Desalination and Water Treatment
www.deswater.com
doi: 10.5004/dwt.2019.24642

170 (2019) 378–393
December

Evaluation of public perception on key sustainability indicators for drinking water quality by fuzzy logic methodologies

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Received 12 April 2019; Accepted 28 June 2019

ABSTRACT

Social acceptance of water quality in urban areas depends on the perception and awareness of the stakeholders and the wider public. Moreover, the significance of social trust in stakeholders appears to be an influential factor affecting social support of water quality. However, efforts on understanding, communicating and engaging with the public and the stakeholder community still remain under examination. Urban water resources management problems are often associated with ecological, political, social and economic development and have caused critical concern to both national and local competent authorities in almost every country for many years. When focusing on water quality, key indicators are used to measure the performance (KPIs) of water companies in evaluating their success to customer satisfaction with zero defects while minimizing the environmental footprint caused by the intermediate procedures up to the point of receiving potable tap water. Stakeholder interviews reveal that these KPIs can be identified from an economic, social, environmental and water company perspective, and they can span from the efficiency of water distribution to operational water losses minimization procedures and from customer supply coverage to aesthetic test compliance. Therefore, future policy for water quality should be designed in a strategic framework, taking into consideration key sustainability indicators emanating from the aforementioned perspectives. In the current paper, a complete showcase is illustrated on how to mobilize local stakeholder's knowledge to extract KPIs for supporting effective strategies by local water companies and initiating policy making by the competent authorities in the process of keeping high water quality standards in a sustainable water resources management environment. Specifically, the application of soft computing methods enables the conceptualization and categorization of stakeholders' notion of strategies that need to be followed. This conceptualization allowed the involvement of fuzzy inference systems to simulate the effects of several policies in a multi-criteria analysis. According to the features, the policy maker initiates, the proposed model succeeds to identify the preferred policy options that can be used in achieving minimal environmental footprint.

Keywords: Drinking water quality; Sustainability; Key performance indicators (KPIs); Public perception; Stakeholders; Social acceptance; Multi-criteria analysis; Fuzzy inference system (FIS); Fuzzy cognitive map (FCM)

1. Introduction

Under the Water Framework Directive (WFD), European Environment Agency has envisaged new development perspectives in the field of urban water management while sustaining natural water resources. Although there is relevant literature [1–4], there is not, however, an established methodology for integrated measuring and evaluating the

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Presented at the Fifth International Conference on Small and Decentralized Water and Wastewater Treatment Plants (SWAT 2018), 26–29 August 2018, Thessaloniki, Greece

sustainability of urban water services in terms of water renewable production, water quality evaluation, sufficient volumes safeguarding and the creation of an indicator planning and evaluation system. Considering the different perspectives and the vast variety in stakeholder bodies for the establishment of evaluation criteria, it is quite difficult to gain solid knowledge in preserving sustainability for urban water distribution activities. Additionally, most of the water utilities mainly focus on the provision of necessary water supplies for their water distribution networks and on a secondary level on the adequate collection of wastewater, disregarding the impact of their actions on citizens. Furthermore, the infrastructures built are usually funded externally thus resulting in inability of maintenance and operation by local municipal authorities. So local authorities put as a first priority to avoid proliferation and propagation of infectious diseases and, the improvement of potable water supplies becomes a task of lower priority. All the aforementioned activities and policy trends result in a gap of policy and decision making for the competent authorities and the water utilities. For all the above-mentioned reasons, urban water quality sustainability has become a major societal objective for the regional stakeholders primarily including the consumers.

Urban water quality sustainability evaluation is considered to be a rather complex process of analyzing and reviewing resources, systems and services throughout the water supply and management operations [5,6]. The initial attempt in achieving a sustainable water cycle belongs to Brown et al. [7]. This attempt took into consideration several social, environmental and economic dimensions mainly exposed by Thornton et al. [8]. The inference stretched in these works was that a formation of water sustainability protocol is hindered by many uncertainties including social, economic, technological, water conservation, health risk and water quality related ones. To overcome the shortcoming produced due to lack of making decisions at least at the competent authorities' level, Bijlsma et al. [9] suggested a participatory approach in policy development as opposed to expert-based policy development, applying an uncertainty perspective to reveal differences between the two approaches.

This transition to water sustainability is a long-termed societal process that basically monitors the interactions between society, technology, policy making, environment, economics and culture [10,11]. However all approaches must be governed by the human right to water availability and all aspects of water management must give great importance to social justice for availability of quality water. A continuous supply of clean and safe drinking water must be ensured for the public health protection [12]. In sustainability studies, the coupling relationship between water environment and social economy appears to be a critical issue under investigation [13]. Water efficiency is vital to life and socio-economic development, especially under predicted climate change situations in the future, which may possibly further intensify the divergence between supply and demand of water resources [14]. Inability to substitute water scarcity raises consciousness towards potential water crises in the future [15]. Thus, competent authorities must develop the policies that will ensure proper operation, maintenance, water treatment and distribution network to provide quality water to local residents according to essential human needs and at an affordable cost. Regardless of the county/region focused, all residents insist on the existence of two components: (a) appropriate water quality at all times in the water distribution network and (b) transparency, information and public reporting of all processes of water supply utilities.

For the case of urban water, optimizing the operation and management through modelling, data mining, machine learning and fuzzy logic methodologies has improved the knowledge about the systems. More specifically, sustainability, resilience and transformation of urban systems that mainly focus on the quality of the urban water are blended with social, environmental and ecological perspectives. Since they often present dramatic changes, they must continuously be adapted to new data. Therefore, to come up with the most appropriate management options, such systems have to be previously tested under conditions that emphasize learning, monitoring and continuous knowledge acquisition [16,17]. The abovementioned introduction of fuzzy decision techniques can be used to find what is the most socially just and acceptable scenario for allocating quality water to local residents. This methodology takes under consideration multi-stakeholder opinions and examines the multi-criteria urban water quality problem under the uncertainties inherent in a decision making process. Alizadeh et al. [18] effectively used this fuzzy multi-objective model in order to simulate and make appropriate decisions for regional management policies relating to groundwater resources. Moreover, Keshtkar et al. [19,20] applied a fuzzy analytic hierarchy process approach to multiple-criteria scenario analysis for demonstrating integrated natural resources and catchment assessment, modelling and management practices.

For most of the European governments and under their local bylaws, water distribution networks (WDNs) are usually non-revenue WDNs [21]. These WDNs suffer from three major problems, namely: (a) apparent losses, (b) real losses and (c) non-revenue authorized consumption. The cause of these losses is the competent authority policies applied for the operations and maintenance, which are the main reason for the water leakage, as well as the poor quality of underground assets. Such WDNs are exactly the bidirectional paradigm where the poor water quality negatively affects the WDN operation and, on a second phase, the poor WDN maintenance negatively affects the water quality on the consumers' tap. For such WDNs, there is significant research done from the point of dealing the presence of uncertainties via probabilistic tools such as Bayesian Networks [22–24] and the prediction of contamination of drinking water [25].

It is worth mentioning that complementary socio-technological perspectives for the issue of urban water quality rarely take into account the sustainability criterion and, more importantly, the societal change due to policy, social justice, economics, health risks and culture. However, when any social aspect in a technological procedure is encountered, additional uncertainty occurs due to the lack of significant amount of data to support or prove any research conjectures. For this reason, a fuzzy inference approach is a more suitable methodology in similar problems, as it succeeds to represent the problem uncertainties using interleaved boundaries of fuzzy variables. More specifically, it has been demonstrated that there is merit in urban water quality monitoring using machine learning methodologies such as artificial neural networks (ANN) and fuzzy systems [26,27]. However, these research works only take into consideration the sensing of chemical parameters/characteristics (e.g., chlorine, turbidity, nitrates, pH, etc.) and nothing that relates to social characteristics and impacts involved.

From the previous discussion, it is clear that any integrated methodology that deals with the urban water quality must synthesize the traditional scientific techniques with a variety of cognitive dimension techniques mediated by fuzzy inference systems to define values and cultural contexts, analyze drivers of change towards resilience and transformation management and produce policy making in complex and uncertain social environments [28,29]. In complementing the method of fuzzy inference systems (FISs), one similar method in involving stakeholder participation is the fuzzy cognitive maps (FCMs) [30–32]. The advantage of this methodology is its applicability in representing both individual and group knowledge while at the same time it seems the most appropriate in modelling processes and decisions in human social systems and in the ecological realm to organize and analyze the interactions between social systems [33–35]. Apart from the recognized benefits, the FCM methodology suffers from general limitations as the study by Kok [36] indicates. The most critical issue is how the involved stakeholders in the social situation under study perceive relationships between various components of the study. For our case, these components correspond to the social key performance indicators in relation to the urban water quality. The produced chains of cause and effect in these social issues of anthropogenic characteristics make the use of FCM of critical importance, however, due to the simplicity in gaining knowledge of the individual weights of participation of the participating social indicators mentioned.

In the current research, a holistic approach is proposed based on stakeholder participation for the creation of a decision support system for use by the competent authorities in relation to the urban water quality. More specifically, our proposed system is an amalgamation of a FIS and a fuzzy cognitive map (FCM) to identify the local social group (regional stakeholders) expectations and consideration regarding the urban water quality of a WDN. Our methodology falls into supervised machine learning process, as it uses examples (via questionnaire data) regarding the importance (weight) of the social issues involved. Both methods are rather semi-quantitative trying to disclose and visualize any collaborative effects deriving from possible types of focus groups and their cooperative opinions in relation to the aforementioned problem. Since input data are not fully qualified with "crisp values", the decision of using fuzzy logic methodology seems apparent in achieving 'de-fuzzification' and highlighting the most relevant aspects that play important role in decision making process of water utilities. On the other hand, the quantitative nature of the FCM produces the individual importance weights of the social aspects involved. This enables the competent authorities with a set policy options to stimulate positive reaction from the regional social bodies in relation to taking decisions for the urban WDN operation and management.

What makes our method innovative is the valorization of the fuzzy theory and the membership functions of fuzzy variables involved, in the water quality management issue. A modified version of the fuzzy-weighted multi-stakeholder technique is used to incorporate uncertainties associated with the opinions of the public and the competent authorities, and therefore fuzzy membership functions and fuzzy ranking are introduced in decision making for urban water governance. Actually, the novelty introduced in this work is trifold, as a set of fuzzy theory methods (FIS and FCM) along with social science methodologies are incorporated in studying important urban water quality issues. The hybrid application of fuzzy logic and FCM is proved to be a useful pattern classification tool in order to classify social perceptions and behaviours towards policies of water governance. This methodology can be fully generalized also in other topics: by transforming any pattern classification problem into a problem of discovering the way the sets of patterns interact with each other and with the classes that they belong to, the problem to be modelled could easily be transformed as a variation of fuzzy set algebra. Actually, the causalities of all fuzzy concepts can then be studied using FCMs.

The paper is structured as follows: in Section 2, we introduce the reader to the basic definitions and aspects of fuzzy logic, which also includes the construction of a Mamdani FIS [37] where we illustrate the building of a rule-based decision support system to measure the quality of potable water in WDNs. Based on extensive research [38,39] and the references therein, six water quality indicators are the most popular, that is: pH, dissolved oxygen, electrical conductivity (EC), oxygen reduction potential, nitrates and temperature. However we do not attempt to testify the plausibility of existed water quality distribution networks but rather we focus on the evaluation of the level of social acceptance for the issue taking in account social KPI's such as: health risk and water quality, assuming that the "Water Quality" defines the public perception of the urban water quality of the region under study and includes all the above water quality indicators. Moreover, we build two fuzzy inference system sub-models: (a) the output variable of the first is the quality of the urban water management solution (well-known indicator as quality of service, QoS) and (b) the output variable in the second fuzzy inference subsystem is defined as the overall social acceptance as this is derived by the QoS above and the location of the water-treatment facility [40]. The output of the second fuzzy subsystem participates as one of the concepts (nodes) in the FCM, which is discussed in Section 3. More specifically, in this section we first introduce the reader into the basic concepts of an FCM, the development of FCMs using experts' knowledge, the development of FCMs using data and various learning methodologies as well as how the inference is succeeded. Then we construct an FCM where we integrate the stakeholders' opinions in an integrated decision making system using multi-criteria analysis and the scenario-based analysis coming from the FIS constructed above. The FCM construction represents additional social issues related to the urban water quality such as: water monitoring, watershed and environmental protection, drought and other emergency preparedness, water affordability and social justice. We designed the FCM so that a partial outcome emanates from the above concepts, and then we feed this sub-FCM to the outcome of the above FIS so that a single output referring to the decision making for water utilities is achieved. In both Sections 2 and 3, we refer to a case study for the municipal water utility company 'DEYA' of Lamia, Greece, and use the responses from a rather large stakeholder body for the city of Lamia, Greece. An FCM steady-state analysis and a dynamic scenario analysis for the social issues are following. Conclusions and future challenges close this manuscript.

2. FIS for evaluating the public perception of drinking water quality

2.1. Concepts of fuzzy logic

Fuzzy theory handles operations of variables under the concept of 'fuzziness' that refers to ambiguity, impreciseness and vagueness. The classification of the value to a certain category or set among a variety of different categories is evaluated via a membership function that defines the certain degree of an entity to be a member of a category. This is opposed to the classical binary consideration of crisp inclusion or exclusion of an entity in a set. Actually, the degree of membership is somewhat subjective and with imprecise boundaries [41,42]. The popularity of fuzzy sets lies on their ability to operate on linguistic variables that are evaluated using qualitative values (categorical data). In most cases, it is also a common practice to include additional terms (mostly adjectives or adverbs: very, low, medium, etc.) in order to add accuracy to these linguistic values [43]. The use of fuzzy variables is shown in creation of an FIS. This is the key unit of a fuzzy logic system having decision making as its primary task (Fig. 1). In an FIS, "IF…THEN" rules are used along with connectors "OR" or "AND", for drawing essential decision rules.

The main phases in creating an FIS using this approach are the following: (a) the definition of the membership functions, (b) the fuzzification process, (c) the inference mechanism via the design of rules, and (d) the fuzzy outcome. We briefly comment on these four phases:

- A membership function (MF) for a fuzzy set A on the universe of discourse X is defined as $\mu_A : X \rightarrow (0,1)$ and is a curve that maps each element of in the input space X into a membership value called the degree of membership (a value between 0 and 1). The membership functions may be chosen from a variety of shapes to fit the needs of the problem modelling. Fig. 2 depicts the curves of the most popular MFs and it includes their names in MATLAB® (simulation and modelling software to design and evaluate FIS).
- *Fuzzification*: The conversion of a crisp input value to a fuzzy one, using the information in the knowledge base. This is performed according to the decided subdivision of the parameters. Although various types of curves can be seen in literature as explained previously, the most popular membership function types used in the fuzzification process are the Gaussian, triangular and trapezoidal.
- *Inference*: The application of the synthesized value of two or more membership functions in order to deduce a result. This process uses fuzzy set theory to map inputs to outputs (features to classes, in the case of fuzzy classification). The rules of this engine are conditional expressions of linguistic form to support the mathematical formalism using the expression ''if…then'' of the logic itself. However, the truthiness or falseness of the consequent is inferred from the degree of truthiness or falseness of the antecedent.
- *De-fuzzification*: Consists of all the steps involved in producing a quantifiable result and outputting a deterministic value from the fuzzy model used in the inference engine of the system. Most popular methodologies for defuzzification include the basic defuzzification distributions, the constraint decision defuzzification, the fuzzy clustering defuzzification, the centre of gravity and area and the generalized level set defuzzification.

2.2. Fuzzy model for public perception of water quality

The decision for developing a combined (synthesized) fuzzy inference model to regulate and undercover the main indicators that affect the public perception of the urban water quality is because of the embedded uncertainty due to vagueness. The nature of uncertainty is the primary factor to represent with membership functions the sustainable indicators in order to derive the level of social acceptance. Therefore, the existence of imprecise public opinion of water quality can be formulated using a variety of membership functions which can affect the decision making process in relation to urban water governance. For the above reasons

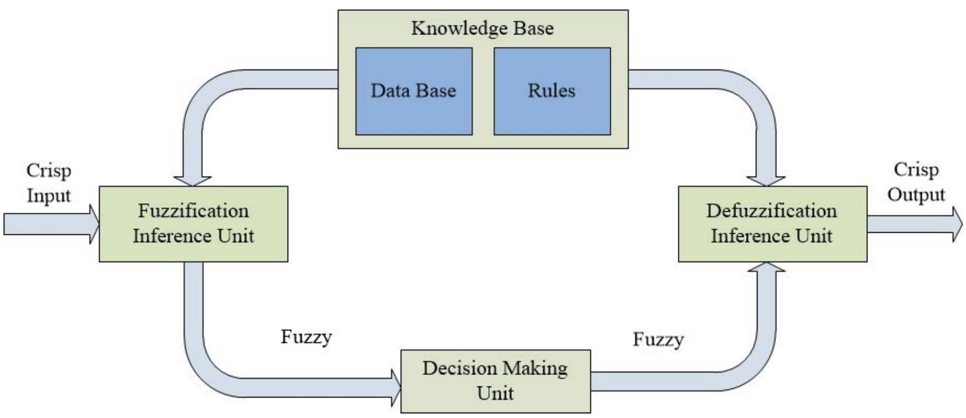
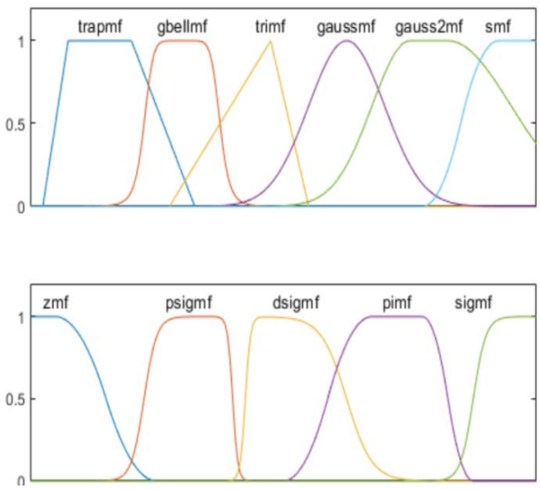


Fig. 1. Components of a typical FIS.



Collection of membership functions in MATLAB	
trapmf	Trapezoidal-shaped MF
gbellmf	Generalized bell-shaped MF
trimf	Triangular-shaped MF
gaussmf	Gaussian curve MF
gauss2mf	Gaussian combination MF
smf	S-shaped MF
zmf	S-shaped MF
psigmf	Product of two sigmoidal MF
dsigmf	Difference between two sigmoidal MF
pimf	Π-shaped MF
sigmf	Sigmoidal MF

Fig. 2. Graphical illustrations of all the membership functions in the MATLAB® fuzzy toolkit.

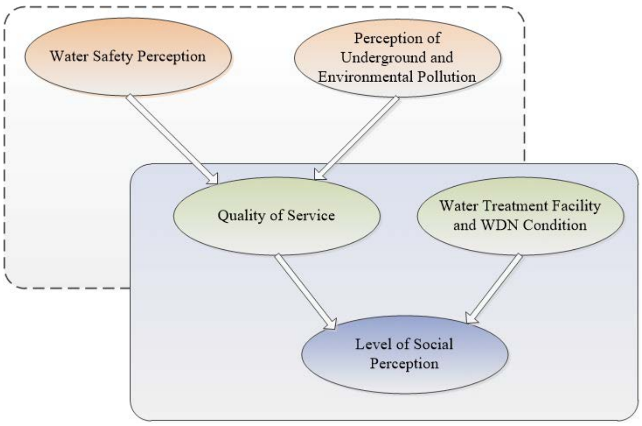


Fig. 3. Conceptual illustration of the composed two sub-model FIS.

and the apparent existence of inaccurate survey data, such methodology selection becomes intriguing. As mentioned before, in order to create fuzzy logic environment, it is necessary to define the input in fuzzy terms, to set up the membership functions for each datum and to establish the fuzzy rules for obtaining the fuzzy output. For our case, it will be a two-step process where first the perception on the service quality of the urban water management solution is derived by three variables: (a) perception of underground and environmental pollution, (b) water safety and (c) perception of the WDN condition. The diagram for this synthesized two sub-model FIS is depicted in Fig. 3.

Note that the entity of the level of social perception in relation to urban water quality cannot be mathematically formulated, thus, quantification of social perception can only be derived by subjective opinions of people. Also, some people (even stakeholders coming from the competent authorities) tend to mix their perception of water safety expressing it in terms of how the water tastes at the tap. Characteristic expressions are related to the level chlorine-type taste. For this reason, linguistic values can be assigned to these opinions scaling in a Likert scale from 0 to 100 assuming values: bad, fair, good, very good and excellent. Assuming the previous linguistic values for the quality of service, we can keep the same gradation for the water treatment facility and WDN condition to keep the two sub-models homogeneous. On the other hand, the fuzzy sets defined for the level of social perception are [40]: totally unacceptable (TU), unacceptable (U), little acceptable (LA), acceptable (A) and totally acceptable (TA).

To apply the information above, we developed three Mamdani FIS corresponding to the use of the triangular, trapezoidal and generalized-bell membership functions. In the following Figs. 4a–d, we depict the Mamdani FIS and the three different membership functions showing only one for each of the fuzzy variables, respectively. After we setup the system in MATLAB, we also set the inference rules for both phases as shown in Tables 1 and 2, respectively. Finally, the 3D decision surfaces produced by the two FIS are shown in Figs. 5a and b, respectively. Especially for the 3D viewer of Fig. 5b using any value combination of the public perception in relation to water quality and any value for the water treatment facility and WDN condition, the overall social perception that will feed the FCM for the decision support system can be determined. Note that this value will be set for the corresponding FCM concept in the map, that is, it will not be allowed to arbitrary changes when evaluating various scenarios and doing steady-state analysis. Since the output of the second FIS is defuzzified, it represents a value between 0 and 100 for the level of the social perception, which will be the concept weight for the FCM. As we show in Section 3, the same scale for the other FCM concepts to keep homogeneity with the FIS is used.

3. Multicriteria analysis and FCM-based urban water governance

3.1. Integration of stakeholders in the urban water governance decision making process

From the social perspective, the most critical issues to deal with the problem of urban water decision-making and water governance are first how to incorporate a holistic

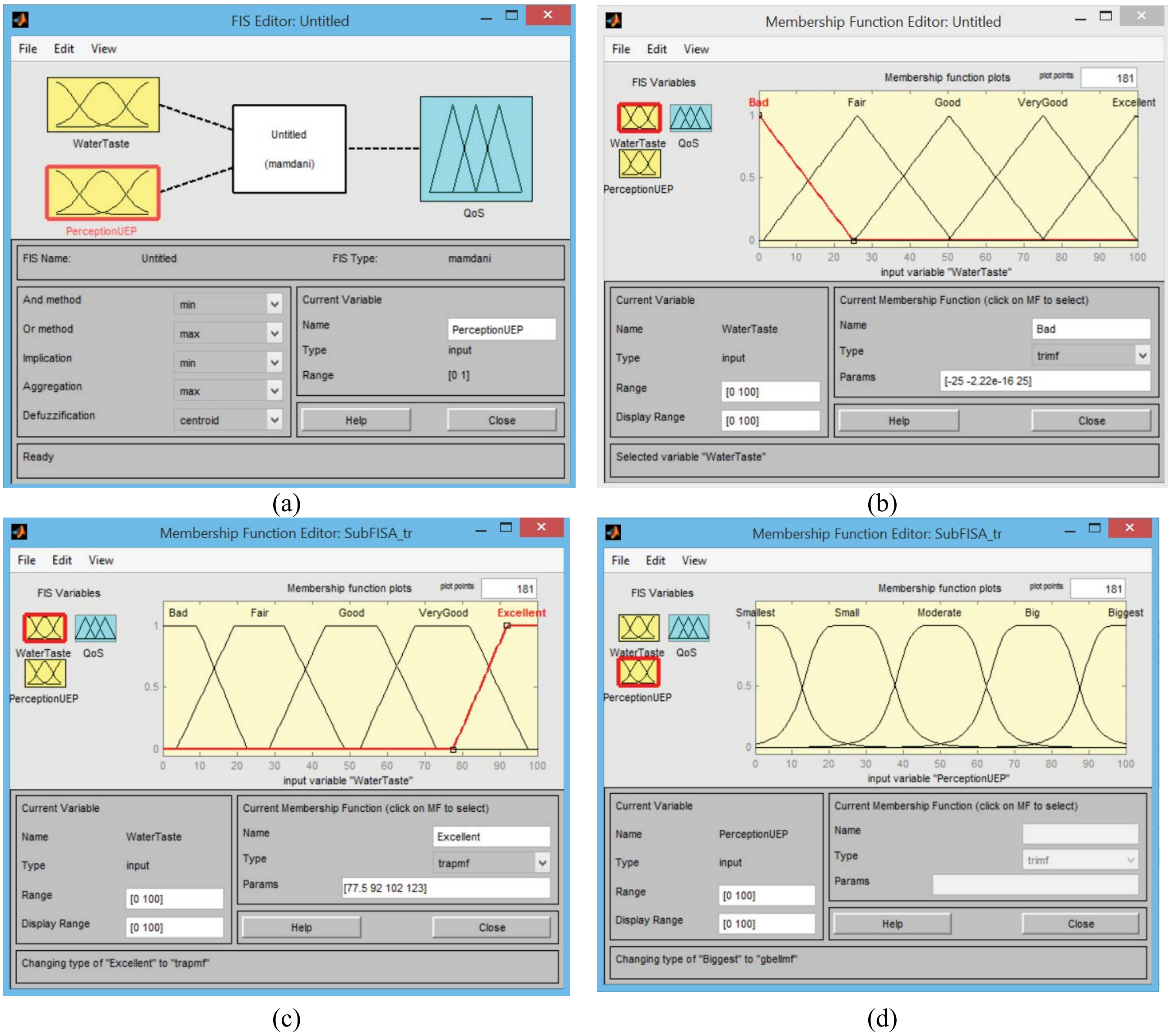


Fig. 4. Mamdani FIS for evaluating: (a) quality of service, (b) triangular MF, (c) trapezoidal MF and (d) generalized bell-shaped MF, for the fuzzy inputs.

Table 1
Fuzzy rules for the quality of service FIS

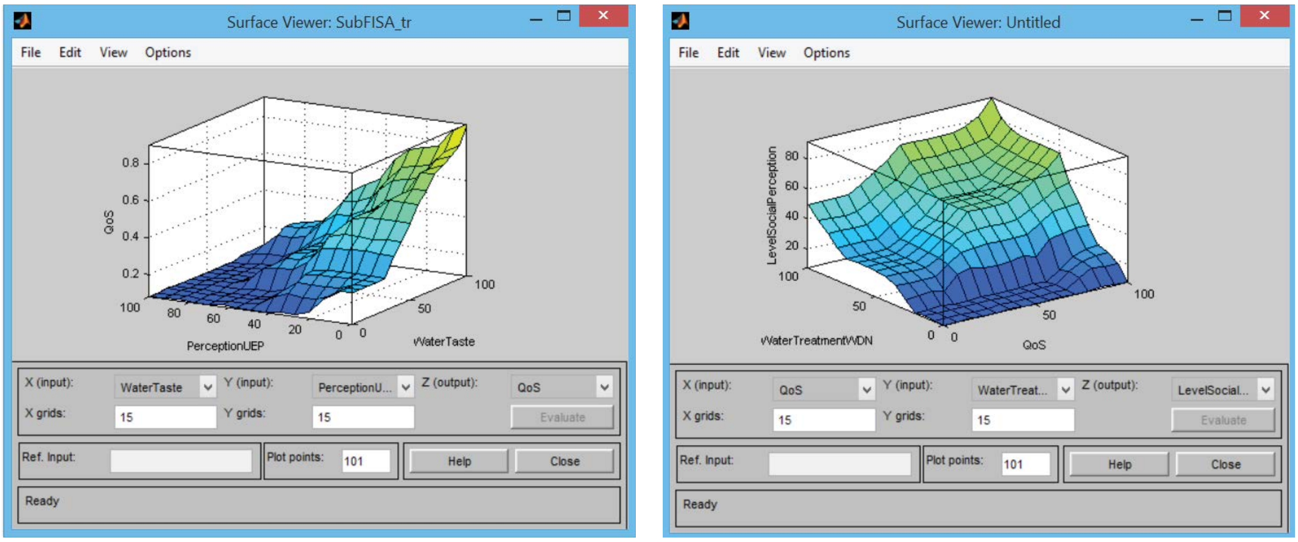
Perception of underground and environmental pollution →					
Water taste ↓	Bad	Fair	Good	Very good	Excellent
Bad	Bad	Bad	Fair	Fair	Good
Fair	Bad	Bad	Fair	Fair	Good
Good	Bad	Bad	Good	Good	Very good
Very good	Bad	Bad	Good	Good	Very good
Excellent	Bad	Fair	Very good	Very good	Excellent

Table 2
Fuzzy rules for the level of social perception FIS

Water treatment facility and WDN condition→					
QoS↓	Bad	Fair	Good	Very good	Excellent
Bad	TU	TU	U	U	LA
Fair	TU	TU	U	U	LA
Good	TU	TU	LA	LA	A
Very good	TU	TU	LA	LA	A
Excellent	TU	U	A	A	TA

approach for the management and second how to integrate this approach with the rest of methodologies (water resources sustainability, health risks, social justice, etc.). For this purpose, dynamic environmental and social system feedbacks that relate to urban water management systems should be included [44].

The primary challenge of holistic management is attacked by the incorporation of knowledge of how and why decisions



(a) (b)

Fig. 5. (a) 3D surface viewer of the QoS FIS and (b) 3D surface viewer of the level of social perception FIS.

are made and what is the social impact of these decisions [45]. According to Hill [46], the concept of water governance must first be comprehended as the process insisting that all involved competent authorities and organizations of common interest should work together with stakeholders to engage shared decision making. This is a shift from previous practices, in which the primary concept was the rule enforcement. Now, it becomes a more flexible approach that integrates public and stakeholder engagement. The need for stakeholder participation in decision making for urban water policies has already been shown to be important [47,48]. However, many barriers have been highlighted by several researchers, including the following: (a) many practices are dependent exclusively on technological methods leaving out any possibility of community engagement inclusion [49], (b) when governance practices engage a large stakeholder body, they usually suffer from the hierarchical engagement style phenomenon (top-down divide) [48] and (c) capacities of communities to participate are not catered for or understood [50].

The aforementioned barriers sometimes cannot be overcome due to the lack of knowledge from the communities (e.g., most people think that the smell of water is tightly coupled with its clarity and potability, which is not always the case). On the other hand, in most public engagements, there is a notable willingness of the community to participate and learn from the process. This is an important factor to the success of the competent authorities' undertaking in relation to urban water decision, both in macro- and microlevel urban water management.

For the case of urban water governance, there is a need of participatory methodologies to deduce effective results for decision making. Such a modelling approach is the FCM, as it is able to gain knowledge through training, and this knowledge can come from stakeholder participation [51]. Furthermore, FCMs allow additional interactions coming from other technologies such as FIS as well as other FCMs [52,53].

3.2. Scenario-based decision-making

In general, the scenario-based methodology enables policy makers to plan and select more sustainable portfolios for future policies. The exhaustive methodology of testing several scenarios is fundamental to mitigating future risks in urban water shortage among many others. Critical evaluation of each scenario enables the competent authorities to advance with decision making while also minimizing the interrelated costs [54,55]. Along these lines, urban water policy makers try to achieve optimal solutions securing the sustainability of regional water resources.

However, at the same time, other stakeholder parties may be engaged in decision making that sometimes contradicts the abovementioned optimal practices, uncovering environmental vulnerabilities, such as drought, usually summer heat waves, overwhelming water demand (especially during summer months), water contamination due to external factors and unfair competition for water resources. For this reason, urban water management has to adapt to a set of interdisciplinary practices and find tools that have the ability in representing structured knowledge and model complex systems. Such a decision making model is the FCM that is explored in the following subsections.

3.3. FCM methodologies

FCMs [30,31,32,55,56] are signed digraphs of semi-quantitative nature used to structure experts' or stakeholders' knowledge and can analyze how these interested parties perceive complex policy systems. FCMs are able to compare co-existed perceptions of various stakeholders combining qualitative and quantitative information. In essence, an FCM is a graph consisting of nodes and directed edges that connect any two nodes representing causal relationships between the nodes. These causal relationships between nodes are not necessarily measured by crisp values, as fuzzified associations may very well be evaluated in order to express the membership function of relation using linguistic terms.

FCMs can be easily constructed by stakeholders because of their graphical nature and their user friendliness. Initially, the set of concepts is determined and then any causal relationship between any two concepts is described "either with an if–then rule that infers a fuzzy linguistic variable from a determined set *T*{influence} = {negatively very very strong, negatively very strong, negatively strong, negatively medium, negatively weak, negatively very weak, zero, positively very weak, positively weak, positively medium, positively strong, positively very strong, positively very very strong} or with a direct fuzzy linguistic weight from set *T*{influence}" [57]. The selection of the FCM methodology to model a decision support system for urban water governance is due to two reasons: (a) FCMs are able to incorporate the details and the value uncertainty of various factors affecting this decision and (b) FCMs are suitable to illustrate the effects of factor changing for the whole systems, even though they are not able to make quantitative predictions.

FCMs build on stakeholder understanding and experience of the system via questionnaires or experts' knowledge or just from the literature. The variety and volume of participants may fluctuate from just few to up to hundreds. Initially, all participants give feedback to the experts and then the experts undertake the task of knowledge extraction and formulation into concepts via a defuzzification process of the linguistic variables. The result is a graph *G* consisting of concepts depicted as a set of nodes C_i (i = 1,2,...n) with their interrelations denoted as w_i (graph directed edges).

For experts to conclude on which concepts to integrate, stakeholders give first feedback prior to knowledge extraction. Especially for decision policies made, this knowledge extraction is succeeded transforming all linguistic variables into numeric values via a defuzzification process. This produces a set of concepts denoted as C_i (i = 1,2,...,n) (graph nodes) with their interrelations denoted as w_i (graph directed edges). The most important representation for the FCM is the adjacency matrix of the weights w_{ij}, where a positive value denotes that an increase (decrease) of the value of concept C_i results to an increment (decrement) of the concept's value C_j, respectively. Similarly, a negative weight w_{ij} indicates that an increase (decrease) in the value of concept C_i results to a decrement (increment) of the concept's value C_j, while a zero weight denotes the absence of relationship between concepts C_i and C_j, respectively. Aggregation of selected FCMs that correspond to individuals may result in a collective map where many variables can be grouped together to formulate a broader concept. In terms of the individual adjacency matrices, these can also be aggregated to form a group matrix [34]. Every concept C_i in the graph (Fig. 6) has a value A_i that denotes the conversion from a fuzzy linguistic value. For the converging of the FCM to a stabilized state, a number of iterations recalculate the concepts C_i using the weights of the edges and an inference rule. In each iteration, the new value of concept C_i indicates the difference in influence of the rest of the concepts. Many inference rules have been used for FCMs with the most important ones by: (a) Kosko's inference, (b) modified Kosko's inference and (c) Rescale inference with their formulas depicted below, respectively:

$$A_i(k+1) = f\left(\sum_{j=1, j\neq i}^{N} w_{ji} \times A_j(k)\right) \tag{1}$$

$$A_i(k+1) = f\left(A_i(k) + \sum_{j=1, j\neq i}^{N} w_{ji} \times A_j(k)\right) \tag{2}$$

$$A_i(k+1) = f\left((2\times A_i(k) - 1) + \sum_{j=1, j\neq i}^{N} w_{ji} \times (2\times A_j(k) - 1)\right) \tag{3}$$

The iterations stop at the step when none of the concepts is changed or the change is less than a predefined threshold which can be bivalent, trivalent, sigmoid or hyperbolic, as shown in the following four equations, respectively:

$$f(x) = \begin{cases} 1 & x > 0 \\ 0 & x \leq 0 \end{cases} \tag{4}$$

$$f(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \tag{5}$$

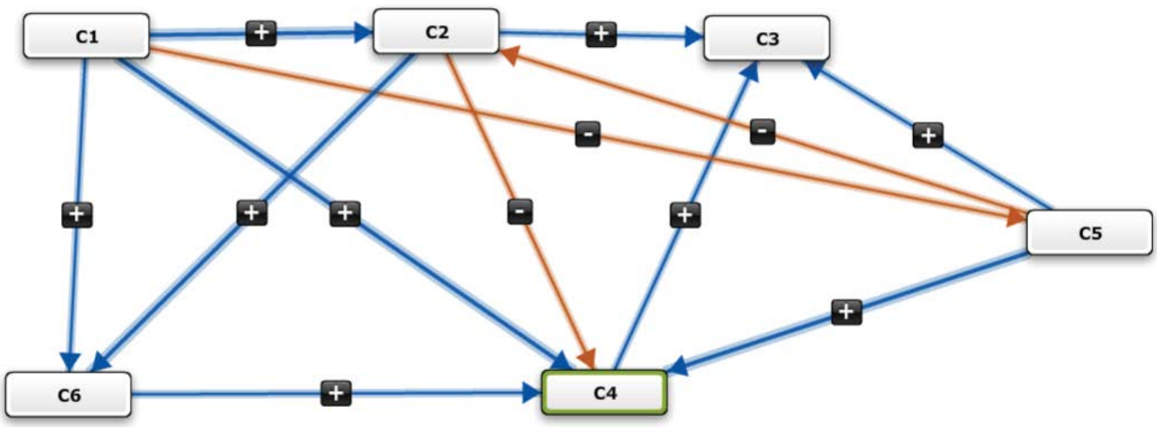


Fig. 6. Typical FCM graph depicting positive and negative causalities between concepts.

$$f(x) = \frac{1}{1+e^{-\lambda x}} \tag{6}$$

$$f(x) = \tan h(\lambda \times x) \tag{7}$$

The following two properties are fundamental when analyzing linguistic variables, especially the so-called transmitter variables (with positive out-degree and zero in-degree). These properties are the density and the centrality of the FCM. The transmitter variables are also called drivers where the receiver variables (zero out-degree and positive in-degree) are the dependent. Finally, the ordinary variables (both zero out-degree and in-degree) are means. The definition of the density and centrality follows:

Density (D) provides information on the connectivity of the FCM and relates the number of connections and the maximum number of possible connections between the FCM's variables:

$$D = \frac{C}{N(N-1)} \tag{8}$$

where D is the density of the map, C is the total number of connections and N is the number of variables.

The degree centrality is a local centrality measure, because it is determined by only its directed connections. The degree centrality of a node is the summation of its absolute incoming (in-degree) and outgoing (out-degree) connection weights:

$$C_D(v) = \sum \left(\mathrm{id}(v) + \mathrm{od}(v)\right) \tag{9}$$

where the in-degree id(v) is the summation of connection weights entering node v, and the out-degree od(v) is the summation of connection weights exiting node v.

The formation of the FCM is done with the help of experts and/or stakeholders whose opinion is noted via questionnaires, surveys, focus-groups or other methods of setting up the weights of the edges between any two concepts. In the case scenario that there are no experts or FCMs are very complex to draw, there are many learning (training) mechanisms that substitute the experts such as: (a) Hebbian-based, (b) population-based and (c) hybrid learning. Hebbian-based methods use available data and a learning formula that is based on several modifications of Hebbian law, to iteratively adjust FCM weights. Typical Hebbian-based methods have been reported in the literature [58–61]. Most of the population-based algorithms include techniques such as simulated annealing, evolution-based and particle swarm optimization [62–67]. At the end, the hybrid method is an amalgamation of the other two, synthesizing the differential evolution algorithm and nonlinear Hebbian learning algorithm, by using both the global search capabilities of evolutionary strategies and the effectiveness of the non-Hebbian learning rule [68].

We consider a new extension of multi-criteria decision analysis (MCDA) using a similar hybrid model that interrelates FIS and FCMs in decision and policy making regarding water governance. More specifically, this approach is preferable to MCDA due to the fact that it represents relative importance among concerning criteria which allow the use of fuzzy linguistic values. The proposed model provides considerable flexibility to decision makers when solving real-world MCDA problems. It should be noticed that the construction of the inner influences among criteria in analytical criteria processing represents a hard task for decision makers. For that reason, the adaptation of FIS and FCM provides a simplification of this process resulting in a simple way the final preferential matrix of criteria with inner influences. The ease of the process comes from the fact that FCMs allow the handling of uncertainties in the form of linguistic values.

4. Application of FCMs in analyzing water governance – steady and dynamic state analysis

4.1. Description of the case study

The effect of the FCM and the FIS discussed in Sections 2 and 3 was tested for the case study of the city of Lamia, Greece. Lamia is located in central Greece, (Fig. 7) with a municipality area of 947 km^2 and of ~75,000 population. Up until 1929, the city of Lamia used to get potable water from sinks, wells and cisterns. The area around the Galaneika district used to be called "wells" indicating the city's water source. From 1929 and after, Lamia's water comes from Gorgopotamos river and several physical reservoirs made around the city capturing the water from the surrounding mountain springs. Occasionally, there are few ructions about the quality of potable water but just recently the Lamia's municipal water utility company ('DEYAL') has really been upgraded and improved its services to residents.

A part of the latest dissemination attempts of DEYAL is the anchoring of the levels (values) of a variety of KPI's related to the chemical characteristics for the water quality. Data similar to these provided in Table 3 shown below are issued every week for the information of local residents (or other stakeholders).

The main goal of this paper is to provide a decision support system for the water utility in order to apply water governance but also to do an investigated assessment of the community attitudes towards the quality of urban water measuring the degree of this acceptance. These issues are coming from a thorough survey polling the local residents, university students and water utility employees. More specifically, the questionnaires were distributed in two locations. First, 35 questionnaires were answered by university students. An appropriate call was sent via email to the students of the two departments of University of Thessaly located in Lamia. The rest of the questionnaires was answered by local residents at the DEYAL premises where residents go to pay their bimonthly water bill. There was not any predetermination on the number of questionnaires so all answers were included in the survey.

As we discussed in Section 2, apart from the social perception and the water quality of service factor, which are the outcomes from the two FIS subsystems, several other factors have been indicated by the survey, namely: (a) water monitoring, (b) watershed and environmental protection, (c) drought and other emergency preparedness, (d) water affordability, (e) health risk and (f) social justice. Around 120 questionnaires were distributed and after that, unification of similar concepts/issues was performed. Three experts were

Fig. 7. Satellite view of the city of Lamia, Greece.

Table 3
Urban water quality KPIs for the city of Lamia, Greece

KPI	EC limits	Gorgopotamos WDN	Taratsa WDN	Mixed WDN
Colour	20	3	3	3
Turbidity	10	1	1	0
Free chlorine	Above 0.00	0.14	0.09	0.12
PACK	–	2	1	4
pH	6.50–9.00	7.92	7.63	7.95
Conductivity	2,500	310	492	365
Alkalinity	–	150	235	–
Hardness	60 min	173	265	–
Calcium Ca	–	57.1	86.8	–
Magnesium Mg	50.0	7.2	11.6	–
Iron Fe	0.20	0.02	0.03	0.03
HCO_3 bicarbonates	–	183	287	–
Cl	200	8	15	–
Sulphur SO_4	250	1	10	1
Phosphates PO_4	6.70	0.07	0.09	0.08
NO_3 nitrates	50.00	4.11	11.22	6.20
Nitrite NO_2	0.100	0.000	0.001	0.000
Ammonium NH_4	0.50	0.00	0.00	0.00

also interviewed, one from the University of Thessaly with expertise in social issues, a chemist and the chief operations manager from the DEYAL water utility. The above unification resulted in an FCM of totally eight concepts including the water quality and the social perception along with the six factors above. Relatively to the interviewing process, at first, we described to the participants the most relevant concepts to water quality and its social implications and also the causal relationships between concepts using mostly natural language, so they could apprehend, understand and share among themselves the new information. It was then easy for the participants to assign negative or positive causality to the map. The values assigned to causality (weights) were of the fuzzy range *T*{influence} = {negatively very very strong, negatively very strong, negatively strong, negatively medium, negatively weak, negatively very weak, zero, positively very weak, positively weak, positively medium, positively strong, positively very strong, positively very very strong}. Finally, the results were defuzzified and entered in the online software "Mental Modeler" [69] to draw the FCM, which is depicted in Fig. 8, and to calculate the following:

- Total number of components
- Total number of connections
- In-degree and out-degree of each component
- Connections per component
- Type of component (driver, ordinary, receiver)
- *Centrality*: Absolute value of either (a) overall influence in the model (all + and – relationships indicated, for entire model) or (b) influence of individual concepts as indicated by positive (+) or negative (–) values placed on connections between components; indicates (a) the total influence (positive and negative) to be in the system or (b) the conceptual weight/importance of individual concepts [31,70]. The higher the value, the greater is the importance of all concepts or the individual weight of a concept in the overall model (Mental Modeler Manual [69])
- C/N: Number of connections divided by number of variables (concepts)
- *Complexity*: Ratio of receiver variables to transmitter variables
- *Density*: Connections number compared with all possible connections number.

4.2. FCM steady-state analysis

Table 4 shows the values for the aforementioned properties of the FCM. Individual concept characteristics (in- and out-degree, centrality, etc.) are depicted in Table 5. The resulted FCM is of manageable complexity thus no sub-divisioning is needed. The correlation of environmental, health and societal concepts is obvious in the map as these issues prioritize the way citizens think about what affects urban water quality.

Experts and stakeholders from DEYAL water utility and the regional community have categorized the social perception and the social justice as the fundamental factors influencing the operation of such utilities. The reason is that the water pricing models used in Greece are affected by the relevant constitutional laws that specify upper thresholds prices per m^3, delay payment policies and fines. Furthermore, experts' and stakeholders' opinions are weighted more than regular resident opinions due to their expertise on the topic. Note that the average was 1.89 ranging from 1 to 4 according to different participants. For the merged FCM shown in Fig. 8, a density of 0.18181 is deduced, with average connections per component raised up to 1.81818.

The hierarchy index of the FCM was calculated to be 0.149, making it very close to 0, which is denoted by Özesmi and Özesmi [34] as highly democratic. From the receiver concepts, the ones with higher centrality were the health

Table 4
General FCM statistics

FCM properties	Value
Total components	11
Total connections	20
Density	0.18181
Connections per component	1.81818
Number of driver components	3
Number of receiver components	4
Number of ordinary components	4
Complexity score	1.33333

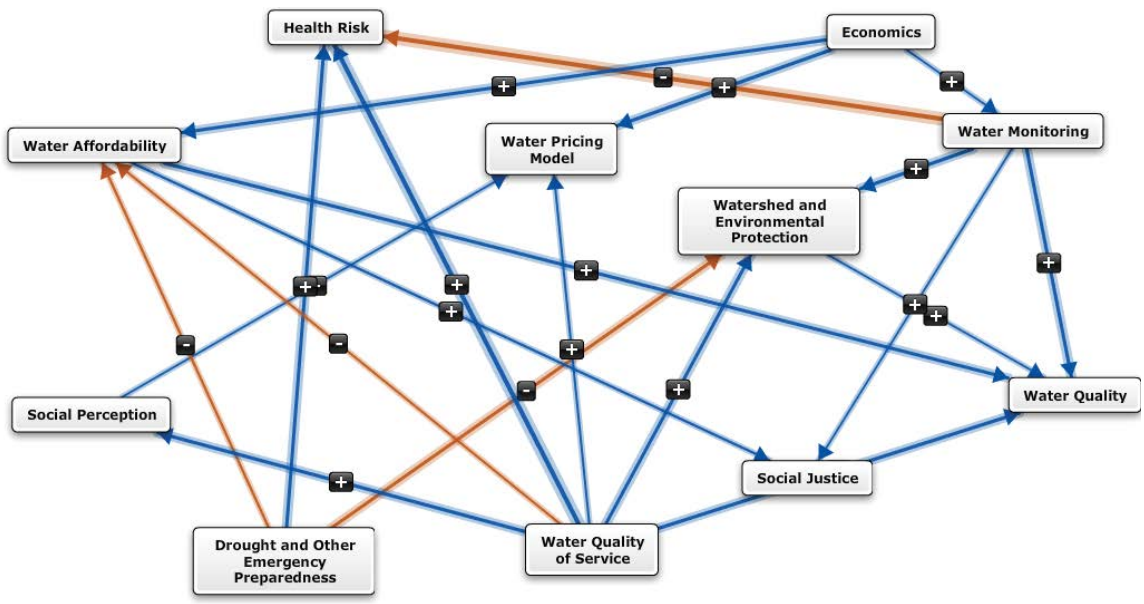


Fig. 8. FCM resulting from the experts and stakeholder analysis.

Table 5
In-degree, out-degree, centrality and type of concepts in the FCM

C#	Concept name	In	Out	Centrality	Type
C1	Social perception	0.51	0.27	0.78	Ordinary
C2	Drought and other emergency preparedness	0	1.579	1.579	Driver
C3	Health risk	2.369	0	2.369	Receiver
C4	Watershed and environmental protection	1.79	0.44	2.23	Ordinary
C5	Water affordability	1.27	1.04	2.31	Ordinary
C6	Water monitoring	0.47	2.29	2.76	Ordinary
C7	Economics	0	1.65	1.65	Driver
C8	Water pricing model	1.31	0	1.31	Receiver
C9	Water quality of service	0	3.58	3.58	Driver
C10	Social justice	0.8	0	0.8	Receiver
C11	Water quality	2.33	0	2.33	Receiver

risk as well as the water quality of service as expected. Also, the most central concepts directly affecting the Water Quality concept were the following, in descending order of their complexity: (a) Water Quality of Service 3.58, (b) Water Monitoring 2.76, (c) Health Risk 2.369, (d) Water Affordability 2.31 and (e) Watershed and Environmental Protection 2.23. This depicts the direct association of the quality of service of the water utilities (primarily) and the environmental issues (second) to affect the public decision for the water quality.

We consider the steady state of the FCM model as the initial scenario to start our analysis, that is, all results from Tables 4 and 5. To evaluate the effectiveness of the model, we compare the worst case and the best case scenario with the steady state. The worst case scenario is set up with all driver concepts to have the value of 0.1. On the opposite side, the best case scenario is set up with all driver concepts to have the value of 1. Fig. 9 shows a decrease of about 6% in the "WATER QUALITY" receiver concept when it is compared with the original steady-state scenario. In the same scenario, the biggest decrease is observed for the "Health Risk" concept with an overall value of 14%. On the opposite side, a slight increase of only 1% in the Water affordability is noted. This indicates that the social perception of water quality is driven mainly by the health risk and the environmental issues and it is inverse to the water affordability. Analyzing the best case scenario (Fig. 10), the focus is on the difference of the ordinary and receiver concepts giving special priority on the final receiver concept of the "Water Quality". More specifically, a 6% increase is observed on the "Water Quality" receiver when it is compared with the original steady-state scenario which was set as the base for the analysis.

Furthermore, the vast majority of ordinary concepts behave similarly with the "Health Risk", "Water Pricing Model" and "Water Monitoring" to show increase of 16%,

Fig. 9. Effect of the driver concepts for the worst case scenario compared with the steady state.

11% and 6%, respectively, and relatively to the steady-state analysis. Similar results have been reached for both the worst and best case scenario analysis, when hyperbolic tangent, bivalent and trivalent inference thresholds are used instead of the sigmoid. Note that the outcome of best case scenario analysis basically demonstrates the effect of the driver concepts in the best case scenario to the other concepts included in the FCM. For our case the driver concepts are 3: (a) Drought and other emergency preparedness, (b) Economics and (c) Water quality of service. The figure shows that the maximization of the above 3 concepts affects negatively the affordability of water. This affect is small (1%) but significantly enough to tell us that there is not direct (analogous) effect of water affordability related to the worst case values of the driver concepts.

4.3. Clamping and fixed driver scenario

The above two scenarios (worst and best case) are not sufficient in determining the final set of edge weights that can be used for the DSS. For this reason, various simulations have been performed focusing on the FCM convergence and the concept defuzzification process afterwards. For the convergence of the FCM, the 'clamping' technique was used [70]. With clamping we can study a specific subset of the concepts and analyze how the weight change on these concepts affects the FCM convergence. Even though the method is not-deterministic (for large FCMs, the concept selection combinatorics are exponential), for small FCMs as in Fig. 8, it works effectively. Leaving out the receiver concepts of this selection, the most intuitive is the selection of the driver concepts resulting into the converged FCM concept values shown in Fig. 11. Finally, Fig. 12 depicts all the concept activation curves per each iteration. As shown in Fig. 12, the convergence is rather fast due to the low causality density edges in the FCM. Simulations are run for all cases of four activation functions (sigmoid, bivalent, trivalent and hyperbolic tangent) as shown in Section 3.3. Any other combination and mixture of driver and ordinary concepts with fixed values can differentiate the resulted values of the receiver concepts. The most affected are the "Health Risk" and the "Water Quality" as discussed in the steady-state analysis.

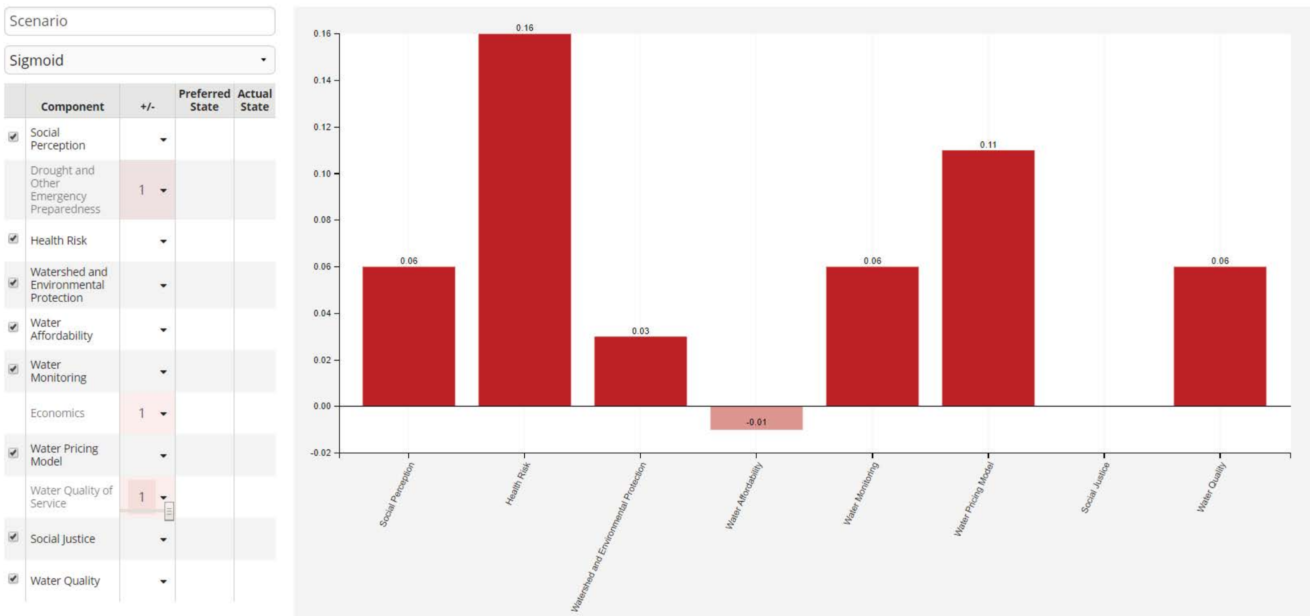


Fig. 10. Effect of the driver concepts for the best case scenario compared with the steady state.

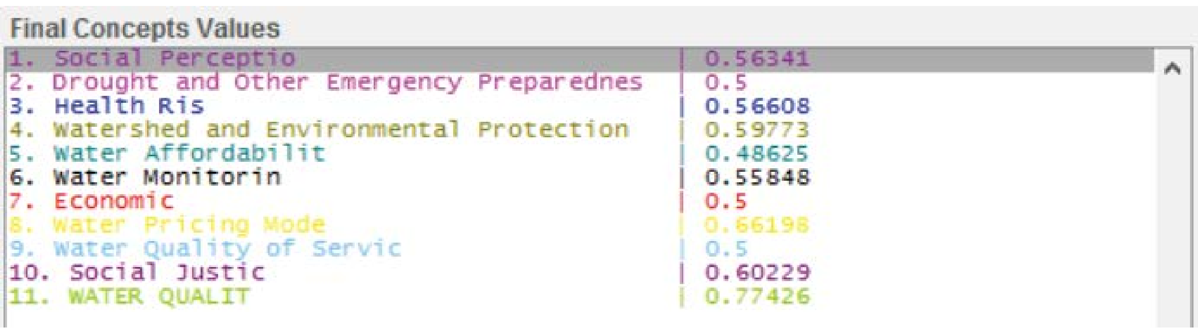


Fig. 11. Indicative dynamic simulation of the FCM and converged values of the "WATER QUALITY" and "Health Risk" concepts.

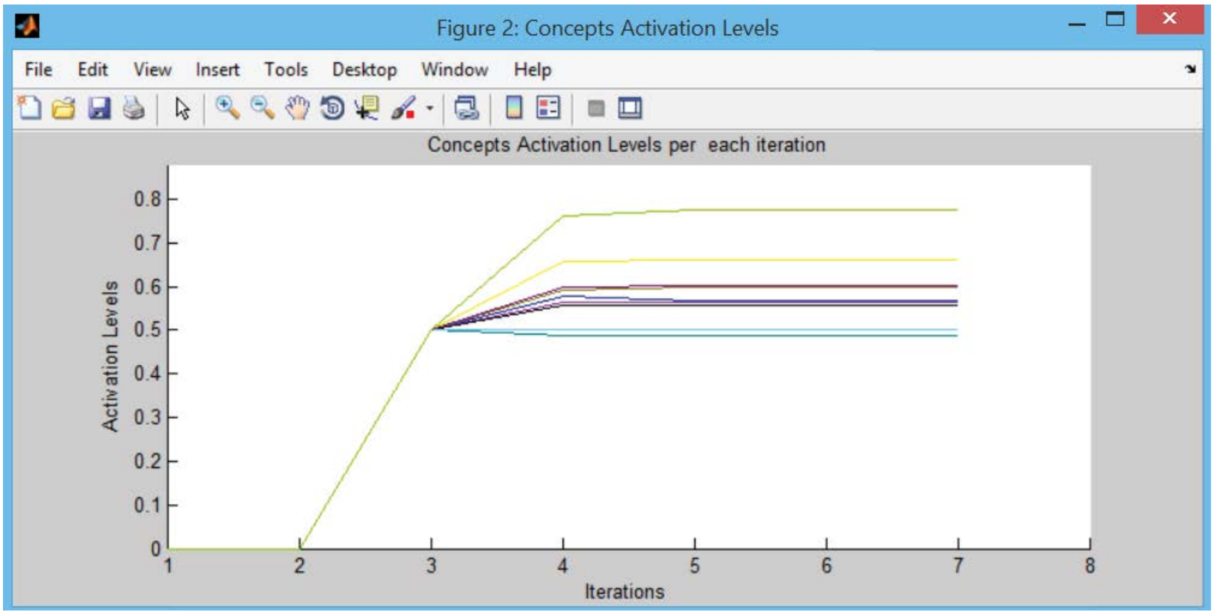


Fig. 12. Corresponding curves of concept activation levels per each iteration.

5. Concluding remarks

The concept of "participation" in urban water quality assessment, planning and decision-making involves all stakeholders and public, which are affected by, are knowledgeable of, or have relevant expertise in or experience of the issue at stake. Several prior studies (focused to urban water governance or even interdisciplinary) have shown that public participatory methods and techniques are useful in supporting sustainable urban development. However, the promotion of new policy formation in relation to water management has to face several kinds of uncertainties (health risk, social justice, technology risk, market dynamics and economic constraints).

In this paper, we stressed the relevance of knowledge gained from local stakeholders' perceptions to reduce the uncertainty related to drinking water quality. We considered multiple sustainability scenarios and KPIs, and we finally used an innovative approach combining FIS and FCMs to show treads and general directions in identifying the most determinant factors they affect the public opinion. Our study included (a) a steady-state analysis, where the FCM resulted as an amalgamation of stakeholder and expert knowledge and (b) a scenario analysis based on clamping and fixed driver concept values. The steady-state analysis defuzzified the increase/decrease of water quality in relation to quality of service given by the water authorities and the social perceptions. In this analysis, we see the close relation between "Water Quality" and "Health Risk". On the other hand, the clamping method set the driver concepts with fixed values and highlighted how the weight change on the driver concepts affected the FCM convergence.

Even though the methodologies depicted were applied on a single case, only the outcome of the model will be affected when the same model is applied on a different use case. In fact, the discovery of the interrelation between the concepts in the FCM does not change. However, the causality weights between the concepts are related by the human perception statistics of the use case under concern. For this reason, FCMs tend to be use case dependent. But this dependency is focused only on how local residents see the effect of the key performance indicators and the concepts of the FCM. Training of the FCM using different experts results in different causalities. For the vast majority of use cases, this does not affect the FCM convergence, which makes the FCM a very good tool showing trends in decision making. In any case, when clear and crisp value data are available, well-defined statistical approaches are preferred. But, for modelling use cases that model data of fuzzy and unclear nature, fuzzy inference and FCMs are proved to be easy to use and effective decision support tools.

The analysis revealed that concepts such as "Water Quality of Service", "Watershed and Environmental Protection" and "Social Perception" are the most influential factors to "Urban Water Quality". This was what both the steady state and the clamping analysis have verified for the FCM. Consequently, building the social cognitive map with a participatory approach and simulating different policy scenarios by means of fuzzy inference is a supportive method to overcome uncertainties and establish rigid regional urban water governance.

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