A feasible and adaptive water allocation model based on effective water demand

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Abstract

Water allocation comprises inevitably problematic fields especially when the consumers are bound to share common water resources. Models need to be developed which generate policies that aim to the settlement of tensions and conflicts originating from the management of shared water resources. Often a starting point of the conflict resolution is an objective water allocation scheme between the interested parts. The definition of entitlements over shared water resources is not an easy task and it requires the use of specific decision tools in order to reach the maximum level of objectivity. To develop such models, the knowledge of the effective water use by the different consumer groups is required.

In most cases, water demand models do not reproduce the actual "effective water required (EWR)", i.e. the water required effectively by consumers under ideal conditions. On the other hand models for decision aid making

for water allocation require this variable as an input. Therefore, it is necessary to develop water demand models which can calculate the EWR for different consumers. In this paper such a modeling concept will be introduced. It is an adaptive concept which uses previous EWR, previous water allocated, environmental and socio-economic conditions to derive policies to determine water to be allocated to different consumer groups in the future. The model combines two water demand approaches, a micro-component-based approach to calculate the EWR and a data-based approach to calculate and predict the future water use if no policies are adaptations are made. The results of the two models will then be used subjected to environmental and socio-economic conditions to determine future policies of water allocation by induction. Due to the uncertainty of the determinants, fuzzy logic theory is applied. This allows imitating the behavior of an administrator and new allocation policies to be adapted. The model can be a decision aid for water distribution planning and such an instrument can be very useful for the local specialists and administrations for justification of the allocation scheme.

1 Problem statement

Foreign and domestic correspondences account of the water situation in Beijing region as dramatic. In 1999, the Beijing residents were forced to draw upon the city's water reserve for the first time (Kwang, 2000). Farmers in the Beijing municipality had it worse because during the dry years of the 1980s, the state council reallocated the Miyun reservoir away from agricultural use for urban use. Also the industry, which holds priority over agriculture, faces the prospect of dry taps if nothing is done (Kwang, 2000). Although china as a whole, containing one-sixth of the world's fresh water resources, appears well endowed, numerous factors contribute to severe water problems. First, China has the world's largest population, and thus per capita water resources are insignificant, and in many places quite scarce. Each Chinese resident only has access to a quarter of the water the average world citizen has access to. The other important factor is that distribution of water is extremely uneven and china's exorbitant economic growth since the 1980s. Another issue, which has to be incorporated into the system, is the rapidly changing land use and technology (water reuse) in Beijing. Statistics of Beijing show that the industry is moving from primary to more and more tertiary. Therefore, the Beijing region requires a good, feasible and adaptive water management system to cope with the rapid changing situations.

2 Introduction

Water resources management is approached as a two phase process, comprising the strategic and the operational management. The objective of the first phase is the selection of measures and projects aiming at fulfilling the present and future water requirements of different consumers while protecting the water resources and the environment thus securing conditions of sustainable development. The most serious difficulty the decision makers face at this strategic level is the uncertainty by which all the determinants are estimated for future time horizons. Another major difficulty in forecasting water demand is its multiplicity of uses, each with a different potential rate of growth in demand; a further complication is the growth in water recycling in industry. In reality, water allocators use simple rules for priorities and percentage of fulfillment of the different consumer groups. Often, these are very subjective. This paper presents a feasible method to increase objectivity in solving problems of water allocation to various users, using fuzzy logic theory. The background of fuzzy logic theory can be found in a variety of books and papers (Zadeh, 1980; Zimmermann, 1996). The method simply realizes the concept of forecasting water requirement and the logic of its management based on administrators' behavior.

The paper is outlined as follows. In section 3, the methodology will be described. The performance of the system will be demonstrated using data from the Beijing region in section 4. Due to the length of the paper, only the results of managing agricultural water requirement will be presented. The paper will be closed with some conclusions.

3 Methodology

3.1 Concept of forecasting water requirement based on administrator behavior

When managing water requirement for a year for a certain consumer group, an administrator forecasts an amount of water using some environmental information of the region and the consumer group itself, and he then assigns a water amount accordingly. In this case, an expert of water management can forecast a certain water amount using the relationship between the necessary information for the forecast and the forecasted water need from experience.

Assuming the function f defines mathematically the relations, water requirement for a year forecasted by an expert can be expressed as follows:

$$Y_W = f(X_D, X_W, X_P, \ldots \\ X_T, X_{GDP}, X_{POP}, X_S) \tag{3.1}$$

where Y_W is the forecasted water requirement for a year, X_D, X_W, X_T, X_P, X_{GDP}, X_{POP}, X_S are the difference between EWR and water previously allocated (WPA) yearly forecasted average temperature, yearly forecasted average precipitation, yearly forecasted gross domestic product, yearly forecasted population and the yearly forecasted sowing area for crops.

The mathematical Eq. (3.1) requires an expert to utilize three kinds of information; he must obtain the past water management results [X_D, X_W], the environmental conditions [X_T, X_P, X_S] and the socio-economic conditions [X_{GDP}, X_{POP}] himself to forecast water requirement for a year. From the viewpoint of systemization however, it is not always easy to define mathematically or physically the function f. In fact, numerical data are not always useful for an expert. Here, a mathematical equation such as Eq. (3.1) can be converted into logical equation which is formed by the algorithm if X is A then Y is B; that is, it presents the criterion variable Y of Eq. (3.1) which corresponds to value B when variable X, equivalent to the predictor variables of Eq. (3.1), gives the value A. Accordingly, the forecasting system of water requirement and allocation can be implemented using fuzzy logic theory.

3.2 The logic of water management based on administrator behavior

The logic of the feasible water management system consists of two stages, the logic of forecast and the logic of decision, as shown in Fig. 1. Of the three stages in the logic of forecast, stage (1) is the process where records of water management policies (distribution to different consumer groups) are obtained. Here, the water management policies are in the form history data. Stage (2) is the process where environmental conditions and socio-economic factors of a year are forecasted and the EWR is calculated. Stage (3) is the process where the previous year water deficit is estimated using information of stage (2) and (1).

Next, the logic of decision and distribution is the process where a certain water amount is decided for different consumer groups using information estimated at stage (3) and (2).

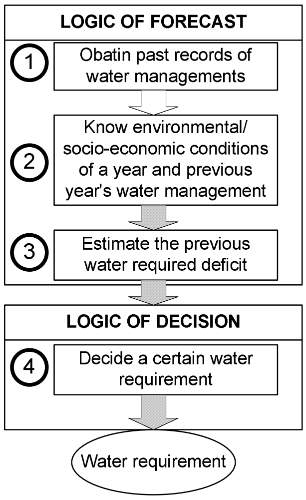

Fig. 1**.** Logic of forecast

The logic of water management described above is realized as depicted in Fig. 2. The stages (1), (2) and (3) of the logic are realized by the modules 1, 2 and 3, respectively. Stage (4) is realized by module 4.

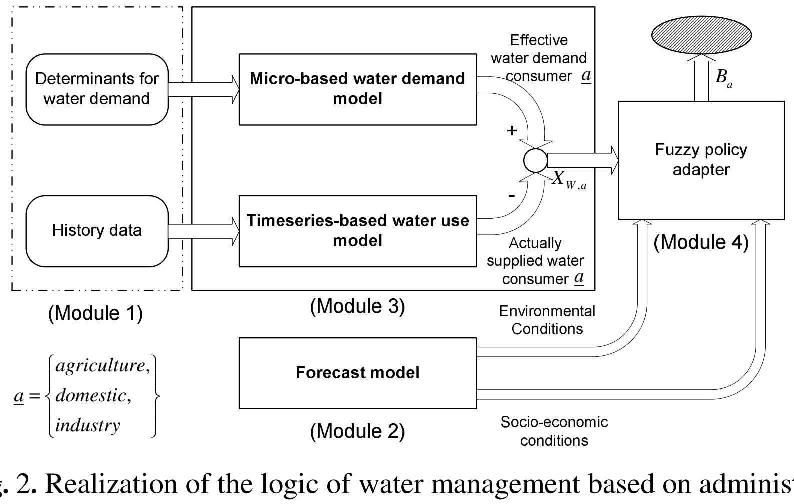

Fig. 2**.** Realization of the logic of water management based on administrator's decision behavior.

3.3 Determination of the previous water required deficit X_D = EWR-PWA

As could be seen in Fig. 2, the model combines two water demand approaches, a micro-based approach to calculate the EWR for a certain consumer and a data-based approach to determine water previously allocated for a certain consumer. Both types of models have been previously presented by the authors in (Karimanzira and Jacobi, 2006 and 2007). Micro-based models were developed for the main consumer groups, residential, industry and agriculture. These models are based on decomposition principles, which divide a water using group into its components. Using this principle, one can model the amount of water effectively required by a component and then combining the water requirements of the components to the total effective water requirement of the specific consumer group rigorously as shown in Fig. 2. This module mainly accounts for the adaptive nature of the system, because the system has to adapt to the changes in the composition of the components such as cropping patterns of a certain year or industrial composition and water saving technology changes. The method has also some delimiting factors, such as huge knowledge requirement of the components but it is very exact for calculating effective water demand. In the following, the micro-based models for the three main consumer groups will be briefly described.

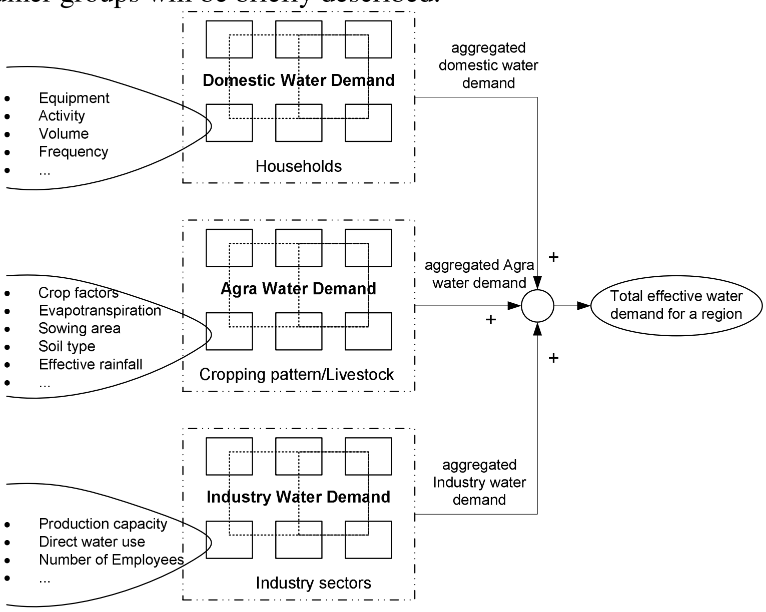

Fig. 3. Calculating effective water demand

3.3.1 Micro-based modeling for agricultural water demand

For the micro-based agricultural water demand model, the method developed by the FAO (Rosegrant et al. 2005) is implemented. It is based on the concept of reference evapotranspiration (ET_0) that allows studying the evaporative power of the atmosphere independently of crop type, crop development and agricultural practices. The reference surface is a 'hypothetical' extensive green grass actively growing (with adequate water) and completely shading the ground. This description is linked with assumptions on physical variables that lead to an unambiguous definition and derivation of ET_0 through the so-called FAO Penman-Monteith equation.

For other type of crops, the evapotranspiration under standard conditions (ET_C) corresponds to disease-free and well-fertilized plants that 'hypothetically' grow under optimum soil water conditions for achieving full production. In other words, it defines the crop water requirement. ET_C is obtained using Eq. (3.2) by multiplying ET_0 with a cultural coefficient (K_c) that varies according to phenological stages and green Leaf Area Index (LAI) with the distinction of initial (from sowing to 10% crop cover), growing (from 10% cover to effective full cover) mid (from full cover to the start of maturity) and late season (until harvest or full senescence). The resulting irrigation water demand is calculated using effective rainfall and can be expressed as in Eqs. (3.3) and (3.4).

$$ET_c = K_c \cdot ET_0 \tag{3.2}$$

$$NIWD = \sum_{cp} \sum_{st} \left(k_c^{cp,st} \cdot ET_0^{st} - P_{eff}^{cp,st} \right) \cdot LAI^{cp} \left(1 + LR \right) + EWD \tag{3.3}$$

$$IWD = NIWD / BE \tag{3.4}$$

Where *NIWD* is the net irrigation water demand, P_{eff} is the effective precipitation, *LR* is the salt leaching factor, EWD is the extra water need, e.g. for crops like rice and *BE* is the basin efficiency.

3.3.2 Micro-based modeling for domestic water demand

In general, there are two leading sources of domestic water consumption data; the first is micro-component based and the other is domestic consumption monitoring. Micro-component measurements have the advantage of simplicity and breakdown consumption into components of specific water use (e.g. toilet flushing, bathing, washing). This reductionism approach aids deterministic modeling of consumption components. It should be emphasized that micro-components are idealized quantities for the averaged population or housing sample. In the case of a large region as in this case, household survey data is used to calculate the average and then aggregated for the total.

3.3.3 Micro-based modeling for industrial water demand

Water demand varies by type of establishment. For example, the water demand of a concrete manufacturing facility will be very different from that of a furniture store. In general, differences in water demand among establishments reflect the type of goods or service being produced. Another indicator of water demand by establishments is the number of people they employ, reflecting size of the operation. In many studies, the number of employees has been found to be highly correlated with water demand and may, in a unit use approach, be used to estimate a water demand coefficient for a group of establishments (Dziegielewski, 1995).

In the micro-based model for the industry, the conditions of the municipal water use structure and its changes in the industrial sectors were analyzed and discussed in terms of the indicators, such as direct water-use coefficient, complete water-use coefficient, water-use multiplier and water-reuse rate. Direct water-use coefficient is the direct consumption coefficient of each production sector, reflecting the direct requirement of water resources by a sector producing unit output value. In addition, each sector consumes water indirectly because raw and processed materials, fuels, motive power and mechanical equipment in the process of production also consume water in the process of being produced. The sum of direct and in direct water consumption coefficient is complete water-use coefficient. It is an important index of water consumed by a sector and reflects the multiplex and indirect relation of various sectors. For the Beijing region 32 industry sectors were identified and their water-use coefficients obtained for an initial year 1998 (Wang, 1998). The forecasting of the following years until new data is obtained is done using Eqs. (3.5) and (3.6).

$$Y_i = e_i \cdot p_i - s_i \tag{3.5}$$

$$M_n = \frac{K \cdot M_0 e^{Y_i \cdot t}}{K + M_0 \cdot \left(e^{Y_i \cdot t} - 1\right)}; \quad \lim_{n \to \infty} M_n = K \tag{3.6}$$

Where Y_i is the growth rate for the industrial water demand for sector i, e_i is the elasticity, p_i is the growth rate of the industrial productivity s_i is the rate of saving water by recycling etc., M_n is the total water demand for year n, M_0 is the total water demand of basis year (in this case 1998), W_i is the weighting factor of the industrial sector water demand as a percentage of the total water demand for all sectors. It is determined by the complete water-use coefficient.

3.4 Determination of the water actually allocated by the experts

The other type of model, which is required by the overall system is for determining the actual water delivered/ or to be delivered to customers if no policy changes are made. The model is based on time series of the allocated water to the different consumer groups, environmental and socio-economic conditions. This has been realized using several types of methods, regression analysis (Karimanzira et al, 2006), Kalman filtering (Jacobi and Karimazira. 2007a) and neural networks (Karimanzira and Jacobi, 2007b).

Water-use is a complex function of socio-economic characteristics, climatic factors and public water policies and strategies. This study therefore develops a model based on the multivariate econometric approach which considers these parameters to forecast and determine water-use. The model applies statistical tools to select suitable demand function and most relevant explanatory variables that have strong relationship with water use. The results indicate that the number of connections, water pricing, public education level, and average annual rainfall are significant variables of water use (Karimanzira et al. 2007c). The developed model is used to forecast the water use in the future in the study area if no policy changes are made.

3.5 Prediction of future water requirement using fuzzy logic theory

The idea of this adaptor is to use the necessary input information and decide a trend of water variation as follows:

$$\begin{aligned} &IF\ X_P\ is\ P_i,\ X_T\ is\ T_j, X_{GDP}\ is\ G_k,\ X_{POP}\ is\ POP_f \\ &AND\ X_w\ is\ W_{a,n}\ THEN\ Y_{w,a}\ is\ B_m \end{aligned} \tag{3.7}$$

In Eq. (3.7), $Y_{w,a}$ indicates the future water requirement of a certain consumer *a*. P_i, T_j, G_k, POP_f, and $W_{a,n}$ are indices for judging input information X_P, X_T, X_{GDP}, X_{POP}, and the past recorded water requirement X_w for consumer a. B_m is the index representing the appearance of Y for consumer *a*.

The above mentioned process can be explained by introducing the idea of fuzzy inference. Therefore, to be able to utilize the information available in practice, indices P_i, T_j, G_k, POP_f, $W_{a,n}$, and B_m are defined as fuzzy sets, respectively, by the following membership function

$$\mu(X) = (-X - b + a)/a, \tag{3.8}$$

where $0.0 \le \mu(X) \le 1.0$ gives the grade of the membership function, *X* is the variable of the fuzzy set, and *a* and *b* are function parameters.

Carrying out fuzzy inference of Eq. (3.8) alongside the logic of Eq. (3.7), an amount of water to be allocated, equivalent to stage (3), is indicated by a fuzzy set. This fuzzy set inferred can support decision making of the administrator, equivalent to the stage (4) of Fig. 2. The logic in Fig. 2 can be formulated by the following inference equation:

Fact: $X'_P,\ X'_T,\ X'_{GDP},\ X'_{POP}$ and X'_W

Rule: $X_P\ is\ P_i\ ,\ X_T\ is\ T_j\ ,\ X_{GDP}\ is\ G_k\ ,\ldots$
$X_{POP}\ is\ POP_f\ and\ X_w\ is\ W_{a,n} \rightarrow Y_{w,a}\ is\ B_m$ (3. 9)

Action: B'

The Rule, Fact and Action correspond to stages (1), (2) and (3), respectively. From B', the following equation can be derived, using X'_W obtained from stage (2)

$$v = B' + X'_W \tag{3.10}$$

v corresponds to the forecasted water requirement and provide the logic of decision. In reality it is very difficult to realize the rule in Eq. (3.9). Accordingly, paying attention to the relationship between water requirement X'_W and its variation Y_W from past records, the fuzzy relation influenced by environmental and socio-economic conditions can be simplified by modifying Eq. (3.9) as follows, which correspond more to how an expert make decisions:

Fact: $P_0, T_0,\ GDP_0,\ POP_0\ and\ W_0$

$$\textbf{Rule:}\ \begin{array}{l} X_w\ is\ W_{a,n}\ \rightarrow\ Y_{w,a}\ is\ B_m\quad under\ X_P\ is\ P_i\ , \\ X_T\ is\ T_j\ ,\ X_{GDP}\ is\ G_k\ \ and\ \ X_{POP}\ is\ POP_f \end{array} \tag{3.11}$$

Result: B'

Here, "under" is an inference factor meaning a restriction of the environmental and socio-economic conditions.

3.5.1 Situation dependent fuzzy inference model

Based on the inference Eq. (3.11), the following model is proposed, using fuzzy set μ'_W of previous year's water requirement, X'_W ,

$$B' = R_{(X_W, dY|P,T,GDP,POP)} \circ \mu'_W \tag{3.12}$$

where $\circ$ is the fuzzy product. The forecasting function $R_{(X_W, dY|P,T,GDP,POP)}$ is just equal to the knowledge of an expert and represents a fuzzy relation between X_W and *dY*, limited by the environmental and socio-economical conditions *P, T, GDP, POP, etc.*.

3.5.2 Simplifying the model structure by decomposition

Based on this rule structure model, the rule base search can further be simplified by dividing the system into three sub-models for agriculture, households and industry. The agricultural fuzzy policy adapter have four inputs, *previous water allocated, deficit, temperature and precipitation* and one output, *water to be allocated* for agriculture. The domestic part has three inputs, *previous water allocated, deficit and population* and *water to be allocated* for households. Where 'deficit' is the difference between the previous water allocated and previous effective water demand calculated by the micro-component based module. On the other hand, the industry sub-model have four inputs, *water allocated, deficit, population and GDP*, and *water to be allocated* for the industry. For the simplified models, the rule bases can be easily extracted from history data as described in the next section.

3.5.3 Rule extraction from data

There are various approaches to fuzzy rule extraction from numerical data for classification (Nozaki et al., 1996; Maher, 1993; Janikow, 1998). For example, Nozaki et al., 1996 proposed an adaptive method for fuzzy rule extraction for classification. Their method consists of two learning procedures: an error correction-based learning scheme and an additional learning procedure. The first learning procedure adjusts the grade of certainty of each rule based on its classification performance. This is followed by an additional learning procedure to realize better classification boundaries between classes. Finally, Nozaki et al., 1996 proposed a rule pruning scheme. Exploratory data analysis, such as clustering, is also used to facilitate rule extraction. For example, Chiu, 2002 used a subtractive clustering method to find clusters in the training data; each cluster is then translated into a fuzzy rule.

Another commonly used approach for rule extraction is to build a decision tree (DT) from the training samples and extract rules from it. This approach is used because semantically a path of a DT and a rule are almost the same. There are different types of DTs (Hayaki and Ozawa, 1996; Safavian and Landgreben, 1991) available, each having its advantages and disadvantages (Janikow, 1998), but probably the most popular one is Quinlan's ID3 (Quinlan, 1992). The main concern about ID3 is that it can deal with categorical data only and the DT generated is a crisp one. Different variations of ID3 are now available where authors have tried to overcome these limitations of ID3 and extract fuzzy rules from the DT (Maher, 1993). The fuzzy DT of Chang and Pavlidis, 1977 used a fuzzy decision function (not the node splitting function) at each internal node. If an internal node *V* has *k* branches, for example, then the fuzzy decision function produces a vector in $[0,1]^k$. Each component of the decision function can be thought of as an edge weight of a branch coming out of the node *V*. Each leaf node of the DT has a crisp label associated with it. For an unknown $x \in \Re$, the firing strength of each path from root to every leaf is computed using either product or minimum of the decision function values on the path. If minimum is used, they call it a *fuzzy decision tree*; for product, it is called a *probabilistic decision tree*. x is assigned the crisp label of the leaf having the highest firing strength.

The method, used in this work is from (Otto, 1995). The authors proposed an algorithm, FuzzyMod®, which combined uncertain reasoning with the rule set produced by ID3 to deal with uncertain and noisy data. In their approach, they start with a DT made by ID3, then the attribute values associated with each branch of the tree is considered to be approximate. Triangularly shaped membership functions are used to model the approximate values. For each attribute value of a data point, a support interval is calculated using the approximate value associated with the corresponding branches of the tree. The classification of a test sample is done by considering the set of support intervals for different possible classifications. Each path from the root to a leaf is then interpreted as a rule. The rules are further pruned and optimized using evolutionary algorithms. The optimization of the fuzzy sets over the number of patterns p is done so that the mean squared error between the model $\hat{y}$ and the system output $f(X)$ is minimized (see Eq. 3.13).

$$s = \sum_{i=1}^{p} \left(y_i - \hat{y} \right)^2 \qquad (3.13)$$

4 Results

4.1 Rules extracted by FuzzyMod®

Due to the length of this paper, only the fuzzy system for the agricultural water requirement will be further discussed. The training data of the fuzzy policy adapter for the agriculture were prepared and applied into FuzzyMod® to extract the rule base. The fuzzy system generated by FuzzyMod® can be seen in Figs. 4 - 6. The main advantage of using this rule extraction method is that it tests for significance of the input variables and eliminates those which are not significant using information gain theory (Entropy). The other advantages are as follows:

- Conditions which are not useful are removed.
- Empty rules and identical rules are removed.
- All rules are grouped according to classes.

- Rules are deleted if the accuracy of the whole set of rules for the class is not lowered.
- Rules are ordered to minimize false positive errors.
- Rules are deleted in turn if accuracy of the whole rule set on the training set is not lowered.

For example, total yearly precipitation was eliminated and this is true, because this variable include no information on its distribution over the year, which actually is required to calculate the water requirement for agriculture. Therefore, precipitation plays an indirect role as described in the determination of effective water demand of a crop.

4.1.1 Relevant inputs[1]

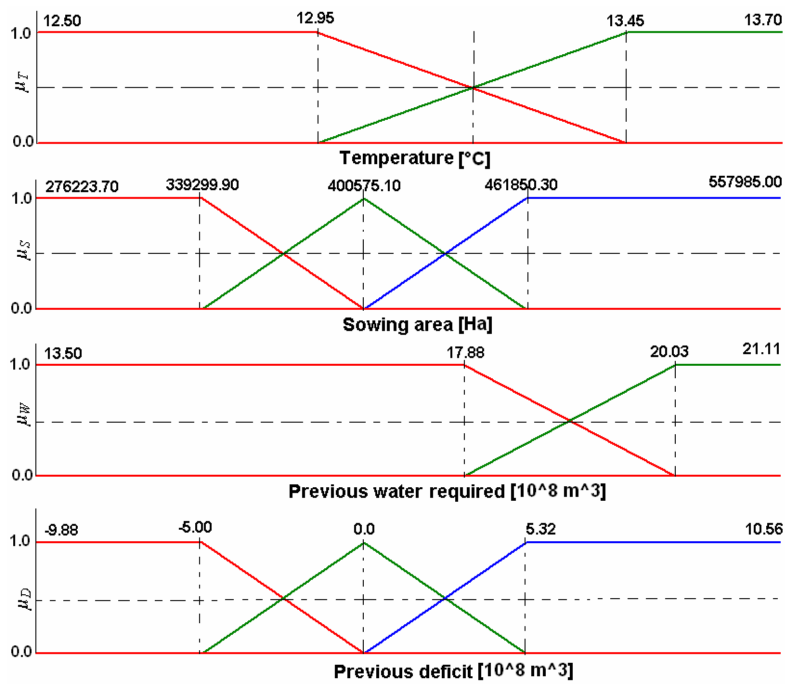

Fig. **4**. **Extracted membership functions of the inputs for the fuzzy system (units are omitted)**

[1]The variable "precipitation" was removed by FuzzyMod® from the list of influencing variables due to less information gain.

4.1.2 Output

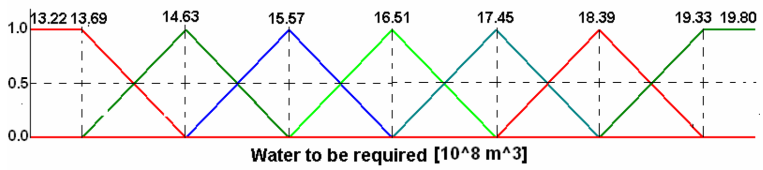

Fig. 5. Extracted membership functions of the output for the fuzzy system (units are omitted)

4.1.3 Rules

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DEFINE RULES
1. IF ( Sowing area = Small ) AND ( Water required = Low )
   THEN (Water to be required := Very very low );
2. IF ( Temperature = Low ) AND ( Sowing area = Medium OR Large ) AND ( Water required = Low )
   THEN (Water to be required := Very very large );
3. IF ( Temperature = High ) AND ( Sowing area = Medium OR Large ) AND ( Water required = Low )
   THEN (Water to be required := large );
4. IF ( Sowing area = Small OR Medium ) AND ( Water required = High )
   THEN (Water to be required := Low );
5. IF ( Sowing area = Large ) AND ( Water required = High )
   THEN (Water to be required := Very large );
6. IF (Sowing area = Small) AND (Previous deficit = small)
   THEN (Water to be required = Very Low)
7. IF (Sowing area = Large) AND (Previous deficit = Large)
   THEN (Water to be required = Very high)
END.
```

Fig. 6. Rules extracted to determine the future water to be allocated

4.2 Prediction results

The results in Fig. 7 - 10 show the one year ahead prediction of water requirement for agriculture as an example. The system was trained using data from 1991-2002. The remaining data from 2003-2005 was used for validation. Figures 7 and 8 with a sum squared error of 4.5763 show the prediction results before optimization and on the other hand Figures 9 and 10 show the results after optimization, where the SSE has decreased to 0.7590. The results show that the fuzzy system is a very important tool for planners and administrators, because the rule produced are quite understandable, it is an imitation of expert decision making behavior. An advantage of the system is that it can always be adapted to new situations on the availability of new data.

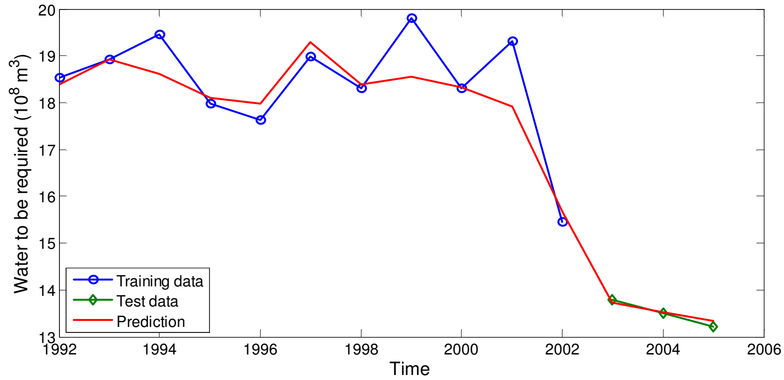

Fig. 7. Prediction results before optimization

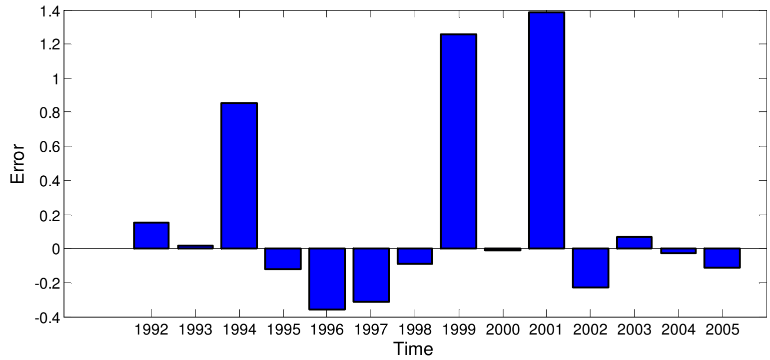

Fig. 8. Prediction errors before optimization: SSE = 4.5763

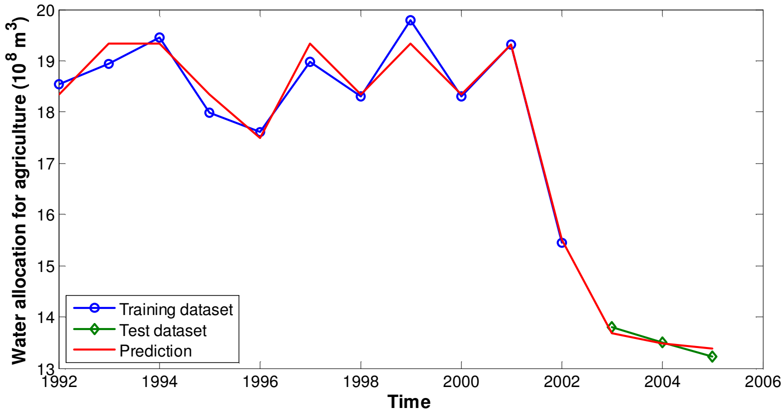

Fig. 9. Prediction results after optimization

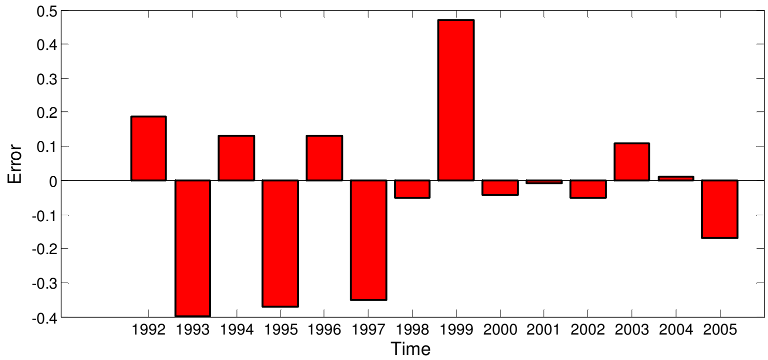

Fig. 10. Prediction errors after optimization (SSE = 0.7590)

5 Conclusions

In the classical formulation of water allocation problems to various users it is customary to use formulations of linear programming in which all the determinants are introduced as crisp numbers. But water supply and distribution still depends on the experience and knowledge of the administrators. This is caused partly by fuzziness of information for water management and uncertainty of the conditions. For this reason, the systematic composition of water management is difficult.

In this paper, attention is paid to fuzzy information and a peculiar logic of water management is formulated through analysis of its actual state and the behavior of an administrator and a forecasting system which can support decision making of the administrator in distribution is proposed using fuzzy theory. The modeling by resolving into micro-components facilitates behavioral understandings as could be seen in the rules. The performance of the system has been tested using data of the Beijing region and the results are very satisfactory. The rules produced by the system are very understandable and correspond to those decisions, a water manager would make under the aspect of objectivity. Water management is originally based on human decisions; therefore, systemization disregarding human relations is meaningless and is never useful.

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