French Centre National de la Recherche Scientifique (CNRS) of the Université de Lille 1, Sciences et Technologies. His section of LIFL is Systèmes Multi-Agents et Comportements (SMAC). He studied Econometrics and Operations Research. He received a Doctorat d’Etat (Ph.D.) in Economics (Operations Research) from the Université de Paris I Panthéon-Sorbonne in 1977.

He is a WSEAS Member since 2010 and a Reviewer for the journals *Ecological modeling* , *Journal of Mathematical Analysis and Applications, Applied Mathematical Modeling* (Elsevier), *WSEAS Transactions on Information Science and Applications* and.International Journal of Economics and Management Engineering (The World Academic Publishing). He taught applied mathematics (optimization techniques) and econometric modeling, microeconomics, theory of games and dynamic macroeconomic analysis. His experience centers are on building and analyzing large scale macro-economic systems, as well as forecasting and simulations.

His research interests include high frequency time-series modeling with application to the foreign exchange market, discrete mathematics (graph theory, combinatorial optimization), stochastic differential games and tournaments, circuit analysis, optimal control under uncertainties. (fuzzy control). His publications consist in writing articles, book chapters and books. The book chapters are on semi-reduced forms (Martinus Nijhoff, 1984), econometrics of technical change (Springer and IISA, 1989), advanced time-series analysis (Woodhead Faulkner, 1989), stochastic differential games (Nova Science, 2009), optimal fuzzy control (InTech, 2009). One book is “Time-delay systems with Applications to Economic Dynamics & Control” (LAP, 2010). One another book is “Nonconvex Optimization in Practice: Theory, Algorithms and Applications”(WSEAS Press, forthcoming 2014).