Optimal Reasoning of Opposing Non-functional Requirements based on Game Theory

Sreenithya Sumesh *S.Sumesh@student.curtin.edu.au*
School of Electrical Engineering,
Computing and Mathematical Sciences
Curtin University, Bentley, WA – 6102, Australia

Aneesh Krishna *A.Krishna@curtin.edu.au*
School of Electrical Engineering,
Computing and Mathematical Sciences
Curtin University, Bentley, WA – 6102, Australia

Chitra M Subramanian *Chitra.Muniyapp@curtin.edu.au*
School of Electrical Engineering,
Computing and Mathematical Sciences
Curtin University, Bentley, WA – 6102, Australia

Abstract

Goal-Oriented Requirement Engineering is a modeling technique that represents software system requirements using goals as goal models. In a competitive environment, these requirements may have opposing objectives. Therefore, there is a requirement for a goal reasoning method, which offers an alternative design option that achieves the opposing objectives of inter-dependent actors. In this paper, a multi-objective zero-sum game theory-based approach is applied for choosing an optimum strategy for dependent actors in the *i** goal model. By integrating Java with IBM CPLEX optimisation tool, a simulation model based on the proposed method was developed. A successful evaluation was performed on case studies from the existing literature. Results indicate that the developed simulation model helps users to choose an optimal design option feasible in real-time competitive environments.

Keywords: Goal models, Requirements engineering, Game theory.

1. Introduction

Any software system's success depends upon the degree to which its requirements are met. During the last two decades, Requirements Engineering (RE) has progressively been developed as a critical area of the software development lifecycle [23]. The elicitation process (one of the most important phases of RE), discovers the stakeholders and identifies the goals/tasks of the system which in turn indicate the objectives that need to be met by the system. In requirement analysis phase, the requirements analyst examines information received from stakeholders to identify their goals from the collected requirements. Stakeholders have hardgoals which indicate the functions the system has to perform. The non-functional goals of the system are represented as softgoals which relate to the qualities desired for the system (accuracy, reliability, performance, etc.). Furthermore, the requirements analyst examines high-level alternative system design options and decides which system design to implement [10].
Goal-Oriented Requirement Engineering (GORE) is a method that models the software system's requirements using goals by eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements [23]. In GORE, goals play a critical role

in understanding the domain and determining the stakeholders' intentions [22]. Goals are elaborated at different levels of abstraction, from strategic concerns to technical matters. Hence, it is a significant, well-thought-out artefact during the early phases of RE [5], [8]. This use of goals is modeled on a multi-view model or goal model that illustrates the way in which goals, actors, states, objects, tasks, and their domain properties are inter-related for the given system [18].

Ever since the mid-nineties, goal models have been prominent in software engineering discipline. In software engineering literature, the i^* goal model is one of the popular and well-known goal models, because it helps goal-oriented modelling of socio-technical systems and organisations. Organisations and socio-technical systems get support in its essential processes with the use of *i** model, as an intentional structure of actors and their dependencies. Reasoning techniques in the i^* goal model enable all types of qualitative analyses [11, 14] or quantitative analyses [9] or even both [1] to be performed.

In real-world, competitive environments, the goals of many stakeholders of complex systems are of a conflicting or opposing in nature. Furthermore, each goal (functional requirement) of a system may have a number of different alternative design options for achieving it. In the *i** goal model, actors have multiple conflicting goals that are dependent on each other. A requirement analyst has to deal with the challenges of these multiple conflicting goals. Requirement-based engineering faces the challenge of identifying an optimal alternative design option for a goal model with conflicting goals. Hence, a novel framework is needed that captures the real issues behind achieving multi-objective optimisation [7]. The implementation of a realistic decision-making process in our approach allows us to go beyond analytical tools, like game-theoretic concepts. This paper proposes a novel methodology based on game theory for system exploration which involves alternative design evaluation. Game theory is a powerful inter-disciplinary tool for the analysis of competitive situations in multi-agent systems [17]. It can adequately characterise the interaction between decision-makers and find optimal solutions under conflicting circumstances, assuming that players are rational and behaving according to their interests.

In previous research [5], game theory-based goal analysis was proposed for each actor in the i^* goal model without considering the dependency relationships among actors. In a real-world competitive environment, when making decisions, decision-makers have to consider the inter-dependent relationships among actors. In this paper, a systematic game theory-based approach is proposed to facilitate decision-making when there are inter-dependent actors in the i^* model by integrating multiple opposing goals together with their significance. To discover the optimal alternative options, a two-person zero-sum game approach is applied to the i^* goal model. In the proposed approach, multi-objective functions are determined to decide their significance. Then, the alternative options for each actor are assessed according to each conflicting softgoal by applying game theory. In the final phase, an optimal solution is found under the circumstances of conflicting goals. A case study is used to illustrate the applicability of the proposed approach. An overview of the existing approaches, techniques and methods related to GORE and more precisely, i^* model, which are closely associated with our approach are presented in the next section.

The paper is organized as follows. Section 2 presents the existing approaches, techniques and methods related to the i^* model, which are closely associated with our proposed approach. The methodology comprising of various steps in our approach and a brief introduction of the methods used in the study are given in Section 3. The evaluation and simulation of the proposed work are described in Section 4. Finally, conclusions are drawn at the end of the paper.

2. Background and Related works

Recent trends in GORE recommend using goals, as a means of discovering the 'whys' in the functionality as opposed to the notion of 'what'. In this section, an overview of the existing approaches, techniques and methods related to the *i** model, that approximate our approach are presented. An interactive, iterative, qualitative analysis method for *i** goal models was proposed by Horkoff and Yu [15]. The uncertainty of making decisions when more than one goal has the same label is the main limitation of this approach. To analyse alternative design options in the KAOS model, Heaven et al. [12] proposed quantitative reasoning based multi-objective optimisation model. However, the main issue with this model is that it does not consider the non-functional requirements of the system. To deal with the conflicts in NFR decision analysis, Mairiza et al. [21] developed a Multi-Criteria Decision Analysis (MCDA) and applied TOPSIS as an MCDA method for prioritising the alternative options. However, the application of TOPSIS for the selection of preferred design solution against conflicting NFRs was not presented. Using the *i** model [3], an inter-actor quantitative goal analysis method was developed for reasoning with non-functional requirements. This method is enhanced by applying a multi-objective optimisation method to find feasible values of softgoals for an alternative selection in the goal analysis process [6], [7]. This furthermore helps in preventing the stakeholders' from imposing his/her subjective preference of values that are being used for the goal based reasoning. However, all these proposals for goal analysis are based on either quantitative or qualitative values used when choosing an alternative design option based on the maximum satisfaction label of non-functional requirements. However, an ambiguity arises when two or more non-functional requirements receive the same type of label during decision-making [15]. This limitation of the qualitative approach to the *i** framework that causes ambiguity in decision making was overcome by Chitra et al. [6], [7]. Chitra et al. developed fuzzy-based optimal quantitative methods for goal analysis in the *i** model. However, the existing literature does not include goals with opposing objective functions in reasoning goal models. In [5], game theory-based goal analysis was proposed but without considering the dependency relationships among the actors. In a real-world competitive environment, when making decisions, decision-makers have to consider the inter-dependent relationships among actors. Overall, using the *i** model, previous research efforts have not been able to develop a systematic game theory-based reasoning approach by reciprocally balancing multiple opposing objectives with their significance. In the next section, the proposed methodology of reasoning opposing non-functional requirements in the *i** goal model is presented.

3. Game Theoretic Approach for Reasoning Opposing Non-functional Requirements

This study aims to provide a more precise decision-making process in real-time competitive environments by integrating multiple opposing objectives with their significance. For the calculation convenience and easy presentation, a two-person zero-sum game [2] is applied in this paper. In the proposed approach, multi-objective functions are determined to decide their significance. To obtain an optimal strategy for player's having opposing objectives, a methodology has been proposed in this paper. The proposed methodology is presented in the following sub-sections.

3.1. Generation of Multi-Objective Functions

In this section, formalisation approach to the opposing non-functional requirements with respect to softgoals, goals, tasks and resource elements based on the Strategic Rationale (SR) model of *i** framework is explained. A directed graph, $G(N, R)$ is represented for SR model in such a way that N indicates softgoals, goals, tasks and resources which represents a collection of nodes and R indicates the links (means-end, task decomposition, dependency and contribution links) which shows a collection of edges [20]. The task of a decision maker is to choose an ideal alternative option from the given choices.

Given an i^* goal model, we aim to choose an optimal design based on its contribution on the softgoals. Impacts are represented as *Make, Help, Hurt, Break, Some-, Some+*. They are symbolized as fuzzy triangular numbers that indicate the extent to which an alternative option fulfils the leaf softgoal [4], [8], [24]. The impacts of the softgoal preferences are backward propagated to the uppermost softgoals in order to evaluate the scores of the same and to achieve the level of satisfaction. Furthermore, a weight ω is assigned to each leaf softgoals based on their relative significance in achieving the goal.

Initially, based on the inter-actor dependency relationship among actors, each top softgoal's scores are evaluated. For details on how to generate scores, readers are directed to [3, 4].

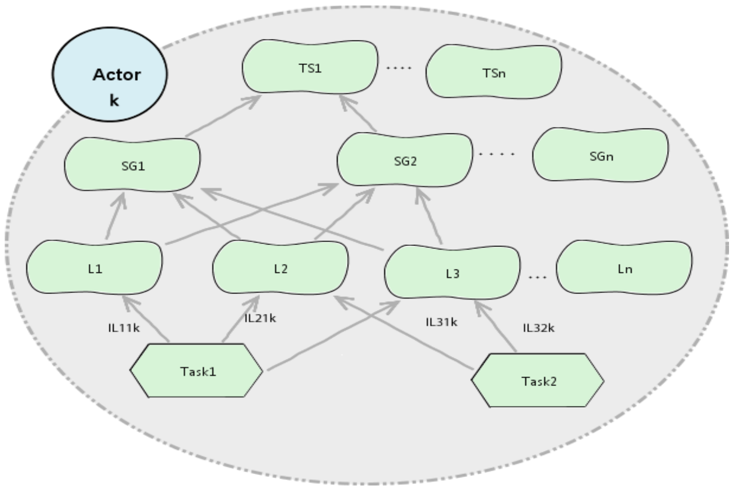

Fig. 1. Directed graph of *i** model

Assume there are *t* hierarchy levels in the directed graph, *G (N, R)* (Figure 1). Let the i^{th} leaf softgoal's weight be $\omega_{L_{ik}}$ and the impact of j^{th} alternative of k^{th} actor on i^{th} leaf softgoal be $I_{L_{ijk}}$. Consider there are m softgoals, n_d dependencies and n_c children for the i^{th} softgoal at level 1. Then, at $t > 1$, the score of any softgoal is calculated by multiplying its impact with each child's score. Thus, a dependency relationship can be generalised in Equation 1 for any softgoal at level $t > 1$.

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

Consequently, the objective functions of top softgoals are generated with the assumption that only softgoal inter-dependency relationships are considered in this proposed approach. For an actor having *n* alternative options, there will be *n* different objective functions for each top softgoal.

The objective functions under n^{th} alternative for each opposing nature (maximisation and minimisation) are given as,

$$f_{i(n)} = S_{SG_{ink}} = Max \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

$$f_{i(n)} = S_{SG_{ink}} = Min \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

Such that $0 \leq \omega_{d_{L_{jk}}} \leq 100 \; for \; d = 1 \; to \; n_c$

(2)

In this paper, the two-person zero-sum game theory approach is applied to choose an ideal strategy for inter-dependent actors. Analogous to game theory, in this proposed approach, game players are considered as the top softgoals with conflicting objective functions of the system and game strategy is treated as the alternative design options of inter-dependent actors in the *i** goal model. Initially, the application of game theory from the actors' perspective having opposing objective functions is investigated with the assumption that each actor in the goal model has the same set of alternative options for achieving his/her opposing objectives.

3.2. Evaluation of the Optimal Solutions of Multi-Objective Optimization Functions

Consider an *i** goal model in which each actor is considered to have two opposing soft goals (SG_1 and SG_2) and two alternative design options (A_1 and A_2). Optimising the objective functions for soft goals individually generates two ideal solutions using Algorithm. 1. The IBM ILOG CPLEX optimisation tool is used for evaluating the optimisation [19].

Let the ideal solutions for the objective functions for softgoals of an actor using two alternative design options, based on Equation 2, is expressed as

$$\left(x_{SG_1A_1}, x_{SG_1A_2}, x_{SG_2A_1}, x_{SG_2A_2} \right) \quad (3)$$

Likewise, for all the actors in the given goal model, the optimal multi-objective function values are generated.

Algorithm 1: Main Module- Optimal Selection

Input: A collection of directed graphs $S = \{S_1, S_2, \dots, S_n\}$ where $G \subseteq S$ having same n number of tasks T, where $G = \{G_1, G_2, \dots, G_k\}$ and each G_i represents $\{T, L, SG, TS\}$ which indicates a set of task, a set of Leaf softgoals, a set of in-between softgoals, a set of top softgoals respectively with each top softgoal associated with opposing variables such as *Max* or *Min.*

```
for Gi ∈ G do
    for task t ∈ T do
        for top softgoals ts ∈ TS do
        if ts is Min then
            Generate minimisation objective function;
        end
        if ts is Max then
                Generate maximisation objective function;
        else
            break;
        end
```

```
        end
    end
end
  Let F_Max ← Max{f_max_1, f_max_2, ... ..., f_max_n };
Let F_Min ← Min{f_min_1, f_min_2, ... ..., f_min_n };
for f_max_i ∈ F_Max do
      Let x_max_i ← optimal(f_max_i, Max); //finding optimal solutions for maximum objective functions
end
for f_min_i ∈ F_Min do
      Let x_min_i ← optimal(f_min_i, Min); //finding optimal solutions for minimum objective functions
end
Generate pay-off matrix, P_TSMax , for maximum objective function values, by integrating x_max's of all Gi∈G
Generate pay-off matrix, P_TSMin , for minimum objective function values, by integrating x_min's of all Gi∈G
Generate decision pay-off matrix P by merging pay-off matrices P_TSMax and P_TSMin
Generate primal linear equation using MaxMin strategy
Generate the optimal solution by solving the primal linear equation
```

Sub Module - Solving Multi-objective functions to obtain the optimal function value

```
Define the objective functions and their constraints based on C;
if C is Max then
    Define maximisation objective function;
end
if C is Min then
    Define minimisation objective function;
else
return (cplex.solve() → W);
end
```

3.3. Objective Integrated Game Theoretic Approach for Pay-Off Matrix Transformation

In this section, the objective function values of top softgoals are integrated for all actors in the goal model that are of the same nature (for example: maximise) under each alternative to generate the pay-off matrix (for each nature). To understand the formation of the pay-off matrix according to the objective function values, let us assume that there are two actors in the same goal model with an inter-actor dependency relationship from *X* to *Y*. Also, assume that both actors have the same alternative options (A_1 and A_2) for reaching their opposing top softgoals (TS_1 (Maximise) and TS_2 (Minimise)). The optimal function values for each actor are represented in Table 1 as a ready reference.

Table 1. Objective functions values

Optimal Function Values	X	Y
$F_{TS1_{A1}}$	$x_{TS1_{A1}}$	$y_{TS1_{A1}}$
$F_{TS1_{A2}}$	$x_{TS1_{A2}}$	$y_{TS1_{A2}}$
$F_{TS2_{A1}}$	$x_{TS2_{A1}}$	$y_{TS2_{A1}}$
$F_{TS2_{A2}}$	$x_{TS2_{A2}}$	$y_{TS2_{A2}}$

Based on the optimal function values shown in Table 1, the pay-off matrices, TS_{Max} and TS_{Min} are generated for each top softgoal by taking the summation of the objective function values that are of the same nature for all actors based on each alternative. Now the pay-off matrix $P_{TS_{Max}}$ for the top softgoal TS_{Max} which has to be maximised for two actors *X* and *Y* under *n* alternatives is generalised as shown below

$$P_{TS_{Max}} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \dots\dots & A_n \end{array} \\ \begin{pmatrix} P_{A_1A_1} & P_{A_1A_2} & \dots\dots & P_{A_1A_n} \\ P_{A_2A_1} & P_{A_2A_2} & \dots\dots & P_{A_2A_n} \\ \dots\dots & \dots\dots & \dots\dots & \dots\dots \\ P_{A_nA_1} & P_{A_nA_2} & \dots\dots & P_{A_nA_n} \end{pmatrix} \end{array}$$

where $P_{A_iA_j} = x_{TS_1A_i} + y_{TS_1A_j}$, for *i*, *j* =*1 to n* (4)

If there are *s* number of actors in an i^* goal model, in such a way that $k \leq s$ actors have the same set of *n* number of alternatives, then each element in the final pay-off matrix of top softgoal that has to be maximised is obtained as:

$$\sum_{i,j=1}^{k} a_{A_lA_r}^{ij} \text{ , where } A_l \geq 0 \; for \; l = n \; and \; A_r \geq 0 \; for \; l = n \quad (5)$$

where a^{ij} denote an element of the pay-off matrix of every combination of i^{th} and j^{th} actor of k resulting from choosing the l^{th} and r^{th} alternative of *n*. Similarly, the pay-off matrix $P_{TS_{Min}}$ for the top softgoal TS_{Min} which has to be minimised for two actors *X* and *Y* under *n* number of alternatives can be generalised.

3.4. Decision Pay-Off Matrix Formation

The overall objective of opposing goals simultaneously can be achieved by merging the pay-off matrices that are obtained separately for each player. This process of integrating objectives with their importance based on alternatives is known as the unification process. An optimal strategy is obtained by analysing the unified pay-off matrices. Now, using TS_{Max} and TS_{Min}, the decision pay-off matrix *P* is generated as shown below:

$$P = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \dots\dots & A_n \end{array} \\ \begin{pmatrix} Z_{A_1A_1} & Z_{A_1A_2} & \dots\dots & Z_{A_1A_n} \\ Z_{A_2A_1} & Z_{A_2A_2} & \dots\dots & Z_{A_2A_n} \\ \dots\dots & \dots\dots & \dots\dots & \dots\dots \\ Z_{A_nA_1} & Z_{A_nA_2} & \dots\dots & Z_{A_nA_n} \end{pmatrix} \end{array}$$

where $Z_{A_iA_j} = p_{A_1A_j} + q_{A_1A_j}$, for *i*, *j* =*1 to n* *(6)*

3.5. Linear Programming Model to Obtain Optimal Strategy and Decision Making

In the last phase, the optimal strategy is obtained by analysing the unified decision pay-off matrix by applying linear programming method [13] to the decision pay-off matrix, shown in Equation 6.

In the case of top softgoal that has to be maximised, (TS_{Max}), follows the Max-Min strategy, the formulation of which is given below as ready reference:
Let the value of the game is v; the strategies are $A_1, A_2 \ldots A_n$; the upper value of the game is $\overline{v}$; the lower value of the game is $\underline{v}$ and the range of the values of the game is $= \overline{v} - \underline{v}$.

$Max\ v,$

Subject to the linear constraints

$$-u \times v + \sum_{i=j=1}^{n} Z_{A_i A_j} \times A_i \geq \overline{v},$$

$$\sum_{i=1}^{n} A_i = 1; \sum_{j=1}^{n} A_j = 1\ A_{i,j} \geq 0\ for\ i,j = 1\ to\ n \tag{7}$$

From Equation 7 all the values are in linear form, and the solution to the game can be found by using a linear programming method. Similarly, player 2 i.e., top softgoal (TS_{Min}), follows the Min-Max strategy. The linear formulation, TS_{Min} is the dual of $TS_{Max,}$. So the solution to the game is found by solving either the formulation of TS_{Max} or TS_{Min}. Thus, the optimal proportion values of the strategies are evaluated by solving either formulation and the strategy with high proportion value is selected.

4. Simulation and Evaluation

The effectiveness and feasibility of the proposed approach (of the *i**goal model) were tested by performing experiments on different case studies from the literature namely Telemedicine system [26], Meeting Scheduler system [4]. The result of the Telemedicine case study is presented in this paper.

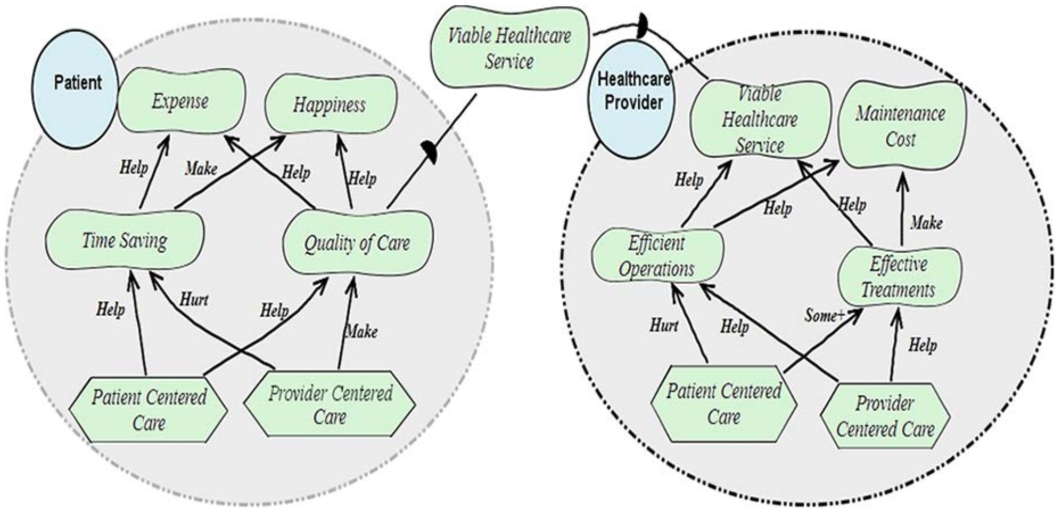

Fig. 2 Simplified SR model for the Telemedicine system (with dependency)

The adapted telemedicine system is shown in Figure 2 with actors, *Patient* and *Health Care Provider*. For more details about the telemedicine system, readers are directed to [26]. The objective of this system is to choose an optimal alternative option regarding its impact on each of the softgoals. The defuzzified values, as shown in Table 2, are used to evaluate the objective functions of each top softgoal.

Table 2. Defuzzified values for impacts

Impact	Defuzzified value
Make	0.8
Help	0.64
Some+	0.48
Some-	0.32
Hurt	0.16
Break	0

The objective function values for both actors, under both alternatives, are given in Table 3 using Equation 2 as a ready reference.

Table 3. Optimal values for the Telemedicine system

Optimal values	Patient	Healthcare Provider
$F_{TS1_{\text{Patient Centered Care}}}$	51.2	30.72
$F_{TS1_{\text{Provider Centered Care}}}$	51.2	40.96
$F_{TS2_{\text{Patient Centered Care}}}$	5.24	12.8
$F_{TS2_{\text{Provider Centered Care}}}$	10.24	51.2

An optimal strategy is obtained using a linear programming model on Equation 7, and the result is shown in Table 4. The results indicate that by choosing the *Provider Centered Care* strategy, the system achieves the opposing top softgoals of inter-dependent actors in the i^* goal model reciprocally.

For evaluating the optimisation model using game theory, a tool was implemented as shown in Figure 3 using Java Eclipse environment integrated with the IBM ILOG CPLEX optimisation tool.

Table 4. Optimal linear formulation for the Telemedicine system

Alternatives	Optimal solution
Patient Centered Care	-9.73
Provider Centered Care	10.73

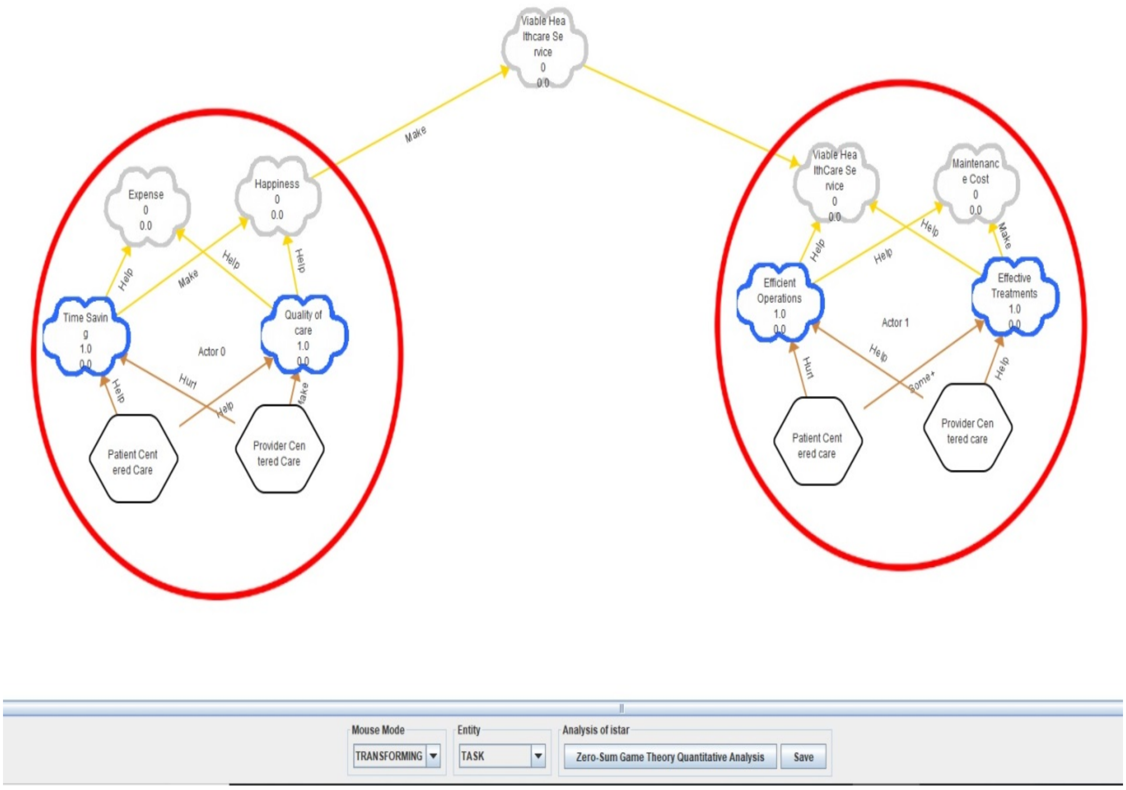

Fig. 3. Tool result for the Telemedicine system (with dependency)

5. Conclusion

A game theory-based goal analysis for the i^* goal model has been proposed in this paper. The proposed model is tested and then evaluated based on the optimal alternative selection by balancing the opposing objectives of dependent actors in the i^* goal model. The proposed approach involves a multi-objective optimisation process in a two-person zero-sum game situation. Further research topics include arriving at optimal solutions for conflicting goals among inter-dependent actors. Also, performing sensitivity analysis, for facilitating valuable input data to help stakeholders in the decision-analysis process.

References

1. 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), pp. 841–877 (2010)
2. Aplak, H., Kabak, M., Köse, E.: A Two Person Zero Sum Game Oriented to Integration of Objectives. Journal of Military Studies. 5 (2), pp. 65–85 (2014)
3. Subramanian, C.M., Krishna, A., Gopalan, R.P.: Quantitative Reasoning of Goal Satisfaction in the i* Framework. In: SEKE. pp. 666–669. (2015)
4. van Lamsweerde, A. Reasoning about alternative requirements options. Conceptual Modeling: Foundations and Applications. Lecture Notes in Computer Science, 5600, pp. 380-397. (2009)
5. Subramanian, C.M., Krishna, A., Kaur, A.: A Game Theory Based Requirement Analysis in the i* Framework. The Computer Journal, Cambridge University Press. (2017)
6. Subramanian, C.M., Krishna, A., Kaur, A.: Optimal Goal Programming of Softgoals in Goal-Oriented Requirements Engineering. In: PACIS. pp. 202. (2016)

7. Subramanian, C.M., Krishna, A., Kaur, A.: Optimal Reasoning of Goals in the i* Framework. In: Software Engineering Conference (APSEC), 2015 Asia-Pacific. pp. 346–353. IEEE (2015)
8. Chou, S.-Y., Chang, Y.-H., Shen, C.-Y.: A fuzzy simple additive weighting system under group decision-making for facility location selection with objective/subjective attributes. European Journal of Operational Research. 189 (1), pp. 132–145 (2008)
9. Franch, X.: On the quantitative analysis of agent-oriented models. In: CAiSE. pp. 495–509. Springer (2006)
10. Franch, X., López, L., Cares, C., Colomer, D.: The *i** Framework for Goal-Oriented Modeling. In: Domain-Specific Conceptual Modeling. pp. 485–506. Springer (2016)
11. Giorgini, P., Mylopoulos, J., Nicchiarelli, E., Sebastiani, R.: Reasoning with goal models. ER. 2. pp. 167–181 (2002)
12. Heaven, W., Letier, E.: Simulating and optimising design decisions in quantitative goal models. In: Requirements Engineering Conference (RE), 2011 19th IEEE International. pp. 79–88. IEEE (2011)
13. Hillier, F.S.: Introduction to operations research. Tata McGraw-Hill Education (2012)
14. 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. pp. 675–682. ACM (2011)
15. Horkoff, J., Yu, E.: Interactive goal model analysis for early requirements engineering. Requirements Engineering. 21 (1), pp. 29–61 (2016)
16. Karagiannis, D., Mayr, H.C., Mylopoulos, J.: Domain-Specific Conceptual Modeling. Springer (2016)
17. Kelly, A.: Decision making using game theory: An introduction for managers. Cambridge University Press (2003)
18. van Lamsweerde, A.: Goal-oriented requirements enginering: A roundtrip from research to practice. In: Requirements Engineering Conference, 2004. Proceedings. 12th IEEE International. pp. 4–7. IEEE (2004)
19. Lima, R.: IBM ILOG CPLEX-What is inside of the box? In: Proc. 2010 EWO Seminar. (2010)
20. Lucena, M., Santos, E., Silva, C., Alencar, F., Silva, M.J., Castro, J.: Towards a unified metamodel for *i*. In: Research Challenges in Information Science, 2008. RCIS 2008. Second International Conference on. pp. 237–246. IEEE (2008)
21. Mairiza, D., Zowghi, D., Gervasi, V.: Utilizing TOPSIS: A Multi Criteria Decision Analysis Technique for Non-Functional Requirements Conflicts. In: APRES. pp. 31–44. (2014)
22. Mylopoulos, J., Chung, L., Yu, E.: From object-oriented to goal-oriented requirements analysis. Communications of the ACM. 42 (1), pp. 31–37 (1999)
23. Sommerville, I.: Integrated requirements engineering: A Tutorial. IEEE software. 22 (1), pp. 16–23 (2005)
24. Subramanian, C.M., Krishna, A., Kaur, A.: Sensitivity Analysis of the *i** Optimisation Model. Journal of Software. 11 (1), pp. 10–26 (2016)
25. Yazdania, S., Linb, Y.-T., Caic, W., Huanga, E.: A Game Theory Perspective on Requirement-Based Engineering Design, 15th Annual Conference on System Engineering Research. Disciplinary Convergence: Implications for Systems Engineering Research. (2017)
26. Yu, E.: Agent-oriented modelling software versus the world. In: International Workshop on Agent-Oriented Software Engineering. pp. 206–225. Springer (2001)