On Fuzzy Qualitative and Quantitative Softgoal Interdependency Graph

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ABSTRACT
Non-Functional requirements serve as criteria for the selection and prioritization of software requirements. The objective of this paper is to propose an efficient method for the prioritization of non functional requirements. In this paper we use $L^{-1}, R^{-1}$ inverse function arithmetic principle and graded mean integration for the elicitation of decision maker’s weight for the qualitative and quantitative softgoal interdependency graph to model the non-functional requirements. Finally the utilization of proposed method is demonstrated with the help of an example.

Keyword
Softgoal Interdependency graph (SIG). Non-functional requirements (NFR), Trapezoidal fuzzy numbers (TFN), FQQSIG.

1. INTRODUCTION
Research in the area of trustworthy software system has received much attention by software engineering community in recent year. In 2014 “Make in India” project was started to increase the number of software product start-up in the country. India software industry is expected to grow to $225 billion by 2020.A software system can only be suitable if it is Trustworthy. Chen et. al.[9,10] define software trustworthiness as a system which have the following characteristic like safety, security, reliability, maintainability etc. Software requirements are classified into functional requirements (FR) and non-functional requirements (NFR). Software system that lack FR i.e. Based on our literature review, we have identified different sets [9, 12, 13, 22, 21, 1] and NFR framework [9] and softgoal Interdependency graph (SIG) [8, 7, 5]. SIG mainly emphasis the importance of qualitative analysis, of NFRs. For example, Zayarar and Sadana [2, 21], proposed a quantitative model that focus on priorities and analyzes the conflict NFRs. Marew [20], presented “quantified softgoal interdependency graph”. In this graph precise values are used to express the degree of satisfaction. This method also used for arithmetic operation to calculate the contribution of NFRs. In 2011, Zhu [15], proposed a NFR tradeoff model in trustworthy software which uses a fuzzy qualitative and quantitative softgoal interdependency graph (FQQSIG). In this method RAGE defuzzication procedure is used to finish the defuzzification transformation process. In this paper, we proposed a fuzzy based approach for the non-functional prioritization using $L^{-1}, R^{-1}$ function arithmetic principle and graded mean integration representation.

This paper is organized as follows: Section II presents the proposed method section III we present a case study of proposed method and finally conclusion and future work.

2. PROPOSED METHOD
In this section we present the proposed method a fuzzy based approach for the NFR tradeoff model in trustworthy software. Proposed method includes the following steps:

Step 1: Identification of stakeholder
Stakeholder identification is a most important activity of a requirements elicitation process. Therefore, the first step of our method is to identify the primary and secondary stakeholders [17, 18]. Primary stakeholders include those who are central to any project initiative, i.e., beneficiaries, financial, politicians, sponsors, and decision maker. Secondary stakeholders include developers, experts, operators etc [19].

Step 2: In this step we decompose the NFRs.
Software requirements are divided into two categories: functional and non-functional [6]. Many researchers, including Boehm [26], Sommerville [25], and Chung [9], present various NFR classifications. These classifications contain the need for different application areas in different conditions. They are helpful for developers to quickly obtain the area knowledge and easily modify software requirements. In 2015 [16] there is another classification of NFR which is based on commonly used NFR’s, on the basis of definition and attributes of NFRs, and on the basis of conflicted NFR’s. In “commonly used NFR”, only those NFRs are considered which are useful for the different types of systems like information system, web based system etc. On the basis of literature review, only five types of NFRs that are commonly used in different types of systems [14] like Performance, Reliability, Usability, Security, and Maintainability. In second type of NFRs which is “on the basis of definition and attribute” is to identify those requirements which are clearly defined in the literature, like, Performance, Security Usability etc. and also identify those requirements which are supported by their attributes like Accessibility, Adaptability, Availability, Efficiency etc. [16]. This classification is further divided on the basis of the following: (i) Have Definition and Attributes (ii) Have Definition (iii) Without Definition and...
Attributes. The third type of classification of NFR is conflicted NFR for example, Accuracy and Performance\textsuperscript{[14, 16]}. Conflicted NFRs further classify into three parts i.e. Absolute conflicted NFRs, Relative Conflicted NFRs and NFRs that are Never Conflicted. There are some NFRs which may conflict with other NFRs [16]. For example, reliability and performance.

Step 3: In this step we collect expert fuzzy assessment.

Step 4: To elicit the DMs weight vectors we use the L$^{-1}$ – R$^{-1}$ inverse function arithmetic principle and graded mean integration representation [27].

Step 5: In this step we construct the FQSIG graph.

3. CASE STUDY

In this section we applied the proposed method with help of five decision makers (DMs) opinion on NFR degree assessment of criteria. In this case study, we use seven ranking parameters i.e. Weak (W), Medium Weak (MW), Fair (F), Medium Strong(MS), Strong (S), Very Strong (VS), Extremely Strong (ES) etc. DMs fuzzy assessment parameter is shown in Table 1.

### Table 1. Trapezoidal Fuzzy Linguistic variables set for NFR.

<table>
<thead>
<tr>
<th>Linguistic variables Set</th>
<th>Abbreviation</th>
<th>Trapezoidal fuzzy numbers S: (n1,n2,n3,n4)(i=1,……,9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1: Weak</td>
<td>W</td>
<td>(0.176,0.235,0.294,0.353)</td>
</tr>
<tr>
<td>S2: Medium Weak</td>
<td>MW</td>
<td>(0.294,0.353,0.412,0.471)</td>
</tr>
<tr>
<td>S3: Fair</td>
<td>F</td>
<td>(0.412,0.471,0.529,0.588)</td>
</tr>
<tr>
<td>S4: Medium Strong</td>
<td>MS</td>
<td>(0.529,0.588,0.647,0.706)</td>
</tr>
<tr>
<td>S5: Strong</td>
<td>S</td>
<td>(0.647,0.706,0.765,0.824)</td>
</tr>
<tr>
<td>S6: Very Strong</td>
<td>VS</td>
<td>(0.765,0.824,0.882,0.941)</td>
</tr>
<tr>
<td>S7: Extremly Strong</td>
<td>ES</td>
<td>(0.882,0.941,1,1)</td>
</tr>
</tbody>
</table>

Fig. 2. Membership functions for a fuzzy set including seven variables.

Step 3: Collect expert fuzzy assessments

In this step to achieve TS system we decompose the Information system and proposed a NFR classification in [16].

### Table 2 Classification of NFRs and their fuzzy assessment by DMs

<table>
<thead>
<tr>
<th>NFRs (i=40)</th>
<th>Primary Layer</th>
<th>Secondary Layer</th>
<th>L1-1</th>
<th>L1-2</th>
<th>L1-3</th>
<th>L1-4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>L1 - Trustiness</td>
<td>D1</td>
<td>D2</td>
<td>D3</td>
<td>D4</td>
<td>D5</td>
</tr>
<tr>
<td></td>
<td>L2 - IS/safety</td>
<td>F</td>
<td>W</td>
<td>MW</td>
<td>VV</td>
<td>F</td>
</tr>
<tr>
<td></td>
<td>L3 - IS/Real</td>
<td>F</td>
<td>VS</td>
<td>ES</td>
<td>S</td>
<td>VS</td>
</tr>
<tr>
<td></td>
<td>L4 - IS/web</td>
<td>MS</td>
<td>S</td>
<td>F</td>
<td>MS</td>
<td>F</td>
</tr>
<tr>
<td></td>
<td>L5 - IS/Real/Web</td>
<td>S</td>
<td>ES</td>
<td>F</td>
<td>MS</td>
<td>S</td>
</tr>
<tr>
<td></td>
<td>L1-1 Provability</td>
<td>S</td>
<td>MS</td>
<td>F</td>
<td>VS</td>
<td>S</td>
</tr>
<tr>
<td></td>
<td>L1-2 Reusability</td>
<td>VS</td>
<td>S</td>
<td>S</td>
<td>MS</td>
<td>VS</td>
</tr>
<tr>
<td></td>
<td>L1-3 Standardizability</td>
<td>MS</td>
<td>VS</td>
<td>F</td>
<td>S</td>
<td>S</td>
</tr>
<tr>
<td></td>
<td>L1-4 Traceability</td>
<td>VS</td>
<td>MW</td>
<td>MS</td>
<td>F</td>
<td>VS</td>
</tr>
</tbody>
</table>
Step 4: Apply $L^{-1}$, $R^{-1}$ inverse function arithmetic principle and graded mean integration for the elicitation decision maker’s weight.

In this paper we apply $L^{-1}$, $R^{-1}$ function arithmetic principal and graded mean method for the elicitation of decision maker’s weight. A brief introduction is given below:

Let $A_1 = (a_1, b_1, c_1)$ and $A_2 = (a_2, b_2, c_2)$ be two trapezoidal fuzzy numbers as Fig. 1. The addition of $A_1$ and $A_2$ at h-level is:

$$A_1@h \oplus A_2@h = (L^{-1}_{A_1(h)} + L^{-1}_{A_2(h)}, R^{-1}_{A_1(h)} + R^{-1}_{A_2(h)})$$

$L_{A_1}$ and $R_{A_1}$ are the functions $L$ and $R$ of fuzzy number $A_1$, respectively. $L^{-1}_{A_1(h)}$ and $R^{-1}_{A_1(h)}$ are the inverse functions of functions $L_{A_1}$ and $R_{A_1}$ at h-level, respectively. $L_{A_2(h)}$ and $R_{A_2(h)}$ are the inverse functions of functions $L_{A_2}$ and $R_{A_2}$ at h-level, respectively.

Suppose the membership functions of $A_1 = (a_1, b_1, c_1)$ is

$$f_{A_1}(x) = \begin{cases} \frac{x-a_1}{b_1-a_1}, & a_1 \leq x \leq b_1, \\ \frac{x-c_1}{b_1-c_1}, & b_1 \leq x \leq c_1, \\ 0, & otherwise \end{cases}$$

Since

$$L_{A_1}(x) = \frac{(x-a_1)}{(b_1-a_1)}, a_1 \leq x \leq b_1$$

$$R_{A_1}(x) = \frac{(x-c_1)}{(b_1-c_1)}, b_1 \leq x \leq c_1$$

Similarly, suppose the membership function of $A_2 = (a_2, b_2, c_2)$ is

$$f_{A_2}(x) = \begin{cases} \frac{x-a_2}{b_2-a_2}, & a_2 \leq x \leq b_2, \\ \frac{x-c_2}{b_2-c_2}, & b_2 \leq x \leq c_2, \\ 0, & otherwise \end{cases}$$

Since

$$L_{A_2}(x) = \frac{(x-a_2)}{(b_2-a_2)}, a_2 \leq x \leq b_2$$

$$R_{A_2}(x) = \frac{(x-c_2)}{(b_2-c_2)}, b_2 \leq x \leq c_2.$$
According to equation 1, we have that

Second, we introduce briefly the graded integration representation method. Chen and Hsieh proposed the graded integration representation method of fuzzy numbers [10, 11, 12] based on the integral value of graded mean h-level of the general fuzzy number. Here, we describe the meaning as follows.

In general, a generalized fuzzy number A is described as any fuzzy subset of the real line R, whose membership function \( u_A \) satisfies the following conditions.

1. \( u_A(x) = 0, \quad -\infty < x \leq c \);
2. \( u_A(x) \) is strictly increasing on \([c, a] \);
3. \( u_A(x) = w, \quad a \leq x \leq b, \) where \( 0 < w \leq 1 \);
4. \( u_A(x) \) is strictly increasing on \([b, d] \);
5. \( u_A(x) = 0, \quad d \leq x \leq \infty \);
6. \( u_A \) is a continuous mapping from R to the closed \([0, 1] \);

Here, a, b, c, and d are real numbers. We denote generalized fuzzy number A in Fig. 1 as \((a, b, c, d; W_A)_{LR} \). When \( W_A = 1 \) we simplify notation as \( A = (a, b, c, d)_{LR} \).

![Fig 1. The graded mean h-level of fuzzy number A = (a, b, c, d; WA)_{LR}.

Let \( L^1 \) and \( R^1 \) be the inverse function of the functions \( L \) and \( R \), respectively; then the graded mean h-level value of the generalized number A is \( h(L_1(A) + R_1(A))/2 \) as shown in figure.

Then the graded mean integration representation of A is

\[
P(A) = \int_0^{W_A} \frac{h(L(h) + R(h))/2}{dh} dh
\]

Then the graded mean integration representation of A is

\[
P(A) = \frac{1}{6}(a + 2b + 2c + d)
\]

Here, a, b, c, and d are numbers. We denote generalized fuzzy number A in Fig. 2 as \( A = (c, a, b, d)_{LR} \). When \( W_A = 1 \), we simplify notation as \( A = (a, b, c, d)_{LR} \).

Generalized triangular fuzzy number \( K = (a, b, c, d) \) is a special case of generalized trapezoidal fuzzy number. The graded mean integration representation of the triangular fuzzy number \( Y \) becomes

\[
\text{TFN}(K) = \frac{1}{6}(a + 2b + 2c + d)
\]

**Step 5: Construct FQQSIG graph.**

In this step we construct FQQSIG graph. FQQSIG is an enhanced version of QSIG. In this step we assigned fuzzy linguistic variable i.e. we take a module of fees slip in this module we decomposes the NFRs through the prioritzation till the last highest value by using fuzzy L^1 - R^1 inverse linguistic variables function as shown in the Fig 4 the last attributes is completeness. After applying equation, we have identify the weights of different measuring parameters i.e. we take an example performance VS=0.853, ES=0.960, S=0.735, MS=0.617, F=0.5. The final output in the figure is after normalized form. The normalized values (Fig. 4) are acquired by dividing the sum of all attributes values in the same layer; for example:0.14=2.82/(4.12+3.66+3.08+3.08+3.05+2.82).
In this paper we present a method for prioritization of NFR using fuzzy linguistic variables when five decision maker involve in this process. The proposed method includes five step that is identifying stakeholders, decomposition of NFRs, collect experts fuzzy assessments, applying $L^1 - R^1$ inverse function arithmetic principle and graded mean integration for the eliciting of decision makers weight and construct FQQSIG graph. In our case study we assume that five decision makers are involved in NFRs weight prioritization method. Future work includes:

1. To apply the proposed method in “Institute Examination System (IES)”.
2. To strengthen the goal oriented elicitation process using proposed method.
5. REFERENCES


