α -CUT FUZZY ANALYTIC NETWORK PROCESS BASED APPROACH TO EVALUATE SIMULATION SOFTWARE PACKAGES

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ABSTRACT

In parallel to computer technology drastically developing, various simulation software packages focusing on solving different kinds of engineering problems have been introduced to the world market. As the result of this, the selection of proper simulation software has been of considerable importance to any simulation analyst in a simulation project. On the other hand, the best satisfying simulation software selection from a possible set of alternatives in the market is a typical multiple criteria decision making (MCDM) problem in the presence of evaluation criteria, and there are many MCDM methods in the literature, which have been used to successfully carry out this difficult and time-consuming process. In this study, the analytic network process (ANP) method is used because it can accommodate the variety of interactions, dependencies and feedback between higher and lower level elements, rather than analytic hierarchy process (AHP). In addition, an α -cut fuzzy logic is integrated with the ANP method to model uncertain human preferences as input information in the decision-making process. Instead of using the classical eigenvector prioritization method in AHP, only employed in the prioritization stage of ANP, An α -cut fuzzy logic method providing more accuracy on judgments is applied. The resulting α -cut fuzzy ANP enhances the potential of the conventional ANP for dealing with imprecise and uncertain human comparison judgments.

Keywords: Multiple criteria decision making, analytic network process, fuzzy logic, software evaluation, simulation

1. Introduction and Literature Review

In a period of continuous change in global business environment, organizations, large and small, are finding it increasingly difficult to deal with, and adjust to the demands for such change. Simulation is a powerful tool for allowing designers imagine new systems and enabling them to both quantify and observe behavior. Currently the market offers a variety of simulation software packages. Some are less expensive than others. Some are generic and can be used in a wide variety of application areas while others are more specific. Some have powerful features for modeling while others provide only basic features. Modeling approaches and strategies are different for different packages. Companies are seeking advice about the desirable features of software for manufacturing simulation, depending on the purpose of its use. Because of this, the importance of an adequate approach to simulation software selection is apparent (Gupta, Verma, and Singh, 2009).

Selecting the most appropriate simulation software tool for an application always requires thought and care. Typical items meriting consideration are the animation required (two- or three-dimensional), the level of programming skill required to use the tool effectively (e.g., familiarity with object-oriented or

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agent-based concepts), the availability of any constructs explicitly needed (e.g., bridge cranes, conveyors, automatic guided vehicles), the level of vendor support for the software, and many other interacting considerations (Vasudevan et al., 2009).

In this study, an approach is presented to help any simulation practitioner select most suitable simulation software based on his/her needs. On the other hand, the best satisfying simulation software selection from a possible set of alternatives is a typical multiple criteria decision making (MCDM) problem in the presence of evaluation criteria, and there are many methods in the literature, which have been used to successfully carry out this difficult and time-consuming process. As one of the most commonly used techniques for solving MCDM problems, AHP was first introduced by Saaty (Saaty, 1981). In AHP, a hierarchy considers the distribution of a goal amongst the elements being compared, and judges which element has a greater influence on that goal. In reality, a holistic approach like ANP invented by Thomas L. Saaty (Saaty, 1996) is needed if all attributes and alternatives involved are connected in a network system that accepts various dependencies. Several decision problems cannot be hierarchically structured because they involve the interactions and dependencies in higher or lower level elements. Not only does the importance of the attributes determine the importance of the alternatives as in AHP, but the importance of alternatives themselves also influences the importance of the attributes (Ayağ and Özdemir, 2007). In addition, a decision maker`s requirements on evaluating simulation software alternatives always contain ambiguity and multiplicity of meaning. Furthermore, it is also recognized that human assesment on qualitative attributes is always subjective and thus imprecise. Therefore, conventional ANP seems inadequate to capture decision maker`s requirements explicitly. In order to model this kind of uncertainity in human preference, α -cut fuzzy logic could be incorporated with the pairwise comparison as an extension of ANP. The α -cut fuzzy ANP approach allows a more accurate description of the decision making process.

In the literature, to the best of my knowledge, a limited number of works has been done for simulation software evaluation recently. Some of them are summarized as follows: Tewoldeberhan et al. (Tewoldeberhan et al., 2002) proposed a two-phase evaluation and selection methodology for simulation software selection. As , phase-1 quickly narrows down the number of sofware package list to a short one, phase-2 matches the requirements of the company with the features of the simulation package more in detail. Various methods are used for a detailed evaluation of each package, participating their vendors in both phases. Hlupic and Mann (Hlupic and Mann, 2002) developed a software tool called as SimSelect that selects simulation software given the required features. It is evident form the material presented within this research that simulation modeling is the "cost-effective" method of exploring "what-if" scenarios quickly, and finding a solution to or providing a better understanding of the problem, as this method is supported by a number of software tools (similar to Simul8) that provide a graphical representation of the business processes through executable models. Seila et al. (Seila, Ceric, and Tadikamalla, 2003) presented a framework for evaluating simulation software alternatives for discrete-event simulation. The proposed framework evaluates nearly 20 software packages, and first tries to identify the project objective, since a common understanding of the objective will help frame discussions with internal company resources a well as vendors and service providers. It is also prudent to define long-term expectations. Other important questions deal with model dissemination across the organization for others to use, model builders and model users, type of process (assembly lines, counter operations, material handling) the models will be focused, range of systems represented by the models etc. Popovic et al. (Popovic, Jaklic, and Vuksic, 2005) developed criteria that can help experts in a flexible selection of business process management tools. They classified the simulation tools selection criteria in seven categories: model development, simulation, animation, integration with other tools, analysis of results, optimization, and testing and efficiency. The importance of individual criteria (its weight) is influenced by the goal of simulation project and its members (i.e., simulation model developers and model users).

Shortly, in this paper, a α-cut fuzzy ANP-based approach is presented to evaluate a set of simulation software alternatives in order to reach to the best software satisfying the needs and expectations of simulation practitioners.

2. α-cut Fuzzy Analytic Network Process (α-cut FANP)

In this work, the α-cut fuzzy ANP method is proposed for simulation software selection problem. The explanation of this proposed approach is given as follows: In order to capture the vagueness, triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are used to represent subjective pair wise comparisons of selection process. Triangular fuzzy numbers (TFNs) show the participants' judgments or preferences among the options such as equally important, weakly more important, strongly more important, very strongly more important, and extremely more important preferred. $F = \left\{ \left(x, \mu_{\tilde{M}}(x) \right), x \in R \right\}$ indicates a fuzzy set, where x takes it values on the real line, $R: -\infty < x < +\infty$ and $\mu_{\tilde{M}}(x)$ is a continuous mapping from R to the closed interval [0, 1]. The element x in the set expresses the real values in the closed interval $[l,u]$, including mean (m) of each triangular fuzzy number. A triangular fuzzy number denoted as $\tilde{M} = [l,u]$ has the following triangular type membership function;

$$\mu_{\tilde{M}}(x) = \begin{cases} 0 & x<l \\ x-l \big/ m-l & l \le x \le m \\ u-x \big/ u-m & m \le x \le u \\ 0 & x>u \end{cases}$$

If x value is less than lower level of a fuzzy number (l), the function gets the value of 0 (zero), bigger than/equal lower level (l) and less than/equal to mean level (m), the function gets the value of $x-l \big/ m-l$, and bigger than/equal mean level (m) and less than/equal to upper level (u), the function gets the value of $u-x \big/ u-m$. Alternatively, by defining the interval of confidence level α, the triangular fuzzy number can be characterized as: $\forall \alpha \in [0,1]$ $\tilde{M}_\alpha = [l^\alpha, u^\alpha] = (m-1)\alpha + l, -(u-m)\alpha + u$

Some main operations for positive fuzzy numbers are described by the interval of confidence, by Kaufmann and Gupta (Kaufmann and Gupta, 1988) as given below;

$$\forall m_l, m_u, n_l, n_u \in R^+,\ \tilde{M}_\alpha = [m_l^\alpha, m_u^\alpha],\ \tilde{N}_\alpha = [n_l^\alpha, n_u^\alpha],\ \alpha \in [0,1]$$

$$\tilde{M}_\alpha \oplus \tilde{N}_\alpha = [m_l^\alpha + n_l^\alpha, m_u^\alpha + n_u^\alpha],\ \tilde{M}_\alpha - \tilde{N}_\alpha = [m_l^\alpha - n_l^\alpha, m_u^\alpha - n_u^\alpha],\ \tilde{M}_\alpha \otimes \tilde{N}_\alpha = [m_l^\alpha n_l^\alpha, m_u^\alpha n_u^\alpha],\ \tilde{M}_\alpha / \tilde{N}_\alpha = [m_l^\alpha / n_l^\alpha, m_u^\alpha / n_u^\alpha]$$

The triangular fuzzy numbers, $\tilde{1}$ to $\tilde{9}$, are utilized to improve the conventional nine-point scaling scheme. In order to take the imprecision of human qualitative assessments into consideration, the five triangular fuzzy numbers ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$) are defined with the corresponding membership function. By using triangular fuzzy numbers ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$), the decision-maker(s) are asked to respond to a series of pair wise comparisons of the criteria. These are conducted with respect to their relevance importance towards the control criterion. In the case of interdependencies, components in the same level are viewed as controlling components for each other. Levels may also be interdependent. Through pair wise comparisons by using triangular fuzzy numbers ($\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$), the fuzzy judgment matrix $\tilde{A}\left(\tilde{a}_{ij}\right)$ is constructed as given below;

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & .. & .. & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & .. & .. & \tilde{a}_{2n} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}_{n1} & \tilde{a}_{n2} & .. & .. & 1 \end{bmatrix}$$

where, $\tilde{a}_{ij}^{\alpha} = 1$, if i is equal j , and $\tilde{a}_{ij}^{\alpha} = \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9}$ or $\tilde{1}^{-1}$, $\tilde{3}^{-1}$, $\tilde{5}^{-1}$, $\tilde{7}^{-1}$, $\tilde{9}^{-1}$, if i is not equal j

For solving fuzzy eigenvalue: A fuzzy eigenvalue, $\tilde{\lambda}$, is a fuzzy number solution to $\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}$. where $\tilde{\lambda}_{\max}$ is the largest eigenvalue of $\tilde{A}$. Saaty (Saaty, 1981) provides several algorithms for approximating $\tilde{x}$. Where $\tilde{A}$ is nxn fuzzy matrix containing fuzzy numbers $\tilde{a}_{ij}$ and $\tilde{x}$ is a non-zero nx1, fuzzy vector containing fuzzy number $\tilde{x}_i$. To perform fuzzy multiplications and additions by using the interval arithmetic and $\alpha - cut$, the equation $\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}$ is equivalent to:

$$\left[a_{i1l}{}^{\alpha} x_{1l}{}^{\alpha}, a_{i1u}{}^{\alpha} x_{1u}{}^{\alpha}\right] \oplus ..... \oplus \left[a_{inl}{}^{\alpha} x_{nl}{}^{\alpha}, a_{inu}{}^{\alpha} x_{nu}{}^{\alpha}\right] = \left[\lambda x_{il}{}^{\alpha}, \lambda x_{iu}{}^{\alpha}\right], \text{ where, } \tilde{A} = \left[\tilde{a}_{ij}\right], \tilde{x}_i = \left(\tilde{x}_1, ..., \tilde{x}_n\right),$$

$$\tilde{a}_{ij}^{\alpha} = \left[a_{ijl}^{\alpha}, a_{iju}^{\alpha}\right], \tilde{x}_i^{\alpha} = \left[x_{il}^{\alpha}, x_{iu}^{\alpha}\right], \tilde{\lambda}^{\alpha} = \left[\lambda_l^{\alpha}, \lambda_u^{\alpha}\right] \text{ for } 0 < \alpha \leq 1 \text{ and all i, j, where i=1, 2… n, j=1, 2… n}$$

α -cut is known to incorporate the experts or decision-maker(s) confidence over his/her preference or the judgments. Degree of satisfaction for the judgment matrix $\tilde{A}$ is estimated by the index of optimism μ. The larger value of index μ indicates the higher degree of optimism. The index of optimism is a linear convex combination (Lee, 1999) defined as; $\tilde{a}_{ij}^{\alpha} = \mu a_{iju}^{\alpha} + (1-\mu) a_{ijl}^{\alpha}, \forall \mu \in [0,1]$. While α is fixed, the following matrix can be obtained after setting the index of optimism, μ, in order to estimate the degree of satisfaction. Both of them are defined in the range [0, 1] by decision-makers. The eigenvector is calculated by fixing the μ value and identifying the maximal eigenvalue.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12}^{\alpha} & .. & .. & \tilde{a}_{1n}^{\alpha} \\ \tilde{a}_{12}^{\alpha} & 1 & .. & .. & \tilde{a}_{2n}^{\alpha} \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ \tilde{a}_{n1}^{\alpha} & \tilde{a}_{n2}^{\alpha} & .. & .. & 1 \end{bmatrix}$$

After defuzzification of each pair wise matrix, the consistency ratio (CR) for each matrix is calculated. The deviations from consistency are expressed by the following equation consistency index, and the measure of inconsistency is called the consistency index (CI); $CI = \frac{\lambda_{\max} - n}{n-1}$. The consistency ratio (CR) is used to estimate directly the consistency of pair wise comparisons. The CR is computed by dividing the CI by a value obtained from a table of Random Consistency Index (RI); $CR = \frac{CI}{RI}$. If the CR less than 0.10, the comparisons are acceptable, otherwise not. RI is the average index for randomly generated weights (Saaty, 1981).

3. Numerical Example

In this section, a numerical example is presented to show the applicability of the α-cut fuzzy ANP for software selection problem. First, to determine evaluation criteria, we utilized the work of Verma et. al. (Verma, Gupta, and Singh, 2008). In their work, they derived the criteria that can be applied to the evaluation of any general or special purpose simulation package, and defined four main groups to develop an evaluation framework. Features within each group are further classified into subcategories based on their characters. The main and subcategories are given as follows:

The main categories:

- Hardware and software considerations: Pedigree, coding aspects, software compatibility, user support, financial and technical features.
- Modeling capabilities: General features, modeling assistance.
- Simulation capabilities: Visual aspects, efficiency, testability, experimentation facilities, statistical facilities.
- Input/Output issues: Input/Output capabilities, analysis capabilities.

Especially, in their work, each subcategory in a main category has also the elements listed more in detail. Furthermore, in the evaluation process, they used different scale system for each subcategory to reach the ultimate simulation software package. But, in our study, we only used the main and subcategories as the evaluation criteria, due to the fact that we should narrow down the number of the criteria to a reasonable level for both less computation time and effectiveness of the method. Finally, we have 4 clusters (based on the main categories) and total 14 criteria (or subcategories) in all the clusters. Also, we formed 5th cluster for alternatives namely, Arena (A1), Flexsim (A2) and Promodel (A3). These alternatives were obtained from a set of possible alternatives by eliminating extreme those. The computation steps of the α-cut fuzzy ANP method included a great deal of pairwise comparisons, constructing un-weighted matrix showing all the interrelations in the hierarchy, calculation of weighted matrix, finding limit matrix and ranking alternatives. As the result of all these efforts, the best simulation software alternative is found out as the first one (A1) among the others.

4. Conclusions

In this paper, we proposed an integrated approach through α-cut fuzzy logic and ANP for simulation software selection problem. The ANP is quite new and vastly improved over the AHP method as it allows for feedback between the hierarchical levels. The ANP methodology also lends itself to quantitative as well as qualitative analysis, which most decision makers are interested in both types of analyses. It integrates these elements in a decision model to capture their relationships and interdependencies across and along the hierarchies. It is also effective as both quantitative and qualitative characteristics can be considered simultaneously without sacrificing their relationships.

In addition, in this work, we utilize a α -cut fuzzy logic to implement the nine-point scaling process of ANP to model uncertain human preferences as input information in the decision-making process, because AHP cannot accommodate the variety of interactions, dependencies and feedback between higher and lower level elements. Instead of using the classical eigenvector prioritization method in AHP, only employed in the prioritization stage of ANP, a fuzzy logic method providing more accuracy on judgments is applied. The resulting fuzzy ANP enhances the potential of the conventional ANP for dealing with imprecise and uncertain human comparison judgments.

For future research, to easily make the calculations of the proposed method, an intelligent system such as expert system can be developed.

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