A Consensus Support Methodology for the Initial Self–Assessment of the EFQM Excellence Model in Healthcare Organisations

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***Abstract*—Healthcare organisations using the European Foundation for Quality Management (EFQM) Excellence Model for self–assessment have found an opportunity to work more effectively and a powerful driver for improvement. Nevertheless, when these organisations address self–assessment processes for the first time the initial effort needed presents many difficulties. The aim of this paper is to offer a consensus support methodology based on fuzzy logic under a linguistic approach that would undoubtedly contribute to conduct self–assessment processes with questionnaires. We assume qualitative evaluation, through linguistic labels, to facilitate the individual responses, and we use the concept of fuzzy majority to calculate the measures which guide the consensus reaching process.**

***Keywords*-EFQM; linguistic modelling; consensus; group decision-making**

I. Introduction

The tremendous impact on the economic resources available is one of today's primary discussion topics in health care. Those who manage health care delivery strive to achieve the highest quality of care possible with the resources available [12]. Quality management is a new approach to the functioning of organisations that is promoting improvement and strengthening its progress.

The Excellence Model has been developed by the European Foundation for Quality Management (EFQM) to structure and review the quality management of an organisation [14]. This model has been widely used in almost all European countries by hospitals, out-patient care, rehabilitation clinics, acute care, primary and specialized care, etc. [4], [14], [15], [18].

Many healthcare organisations start to apply the EFQM Excellence Model by doing an initial self–assessment as EFQM promotes. Self-Assessment is a comprehensive, systematic and regular review of an organisation's activities and results referenced against the EFQM Excellence Model [3].

Among the different approaches proposed by EFQM, we focus on questionnaire approach, the easiest way to perform self–assessment. However, questionnaires still present some difficulties, especially the lack of experience of the organisations that are seeking to implement this model.

In this paper, we present a consensus support methodology based on fuzzy logic under linguistic approach to conduct self–assessment processes with questionnaires for healthcare organisations using the EFQM Excellence Model.

We are assuming a group of evaluators, who express their opinions about the set of questions and attempt to reach a collective decision with the maximum possible consensus on each question.

The usual way of implementing the Excellence Model is based on quantitative scales and all the measures are calculated in a numerical context. Our approach simplifies the individual assessments to be made by each member of the evaluation team using qualitative scales instead of numerical values. We assume that all the questions are assessed by means of linguistic terms [1], [2], [6], [17]. In a more realistic approach, a scale of certainty expressions would be presented to the evaluators and, in such a way, they could provide their vague knowledge about the questions.

On the other hand, we propose to apply a consensus process to reach a good agreement on the answers given by the evaluators to each question. The consensus process consists on counting the number of individuals that are in agreement over the linguistic value assigned to each question, and the aggregation of that information under a fuzzy majority. This consensus process uses two kinds of consensus measures [8]:

- *Linguistic consensus degrees,* which are used to assess the current consensus existing among members of the evaluation team.
- *Linguistic distances,* which are used to evaluate the distance from individuals' opinions to the current consensus reached by the evaluation team.

The paper is set out as follows. In Section II, a brief review of the EFQM Excellence Model and the fuzzy linguistic approach are showed. Section III describes the consensus support methodology based on fuzzy linguistic information. Finally, in Section IV, some conclusions are pointed out.

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II. PRELIMINARIES

In this section, firstly we provide a brief description of the EFQM Excellence Model and the self–assessment process. Afterwards, we briefly review the fuzzy linguistic approach and the linguistic quantifiers.

A. EFQM Excellence Model and the Self–Assessment Process

The EFQM Excellence Model is a non-prescriptive framework for quality management which is used in all types of organisations, regardless of sector, size, structure or maturity [14]. The use of this model in the healthcare sector has been recommended by different publications [10], [16].

The EFQM Excellence Model [3], [14], [15] consists of nine criteria: five of these are *enablers* or *agent*, criteria 1–5 (leadership, people, policy and strategy, partnership and resources, and processes) which attempt to measure the extent an organisation is oriented according to the principles of Total Quality, and cover the process, the structure and the means of an organisation; and four are *results*, criteria 6–9 (people results, customer results, society results, and key performance results) which cover the aspects of performance in a broad way and attempt to measure how this orientation affects what the organisation achieves.

This model is based on the premise that [3]: "Excellent results with respect to Performance, Customers, People and Society are achieved through Leadership driving Policy and Strategy, that is delivered through People, Partnerships and Resources and Processes"

Each criterion of the EFQM Model includes a number of subcriteria, the enablers are broken down into 24 subcriteria and the results in 8 subcriteria [14]. There is a dynamic relationship between enablers and the results, as excellence in the enablers will be visible in the results [15].

The assessment of the quality of an organisation is based, on the one side, on the EFQM Model with the nine criteria and the 32 subcriteria; on the other side it is based on a measuring instrument called RADAR (Results, Approach, Deploy, Assess and Review) applied to the assessment of each subcriterion [12], [14]. This sequence of Results, Approach, Deployment, Assessment and Review is the internal logic of the model [3].

The EFQM approach is applied in three ways: first it is used as a frame of reference for the quality management of an organization; second it is as self-assessment tool; and third the criteria of the model are used for the national or European Quality Awards [14].

The use of the EFQM Excellence Model as a framework for organizational self–assessment has spread to many companies in Europe since its introduction [5]. Self–assessment is a process of internal reflection by which one can make a diagnosis of the level of organizational excellence, and know its behaviour with respect to the criteria that make up the model, representing a valuable tool for continuous improvement.

Therefore, the Self-Assessment process offers organisations an opportunity to learn: to learn about the organisation's strengths and weaknesses, about what *excellence* means to the organisation, about the organisation's progress on the journey to excellence, how far it still has to go and how it compares with other organisations [3].

Self–assessment can be carried out in different ways more or less complex, depending on the degree of maturity of the organisation, knowledge of the model itself with the people who perform it and the results being sought. EFQM proposes different approaches for self–assessment: the award simulation approach, the pro-forma approach, work meetings, questionnaires and improvement matrices [3], [14], [18]. All these approaches are valid, although the use of each of them entails advantages and disadvantages associated to be taken into account when choosing the medium to use.

We focus on questionnaire approach that is a team activity with the members of the evaluation team considering the organisation's position against each of the sub-criteria. In the questionnaire approach, over the answer to a serie of questions designed to observe the organisation status, we can make a diagnosis of the organisation and know what is its behaviour with respect to the Excellence Model's criteria.

Through the questionnaire, criteria scores have to be obtained by consensus among the participants, so it would be possible to assess the level of excellence in the management of the organisation in relation to the enabler criteria, and the results obtained by the organisation in relation to the results criteria of the model.

B. Fuzzy Linguistic Approach and Linguistic Quantifiers

Many problems in the real world cannot be expressed with precision in a quantitative form, but rather in a qualitative one. In that case, a better approach may be to use linguistic assessments instead of numerical values. The *fuzzy linguistic approach* is an approximate technique appropriate to deal with fuzzy and vague qualitative aspects of problems [20]. It models linguistic information by means of linguistic terms supported by *linguistic variables*. These are variables whose values are not numbers but words or sentences in a natural or artificial language. A linguistic variable is defined by means of a syntactic rule and a semantic rule. The fuzzy linguistic approach is less precise than the numerical one, but, however, it presents the following advantages:

1) The linguistic description is easily understood by human beings even when the concepts are abstract or the context is changing.
2) It diminishes the effects of noise since, as it is known, the more refined assessment scale is, then more sensitive to noise (linguistic scales are less refined than numerical scales and consequently they are less sensitive to error apparition and propagation).

This approach has been successfully applied to different areas, such as, quality evaluation on the Web [13], information retrieval [9], etc.

The *ordinal fuzzy linguistic approach* [6], [7], [9] is a very useful kind of fuzzy linguistic approach used for modeling the computing with words process as well as linguistic aspects of problems. It facilitates the fuzzy linguistic modeling very much because it simplifies the definition of the semantic and syntactic rules. It is defined by considering a finite and totally ordered label set $S = \{s_i\}, i \in \{0, \ldots, \mathcal{T}\}$ in the usual sense, i.e., $s_i \geq s_j$ if $i \geq j$, and with odd cardinality. We have to select the appropriate term set defining the level of discrimination among different degrees of uncertainty, i.e., the "*granularity of uncertainty*" [21]. Typical values of cardinality used in the linguistic models are odd values, such as 7 or 9, where the mid term represents an assessment of "approximately 0.5", and the rest of the terms being placed symmetrically around it. These classical values seems to fall in line Miller's observation about the fact that human beings can reasonably manage to bear in mind seven or so items [11]. The semantics of the linguistic term set is established from the ordered structure of the label set by considering that each linguistic term for the pair $(s_i, s_{\mathcal{T}-i})$ is equally informative.

In any linguistic approach we need management operators of linguistic information [7]. An advantage of the ordinal fuzzy linguistic approach is the simplicity and quickness of its computational model. It is based on the symbolic computation [7] and acts by direct computation on labels by taking into account the order of such linguistic assessments in the ordered structure of linguistic terms. This symbolic tool seems natural when using the fuzzy linguistic approach, because the linguistic assessments are simply approximations which are given and handled when it is impossible or unnecessary to obtain more accurate values. Thus, in this case, the use of membership functions associated to the linguistic terms is unnecessary.

Usually, the ordinal fuzzy linguistic model for computing with words is defined by establishing (i) a negation operator, (ii) comparison operators based on the ordered structure of linguistic terms, and (iii) adequate aggregation operators of ordinal fuzzy linguistic information.

In most ordinal fuzzy linguistic approaches the negation operator is defined from the semantics associated to the linguistic terms as $Neg(s_i) = s_j \mid j = \mathcal{T} - i$; and there are defined two comparison operators of linguistic terms:

- Maximization operator: $MAX(s_i, s_j) = s_i$ if $s_i \geq s_j$.
- Minimization operator: $MIN(s_i, s_j) = s_i$ if $s_i \leq s_j$.

An important aggregation operator of ordinal linguistic values based on symbolic computation is the LOWA operator [7]. The *Linguistic Ordered Weighted Averaging* (LOWA) is an operator used to aggregate non-weighted ordinal linguistic information, i.e., linguistic information values with equal importance [7]:

Definition Let $A = \{a_1, \ldots, a_m\}$ be a set of labels to be aggregated, then the LOWA operator, F, is defined as:

$$\begin{aligned} F(a_1, \ldots, a_m) &= W \cdot B^T = \mathcal{C}^m\{w_k, b_k, k = 1, \ldots, m\} \\ &= w_1 \odot b_1 \oplus (1 - w_1) \odot \mathcal{C}^{m-1}\{\beta_h, b_h, h = 2, \ldots, m\}, \end{aligned}$$

where $W = [w_1, \ldots, w_m]$ is a weighting vector, such that, $w_i \in [0, 1]$ and $\Sigma_i w_i = 1$. $\beta_h = w_h / \Sigma_2^m w_k$, and $B = \{b_1, \ldots, b_m\}$ is a vector associated to A, such that, $B = \sigma(A) = \{a_{\sigma(1)}, \ldots, a_{\sigma(m)}\}$, where, $a_{\sigma(j)} \leq a_{\sigma(i)} \ \forall \ i \leq j$, with σ being a permutation over the set of labels A. $\mathcal{C}^m$ is the convex combination operator of m labels and if $m = 2$, then it is defined as:

$$\mathcal{C}^2\{w_i, b_i, i = 1, 2\} = w_1 \odot s_j \oplus (1 - w_1) \odot s_i = s_k,$$

such that, $k = \min\{\mathcal{T}, i + round(w_1 \cdot (j - i))\}$, $s_j, \ s_i \in S$, $(j \geq i)$, where *"round"* is the usual round operation, and $b_1 = s_j$, $b_2 = s_i$. If $w_j = 1$ and $w_i = 0$, with $i \neq j \ \forall i$, then the convex combination is defined as: $\mathcal{C}^m\{w_i, b_i, i = 1, \ldots, m\} = b_j$.

The LOWA operator is an "or-and" operator [7] and its behavior can be controlled by means of W.

An important question of the LOWA operator is the determination of the weighting vector W. In [19] it was defined an expression to obtain W that allows to represent the concept of fuzzy majority by means of a fuzzy linguistic nondecreasing quantifier Q [22]:

$$w_i = Q(i/n) - Q((i-1)/n), \ i = 1, \ldots, n.$$

When a fuzzy linguistic quantifier Q is used to compute the weights of LOWA operator ϕ, it is symbolized by F_Q.

We will use two types of fuzzy non-decreasing relative quantifiers. One, denoted Q^1 and numerical valued,

$$Q^1 : [0, 1] \rightarrow [0, 1]$$

and defined as follows,

$$Q^1(r) = \begin{cases} 0 & \text{if } r < a \\ \frac{r-a}{b-a} & \text{if } a \leq r \leq b \\ 1 & \text{if } r > b \end{cases}$$

with $a, b, r \in [0, 1]$.

And the other relative quantifier, denoted Q^2, linguistically valued on a label set $L = \{l_i\}, \ i \in J = \{0, \ldots, U\}$,

$$Q^2 : [0, 1] \rightarrow L$$

and defined as follows,

$$Q^2(r) = \begin{cases} l_0 & \text{if } r < a \\ l_i & \text{if } a \leq r \leq b \\ l_U & \text{if } r > b \end{cases}$$

l_0 and l_U are the minimum and maximum labels in L, respectively, and

$$l_i = Sup_{l_q \in M}\{l_q\},$$

$$M = \{l_q \in L : \quad \mu_{l_q}(r) = Sup_{t \in J} \; \{\mu_{l_t}(\frac{r-a}{b-a})\}\}$$

with $a, b, r \in [0, 1]$.

III. A Methodology to Perform the Initial Self–Assessment of Healthcare Organisations Based on Group Decision–Making Consensus

If we review the typical self–assessment process of an organisation based on the questionnaire approach, we can found the following stages:

1) *Selection of Evaluation Team*
2) *Individual Self–Assessment through the questionnaire*
3) *Consensus in the evaluation of the questionnaire*
4) *Prioritization of areas for improvement*
5) *Design and implementation of Improvement Plan*
6) *Monitoring of Improvement Plan*

In this paper we focus on stages 2 and 3 of the self–assessment process.

A. Individual Self–Assessment Through the Questionnaire

We consider a questionnaire $Q = \{q_1, \ldots, q_n\}$ complying with the requirements of the Excellence Model and the evaluation team $E = \{e_1, \ldots, e_m\}$ composed of representative staff of the organisation, preferably with management responsibilities, and all members have the same importance degree. Because evaluators could have a vague knowledge about the available evidences, they cannot estimate them with an exact numerical values. A more realistic approach may be to use linguistic assessments instead of numerical values, that is, to suppose variables which participate in the problem are assessed by means of linguistic terms [1], [2], [6], [8], [17]. A scale of certainty expressions linguistically assessed, S, would be presented to the individuals, who could use it to describe their degrees of certainty for answering the questions with respect to the available evidences.

Then, each member of the evaluation team $e_k \in E$ makes his individual assessment of the questionnaire Q, thinking about the management and performance of the organisation, and taking into account the available evidences for providing his opinion into the term set, S,

$$\phi : Q \to S,$$

where $\phi(q_i) = p_i^k \in S$ represents the linguistically assessed answer of evaluator e_k to the question q_i.

For example, we could use the following seven linguistic label set, S, that represents the degree of available evidences, and their respective associated semantics:

$Totally$	$(1, 1, .25, 0)$
$Very\_Much$	$(.75, .75, .15, .25)$
$Much$	$(.6, .6, .1, .15)$
$Enough$	$(.5, .5, .1, .1)$
$Little$	$(.4, .4, .15, .1)$
$Very\_Little$	$(.25, .25, .25, .15)$
$Nothing$	$(0, 0, 0, .25)$

Since the available evidence are those that justify the choice made in response to each of the questions, in extreme values of the scale we have the option of *Nothing*, that corresponds to the unavailability of evidences, and *Totally*, that corresponds to total availability of evidences.

We assume that Q^k represents the set of all responses linguistically assessed into the term set S make by the evaluator $e_k \in E$ when he has filled in the questionnaire Q.

B. Consensus in the Evaluation of the Questionnaire

Once the individual self–assessments have been done, the consensus reaching process on the evaluators' opinions is a requirement of the Excellence Model.

Usually, the members of the evaluation team have disagreeing opinions. A consensus meeting is carried out involving all members of the evaluation team where a moderator, highlighting those evidences where there are consensus and disparity of opinion, tries to persuade the individuals to update their opinions. Several iterations are necessary to achieve the highest possible consensus. In each stage of the process, the degree of consensus and the distance from an absolute consensus is measured.

As we said at the beginning, we present a methodology adapting the idea proposed in [8]. This methodology is based on the calculation of two consensus measures which used jointly describe with a great exactness the current consensus situation, and help the moderator in the consensus reaching process:

- *Linguistic consensus degrees:* Used to evaluate the current consensus existing among members of the evaluation team.
- *Linguistic distances:* Used to evaluate the distance from individuals' opinions to the current consensus reached by the evaluation team.

These measures are calculated repeating the following three processes until an acceptable consensus degree is achieved:

- *Counting process:* From linguistic values given by the evaluators, the number of them who are in agreement on each question is calculated.
- *Coincidence process:* To obtain the coincidence degree, that is, the proportion of evaluators who are in agreement in their responses to each question, and also to find out the consensus labels, that is, the team opinion on each question.
- *Computing process:* To calculate the two consensus measures using the above information.

1) Counting Process: We define an array L for the $T + 1$ possible labels that can be assigned as preference value. Each component $L_i[s_t]$, $i = 1, \ldots, n$, $t = 0, \ldots, T$ is a set of evaluators' identification numbers, who selected the value s_t as response value for the question q_i according to the expression:

$$L_i[s_t] = \{k \ / \ p_i^k = s_t, \ k = 1..m\}, \forall s_t \in S.$$

From the array L, we define the coincidence array L^C to store information referred to the number of evaluators who have chosen the same label s_t assigned as answer of question q_i. The components of this array are obtained as:

$$L_i^C[s_t] = \sharp(L_i[s_t]), \forall s_t \in S.$$

where # stands for the cardinal of the term set.

2) Coincidence Process: We consider that *coincidence* exists over a linguistic label assigned as answer to a question when more than one evaluator have chosen that label. According to this *coincidence* concept we define the following label sets, C_i, for each question q_i, which contains linguistic labels which have been selected by more than one individual:

$$C_i = \{s_j \ / \ L_i^C[s_j] > 1, \ s_j \in S\}.$$

In this coincidence process, we first find out the consensus label on the response value of each question q_i, thus, we calculate the *label consensus*, LC_i, the average of the selected labels; and then, we obtain the *coincidence degree*, CD_i, i.e., the number of evaluators who selected each one of the above consensus labels.

We obtain each element of the *label consensus*, LC_i, as the aggregation of linguistic indexes s_t, of the components of $L_i^C[s_t]$, such that, $L_i^C[s_t] > 1$. That is, the aggregation of those linguistic labels s_t, which have been chosen by more than one evaluator to answer the question q_i.

From the label sets, C_i, and using the LOWA operator F_{Q^1} based on the concept of fuzzy majority, represented by the relative quantifier Q^1, we calculate each LC_i, according to the following expression:

$$LC_i = \begin{cases} F_{Q^1}(c_1, \ldots, c_r) & \text{if } \sharp(C_i) > 1 \quad \text{and } c_j \in C_i, \\ & \qquad\qquad\qquad j = 1, \ldots, r \\ c_r & \text{if } \sharp(\mathrm{C}_i) = 1 \quad \text{and } c_r \in C_i \\ Undefined & \text{otherwise} \end{cases}$$

where r=$\sharp(\mathrm{C}_i)$.

The coincidence degree CD_i represents the proportional number of individuals whose preference values have been used to calculate the consensus label LC_i. Each component of CD_i is defined as follows:

$$CD_i = \begin{cases} \frac{\sum_{s_j \in C_i} (L_i^C[s_j]/m)}{\sharp(C_i)} & \text{if } \sharp(C_i) \neq 0 \\ 0 & \text{otherwise} \end{cases}$$

3) Computing Process: As we have mentioned, we calculate two consensus measures, *Linguistic consensus degree* and *Linguistic distance*.

Linguistic consensus degree: This measure is defined on the labels assigned as answer to the question q_i, and is denoted by LCQ_i. It indicates the consensus degree existing among all the values attributed by the m evaluators to the concrete question q_i. Each component LCQ_i is calculated as follows:

$$LCQ_i = Q^2(CD_i), \ i = 1, \ldots, n.$$

This measure helps the moderator to decide about the necessity to continue the consensus reaching process.

Linguistic distance: The idea is based on the evaluation of the approximation among individuals' opinions and the current consensus labels of each question. This measure is defined on the consensus label of each question q_i calculating the distance between the opinion of an evaluator e_k concerning that question and its respective consensus label. It is denoted by D_i^k, and obtained as:

$$D_i^k = \begin{cases} p_i^k - LC_i & \text{if } p_i^k > LC_i \\ LC_i - p_i^k & \text{if } LC_i >= p_i^k \\ s_T & \text{otherwise} \end{cases}$$

with $i = 1, \ldots, n$ and $k = 1, \ldots, m$.

This measure helps the moderator to identify which evaluators are furthest from current social consensus labels, and in what question the distance exists.

Finally, once the individual self–assessments have been done and the consensus for each question has been reached, we have to calculate the corresponding scores for each subcriterion and criterion of the EFQM Excellence Model. This aspect is outside of our objectives in this paper and will be addressed in future research.

IV. Conclusions

This paper describes a consensus support methodology based on fuzzy logic under linguistic approach that can contribute positively to conduct self–assessment processes for healthcare organisations which face the EFQM Excellence Model for the first time.

We have addressed two phases of the self–assessment process. On the one side, on the individual self-assessment through the questionnaire, we have used fuzzy linguistic techniques to model the subjectivity associated to individual assessments, because of the difficulty for evaluators to express with precision the available evidence in questionnaire response. The qualitative evaluation, through linguistic labels instead of numerical values, is particularly user friendly and facilitates the individual responses as a more natural way to communicate information.

On the other side, the consensus reaching process, a team activity where a moderator seeks to reach consensus in the answer to each question of the questionnaire, has been carried out based on two consensus measures, the *linguistic consensus degrees* and the *linguistic distances* in each stage of the process. There are other ways to undertake the general consensus process for the initial self–assessment, but require prior training and greater time commitment. However, the presented methodology contributes to the homogenization of the process and facilitates the task of guiding the consensus process by the moderator in a simple and practical way.

In future research, following the self–assessment process, the methodology could support healthcare organisations establishing priorities of improvement areas, monitoring their progress, and directing their operation towards a continuous improvement.

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