Fairness Analysis in Goal-Oriented Requirements Selection

Hiroki Horita and Junji Noguchi

Abstract—**Requirements analysis is an important step in business information system development. Goal-oriented requirements analysis is a powerful method that captures requirements to be satisfied in business information systems as goals and derives means for achieving goals or alternative means. The difficulty in this analysis is that it is difficult to analyze manually when the combination of goals is huge, and to take into account the preferences of the various stakeholders. It is difficult to satisfy the requirements of all stakeholders at the same time because preferences are different and trade-offs for each stakeholder. Therefore, there is a risk that the requirements of some stakeholders may be ignored. Therefore, in this paper, we propose a method using multi-objective optimization to take into account stakeholder preference and to make goal selection with emphasis on fairness. Our method performs a goal selection having both high utility and fairness of the entire stakeholders. We evaluated by a case study and showed the effectiveness.**

Index Terms—**Goal-oriented requirements analysis, fairness, business information systems, decision sciences.**

I. INTRODUCTION

In recent years, goal-oriented requirements analysis has attracted attention. This is a method that captures stakeholder requirements to be achieved in business processes and business information systems as goals, refines the goals to achieve the abstract top goals, and decompose them into concrete goals. Various goal models have been proposed for goal oriented requirements analysis (e.g.: KAOS [1], i* framework [2], GRL [3] and AGORA [4]). In order for an organization to achieve business goals, it is necessary to select an appropriate combination from many goals. For example, it is assumed that situations such as solving the increase of workload by increasing the number of personnel or solving the task by introducing the information system would be solved. In general, there are multiple ways to solve the problem. In order to select the goal to be achieved, it is necessary to consider the requirements of various stakeholders.

Stakeholders involved with an organization are diverse. There are employees, managers, and IT consultants and software engineers of other companies with business connections. Requirements of stakeholders are also diverse, with different preferences for business information systems and business processes. For example, employees do not like to be asked for a long password to use the information system

or to strictly restrict the use of USB memory. In other words, employees place greater emphasis on usability than security. On the other hand, company presidents have a different preference that security is more important than usability. Therefore, it is difficult to realize all the requirements of various stakeholders, so it is necessary to select by some criteria or means. In AGORA [4], which is a type of goal-oriented requirements analysis method, each goal has an attribute value of an integer of -10 to 10 called a preference matrix assigned by each stakeholder, and can be used as a criterion for selecting a goal. Using such a method encourages organizations to make good goal choices. However, a small number of opinions may be ignored, as in many cases they will generally make a good choice. In recent years, fairness has become important in the world [5], and it is better to be able to select goals in consideration of this concept.

In this paper, we propose a method of goal selection in consideration of stakeholder fairness. Considering fairness is an overlooked point in many goal selection methods. In goal selection, when the number of goals increases, the combination of goals increases explosively. Therefore, it is difficult to scrutinize each combination. Therefore, in this paper, we use genetic algorithm, which is a kind of meta-heuristic algorithm. By doing so, there is a high possibility of being able to cope with the increase in the scale of the analysis target. Furthermore, when selecting goals, it is preferable not only to consider fairness but also to increase the degree of satisfaction of the entire stakeholder. Therefore, we deal with this problem as a multi-objective optimization problem using genetic algorithm [6], since there are two objective functions.

The rest of the paper is organized as follows: In Section II backgrounds of this research are explained. Section III introduces our proposed method. Section IV describes the evaluation of our proposed method. Section V presents the related works. Section VI concludes.

II. BACKGROUNDS

In this section, we explain AGORA goal model, fairness and genetic algorithm. These are important for the background of our research.

A. AGORA

AGORA (Attributed Goal- Oriented Requirements Analysis method) is a kind of goal model proposed by Kaiya *et al*. [4]. The feature of AGORA is that the goal has an attribute value, such as satisfaction, from what for each goal of the stakeholder. By evaluating each other's, not only self-report but also more accurate satisfaction can be

estimated. By utilizing the preference matrix assigned to each goal, it becomes a guideline for performing goal selection. Fig. 1 is a legend of the AGORA goal model. The goal model obtains more specific goals by decomposing the top goals many times. AGORA has two types of decomposition. AND decomposition is a decomposition method in which all the child goals must be achieved for the parent goal to be achieved. The OR is a decomposition method in which one or more child goals must be achieved for the parent goal to be achieved. In other words, OR decomposition can represent alternative means for achieving the parent goal. In the preference matrix, each stakeholder decides his own preference and the preference of other stakeholders in the range of -10 to +10. The closer to -10, the worse, and the closer to +10, the better. Fig. 1 is an example of the AGORA goal model. Fig. 2 shows the legend of the AGORA goal model. In the AGORA goal model in Fig. 1, the top goal "*Production cost reduction*" is decomposed into two child goals, "*Production efficiency*" and "*Strength trouble-shooting*" using AND-decomposition. Therefore, in order to achieve the parent goal "*Production cost reduction*", both the child goals "*Production efficiency*" and "*Strength trouble-shooting*" must be achieved. In addition, since goal "*production efficiency*" is decomposed using OR-decomposition, it is necessary to achieve child goals such as "*Streamlining of manufacturing operations*" or "*Flexible Staffing*" or both. In Fig. 1, the top goal has a preference matrix. In AGORA, it is possible for all goals to have a preference matrix, but this time only the top goal has the matrix for simplicity. The preference matrix is obtained by inferring the preference of two or more stakeholders with any goal and the degree of preference that other stakeholders may assume. Each row is an evaluator, and each column is an evaluatee. That is, one row and one column is -5, which represents the degree of preference of the user (U) for the goal "*production cost reduction*". Also, the preference matrix used this time is 3 × 3, but the type of stakeholder is not limited to three.
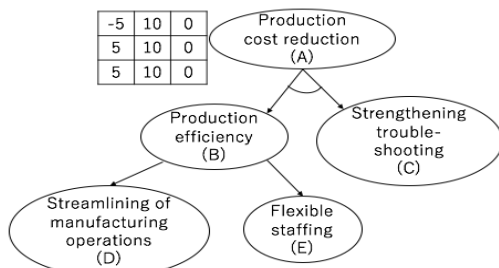

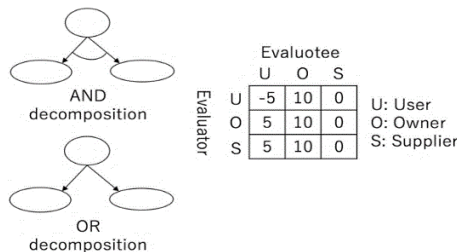Fig. 1. A Partial AGORA goal model.

Fig. 2. AGORA Goal model legend.

B. Fairness

Fairness is considered as an important aspect to be considered in modern society. Finkelstein *et al.* argue for the benefits of considering fairness when developing business information systems as follows. "The ability to automatically search for optimal regions of the 'fairness space' has applications in negotiation, mediation and conflict resolution during the requirements analysis process. It provides an unbiased and thorough exploration of tradeoffs and tensions within the multi-dimensional and complex space of customers and their requirements [7]". In addition, Brun *et al.* insists on the important point in the information system development in consideration of fairness as follows. "(1) eliciting and specifying requirements that capture fairness properties, (2) architecting and designing systems while adhering to their fairness concerns, (3) validating and verifying fairness properties of the resulting software products, and (4) maintaining the fairness properties as the software evolves" [5]. Our proposed method contributes to these solutions.

There are only a few studies that consider fairness in Business Information Systems. Finkelstein *et al.* worked on fairness in next release problem [7]. Galhorta *et al.* worked on fairness in testing [8]. We worked on fairness in goal selection.

C. Genetic Algorithm and Multi-objective Optimization

Genetic algorithm (GA) is an algorithm that simulates the evolution process of an organism. As an organism evolves, it remains suitable for the environment around the individual, and is more likely to leave more offspring. Conversely, things that are not suitable for the surrounding environment will be deceived. Evolution of living things is done by such selection. The genetic algorithm is to match individuals to solution candidates, to adapt the adaptability to the environment to objective functions, and execute operators corresponding to selection, crossover, and mutation in such an organism's evolution process. By imitating the evolution process of a living thing like this, a good solution can be found. In addition, genetic algorithms do not search all possible combinations, they can find approximate solutions quickly.

We use multi-objective optimization to make fair goal selection. In the solution of Multi-Objective Optimization Problems there exist multiple and possibly conflicting objectives to be optimized simultaneously [7]. In general, there is no optimal solution. Even if one objective function takes a minimum, another objective function does not necessarily take a minimum. In multi-objective optimization with GA, when the fitness of individuals of the last generation is plotted on a graph, it will curve. This curve is called a Pareto front, and the solution on which the objective function is placed on the Pareto front is called a Pareto optimal solution. The solutions on the Pareto front are all optimal solutions, so choose the one you like.

III. PROPOSED METHOD

This section explains the details of our proposed method. In this paper, by multi-objective optimization using genetic algorithm, fair goal selection is performed for various stakeholders. In this paper, the combination of goals is expressed as a chromosome. A chromosome is expressed as a collection of genes, and it is represented as 1 to select each

goal, 0 as no selection. For example, in Fig. 3, when the number of goals is five, and each goal name is A, B, C, D, E, and an individual [1, 1, 0, 1, 0] which is an example of a chromosome, goals A, B, D are selected, and goals C and E indicate that they were not selected. In this paper, individual is a solution, that is, a combination of goals.
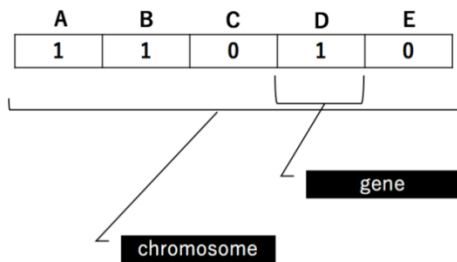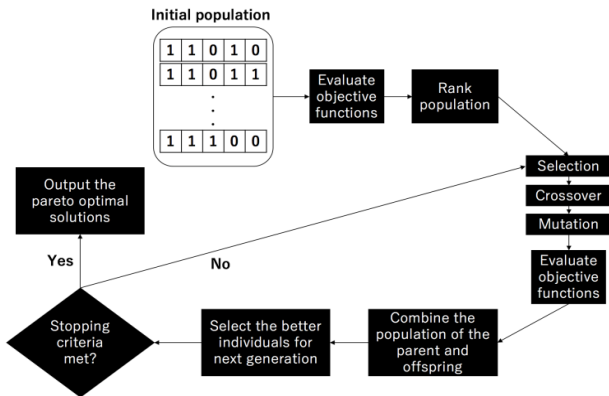

Fig. 3. 5 bit chromosome.

Fig. 4. Flow of genetic algorithm.

A. Fairness Goal Selection

We explain fairness goal selection in this section. The following two objective functions are set up in this paper in order to make fair goal selection. We define two objective functions. We maximize the objective function 1 and at the same time minimize the objective function 2.

- Objective function 1

$$\textbf{Maximize } \sum_j^m \sum_{i=0}^n value(g_i, s_j) \cdot x_i$$

- Objective function 2

$$\textbf{Minimize } \sigma(VA) \; where \; VA_j = \sum_{i=0}^n value(g_i, s_j) \cdot x_i$$

$value(g_i, s_j)$ represents the preference of stakeholder s_j when goal g_i is selected. x_i is 1 or 0, which represents whether the goal g_i has been selected. For these, the sum from goal 0 to n and stakeholder 0 to m is calculated. The larger this value, the higher the preference of the entire stakeholder.

The vector $VA = VA_1,…,VA_m$ represents the fulfilled value for each stakeholder. $\sigma()$ represents standard deviation. In this paper, the smaller the variation in preference among stakeholders, expressed by standard deviation, is considered fairer.

B. Flow of Proposed Method

In this section, we explain the proposed method along the flow in the Fig. 4.

Step 1) Generation of initial population

First, a predetermined number of individuals are generated and used as individuals of the initial population. That is, several individuals with genes corresponding to the number of goals are prepared. At this time, the value (0 or 1) of each gene is determined randomly.

Step 2) Individual evaluation

In order to generate each individual by changing generations of each individual, it is preferable to evaluate each individual and multiply good individuals in each generation to generate better individual. The evaluation of individuals in this method is performed using the goal's decomposition relation and the preference matrix assigned to each goal, and an evaluation value is given according to the number of objective functions.

In the evaluation using goal decomposition relations, it is confirmed whether the combination of goal selection represented by 0, 1 is a possible combination of goal decomposition relations. In the AGORA goal model to be used this time, there are AND decomposition and OR decomposition of goal decomposition relations. Therefore, we extract constraints to be considered from the AGORA goal model. In the case of AND decomposition, any child goals need to be achieved in order to achieve a parent goal. In the case of OR decomposition, any one of the child goals needs to be achieved. If all the constraints are observed, we will move on to the process of confirming the preference matrix. If even one is violated, the objective function to be maximized returns a low value, and the objective function to be minimized returns a high value, resulting in a low evaluation. In other words, when a combination that cannot occur due to the goal model structure is selected, the evaluation value is lowered.

For example, to explain using the example in Fig. 1, although [1, 1, 1, 0, 1] and [1, 1, 1, 1, 1] do not violate the constraint of goal selection, [1, 0, 0, 0, 1] violates the constraints. In Fig. 1, the top goal "*Production cost reduction*" is decomposed using AND-decomposition, it is necessary to achieve all its child goals "*Production efficiency*" and "*Strengthening trouble-shooting*", in order to be achieved. Therefore, all the elements from the first to the third of the individual corresponding to these goals must be 1. [1, 0, 0, 0, 1] violates the goal constraint because the second and third elements are against it. That is, it is a situation where top goals can not be achieved. In such cases, the objective function returns a bad evaluation value. This way, bad goal combinations are less likely to remain in later generations.

For individuals that do not violate the goal constraints, the preference matrix is used to calculate the fitness. We use the two objective functions defined in Section Ⅲ.A to find the degree of fitness. It then returns the sum of preference of all goals and the Standard deviation of preference for all goals by stakeholder.

Step 3) Selection, Crossover, Mutation

Once the fitness of each individual is determined, a selection, crossover and mutation are conducted next. This encourages generating stronger individuals. Basically, the mechanism is such that highly fitness individuals leave more offspring. When a good individual is selected by selection, crossover is performed on the selected individual to create a new individual. Finally, a mutation is performed. This is a

process that mutates a part of the chromosome with a certain probability. Only crossover can generate children dependent on their parents, but mutation can generate diverse children. In this way, it is possible to select a combination of goals that is fair and has a large overall utility. The final solutions are all equally good, and decision makers can choose among them.

IV. EVALUATION

In this section, we show the evaluation results. We use the AGORA goal model used in Sato *et al.* [9] as a case study. Fig. 5 shows the AGORA goal model. Each goal has a preference matrix assigned by the user (U), the manager (M) and the developer (D). The information is described in Table I. We make goal selection using this our proposed method for this AGORA goal model. We use NSGA- II (Non-dominated Sorting Genetic Algorithms-II) [10] as a multi-objective optimization algorithm. For that purpose, we use the python library deap [11].
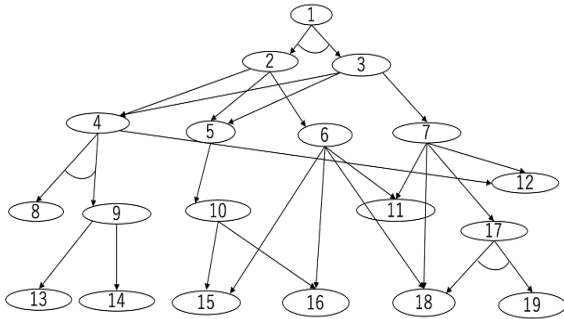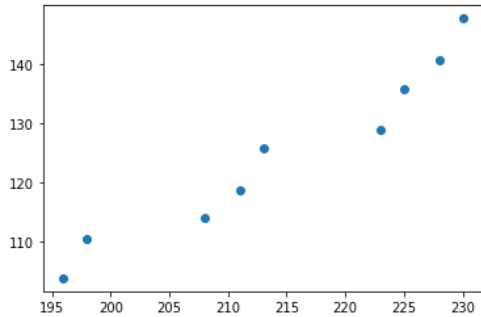

Fig. 5. An AGORA goal model.

Fig. 6. Scatter plot of goal selection results.

We set the number of generations as 500 and the initial number of individuals as 100 and performed the experiment. Table II represents goal selection results. This result shows that there are 9 pareto optimal solutions. The combination of goals selected for each solution, value of objective function1 and objective function 2 are described. It was found that none of the solutions violated the constraints of goal's parent-child relationship, AND-decomposition and OR-decomposition in Table II. Fig. 4 is a scatter plot of the results. The vertical axis represents the Objective function 2, and the horizontal axis represents the objective function 1. It can be read that these two elements are tradeoff. Higher values for objective function 1 are better, while lower values for objective function 2 are better. In order to increase the total satisfaction, it is necessary to allow for stakeholder satisfaction variations. To reduce the stakeholder satisfaction variation, that is, to achieve fairness, the total satisfaction is reduced. It is thought that such results can be used as a means of decision making.

TABLE I: GOAL NUMBER, GOAL NAME, PREFERENCE MATRIX

Goal Number	Goal Name	Preference Matrix		
1	Production cost reduction		U	M	W
		U	-5	10	0
		M	-5	10	0
		W	-5	10	0
2	Production efficiency	7	8	7
		8	8	6
		8	9	7
3	Strengthening trouble-shooting	9	9	0
		8	9	0
		9	8	0
4	Streamlining of manufacturing operations	8	8	8
		9	8	7
		7	8	9
5	Flexible staffing	-2	5	0
		8	8	0
		8	9	2
6	Advancement of production plan	-5	-3	-3
		0	8	-2
		0	-1	-8
7	Visualization of manufacturing process	8	6	0
		8	8	0
		8	7	-7
8	Improving planning	5	5	6
		7	4	7
		7	3	7
9	Productivity improvement	3	8	3
		2	9	4
		3	8	3
10	Addition of multi-skilled workers	0	5	2
		0	-4	0
		0	4	0
11	Immediate understanding of equipment operation status	8	8	0
		7	10	0
		7	9	-4
12	Early notification of defect occurrence	8	9	-3
		7	8	0
		8	8	0
13	Generalization of machines	8	-2	-8
		8	5	0
		-5	0	0
14	Reduction of manufacturing incidental work	-9	3	3
		5	5	4
		5	6	5
15	Maintenance of manufacturing procedure manual	8	7	7
		7	5	7
		7	6	9
16	Planning by simulation	0	3	0
		0	9	0
		8	2	-9
17	Quickly grasp inventory status	9	3	0
		8	5	0
		8	4	0
18	Instantly track progress	-3	7	0
		8	9	0
		8	8	-2
19	Instantly grasp the completed quantity	8	8	0
		9	8	0
		8	8	0

TABLE II: GOAL SELECTION RESULTS

	Goal Combination	Objective function 1	Objective function 2
Solution 1	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	230	147.71
Solution 2	1,2,3,4,5,6,7,8,9,10,11,12,14,15,16,17,18,19	228	140.76
Solution 3	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,17,18,19	225	135.79
Solution 4	1,2,3,4,5,6,7,8,9,10,11,12,14, 15,17,18,19,20	223	128.88
Solution 5	1,2,3,4,6,7,8,9,10,11,12,13,14,15,17,18,19,20	213	125.79
Solution 6	1,2,3,4,6,7,8,9,10,11,12,14,15,17,18,19,20	211	118.83
Solution 7	1,2,3,4,5,6,7,8,9,10,11,14,15,17,18,19,20	208	113.99
Solution 8	1,2,3,4,6,7,8,9,10,11,13,14,15,17,18,19,20	198	110.64
Solution 9	1,2,3,4,6,7,8,9,10,11,14,15,17,18,19,20	196	103.93

V. RELATED WORKS

Goal-oriented requirements analysis is used in various fields such as business analysis [12], decision support [13], and requirements prioritization [14]. Here we describe a method to support decision making on business information systems related to this paper. Heavens *et al.* proposed optimizing the system design by applying a multi-objective optimization [15]. Sato *et al.* proposed goal selection algorithm based on graph theoretical approach [16]. Sagrado *et al.* proposed Ant Colony Optimization algorithms to select requirements [17]. Li *et al.* develop a decision support framework METRO for the Next Release Problem to manage algorithmic uncertainty and requirements uncertainty [18]. Aydemir *et al.* frame the Next Release Problem in terms of constrained goal models [19]. Although these papers are effective for decision making, they do not fully consider the perspective of fairness. On the other hand, Finkelstein *et al.* proposed a solution for the next release problem that takes fairness into consideration [7]. However, their method does not take into consideration the relationship of goals and can not be used for goal selection in goal models. Our method can support goal selection in consideration of the relationship between goals such as AND-decomposition and OR-decomposition and fairness in goal models.

VI. CONCLUSION

In this paper, we proposed a method to make fair goal selection for various stakeholders on AGORA goal model. By using this research, it is possible to support goal selection in which the degree of satisfaction does not differ greatly among stakeholders.

The future work is to consider the differences in stakeholder preferences within the same group. At present, it is assumed that there is no significant difference in preferences within the same stakeholder group such as users and managers. However, User 1 and User 2 may have different preferences. It is a future work to consider this. In addition, the study of the definition of fairness and the confirmation of the scalability of the proposed method are future works.

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