Strategy Assessment Using Goal Models: Software Industry as a Case Study Example

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Abstract

The public policy aims to achieve specific desirable goals despite unstructured and scattered information and many constraints, like time and cost. Despite the availability of various tools and services for evaluating different alternatives for decision-making for policymakers, a systematic process for evaluating these alternatives is yet to find. This paper proposes a framework for assessing public policy alternatives based on goal models. It provides a method to describe a strategy in terms of a goal model. By employing a goal model evaluation technique, the timely success of the possible alternatives to implement this strategy is then estimated, quantifying the expected success of the final goal and the required time and cost to reach that success point for each alternative. The public policy of the software industry in a growing economy country is presented as a case study example. The results and the findings are discussed.

Keywords

Goal model, goal modeling, strategy assessment, public policy formulation, policy-making, strategy formation, strategic decision-making

1. Introduction

Policy-making has been practiced by policymakers almost everywhere for centuries since the ancient civilizations, however not being formalized or theorized, aiming at deciding new plans for a government, affecting the general good of all the people [1, 2]. At the core of the policy-making process comes strategic decision-making and strategy formation. A strategy is a long-term plan of action [2] but has a simple yet powerful definition as an answer to two questions, firstly "where do you want to go?" then, "how do you want to go there?" [3, 4]. The strategic decision-making process can take the rational style characterized by thorough research and logical evaluation of alternatives, using facts and information, analysis, and a step-by-step procedure to come to logically sound decisions [5, 6, 7]. On the other hand, the intuitive decision-making style relies on hunches [6]. Intuitive decisions are made relatively quickly, with limited information, and often changed if the intuition was in error which is likely to happen [7]. The rational

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model of decision-making is then a more advanced type of decision-making model [8]. Several research works [9, 10, 11, 12] formulated models for implementing rational decision making. They share similar ideas starting with identifying the goals, identifying all possible alternatives, and evaluating them to attain the best choice. When it comes to public policy-making, where decisions affect the masses for a longer time, the decision-making process becomes more complex and more critical, increasing the need for a more rational and deeper analysis before decisions are taken at that level. A higher degree of vagueness and uncertainty in data can be faced. More alternatives can exist, which can open debates on selecting the best strategy to adopt, bringing politics to the scene.

A graphical representation of a strategy would be preferred during the strategic decision-making process, which can be achieved by employing goal models. They can help describe how to reach the final goal through a course of effects initiated by actions to be taken. Other research works [13, 14] share similar concepts ending with methodologies that employ goal model reasoning for strategic decision-making but not accounting for the time required to execute strategies and for the final goal to reach success.

In this paper, we provide a method to describe a strategy in terms of a goal model. The timely success of the possible alternatives to implement this strategy is then estimated by applying some goal model evaluation technique, quantifying for each alternative the expected success of the final goal and the required time and cost to reach that success point. Such a method helps to find answers to simple but hard-to-answer questions: What is the expected success of our final goal if we go this way? When do we expect this success to happen? Numerous what-if scenarios can then be described, supporting rational decision-making. We build on the goal model evaluation work found in [15], based on the state-space representation of systems at its core for a faster evaluation of the final goal success with respect to time. Section 2 describes the details of the proposed methodology. An example from the software industry is presented in Section 3, and the obtained results are discussed in Section 4.

2. Proposed evaluation model

Here we consider a *strategy* being an arrangement of tasks and goals in the form of a goal model from the policymaker's perspective. This arrangement is his plan that reflects his understanding and intention of how to attain his final goal, starting from specific tasks, passing through intermediate goals that finally contribute to the final goal, regardless of any required resources. Allocation of resources, as well as estimation of success, are limited to tasks only. For simplification, we consider that all types of the required resources be expressed in terms of the necessary fund to complete those tasks. The accumulated required costs along the time of execution of a task form the *cost curve*. The cost curve is required to grow the expected success level of the task from some initial success point (greater than or equals to zero) to one for complete success, forming the *success curve*.

The values of the success of tasks propagate up-wards along the contribution paths in the goal model and eventually develop the success of the final goal. A question arises here, especially in case of insufficient funding: Shall we allocate all required budgets, as defined by the cost curves, to all the tasks in that strategy? More specifically, what will happen if we disburse the available funds to some specific tasks only? Different combinations of the selected tasks to adopt, ignoring the other tasks, lead to different success curves of the final goal; therefore, the time to reach a specific success level of the final goal will also be affected. We call such a combination of tasks a *policy*. It reflects the policymaker's priorities to achieve the final goal best considering the available limited budget for the strategy. An extreme policy is to adopt all the tasks in the strategy, while another extreme policy is to adopt a single task. A typical policy has those tasks whose accumulated costs are acceptable within the budget, and the final goal's success is reasonable. If a strategy has two tasks T_1 and T_2, then the possible policies for this strategy can be expressed as the set of the tuples $\{(\emptyset, \emptyset), (T_1, \emptyset), (\emptyset, T_2), (T_1, T_2)\}$, where $\emptyset$ indicates the lack of the corresponding task in a policy. Furthermore, a task may have several alternatives for cost/success curves. If T_1 has alternatives T_{1A} and T_{1B}, and T_2 has alternatives T_{2A} and T_{2B}, then a policy for this strategy can then be either one of $\{(\emptyset, \emptyset)$, $(T_{1A}, \emptyset)$, $(T_{1B}, \emptyset)$, $(\emptyset, T_{2A})$, (T_{1A}, T_{2A}), (T_{1B}, T_{2A}), $(\emptyset, T_{2B})$, (T_{1A}, T_{2B}), $(T_{1B}, T_{2B})\}$.

Computing the success curve of the final goal for a given policy is achieved by employing the goal model evaluation technique described in [15]. This technique allows representing inputs as time series, considers latency parameter of goals, and provides a time series for the output. Relating the success curve of the final goal, which is the outcome of the policy, to the policy's resultant cost curve can formulate an assessment of the strategy employing that policy. Prior assessment of policy alternatives can provide predictions of the possible outcome of that policy alternative and assist policy-making decision support.

The trending $i*$ language has been chosen in this research as the foundation for goal modeling since it supports positive and negative contribution relationships between nodes. It also has the distinction between tasks and other intentional elements like softgoals, which is the $i*$ representation of what we earlier called goals. However, only a subset of the core $i*$ language is supported. For example, tasks and softgoals are the only supported node types, and the relationship types from a task to a softgoal or from a softgoal to another are limited to "helps" and "hurts" contribution types. Other relationships like AND/OR decomposition cannot be compatible with the used evaluation technique, which requires linear relationships. On top of $i*$, we designate a latency value for each goal (softgoal) as described in [15] and a weight value for each contribution to that goal.

The goal model graphical editor and evaluation tool from [15] has been developed to accommodate the new data model and concepts, e.g., the data entry of tasks cost/success, goal latencies and the new evaluation graphical user interface.

The proposed steps to evaluate possible strategy implementation alternatives are:

1. Develop the goal model that represents the strategy to achieve the final goal
2. For each goal, estimate the latency parameter and the weights of contributions from other nodes. Weights should sum up to the value of 1.0
3. For each task, determine the best cost and success curve parameters that best matches its expected performance
4. Define policy alternatives by selecting combinations of tasks, and then review the expected success curve for these combinations

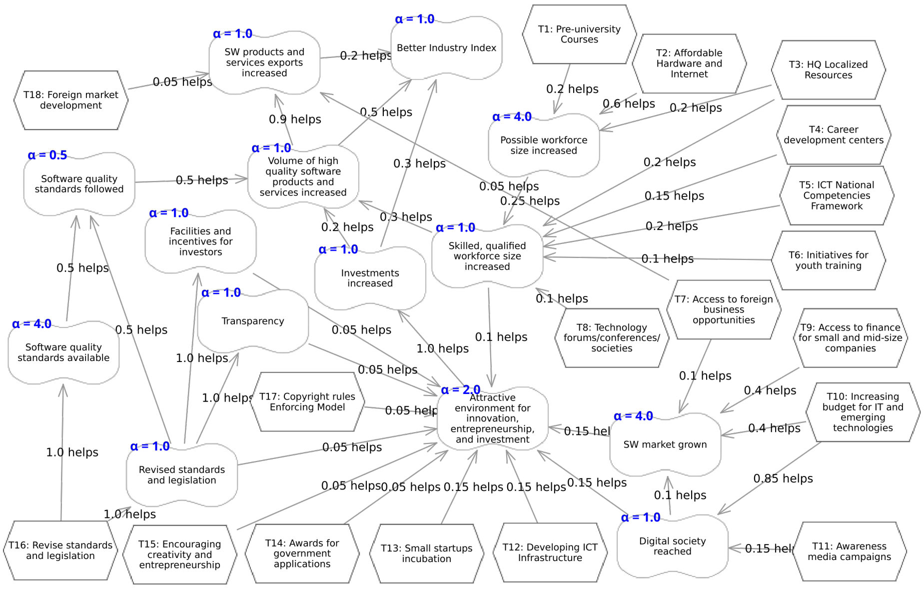

Figure 1: The goal model for software industry prosperity based on *i**. Goals are represented as dented rounded rectangle softgoals and tasks as hexagon-shaped nodes

While the evaluation tool supports at its core any time series, it currently supports graphical-based data entry of only two parametric patterns for cost/success curves; namely the sigmoid curve (that corresponds to bell-shaped differential costs for cost curves) and the linear curve (corresponding to constant differential cost for cost curves, and a constantly developing success for success curves).

3. Example from software industry policy-making

The governmental agency concerned with the software industry in a country with a fast-growing economy is interested in making it a key contributor to its economic growth. The goal model in Figure 1 has been developed to represent this strategy. The final goal, named "Better Industry Index," is to foster the industry's prosperity. The arrangement of goals and their relations in that graph is the agency's plan, or strategy, to attain that goal. Three sub-goals contribute to the final goal, "Better Industry Index," and each of those sub-goals has a contribution from other nodes until the contribution comes from a task that requires to be executed, without any further contribution from other nodes. The estimated cost/success curves for the tasks in the goal model are shown in Figure 2. An example task in this figure is T_3, whose target is to provide high-quality localized training resources. As indicated by its cost curve, this task is estimated to have a constant cost starting early and ending at about 0.3 million USD after five months. The expected success of this task has the shown sigmoid-like shape.

The goal model and the cost/success curves come from experts in the industry but are entirely hypothetical and are not intended to be relevant to a specific country or specific time, and not considering the industry's current conditions. They are intended only to seem reasonable to demonstrate the point of the research.

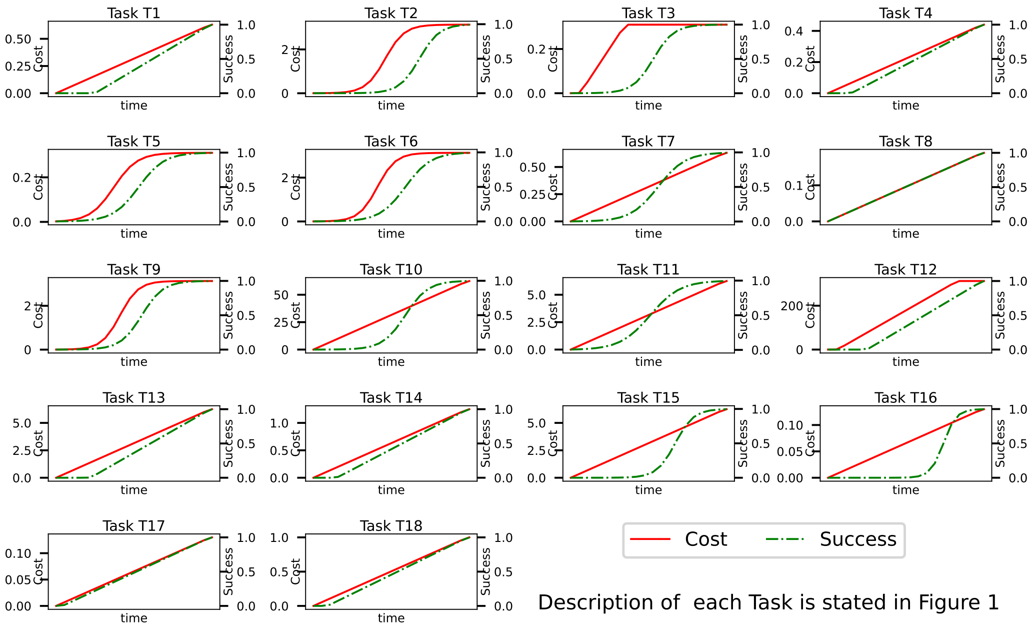

Figure 2: The cost/success curves for the tasks in the goal model in Figure 1. The cost curve is measured in one million USD, success is between 0 and 1, and the time duration is 12 months.

Table 1
The outputs for the cost, success, and success to cost ratio of the final goal, sorted by the cost in ascending order. The cost is expressed in 1 million USD.

Task	Cost	% final success	Success / cost	Task	Cost	% final success	Success / cost
T_{16}	0.13	40.4%	3.108	T_{14}	1.25	2.2%	0.018
T_{17}	0.13	2.2%	0.169	T_6	3.13	2.5%	0.008
T_8	0.19	2.5%	0.132	T_9	3.13	2.6%	0.008
T_3	0.31	6.2%	0.200	T_2	3.13	3.7%	0.012
T_5	0.31	4.9%	0.158	T_{13}	6.25	6.5%	0.010
T_4	0.44	3.7%	0.084	T_{15}	6.25	2.2%	0.004
T_1	0.63	1.2%	0.019	T_{11}	6.25	1.1%	0.002
T_7	0.63	1.6%	0.025	T_{10}	62.50	8.7%	0.001
T_{18}	1.00	1.0%	0.010	T_{12}	312.50	6.5%	<0.001

4. Results

When individual tasks were selected as policy alternatives, the results in Table 1 were obtained as the output. For example, if T_3 was the only selected task to achieve the

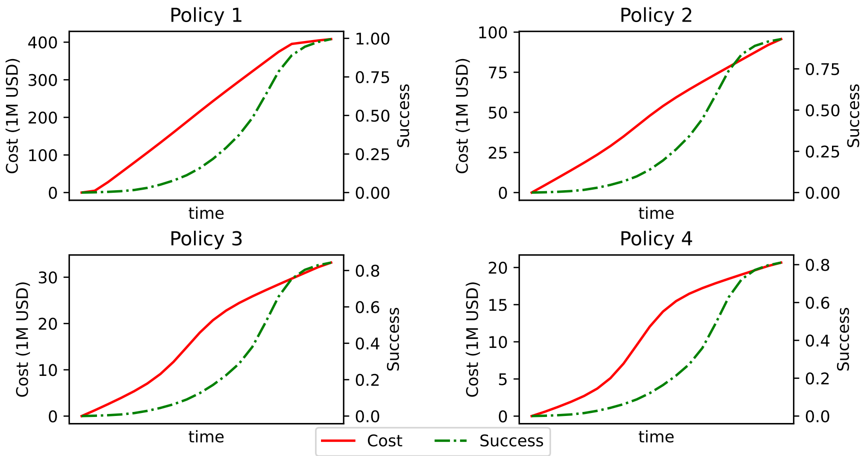

Figure 3: The cost/success curves of the final goal "Better Industry Index" for few policies of interest.

final goal of "Better Industry Index", which is an extreme alternative, then the overall cost would be the 0.31 million USD coming from its cost curve, while the final expected success of the final goal not exceeding 6%, therefore the success to cost ratio is 0.2.

Two interesting findings can be figured out from these results: First, the task that has the maximum share to the satisfaction of the final goal, if applied exclusively, has the least cost. Second, 85% of the contribution of the success of the final goal comes from only 8% of the cost of all tasks by excluding only the two most costly tasks. Few remarkable policies can be figured out from the obtained results. Policy 1: Employing all considered tasks, Policy 2: Excluding the costliest task only (T_{12}), Policy 3: Excluding the two most costly tasks (T_{12}, T_{10}), Policy 4: Excluding the policies with the least four success-to-cost ratios (T_{12}, T_{10}, T_{11}, T_{15}). The cost/success curves for these four policies are shown in Figure 3. This figure tells that if Policy 1 has been adopted, it is expected to spend 400 million USD almost constantly throughout the execution of the strategy to reach success through a shifted sigmoid success curve reaching 100% at the end of the course, reaching 50% success after about eight months. On the other hand, if Policy 4 has been adopted, the cost would be only 20 million USD spent through a sigmoid-like curve, with the maximum success of 80%, reaching 50% success after nearly an equivalent period as in Policy 1.

5. Conclusion

In this paper, we introduced a framework for assessing policy-making strategies based on goal modeling. We have introduced or redefined the terms of strategy, task cost/success curve and policy alternative. After a strategy became defined as described in the proposed framework and all tasks cost/success were available, it was possible to examine policy alternatives yielding the expected consequent cost and success performance of the final goal with respect to time. The policymaker can then gain access to a systematic procedure to choose among different policy alternatives. However, due to the employed evaluation algorithm, which uses the state-space representation of systems for examining the dynamics of the satisfaction flow from tasks up to the final goal, the goal model is limited to have only the "helps" and "hurts" contribution types of relationship between nodes in the $i*$ based goal model. Supporting graphical-based data entry of more options for cost/success curves can be possible in future work since the evaluation tool supports at its core any time series. Defining policy alternatives and the interpretation of the resultant success curve are currently performed manually. Automated scanning of all alternatives, possibly with predefined constraints, is considered as the next task. Moreover, implementing task cost/success curve alternatives would also be an important future contribution.

References

[1] Policy-making in Cambridge Dictionary, 2021. URL: https://dictionary.cambridge.org/dictionary/english/policy-making.

[2] P. H. Collin, Dictionary of politics and government, Bloomsbury, 2004.

[3] K. M. Eisenhardt, Strategy as strategic decision making, MIT Sloan Management Review 40 (1999) 65.

[4] Making Strategy, The Economist, 1 March, 1997.

[5] S. P. Robbins, T. A. Judge, Organizational Behavior, 12th Edition, Prentice Hall, 2006.

[6] S. G. Scott, R. A. Bruce, Decision-making style: The development and assessment of a new measure, Educational and psychological measurement 55 (1995) 818–831.

[7] F. A. Russ, K. M. McNeilly, J. M. Comer, Leadership, decision making and performance of sales managers: A multi-level approach, Journal of Personal Selling & Sales Management 16 (1996) 1–15.

[8] F. C. Uzonwanne, Rational Model of Decision Making, Springer International Publishing, Cham, 2016, pp. 1–6. doi:10.1007/978-3-319-31816-5_2474-1.

[9] L. Mann, R. Harmoni, C. Power, The GOFER course in decision making, Teaching decision making to adolescents (1991) 61–78.

[10] I. L. Janis, L. Mann, Decision making: A psychological analysis of conflict, choice, and commitment, Free press, 1977.

[11] K. L. Guo, DECIDE: a decision-making model for more effective decision making by health care managers, The health care manager 39 (2020) 133–141.

[12] J. Pijanowski, The role of learning theory in building effective college ethics curricula, Journal of College and Character 10 (2009).

[13] J. Horkoff, D. Barone, L. Jiang, E. Yu, D. Amyot, A. Borgida, J. Mylopoulos, Strategic business modeling: representation and reasoning, Software & Systems Modeling 13 (2014) 1015–1041. doi:10.1007/s10270-012-0290-8.

[14] Q. Ma, S. de Kinderen, Goal-based decision making, in: Requirements Engineering: Foundation for Software Quality, Springer International Publishing, 2016, pp. 19–35.

[15] M. Abdel-Monem, I. El-Maddah, H. K. Mahdi, Goal model evaluation based on state-space representation, IEEE Access 8 (2020) 205111–205123. doi:10.1109/ACCESS.2020.3037210.