AHP based Optimal Reasoning of Non-functional Requirements in the $i*$ Goal Model

Sreenithya Sumesh
Curtin University
Bentley, Australia *s.sumesh@postgrad.curtin.edu.au*

Aneesh Krishna
Curtin University
Bentley, Australia *A.Krishna@curtin.edu.au*

Chitra M Subramanian
Curtin University
Bentley, Australia *chitra.muniyapp@curtin.edu.au*

Abstract

Goal-Oriented Requirements Engineering (GORE) has been found to be a valuable tool in the early stages of requirements engineering. GORE plays a vital role in requirements analysis like alternative design/ goal selection during decision-making. The decision-making process of alternative design/ goal selection is performed to assess the practicability and value of alternative approaches towards quality goals. Majority of the GORE models manage alternative selection based on qualitative approach, which is extremely coarse-grained, making it impossible for separating two alternatives. A few works are based on quantitative alternative selection, yet this does not provide a consistent judgement on decision-making. In this paper, Analytic Hierarchy Process (AHP) is modified to deal with the evaluation of selecting the alternative strategies of inter-dependent actors of $i*$ goal model. The proposed approach calculates the contribution degrees of alternatives to the fulfilment of top softgoals. It is then integrated with the normalized relative priority values of top softgoals. The result of integration helps to evaluate the alternative options based on the requirements problem against each other. To clarify the proposed approach, a simple telemedicine system is considered in this paper.
Keywords: Requirements engineering, Goal models, AHP, Decision-making.

1. Introduction

Goal models play a vital role in the early phases of Requirements Engineering (RE) and is a significant tool for alternative design/ goal selection technique [21, 15]. Alternative selection is a decision-making technique in requirements analysis or design alternatives that can be used to assess their achievability and feasibility with softgoals as the choosing criteria [20, 32, 3]. In Goal-Oriented Requirement Engineering (GORE), techniques like i∗ model [9, 35, 10], Tropos model [11, 4], Knowledge Acquisition in Automated Specification (KAOS) [8], and Goal Oriented Requirements Language (GRL) [3] strategy are utilized for refining, decomposing and reasoning the requirements of the stakeholders [20, 14, 12]. Goal models help to achieve top- level objectives within the hierarchies of requirements. Each alternative selection is evaluated by prioritizing quality requirements. The impact of bottom-level requirements are hierarchically structured to satisfactorily achieve top goals. Based on the importance of these contributions, the alternative options that best suit the requirements of the stakeholder is identified and sought after. However, when it comes to the consistency of decision-making, eliciting the contribution values of different alternatives towards final goals is a serious problem. Therefore, the need for a systematic approach that can perform the degree of satisfaction of goals persistently and in a consistent manner becomes important. So, in this paper a systematic method is developed for deciding a consistent optimal alternative design option for inter-dependent actors in the i∗ model by combining the advantages of AHP-based approaches and quantitative satisfaction propagation-based approaches.

2. Background and Related Works

In vast majority of the existing GORE frameworks, requirements analysis is organized and carried out based on qualitative goal models [34, 7, 5, 1, 2]. Qualitative analysis uses qualitative estimations such as 'denied' or 'satisfied' to label goals satisfaction status. In order to label softgoals satisfaction status, the qualitative estimations used are 'satisfied', 'weakly satis- fied', 'undetermined', 'conflicting', 'weakly denied' or 'denied' for assessing the degree of goal satisfaction achieved. Although qualitative reasoning provides a fast approach in evaluating goals in the early stages of requirement engineering, the labels for representing contributions are ambiguous and too coarsely-grained to be able to differentiate among alternatives during propagation [13]. This is because a qualitative propagation method frequently brings about undetermined or conflicting goal satisfaction status; different alternatives usually lead to same results for softgoals for example, both weakly denied or strongly satisfied; qualitative satisfaction status is coarse-grained and correspondingly cannot disclose to what degree the goals are denied or satisfied.

The limitations mentioned above with the qualitative propagation procedure have given rise to the need for addressing quantitative goal models. Letier et.al [16] conducted a dedicated alternative selection based on objective criteria, however, they require particular information, for example, the distribution functions of quality variables. Such extra information, however, is difficult to get in many situations at the early phase of RE. A few works [3, 17] offer quantitative analysis techniques by using numbers to denote the strength of links however they do not provide guided strategies to acquire these strength-value numbers.

In this paper, we depict how the Analytic Hierarchy Process (AHP) is applied in *i*∗ goal model to quantitatively assess the contribution relationships between functional and non-functional requirements with opposing objectives. Thus, AHP integrated with GORE approach helps to provide reasoning of non-functional requirements to make informed decisions. The AHP [22] can be used to encourage the quantification reasoning, since it is hard for stakeholders to provide exact contribution values directly. An existing work incorporate AHP with goal models for alternative selection [18, 36]. In this work, stakeholders are subjectively assigning the relative priority of each softgoals with the main goals based on the Saaty's pairwise comparison scale [22]. Since it is a subjective judgement, it may not be accurate for goal formulations. It is also crucial to assign definite numbers to the stakeholder's requirements, as requirement elicitation may involve distinct stakeholders. They have diverse preferences for the same requirements. The rationale behind this is that distinct stakeholders have different levels of knowledge, training and skills [31].

In *i*∗ goal model, Chitra et al. [25, 28] developed a quantitative goal analysis method to decide on alternative design options. To avoid ambiguity in the usage of numeric numbers for the purpose of quantitative analysis, fuzzy numbers are used. Later, in order to enhance this method, a multi-objective optimization method is applied for finding the optimal values of soft- goals for alternative selection in goal analysis [24, 26]. It also prevents the decision analyst from imposing his/her own subjective preference of values being used for the goal analysis process. However, the literature shows that the qualitative and quantitative goal analysis process for the *i*∗ and other goal models do not include goals with opposing objective functions having inter- actor dependency. In contrast, AHP, fuzzy mathematical application and optimization tool are used in this study as they are essential tools for quantitative goal analysis. The quantitative goal analysis helps to find an optimal strategy with opposing objective functions in the requirement- based engineering design [30, 29]. This proposal examines how requirement-based engineering design can deliver a consistent optimal design outcome. In literature, we identify that the elicitation process of the existing goal-oriented requirements frameworks like $i*$ models do not support the prioritization of the multi-objective requirements of inter-dependent actors in the decision-making process. This problem can be overcome by a combined AHP and quantitative satisfaction fuzzy-based propagation approach to prioritize the requirements.

In the proposed approach, we modified the AHP by calculating the optimal relative priority of each requirements towards the main goal. This will enhance the consistency on decision-making process. Based on the $i*$ goal model, an alternative selection algorithm is designed through AHP. Overall, no previous research efforts have been able to develop a systematic method for deciding on a consistent optimal alternative design option for inter-dependent actors in the $i*$ model by combining the advantages of AHP and quantitative reasoning. In order to illustrate the application of the proposed approach, a simple telemedicine $i*$ goal model adapted from [32] is considered in this paper. The methodology of reasoning opposing goals based on inter-actor dependency by applying AHP is given in Section 3. Conclusions and future works are drawn at the end of the paper.

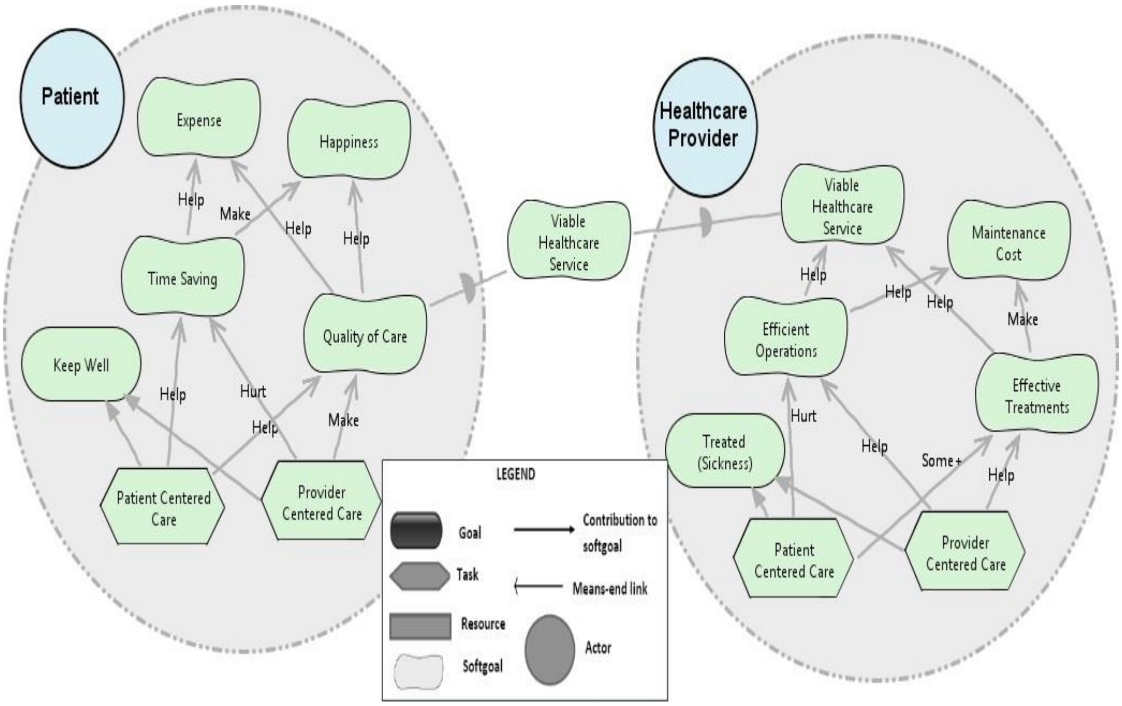

Figure 1. Simplified $i*$ goal model for Telemedicine System [33]

3. Requirements analysis using AHP

The proposed research presents a multi-objective optimization based decision-making approach in GORE by modifying the AHP. Unlike traditional decision-making process, T L Saaty de- signed AHP based on pair-wise comparisons that enable consistent judgements that improve the precision of decision-making, and further, enable accurate priority calculations. The AHP includes an objective evaluation approach. It also provides a method for checking the consistency of the evaluation and alternatives. During complex decision-making that involve multiple opposing goals, the initial step is to decompose the primary objectives into its constituent sub-objectives, progressing from a generic goal to a specific goal. In its simplest form, this hierarchical decomposition involves a goal level, softgoals levels, and an alternative level. Each softgoal can be further decomposed depending on the decision-making problem. To

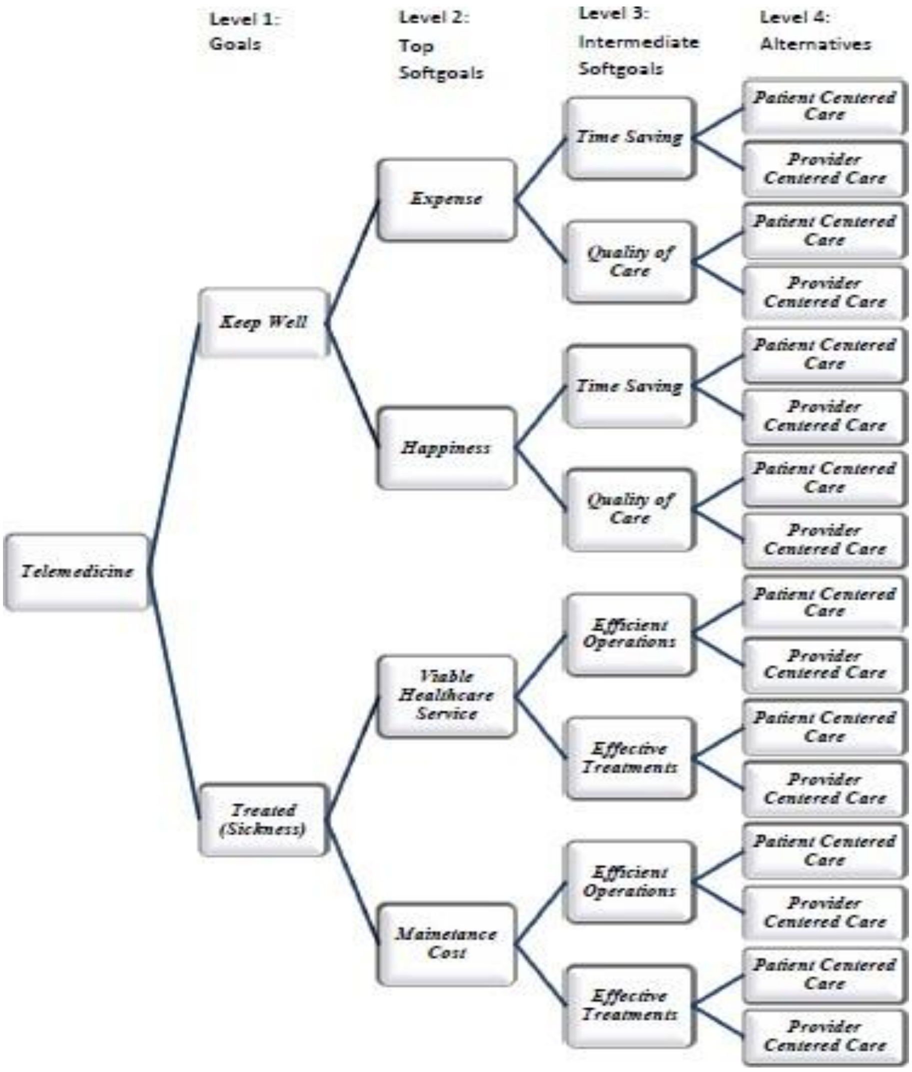

Figure 2. Hierarchical Model of Telemedicine System

explain the proposed method, a simple telemedicine i∗ goal model, as shown in Figure: 1, is considered in this paper. It shows two actors, Patient and Healthcare Provider that are considerably simplified, but nevertheless require some kind of reasoning namely selection of an ideal alternative. The main non-functional requirements or softgoals of the actor Patient are the Expense of the treatment and Happiness obtained from the remote treatment, which depend upon the softgoals Time Saving and Quality of Care. There are two alternative ways of obtaining treatment for the Patient. It is either via Patient Centered Care or Provider Centered Care. The Patient has to choose an alternative option so that his/her Expense should be less and Happiness should be more. The actor Health Care Provider has two main non-functional requirements or softgoals namely Viable Healthcare Service and Maintenance Cost representing the Health Care Provider's aiof providing services in the telemedicine system. The telemedicine system's goals, Keep Well of Patient and Treated (Sickness) of Health Care Provider can be implemented in one of two ways and thus is OR decomposed into two tasks known as Patient Centered Care and Provider Centered Care. The decision-making process of this telemedicine system is to select an alternative option that increases the Viable Healthcare Service of the Health Care Provider and the Happiness of the Patient and at the same time decreases the Maintenance Cost of the Health Care Provider and the Expense of the Patient. Figure: 2 illustrates the typical hierarchical structure of the telemedicine system where the primary organizational objective is placed on the top level while the alternatives are at the bottom level. Between the goal and alternatives lies the characteristic element of the decision-making problem such as the softgoals. Each softgoal has a local, and global priority to accomplish the main goal. The pair-wise comparison judgements about the importance of each softgoal towards main goal and the importance of each alternative towards each goal should be consistent. The pair-wise comparison matrix is said to be consistent if all its elements follow the transitivity and reciprocity rules [22].

In the proposed approach, we evaluate the contribution of each alternative options through softgoals towards the high-level goals as shown in Figure: 2. Given a goal model with alternative design options, fuzzy values are assigned to the correlation between these alternatives and the softgoals. By backward propagation of these values to the goals (that are higher in hierarchy), the levels of goal satisfaction or the relative priorities of the softgoals to the main goal are derived.

3.1. Methodology

The proposed methodology is presented in the following sub-section, to obtain an optimal strategy for inter-dependent actors having opposing objectives.

Framework for the AHP analysis

The initial stage of the proposed approach is called decision modelling. This step involves con- structing a hierarchical model for reasoning of the decision-making problem. Figure: 2 shows the hierarchical model for the telemedicine model. The first level in the hierarchy represents the goals of the system to be modelled; in our example, Keep Well and Treated (Sickness). The top softgoals constitute the second level in the hierarchy. In our example, four top softgoals are mentioned: Expense, Happiness, Viable Healthcare Service and Maintenance Cost. Intermedi- ary softgoals are mentioned in the third level of the hierarchy. The fourth level represents the available alternative ways to achieve the main goal. In the example of the telemedicine model, the Patient Centred Care and Provider Centred Care are the alternatives. This is a crucial step in AHP process. Because, during complex decision-making problems, it is required to ask the stakeholders to guarantee that all softgoals and possible alternatives options have been consid- ered.

Deriving Priorities for the top softgoals

All the softgoals will not have the similar significance towards the main goal. Therefore, the second step in the AHP analysis is to determine the relative priorities for the softgoals. In the proposed approach, we evaluate the contribution that each alternative options have upon the top softgoals.

Given a goal model with alternative design options, fuzzy values are assigned to the correlation between the alternatives and the softgoals. By backward propagation of these values to the top softgoals, the levels of goal satisfaction or the relative priorities of the softgoals to the main goal are derived. It is called relative because the obtained softgoal priorities are calculated as a ratio concerning each other. For deriving the relative priorities of each softgoals, a generalised complete structure of an i^* goal model is modelled in terms of softgoals, goals, tasks and resources. Given an i^* goal model, our aim is to find the priority of top softgoal according to the impact of each alternative on top softgoals. Assigning values to impacts of alternatives to softgoals can lead to imprecision because many analysts assign different values and sometimes they are subjective. Therefore, the proposed approach assigns a judgement within a range which can be defined by a fuzzy number rather than giving one numerical value. Therefore, impacts are given as *Make; Help; Hurt; Break; Some-; Some+*, which are represented as triangular fuzzy numbers. It indicates the extent to which an alternative option fulfils the leaf softgoal [32]. For simplicity of calculation, de-fuzzification is used to convert the impacts which are represented in fuzzy numbers to quantifiable values [6], shown in Table: 1, which are used to evaluate the scores of each softgoal. The impacts are propagated to the top softgoals, to find the level of satisfaction or scores of top softgoals towards main goal.

Table 1. De-fuzzified impact values in Telemedicine system

Impact	Fuzzy value	De-fuzzified value
Hurt	(0, 0.16, 0.32)	0.16
Make	(0.64, 0.8, 1)	0.8
Some−	(0.16, 0.32, 0.48)	0.32
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64

In addition to impacts, each leaf softgoals are assigned a weight ω based on their relative importance to achieve the goal. Firstly, the scores of each top softgoals of each actor based on its inter-actor dependency under each alternative is calculated. For details on representing goals, weights, impacts and alternatives, readers are directed to [25, 24]. Consider the case of t hierarchy levels in the hierarchy structure, with leaf softgoal (SG) at level zero. Let $\omega_{L_{ik}}$ represents the weight of i^{th} leaf softgoal and $I_{L_{ijk}}$ means the impact of i^{th} leaf softgoal of j^{th} alternative of k^{th} actor, S_{idby} means the score of the i^{th} softgoal with its b^{th} dependent having y children, I_{dLijk} means the impact of the dependent on i^{th} leaf softgoal of j^{th} alternative of k^{th} actor and I_d is the b^{th} dependent impact.

At level 1, if there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal, then the score of any softgoal at $t > 1$ is found by taking the product of its impact and each child score. For complete details on the formalization of the below equation, readers are directed to [27]. The score of a softgoal at level t for an actor with a dependency relationship can be generalized as:

$$S_{SG_{i_t jk}} = \prod_{l=1}^{m} I_{ijl} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{ijk}}} \times \omega_{d_{L_{ijk}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\} \tag{1}$$

Then the objective functions of top softgoals under each alternative for an actor are created from Equation: 1. If there is an inter-actor dependency relationship, then it is necessary to consider both strategic dependency and strategic rationale diagrams of the i^* goal model with the assumption that only softgoal inter-dependency relationships are taken into account in this approach. Consider that if there are n numbers of alternative options for an actor, then there are n maximum and minimum objective functions for each top softgoal.

In the next step, these multi-objective functions of opposing goals (maximum and minimum in nature) are optimized using IBM CPLEX optimizer [19]. This tool helps to generate the multi-objective function values for all the actors in the goal model. These optimal values refer to the score (importance) of each top softgoal under each alternative to fulfil the stakeholder's objectives.

To improve the readability in writing, certain terms in telemedicine case study are abbreviated as shown in Table: 2. The objective function values for telemedicine system generated from CPLEX are shown in Table: 3. Thus GORE approach helps to determine the scores (satisfaction values) of top softgoals concerning the contribution of each alternative to accomplish the goal for comparison between softgoals. The importance of each softgoal towards main goal is different. So it is required to generate the pair-wise comparison matrix (PCM), by deriving the relative priority of each softgoal, concerning each of the others, towards the main goal by pair-wise comparisons. Elements in PCM have a value obtained from the objective function values as shown in Table: 3 to show the relative importance in each of the compared pairs of softgoals. In PCM, the importance of a softgoal is compared with itself; for instance, *Expense* versus *Expense*; the input value is one which compares to the measure of equal significance towards the main goal. This implies that the ratio of the significance of a given softgoal concerning the importance of itself will always be equal. The PCM shows the pairwise relative priorities among all softgoals involved in the decision-making process.

Table 2. Abbreviation of terms in Telemedicine system

Terms	**Abbreviation**
Patient	P
Healthcare Provider	HCP
Expense	E
Happiness	H
Viable Healthcare Service	V HS
Maintenance Cost	MC
Patient Centered Care	PaCC
Provider Centered Care	PrCC

After constructing PCM, the AHP calculates the overall relative importance of each softgoal. The overall relative importance calculation includes averaging over normalized columns to estimate the eigenvalues of the PCM (divide each element by the total summation of all the elements in each column). Using this normalized matrix, the overall relative importance of each softgoal can be obtained by simply averaging each row and is an estimation of eigenvalues of the matrix.

The PCM representation of the overall relative importance of each top softgoals of telemedicine case study with respect to *PaCC* is given as

$$\text{PCM}_{PaCC} = \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} \begin{bmatrix} 0.0524 \\ 0.5125 \\ 0.308 \\ 0.128 \end{bmatrix}$$

Table 3. Objective function values of each top softgoals in Telemedicine system with respect to each alternative

Top softgoals for actor *P*	*PaCC*	*PrCC*
H	51.2	51.2
E	5.24	10.24
Top softgoals for actor *HCP*	*PaCC*	*PrCC*
V HS	30.72	40.96
MC	12.8	51.2

The PCM representation of the overall relative importance of each top softgoals of telemedicine case study with respect to *PrCC* is given as

$$\text{PCM}_{PrCC} = \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} \begin{bmatrix} 0.07 \\ 0.33 \\ 0.27 \\ 0.33 \end{bmatrix}$$

Once the overall relative importance of softgoals have been obtained, it is necessary to check whether they are consistent or not. For this purpose, a consistency ratio (CR) is calculated by comparing the consistency index (CI) of the obtained PCM versus CI of a random-like matrix (RI). Saaty [23] provided the obtained RI value for matrices of various sizes.

Saaty [23] has shown that a *CR* of 0.10 or less is adequate to proceed with the AHP reasoning. In the event that the consistency ratio is more than 0.10, it is required to change the contributions assigned to find the reason for the inconsistency and revise it. The *CI*, which shows the result accuracy of PCM, has to be calculated first for finding *CR*,

$$CI = (\lambda_{max} - n)/\,(n - 1)$$

where λ_{max} represents the maximum principal eigenvalue of the PCM. If λ_{max} is closer to number of requirements (*n*), then the judgement errors will be less, and the results will be more consistent. For obtaining λ_{max}, firstly multiply PCM by priority column matrix. Secondly, divide each element in the obtained result matrix by the corresponding element in the priority matrix. Thirdly, average all the elements in the result matrix obtained in second step. This average value gives the value of λ_{max} which can then be used for calculating CI. For example, the *CR* of the relative importance of top softgoals with respect to the alternative, *Patient Centered Care* is calculated and its value is 0.0034. As a general rule by Saaty, *CR* of 0.10 or less is considered acceptable. So the obtained result for *PaCC* is ideal. Similarly, the *CR* of the relative importance of top softgoals with respect to the alternative, *Provider Centered Care* is calculated and its value is 0.003. This CR value is also considered as acceptable. So the obtained result for *PrCC* is also ideal. The proposed approach for finding the relative importance of each top softgoals towards main goal is considered as consistent, so the decision-making process using AHP is proceeded to next step.

Table 4. Propagated impact score of alternatives towards top softgoal

	E	*H*	*VHS*	*MC*
PaCC	5.12	5.28	1.76	1.92
PrCC	5.6	5.76	2.56	2.72

Derive Relative Local Priorities of each Alternatives

In this step, the relative priorities of each alternative are calculated concerning each top softgoal included in the decision-making model. For this, PCM is constructed (using the propagated (summation) impact score of each alternative to top softgoals from Table: 4) for each alternatives, with respect to each specific top softgoal. In the telemedicine example, two alternatives *Patient Centered Care* and *Provider Centred Care*, and four top softgoals are mentioned. So there are four pair-wise comparison matrices.

With respect to *Expense*, the PCM representation of the relative local priority of *PaCC* and
PrCC is given as,

$$PCM_E = \begin{bmatrix} 0.48 \\ 0.52 \end{bmatrix}$$

With respect to *Happiness*, the PCM representation of the relative local priority of *PaCC* and *PrCC* is given as,

$$PCM_H = \begin{bmatrix} 0.48 \\ 0.52 \end{bmatrix}$$

With respect to *V iableHealthcareService*, the PCM representation of the relative local priority of *PaCC* and *PrCC*,

$$PCM_{VHS} = \begin{bmatrix} 0.41 \\ 0.59 \end{bmatrix}$$

With respect to *Maintenance Cost*, the PCM representation of the relative local priority of *PaCC* and *PrCC*,

$$PCM_{MC} = \begin{bmatrix} 0.42 \\ 0.58 \end{bmatrix}$$

By averaging over normalized columns to estimate the eigenvalues of obtained PCM's of each alternatives with respect to all top softgoals, the local priorities of alternatives are calculated. The consistency will be checked only if the number of elements that are compared pairwise are three or more [23]. In this case only two alternatives are compared in PCM, therefore, there is no requirement to calculate consistency. This means, the calculated local priorities are consistent.

Derive Overall Priorities

In this step, the overall priority for each alternative is calculated. This means priorities that take into account not only our preference of alternative options for each softgoal yet in addition the way that each softgoal has a different weight to achieve the goal.

Table 5. Overall Priorities of Alternatives towards Main Goal

	E	*H*	*VHS*	*MC*
Top softgoals priority w.r.t *PaCC*	0.05	0.51	0.31	0.13
PaCC **local priority**	0.48	0.48	0.41	0.42
Top softgoals priority w.r.t *PrCC*	0.07	0.33	0.27	0.33
PrCC **local priority**	0.52	0.52	0.59	0.58

Table 6. Overall priorities of alternatives towards main goal

Alternatives	**Overall priority**
PaCC	0.4505
PrCC	0.5587

For example, the *Expense* top softgoal has a priority of 0.0524 with respect to the *Patient Centered Care* alternative and the *Patient Centered Care* has a local priority of 0.48 relative to *Expense*; therefore, the weighted priority, with respect to *Expense*, of the *Patient Centered Care* is 0.024.

Similarly, it is necessary to obtain the *Patient Centered Care* weighted priorities with respect to *Happiness*, *Viable Healthcare Service* and *Maintenance Cost*. Now the alternative options can be ordered based on their overall priority as shown in Table: 6.

In other words, given the importance of each top softgoal (*Expense*, *Happiness*, *Viable Healthcare Service* and *Maintenance Cost*), the *Provider Centred Care* is preferable (overall priority = 0.5587) compared to the *Patient Centered Care* (0.4505). When the number of the levels in the hierarchy increase, the number of pair comparisons also increase. So to build the AHP model takes much more time and effort but has been demonstrated easy. Another limitation of AHP is that if the consistency index is above 10%, then it is required to reconsider the stakeholder requirements.

4. Conclusion

In this paper, the quantitative reasoning of the *i** goal model of inter-dependent actors that have opposing objectives is integrated with AHP to solve multi-objective decision-making problem of alternative selection. In this paper, a modified AHP is proposed to drive the procedure of alternative selection. Hence an ideal alternative option is chosen using the proposed approach for inter-dependent actors in the *i** goal model by balancing the opposing goals reciprocally. This research showed that quantitative based fuzzy judgements for this study were quite consistent. Thus the proposed AHP methodology is an easy applicable decision-making approach that assist the decision maker to precisely decide the judgements. The primary difficulty in applying AHP to multi-objective reasoning is the potentially large number of paired comparisons, when the number of levels in the hierarchical structure is increased. However, the paired comparisons have been demonstrated to be relatively easy. Further research topics include performing sensitivity analysis to aid requirements analyst in the decision-making process.

References

1. Affleck, A., Krishna, A.: Supporting quantitative reasoning of non-functional require- ments: A process-oriented approach. In: Proceedings of the International Conference on Software and System Process, Zurich, Switzerland, June 2-3, 2012. pp. 88–92. IEEE Press (2012)
2. Affleck, A., Krishna, A., Achuthan, N.R.: Non-functional requirements framework: A mathematical programming approach. The Computer Journal **58**(5), 1122–1139 (2014)
3. Amyot, D., Ghanavati, S., Horkoff, J., Mussbacher, G., Peyton, L., Yu, E.: Evaluating goal models within the goal-oriented requirement language. International Journal of Intelligent Systems **25**(8), 841–877 (2010)
4. Bresciani, P., Perini, A., Giorgini, P., Giunchiglia, F., Mylopoulos, J.: Tropos: An agent-oriented software development methodology. Autonomous Agents and Multi- Agent Systems **8**(3), 203–236 (2004)
5. Burgess, C., Krishna, A., Jiang, L.: Towards optimising non-functional requirements. In: Quality Software, 2009. QSIC'09. 9th International Conference on. pp. 269–277. IEEE (2009)
6. Chou, S.Y., Chang, Y.H., Shen, C.Y.: A fuzzy simple additive weighting system un- der group decision-making for facility location selection with objective/subjective at- tributes. European Journal of Operational Research **189**(1), 132–145 (2008)
7. Chung, L., do Prado Leite, J.C.S.: On non-functional requirements in software engi- neering. In: Conceptual modeling: Foundations and applications, pp. 363–379. Springer (2009)
8. Dardenne, A., Fickas, S., van Lamsweerde, A.: Goal-directed concept acquisition in requirements elicitation. In: Proceedings of the 6th international workshop on Software specification and design, Como, Italy. pp. 14–21. IEEE Computer Society Press, Italy, Italy (25–26 Oct 1991)
9. Eric, S., Giorgini, P., Maiden, N., Mylopoulos, J.: Social modeling for requirements engineering. Mit Press (2011)
10. Franch, X., López, L., Cares, C., Colomer, D.: The *i** framework for goal-oriented modeling. In: Domain-Specific Conceptual Modeling, vol. 1, pp. 485–506. Springer, Switzerland (2016)
11. Giorgini, P., Mylopoulos, J., Sebastiani, R.: Goal-oriented requirements analysis and reasoning in the tropos methodology. Engineering Applications of Artificial Intelligence **18**(2), 159–171 (2005)
12. Horkoff, J., Yu, E.: Analyzing goal models: different approaches and how to choose among them. In: Proceedings of the 2011 ACM Symposium on Applied Computing, TaiChung, Taiwan. pp. 675–682. ACM (21–25 Aug 2011)
13. Horkoff, J., Yu, E.: Comparison and evaluation of goal-oriented satisfaction analysis techniques. Requirements Engineering **18**(3), 199–222 (2013)
14. Horkoff, J., Yu, E.: Interactive goal model analysis for early requirements

engineering. Requirements Engineering **21**(1), 29–61 (2016)

15. Van Lamsweerde, A.: Goal-oriented requirements enginering: A roundtrip from re- search to practice. In: 12th IEEE International Requirements Engineering Conference Proceedings, Kyoto Japan, 6-10 September. pp. 4–7. IEEE Computer Society (2004)
16. Letier, E., Van Lamsweerde, A.: Reasoning about partial goal satisfaction for require- ments and design engineering. In: ACM SIGSOFT Software Engineering Notes, New- port Beach, CA, USA. vol. 29, pp. 53–62. ACM New York, NY, USA (31 Oct 2004)
17. Liaskos, S., Hamidi, S., Jalman, R.: Qualitative vs. quantitative contribution labels in goal models: Setting an experimental agenda. In: iStar. pp. 37–42. Citeseer (2013)
18. Liaskos, S., Jalman, R., Aranda, J.: On eliciting contribution measures in goal mod- els. In: Requirements Engineering Conference (RE), 2012 20th IEEE International. pp. 221–230. IEEE (2012)
19. Lima, R.: Ibm ilog cplex-what is inside of the box? In: Proc. 2010 EWO Seminar, 12 July 2010. pp. 1–72. Carnegie Mellon University USA (2010)
20. Mylopoulos, J., Chung, L., Liao, S., Wang, H., Yu, E.: Exploring alternatives during requirements analysis. IEEE Software **18**(1), 92–96 (2001)
21. Nuseibeh, B., Easterbrook, S.: Requirements engineering: a roadmap. In: Proceedings of the Conference on the Future of Software Engineering,Limerick, Ireland — June 04 - 11, 2000. pp. 35–46. ACM, NY, USA (2000)
22. Saaty, R.W.: The analytic hierarchy process—what it is and how it is used. Mathemati- cal modelling **9**(3-5), 161–176 (1987)
23. Saaty, T.L.: Decision making with the analytic hierarchy process. International journal of services sciences **1**(1), 83–98 (2008)
24. Subramanian, C., Krishna, A., Kaur, A.: Optimal reasoning of goals in the i* frame- work. In: Software Engineering Conference (APSEC),New Delhi India, 1-4 Dec. pp. 346–353. APSEC Asia-Pacific (2015)
25. Subramanian, C., Krishna, A., Kaur, A.: Reasoning about goal satisfaction for early requirements engineering in the i* framework using inter-actor dependency. In: 19th Pacific Asia Conference on Information Systems, Singapore, July 5-9. p. 89. PACIS 2015,Singapore (2015)
26. Subramanian, C., Krishna, A., Kaur, A.: Optimal goal programming of softgoals in goal-oriented requirements engineering. In: PACIS. p. 202 (2016)
27. Subramanian, C., Krishna, A., Kaur, A.: Game theory-based requirements analysis in the *i** framework. The Computer Journal **61**, 1–20 (2017)
28. Subramanian, C., Krishna, A., Kaur, A., Raj, G.: Quantitative reasoning of goal satisfac- tion in the *i** framework. In: The 27th International Conference on Software Engineer- ing and Knowledge Engineering, SEKE 2015, PA, USA, July 6-8, 2015. pp. 666–669. KSI Research Inc. and Knowledge Systems Institute Graduate School USA (2015)
29. Sumesh, S., Krishna, A., Subramanian, C.M.: Optimal reasoning of opposing non- functional requirements based on game theory. In: In proceedings of 27th International Conference On Information Systems Development (ISD2018),Lund, Sweden: Lund University. p. 11 (2018)
30. Sumesh, S., Krishna, A., Subramanian, C.M.: Game theory-based reasoning of oppos- ing non-functional requirements using inter-actor dependencies. The Computer Journal **143**, 27 (2019)
31. Wang, X.T., Xiong, W.: An integrated linguistic-based group decision-making approach for quality function deployment. Expert Systems with Applications

38(12), 14428– 14438 (2011)

32. Yu, E.: Agent-oriented modelling software versus the world. In: International Workshop on Agent-Oriented Software Engineering, Montreal, Canada. vol. 2222, pp. 206–225. Springer, Berlin, Heidelberg (29 May 2001)
33. Yu, E.: Modelling strategic relationships for process reengineering. Social Modeling for Requirements Engineering **11**, 178 (2011)
34. Yu, E.S.: Towards modelling and reasoning support for early-phase requirements engi- neering. In: Proceedings of the Third IEEE International Symposium on Requirements Engineering. pp. 226–235. IEEE Computer Society Washington, DC, USA (05-08 Jan 1997)
35. Yu, E.S., Mylopoulos, J.: From er to ar modelling strategic actor relationships for busi- ness process re-engineering. International Journal of Cooperative Information Systems **4**(02n03), 125–144 (1995)
36. Zhao, T., Zhao, H., Zhang, W., Jin, Z.: Goal model driven alternative selection: a quanti- tative approach. In: 2015 IEEE International Model-Driven Requirements Engineering Workshop (MoDRE). pp. 1–10. IEEE (2015)