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Computing a global performance index by fuzzy set approach

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Abstract

This paper introduces a new methodology for analyzing and computing the overall hydraulic performance for each single component in the network and for the whole water distribution system. Water required and supplied, are considered as the main asset to carry out the hydraulic analysis. The methodology is based on hierarchical system approach that begins by evaluating the hydraulic performance through a set of three indicators that are reliability, resiliency, and vulnerability. Then the Analytic Hierarchy Process (AHP) is being used in order to assign weight for each indicator. Finally, fuzzy logic technique is applied which allows the aggregation of all previous indicators into one single index that depict the system condition whether is poor, good or somewhere in between.

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Keywords: Reliability; Resiliency; Vulnerability; Analytic Hierarchy Process; Fuzzy logic;

1. Introduction

Performance assessment of water distribution system (WDS) has been extensively reported in the research and practice literature. The nodal pressure and the available water volume are strongly interrelated, and both are very important for reliability assessment. Fujiwara and Ganesharajah (1993) established a reliability assessment methodology based on the Markov Chain, where they express the hydraulic reliability in terms of available pressure, and they assumed that the effectiveness of the WDS from a node is reduced due to insufficient nodal pressure. In the same context, Tabesh et al. (2001) presented an extended period reliability assessment method

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based on the semi-pressure driven simulation where nodal available water volume changes with the nodal available pressure. Therefore, a consumer receiving water with low pressure and consumer receiving the same volume of water with high pressure do not have the same level of satisfaction. In this study, water demand and supplied are considered as the main asset to be included in the computation of system performance. Demands are defined as the variable that reflects various water requirements and are generally well known for the whole network at each particular node at particular time. While, the water supplied are evaluated using Adjusted Demand Driven simulation according to the previous study of Ermini et al. (2006). Therefore, the hydraulic reliability is assessed based on the nodal available water, taking into consideration the pressure condition.

Nevertheless, the reliability measure alone is not capable to determine how quickly the system recovers and returns to satisfactory state, and how to evaluate the failure severity.

Two indicators are usually used to quantify these system characteristics named resiliency and vulnerability. Hashimoto et al. (1982) defined resiliency, as a measure of how fast a system is likely to return to a satisfactory state once the system has entered an unsatisfactory state, and vulnerability as a measure of the likely damage of a failure event. Since the publication by Hashimoto et al. (1982) and Fiering (1982), the concepts of resiliency and vulnerability have been widely discussed; see for e.g., Moy et al. (1986), Kundzewicz and Laski (1995), and Srinivasan et al. (1999).

In the present paper the originals' Hashimoto resiliency and vulnerability indicators are used to examine the performance of water distribution network through the evaluation of the water supplied at each node with reference to the imposed demands, and a fuzzy set approach was proposed to combine all the indicators into one global index which gives a synthetic and objective evaluation of the water distribution system performance.

Many studies are proposed in the literature to aggregate reliability-resiliency-vulnerability (**Re-Res-Vul**) in order to assess the whole system performance. For water resource systems, Loucks (1997) expressed the sustainability criteria of a scenario as a product of **Re-Res-Vul**, which thereafter has been applied to existing system by Kay (2000), and Kjeldsen and Rosbjerg (2001). The studies mentioned above investigate the most appropriate combination only with regards to monotonic behavior. On the other hand, water distribution is a complex engineering system that is related to pressures, flows and quality behaviors. Therefore, it is more appropriate to use an advanced methodology that can overcome this kind of problem.

Fuzzy logic was founded in 1965 by Zadeh to solve the problem of approximate knowledge that cannot be represented by conventional method, especially when the available information (measured data) is vague and too imprecise to justify the use of numbers. As a solution, fuzzy logic provides a language with syntax and semantics to translate qualitative knowledge into numerical reasoning. The approach of fuzzy logic has been widely used in many areas in water resources as reported in Bogardi and Duckstein (2002), and Zimmermann (1986). A detailed description of fuzzy logic will be presented in the next section and further details can be found elsewhere in Bogardi and Duckstein (2002), and Kaufmann and Gupta (1991).

This present paper introduce a system approach that start by evaluating the hydraulic performance through a set of three indicators **Re-Res-Vul** and then apply Analytic Hierarchy Process (AHP) to assign weight for each performance indicators (PIs), together with fuzzy logic to combine all the indicators into one overall index that depict the system condition.

2. Structure of performance measurement methodology

The proposed methodology involves a hierarchical approach whose main steps are summarized as following (see Fig. 1):

- Estimation of PIs
- Assigning weight using AHP
- Fuzzification of the estimated PIs using fuzzy logic technique
- Fuzzy inference and aggregation of the PIs
- Defuzzification process

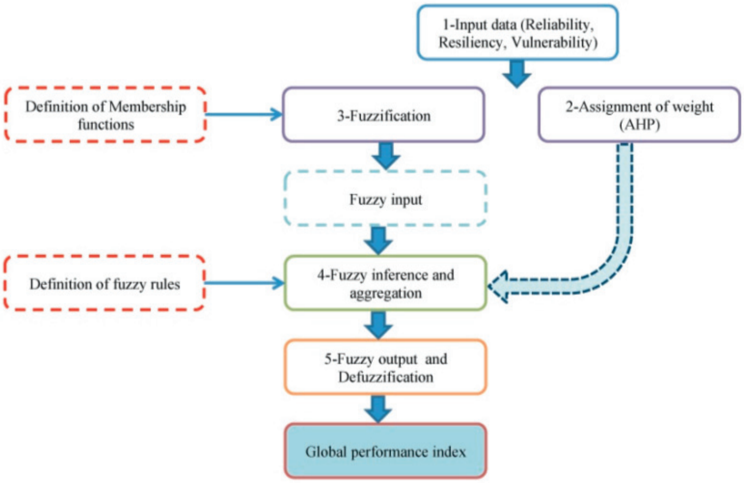

Fig.1. Proposed methodology

3. Estimation of PIs

As previously mentioned the definition and evaluation of reliability, resiliency, and vulnerability are based on the assumption that the distribution network under consideration at given time "*t*" can be either a satisfactory "*S*" state or an unsatisfactory/failure "*F*" state. In this study the focus is on water distribution system, and therefore, the "*S*" state occur when WDS is able to meet water demand and, hence the "*F*" state occur when supply cannot meet demand. Moving from the time step "*t*" to "*t*+1", the system can either remain in the same state or migrate to the other state. The failure event at a particular node "*j*" is evaluated for each time step "*t*", and the corresponding deficit volume denoted $\boldsymbol{v}$ is calculated according to Eq. (1) as the difference between demand and available water during time.

$$v_j = \left(D_{j,des} - D_j\right) \tag{1}$$

Where, $\boldsymbol{D_{j,des}}$ and $\boldsymbol{D_j}$ are the desired demand and the available water at node "*j*", respectively.

3.1. Reliability

Water required and supplied, are considered as the main asset in the computation of system reliability. As previously mentioned, in WDS the nodal available water volume depends essentially on the available nodal pressure. Therefore, consumer satisfaction depends on both available pressure and water volume. According to Ermini et al. (2006), Demand Adjusted Epanet Analysis is applied in this study, where water demand at a particular node is fixed and flow delivered within the network is calculated. The model takes into account the pressure condition at each node to check the availability of water. The process for calculating the water supplied is based on iterative logical process starting from a pre-assigned demand allocation and calculating the demand driven according to Eq. (2):

$$D_j = \begin{cases} D_{j,des} & if \quad P_j \geq P_{j,des} \\ D_{j,des} * \sqrt{\dfrac{(P_j - P_{j,\min})}{(P_{j,des} - P_{j,\min})}} & if \quad P_{j,\min} < P_j < P_{j,des} \\ 0 & if \quad P_j \leq P_{j,\min} \end{cases} \tag{2}$$

Where, D_j and $D_{j,des}$ are the available and the desired water demand at a particular node "*j*", respectively. P_j is the available pressure at node "*j*", $P_{j,min}$ and $P_{j,des}$ are the acceptable minimum level of pressure and the desired level of pressure at a particular node "*j*", respectively.

Based on the available water and nodal pressure, the reliability at a particular node "*j*" is estimated by Eq. (3).

$$\mathrm{Re}_j = \begin{cases} 0 & if \quad P_j \leq P_{j,des} \\ D_j / D_{j,des} & if \quad P_{j,\min} < P_j < P_{j,des} \\ 1 & if \quad P_j \geq P_{j,des} \end{cases} \tag{3}$$

Where, $\mathbf{Re_{,j}}$ is the estimated reliability of node "*j*" in terms of water demand satisfaction.

3.2. Resiliency

A wide number of alternative concepts of resiliency have been proposed in the literature; see for e.g., Fiering (1982), and Holling (1996). In water resource system, resiliency generally has been introduced as a measure of how quickly a system recovers from failure once failure has occurred. Hashimoto et al. (1982) introduced two equivalent definitions of resiliency (**Res**). One is a function of the expected value of the length of time a system remains unsatisfactory after a failure. The second is based on the probability that a system will recover from failure in a single time step, and it is considered here by applying Eq. (4):

$$\mathrm{Re}\,s_j = \Pr\left(D_{t+1} \in S \mid D_t \in F\right)_j = \frac{\Pr\left(D_t \in F \;\; AND \;\; D_{t+1} \in S\right)_j}{\Pr\left(D_t \in F\right)_j} \tag{4}$$

Where, $\mathbf{Res_j}$ is the resiliency of node "*j*". D_t and D_{t+1} are the water supplied at a particular node "*j*" at time step "*t*" and the water supplied at the same node at the time step "*t*+1", respectively. Pr is the probability and the other parameters are defined previously.

If there are not supply deficits, by definition system is considered fully resilient.

3.3. Vulnerability

Hashimoto et al. (1982) defined the vulnerability as a measure of the magnitude of system failure. In this study the vulnerability measure is based on the total water deficit experienced during a failure event at a particular node and is expressed as:

$$Vul_j = \left(D_{j,des} - D_j\right) \tag{5a}$$

Where, $\mathbf{Vul_j}$ is the vulnerability expressed in terms of water deficit at a particular node "*j*".

For a better understanding of system behavior, the vulnerability is then expressed in dimensionless form using Eq. (5b).

$$Vul_j = \frac{\left(D_{j,des} - D_j\right)}{\left(D_{j,des}\right)} = \frac{v_j}{\left(D_{j,des}\right)} \tag{5b}$$

Where v_j is the water deficit at a particular node "j".

4. Assignment of weights

The assignment of weight reflects the relative importance of the indicators defined previously. In fact, the relative weight is subjective and this subjectivity is usually awarded on the basis of expert opinions and policy makers. Several techniques for subjective weighting are presented in literature, such as multi-attribute utility theory introduced by Keeney and Raiffa (1976), utility theory additive defined by Jacquet and Siskos (1982), ordered weighted averaging by Yager (1988) and Analytic hierarchy process (AHP) developed by Saaty (1980). In this paper AHP technique is applied as it is widely used around the world in a wide variety of decisions situations, and has been reported to be a simple but very effective subjective weighting method; Zahedi (1988). AHP allows users to assess the relative weight of multiple indicators in an intuitive manner. The weight of each indicator is achieved basically by pairwise comparison. The basic procedure to carry out the AHP consists of three steps:

- Step 1: Priority setting of the performance indicators by pair-wise comparison and development of the judgment matrix; in this step the relative importance of reliability, vulnerability and resiliency are judged by a pairwise comparison, where for each pair of indicators the experts are required to respond to a question such as "how important is the indicator A compared to indicator B?". Rating the relative priority of each indicator is done by assigning a value using Saaty's intensity scale, whereas the reciprocal of this value is assigned to the other indicator in the pair.
- Step 2: Compute the priority vector; having a comparison matrix, now we would like to compute the priority vector, which is the normalized Eigen vector of the matrix. The calculation of the priority vector is commonly performed by one of the mathematical techniques such as eigenvectors, mean transformation, or geometric mean. In this paper we applied the geometric mean technique.
- Step 3: Check the Consistency of the Judgment Matrix; AHP allows some inconsistency in judgment because human is sometimes inconsistent. In order to check the level of inconsistency, Saaty (1988) developed a ratio called Consistency Ratio (CR):

$$CR = \left(CI/RCI\right) \times 100 \tag{6a}$$

Where, CI = consistency index (Eq.6b); and RCI = random consistency index (Eq. 6c)

$$CI = \left(\lambda_{\max} - n\right)/\left(n - 1\right) \tag{6b}$$

$$RCI = \left(\bar{\lambda}_{\max} - n\right)/\left(n - 1\right) \tag{6c}$$

Where, λ_{max} is the maximum eigenvalue of the judgment matrix; n is the dimension of the pairwise comparison judgment matrix; and $\bar{\lambda}_{max}$ is the average eigenvalue of the judgment matrix derived from randomly generated reciprocal matrices using the scale 1/9; 1/8;…; 1/2; 1; 2;…; 8; 9 and the pairwise comparison for a very large sample. For the present judgment matrix (3×3 comparisons), RCI= 0.58 (see Index Saaty).

Saaty (1988) recommended that the CR should be less than or equal to 10% for decision makers to be consistent in their pairwise judgment. Saaty has also shown that the closer the value of computed λ_{max} is to n, the more consistent the observed values of the matrix are.

Table 1 illustrates how the AHP was used to generate the priority vector and the consistency ratio of the judgment matrix.

The priority vector of the judgment matrix (the last column of table 1) is the normalized geometric mean of the respective rows of the judgment matrix and represents the vector of weights $\boldsymbol{W}$ as shown in Eq. (7). Finally, the consistency of the judgment matrix is calculated by employing Equations (6a)–(6c). In this example, the CR is 4.6% which is less than 10%, so the judgment matrix is consistent.

$$W = [W_{\mathrm{Re}} \quad W_{\mathrm{Re}s} \quad W_{Vul}] = [0.69 \quad 0.09 \quad 0.22] \tag{7}$$

Table 1. Judgment Matrix and consistency test results

Indicators	Reliability	Resiliency	Vulnerability	Priority vector
Reliability	1	6	4	0.69
Resiliency	1/6	1	1/3	0.09
Vulnerability	¼	3	1	0.22
Column Sum.	1.42	10	5.33	1.00
n=3; λmax = 3.054; CI=0.0268; RCI= 0.58; CR = 4.6%< 10%				

5. Fuzzification of the estimated PIs

Fuzzy logic is a mathematical theory pioneered by Zadeh (1965), which is designed to model the vagueness or imprecision of human cognitive processes. Fuzzy logic is based on a linguistic approach in which words and or phrases of natural languages are used instead of numbers. A linguistic variable is one that takes on linguistic values such as “good” for a variable describing system performance in terms of water supplied with respect to water required. That is, a linguistic variable takes on values that have clear intention (the performance of the distribution network is good), but with vague extension (we do not know the true failure load). In contrast to a crisp number whose value is precisely defined, a fuzzy number is a fuzzy set defined on the set of real numbers whose numeric meaning is vaguely defined. For example, the word “very good” as a statement potential consequences is a fuzzy number in the sense that express magnitude without precise quantification.

In others words, fuzzification is a procedure through which the input variables are converted into fuzzy set. Such conversion is performed through the membership functions (MFs). A MF is function which associates a value (usually numerical) with the level of membership to the set. By definition, the real number that represents the level of membership takes a 0 value when the element does not belong to the set and 1 when it belongs to it completely. MFs can be of several types, the simplest are made up with straight lines, while the most used are triangular and trapezoidal shaped MFs; see Fig. (2.a). In this paper, the two latter shaped MFs are employed due to their simplicity in the calculation and are given by the following expression, Eq. (8):

$$ZFN = \begin{cases} 0 & if \quad x < a \quad or \quad x > d \\ \left(\dfrac{x-a}{b-a}\right) & if \quad a \le x \le b \\ 1 & if \quad b \le x \le c \\ \left(\dfrac{d-x}{c-b}\right) & if \quad c \le x \le d \end{cases} \qquad TFN = \begin{cases} 0 & if \quad x < a \quad or \quad x > c \\ \left(\dfrac{x-a}{b-a}\right) & if \quad a \le x \le b \\ \left(\dfrac{c-x}{c-b}\right) & if \quad b \le x \le c \end{cases} \tag{8}$$

For ZFN (trapezoidal fuzzy number), *a* is the minimum value, *d* is the maximum value and *b* and *c* are the most likely values. For TFN (triangular fuzzy number) *a* and *c* are the minimum and the maximum values, respectively, where *b* is the most likely value.

To select the number of MFs associated with each indicator, some studies such as conducted by Miller (1956), suggest that the maximum number of chunks of information is on the order of seven, plus or minus two. The most commonly used types of scales are summarized in table 2.

Table 2. Scale types (Rahman, 2007)

Scale types	Example
3 point scale	Poor-adequate-good
4 point scale	Poor-fair-satisfactory-good
5 point scale	Poor-fair-satisfactory-good-excellent

To simplify the analysis, the MFs of reliability, resiliency and vulnerability are classified into four granularity levels: poor, fair, satisfactory, and good. In this classification, the good level indicates the highest possible level of a system's performance that is technically feasible. The satisfactory level indicates a performance that is acceptable but lower than the good level. Similarly, the fair level is lower than the satisfactory level and requires further improvement. The performance level below fair is poor, it is not acceptable for the current condition, and it requires immediate plans for improvement. Table 3 summarizes the values used to construct the MFs of the four granularity levels for each indicator.

Table 3: definition of linguistic variable

			Performance Levels													
Linguistic variable (*La, Lc*)			Poor				Fair			Satisfactory			Good			
Threshold			a	b	c	d	a	b	c	a	b	c	a	b	c	d
PIs %	Input	Reliability	0	0	40	-	20	40	60	40	60	85	60	85	100	100
		Resiliency	0	0	40	-	20	40	60	40	60	85	60	85	100	100
		Vulnerability	15	25	100	100	10	15	25	0	10	15	0	0	10	-
	output	GP (global performance)	0	20	40	-	20	40	60	40	60	85	60	85	100	100
		Centroid (C_{Lc}) %	20				40			61.7			85			

If we assume that the Reliability **Re** at a particular node was estimated and had a certain value of 77.5%. When the value is mapped on the established fuzzy scale (Fig.2.b), it intersects with different membership functions that result from the four granularity level. As shown in Fig. (2.b) **Re**= 77.5% does not intersect with the poor and the fair MFs (μ_{poor} =0; μ_{fair} =0), it intersects with the satisfactory and good MFs at (μ_{satis} =0.30; μ_{good} =0.70), thus the fuzzified four levels for the **Re** will be [0, 0, 0.30, 0.70]. Similarly, the same procedure is repeated for the other input indicator assuming **Res**= 100% and **Vul**=22.5%, and then the fuzzy values of the three indicators under four granularity levels are plotted in an assessment matrix ***A***, Eq. (9).

$$A=\begin{bmatrix} \mu_{j,poor}^{\mathrm{Re}} & \mu_{j,fair}^{\mathrm{Re}} & \mu_{satisfactory}^{\mathrm{Re}} & \mu_{good}^{\mathrm{Re}} \\ \mu_{j,poor}^{\mathrm{Re}s} & \mu_{j,fair}^{\mathrm{Re}s} & \mu_{satisfactory}^{\mathrm{Re}s} & \mu_{good}^{\mathrm{Re}s} \\ \mu_{j,poor}^{Vuk} & \mu_{j,fair}^{Vul} & \mu_{satisfactory}^{Vul} & \mu_{good}^{Vul} \end{bmatrix}=\begin{bmatrix} 0 & 0 & 0.3 & 0.7 \\ 0 & 0 & 0 & 1 \\ 0.75 & 0.25 & 0 & 0 \end{bmatrix} \quad (9)$$

Where, μ_{poor}, μ_{fair}, μ_{satis}, and μ_{good} are the four granularity levels of fuzzy set generated after the fuzzification operation.

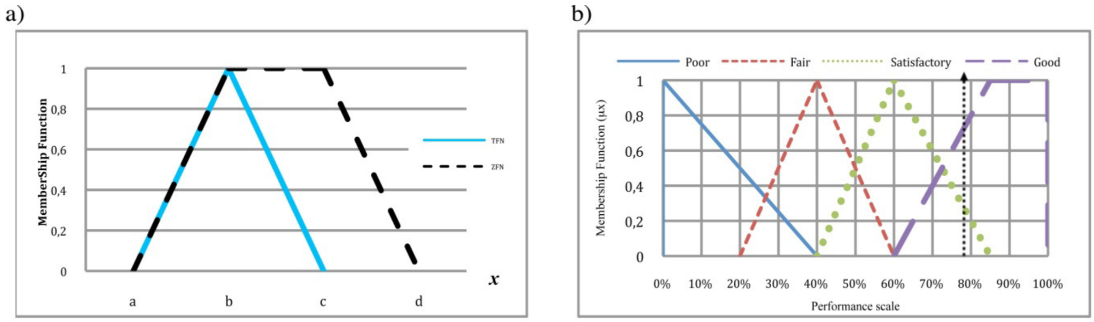

Fig. 2. (a) TFN (solid line) and ZFN (dashed line) membership functions; (b) performance scale for reliability and resiliency

6. Fuzzy inference and aggregation of the PIs;

After the definition of fuzzy set of each indicator which comes from the fuzzification process, it is necessary to insert in the decisional engine the rules which supply the fuzzy output. The rules are usually made up of an "*if-then*" structure, which in its turn is made up of an antecedent which define the conditions, and consequent which defines the action. For each input variable of the model, in the antecedent we have a form type (x is *La*), where x can be an indicator (**Re-Res-Vul**) and *La* is a linguistic label revealing a fuzzy set (in this case *La* = poor, fair, satisfactory or good; see table 3), while the consequent (*Lc*) determines the condition of outputs (global performance "***GP***") (is defined similarly to the antecedent "*La*"). In fact the proposed method shares an idea with the method originally developed by Shaheen (2005). The idea is the use of the weight (already calculated using AHP) associated with each indicator to generate the equivalent impact of the rules. Fig. (3) shows the steps followed in finding the equivalent performance of different combinations of the three indicators.

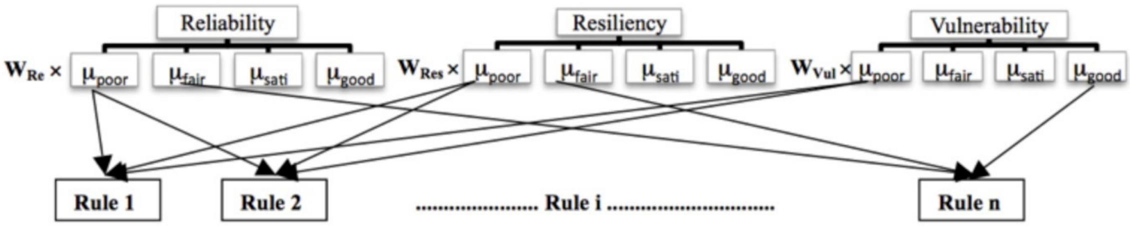

Fig. 3. Proposed methodology for fuzzy rules extraction

The Mamdani fuzzy rules system type is used in the fuzzy model, which has an advantage over the other methods of being easier to understand, and the consequents of the system (the four granularity levels of Global Performance) is defined in terms of fuzzy sets as explained in table 3. The Mamdani method is based on a simple structure of Max operation as follows:

$$R^{i} = if(\mathrm{Re}\quad is\, L_a)*W_{\mathrm{Re}}\, and(\mathrm{Re}\, s\quad is\, L_a)*W_{\mathrm{Re}\, s}\, and(Vul\quad is\, L_a)*W_{Vul}\, then\, GP\quad is\, L_c \quad (10)$$

Where, R^i is the i^{th} rule; **Re**, **Res** and **Vul** are the fuzzy set inputs, ***GP*** (global performance) is the fuzzy output and $\mathbf{W_{Re}}$, $\mathbf{W_{Res}}$ and $\mathbf{W_{Vul}}$ are the weight associated to reliability, resiliency and vulnerability, respectively, and *La* and *Lc* describe the antecedent and the consequent linguistic variable, respectively as defined in table 3.

In this study, the consequent linguistic variable *Lc* of the ***GP*** is standardized on a list of four linguistic variables (poor, fair, satisfactory, good as shown in table 3). The number of rules of different performance combinations needed to cover all the combination possibilities can be found as:

Number of rules:

× 4 *Re* Conditions (poor, fair, satisfactory, good)

× 4 *Res* Conditions (poor, fair, satisfactory, good)

× 4 *Vul* Conditions (poor, fair, satisfactory, good)= 64 Rules

Once, the aggregation has been done, the fuzzy ***GP*** for the previous example can be plotted on the form of Eq. (11):

$$GP = \left[\mu_{poor}^{GP} \quad \mu_{fair}^{GP} \quad \mu_{satisfactory}^{GP} \quad \mu_{good}^{GP}\right] = [0.17 \quad 0.05 \quad 0.21 \quad 0.57] \tag{11}$$

Where, ***GP*** is the global performance under four granularity levels.

7. Defuzzification process

Once fuzzy inference is defined, it is necessary to turn the data coming from the evaluation of rules into real numerical data. This process is the opposite of fuzzification where the fuzzy numbers are converted to crisp numbers. There are many defuzzification methods that convert the fuzzy consequents of all established fuzzy rules to a crisp value. The defuzzification can be performed with several techniques, including the centroid method, mean-max membership operation, a maximum operator, first of maximum, last of maximum, and mean of maximum. One of the commonly applied techniques for defuzzification is the centroid method, and it has been applied in this study. Lee (1996) proposed a simple defuzzification technique as follows (Eq.12):

$$I_{GP} = GP \times [C_{Lc}]^T \tag{12}$$

Where, $\boldsymbol{I_{GP}}$ is global performance index expressed in crisp value, $\boldsymbol{C_{Lc}}$ is the centroid of a fuzzy ***GP*** under four granularity levels (given in table 3), ***GP*** is given by Eq. (11), and *T* is the symbol that indicates the transpose of the vector $\boldsymbol{C_{Lc}}$.

Continuing with the same example, the corresponding defuzzified results will be the global performance index ($\boldsymbol{I_{GP}}$) of one single component (node), Eq. (13):

$$I_{GP} = GP * [C_{Lc}]^T = [0.17 \quad 0.05 \quad 0.21 \quad 0.57] * \begin{bmatrix} 0.200 \\ 0.400 \\ 0.617 \\ 0.850 \end{bmatrix} = 67.27\% \tag{13}$$

For absolute favorable condition, the calculated global performance ($\boldsymbol{I_{GP}}$) should be close to unit and for absolute unfavorable condition the calculated performance should be close to zero. However, by using the centroid method in the defuzzification process, it is not possible to obtain these two extreme values due to the nature of approximation. Therefore, the calculated crisp value has been normalized between 0 and 1 by using Eq. (14)

$$I_{GP,N} = \frac{I_{GP}^{C} - I_{GP,\min}^{C}}{I_{GP,\max}^{C} - I_{GP,\min}^{C}} = \frac{67.27 - 20}{85 - 20} = 72.72\% \tag{14}$$

Where, $\boldsymbol{I_{GP,N}}$ is the normalized performance for any condition, $\boldsymbol{I^{C}_{GP}}$ is the performance for any condition calculated by center of gravity method, $\boldsymbol{I^{C}_{GP,min}}$ is the minimum performance of extreme unfavorable condition calculated by the center of gravity, and $\boldsymbol{I^{C}_{GP,max}}$ is the maximum performance of extreme favorable condition calculated by center of gravity method.

8. Conclusion

As illustrated in this paper, using analytic hierarchy process together with fuzzy logic technique, it is possible to combine different performance indicators into one index in order to assess the global performance of a system.In fact, due to the complexity of WDS it is extremely important to consider together different point of view in order to understand the real response of the system that is related not only to a specific behavior expressed through specific indicator, but it also depends on several aspects that are related to hydraulic and water quality satisfactions, adequacy and so forth.Further studies are in progress to apply the proposed methodology to a real case, but the results are not yet available to be included in the paper.

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