Strategic Planning Technology: Application Aspects of Artificial Intelligence Linguistic Generative Models

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Abstract
A technology for strategic planning that enables the formal construction of realistic long-term plans using all available knowledge in various weakly structured domains (regional development, military sphere, business, IT, education, and so on) is proposed. This technology is based on group construction of a goal-oriented model of the subject domain, which is built through the decomposition of the main strategic goal and considers the temporal and resource characteristics of the system's components, along with their interconnections. The usage of linguistic generative models of artificial intelligence is suggested at certain modeling stages. It is demonstrated that artificial intelligence tools contribute to enhancing the adequacy of subject domain models, thus improving the quality of recommendations generated by strategic decision support systems. Nevertheless, it is essential to note that these tools do not replace the involvement of expert teams in the modeling process. Instead, they serve as additional rather than primary tools in the strategic planning sphere.

Keywords
decision-making support, strategic planning, modeling of subject domains, linguistic generative models of artificial intelligence

1. Introduction

The importance of proper and scientifically sound strategic planning and a reasonable development strategy in various fields cannot be overstated. In fact, in any field of activity, a person wants to know what to do to achieve a certain goal. In addition, success directly depends on choosing the most effective way to achieve the desired result.

Explanatory dictionaries provide a definition of "Strategy" (derived from the Greek word στρατηγία, meaning the art of the commander) as a broad, high-level plan for a long-term activity, outlining a path to accomplish a complex objective. In this context, there's a notable similarity with the definition of a system in system analysis [1], which characterizes a system as a collection of interconnected components working toward a specific goal. These definitions highlight the essential role of a goal in both terms. Indeed, a system, as an abstract concept, cannot exist independently of a goal for its operation, and a strategy represents the means to achieve the goal of this system. Consequently, within the framework of system analysis, the term "strategy" can be described as the most efficient approach to attain the optimal (maximum) of the system's goal function.

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Some modern specialists who have successful experience in creating long-term plans in the field of entrepreneurship (strategists) argue that strategy development is a creative rather than an analytical process [2]. Thus, they indirectly confirm the lack of formalization and study of this problem at present. Moreover, this confirms the impossibility of analytical presentation of the purpose of functioning in the areas of application of strategic plans, for example, such as business, economy, sustainable development, military, public administration, etc. After all, it is the inability to set an analytical goal of functioning that is considered to be the main property that classifies systems as weakly structured.

Management tasks often require the development of strategies, any of them is a long-term, consistent, constructive, rational, ideologically backed, and resistant to uncertainty plan, which is accompanied by constant analysis and monitoring during implementation and is aimed at achieving success in the end. The strategy has the ability to move from abstraction to specifics in the form of concrete plans for functional units.

When choosing methods for building strategies, it can be argued that the methods of economic analysis do not fully meet the requirements. For example, from a purely economic point of view, space program projects related to commercial launches and telecommunications always outperform any scientific or innovative projects in the short term. When it comes to evaluating projects in the long term, economic analysis is mostly incapable of providing reliable conclusions. However, the practice of the leading space powers, in particular the United States, shows that in the long run, innovative research projects bring economic benefits [3]. In particular, the National Aeronautics and Space Administration (NASA) states that the Apollo space mission projects have fully paid off in about 30 years, mainly due to the widespread introduction of innovations into the economy that were first proposed in the preparation of these space projects. Such innovations include a whole range of goods and services that have given a significant impetus to the development of the economy (ranging from household water filters to sports shoes designed as astronaut shoes).

Strategy development is often characterized by a lack of deterministic information and knowledge about the subject domain. Under such conditions, experts are usually the only source of information necessary for an adequate description of the subject domain [4], and expert decision support methods are the tools that will allow to form a knowledge base of the subject domain and evaluate projects.

In the past, strategy development began with attempts to evaluate scenarios formulated by experts in the chosen field. Later, these attempts had to be abandoned due to the large number of scenarios to be considered and the inexpediency of delegating to experts the function of allocating resources among the projects. In fact, in this sense, a strategy is a defined set of projects for which certain funding has been allocated for a rather distant future (for example, for the space industry, this is at least 15 years).

Therefore, in the following discussion, strategy building is the allocation of resources between projects over time. This allocation should be determined at the beginning of each stage of the strategic plan implementation when allocating resources for the next stage, as well as in case of unplanned significant changes in the planning area that were not foreseen when modeling this subject domain.

The availability of artificial intelligence (AI) tools [5, 6] significantly expands the scope of its application, confidently leading to its implementation in knowledge management systems of organizations [7]. This has become especially noticeable over the past year with the introduction of wide access to the use of linguistic models, such as ChatGPT [8] from the OpenAI laboratory, and others like it. As for the latter, the ChatGPT chatbot made available to the general public is a linguistic generative model. It is designed to process natural language and generate text based on textual input. The GPT-3.5 model, on which ChatGPT is based, is known for its ability to generate natural texts, answers to questions, and other linguistic tasks.

The main idea of this paper is to investigate the possibilities of using AI tools to improve the adequacy of subject domain models used to formulate strategic plans. The weakly structured subject domains [1] that the decision makers (DMs) deal with have certain features that significantly complicate the process of their modeling. For example, the absence of benchmarks for comparison and evaluation leads not only to difficulties in validating the recommendations generated by decision support systems (DSS), but also to the impossibility of applying known methods for assessing the adequacy of models. The main factors affecting the adequacy of subject matter models are the completeness of the model's representation of the components of the modeled weakly structured system and their interrelationships, as well as the correct (without distortion) representation of expert knowledge in these models. These two factors should be enhanced by the use of AI tools, namely, their linguistic generative model.

This paper offers a description of the tools that allow DMs to build long-term plans to achieve certain strategic goals in the economic and other spheres of life. At the same time, considerable attention is paid to the peculiarities of using AI tools to improve the adequacy of subject matter models on the basis of which strategies are built. The absence of such tools at the present stage only confirms the relevance of this study. The main drivers that give hope for creating such an effective toolkit for the ERP include the use of: a) a systematic approach to solving a set of research tasks and b) developed methods for analyzing and using all available knowledge about the system.

Further analysis has also shown that most of the requirements for strategic planning tools are satisfied by the Solon family of DSSs [9] due to the appropriate set of tools, and as for the need to consider risks and threats, it seems quite realistic to meet it without going beyond the current DSS.

2. Technology for building strategic plans

Given that the essence of strategy lies in its role as a means to attain a goal, the concepts of strategy and goal are inherently intertwined. As a result, the adoption of a goal-based approach was proposed in the methodology of constructing strategic plans. This approach centers on modeling the subject domain as a complex, loosely structured system comprising interconnected components, namely goals, which exert influence on one another.

When employing the goal-based approach, the initial step involves formulating the principal goal to be achieved through the implementation of the strategy. Typically, this strategic goal is articulated by decision-makers, which may encompass senior government officials, politicians, and business leaders.

In strategic planning, it is imperative that the main goal is phrased to meet specific criteria:

- The goal should be sufficiently broad, with the level of its attainment capable of varying over time, aligning with the temporal perspective within the strategy (e.g., 3, 5, or 10 years).
- Ideally, the achievement of the goal should not be contingent on or in conflict with the goals pursued by other market players. For instance, a goal like "Becoming the top seller in the region" is not ideal, as it can be accomplished through market expansion and increased sales, but also by undermining other leading players in the market.
- In general, the extent of achievement of the main goal should not be gauged through a single numerical measurement, implying that the nature of the goal is qualitative, not quantitative. A quantitative goal would make the task of devising a strategy simpler and less substantial.

It's evident that all of these requirements for the main goal (strategic goal) are interrelated.

Additionally, it's worth noting that the goal-based approach involves deriving the characteristics of the main goal from the characteristics of other system components - goals that directly or indirectly impact the achievement of the main goal. These components, generated during the decomposition process, include specific goals that remain unaltered and act as solution options / activities / projects.

2.1. Model of the subject domain

It's important to assess the achievement of the strategic goal over time when building a strategy. The subject domain model is created to enable this, in the form of a goal hierarchy graph from the decomposition of the main goal. Arbitrary influences/links between goals are added to increase model adequacy. The resulting graph has a hierarchical tree-like structure but is a network in general.

2.1.1. Goal model

Goals are graph vertices representing components of the main goal from decomposition. Goals have a formulation describing what is to be achieved.

There are two goal achievement processes:

- Linear: Progress towards goal impacts other goals;
- Threshold: No impact until threshold percentage achievement.

Goals can be quantitative or qualitative depending on the knowledge to assess achievement.one.

2.1.2. Project model

Projects are goals achieved through specific actions. Projects have estimated duration and resources required, distinguishing them from goals. The project model accounts for the degree of implementation depending on financing. The piecewise continuous linear function shown in Fig. 1.

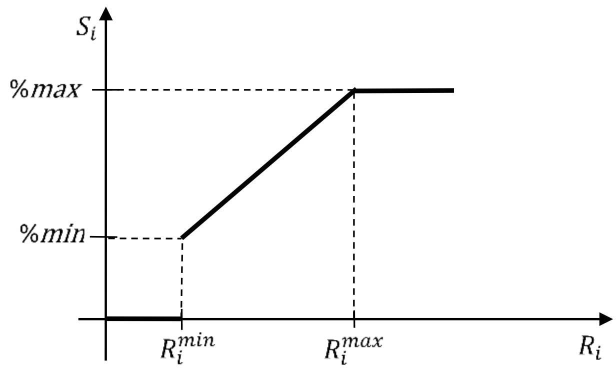

Figure 1: Dependence of the degree of implementation of the *i*-th project on its funding

In Fig. 1 R^{max} is the amount of financial resources required for the full completion of the i-th project, R^{min} - is the minimum amount of resources without which the project cannot be completed (i.e., if these resources are allocated, the degree of project implementation will be *%min*).

2.1.3. Influence properties

Some goals influence others in the model. Influences are identified during decomposition. In the graph model, influences are arcs from influencing to influenced goal vertices.

Goals, as components of the system, are interconnected: some goals influence others within the model. The influences are identified during the decomposition of a particular goal and at the same time as the formulation of the components of that goal. The components influence the goal and are usually called sub-goals, while the goal that is influenced by the sub-goals is sometimes called the super-goal of these sub-goals. Influences have a number of properties, one of the main of which is a relative indicator, the so-called partial impact factor (PIF). PIFs are defined as a measure of the direct impact of sub- goals on their super-goal. These coefficients show the relative magnitude of the impact of a particular sub-goal on a given goal compared to other sub-goals of that goal.

It should be noted that when building a model, it is possible to provide alternative options (ways) of achieving each goal. Each option for achieving a given goal is represented by a set of sub- goals that are compatible with each other. In this context, sub-goals are compatible if the achievement of one sub-goal does not impede the achievement of another (incompatible sub-goals cannot be achieved simultaneously). Such groups of compatible goals are identified during the decomposition by providing information on the compatibility of each pair of sub-goals. The PIFs are normalized and for each *k*-th group of compatible sub-goals the following equality holds:

$$\sum_{j=1}^{K} \left| w_{ij}^{(k)} \right| = 1, \tag{1}$$

where $w_{ij}^{(k)}$ is the PIF of the *j*-th sub-goal upon the *i*-th goal within the *k*-th group of compatible sub-goals; *K* is the number of compatible sub-goals in the *k*-th group.

The PIF before normalization (1) is determined based on the relative impact of a sub-goal on a specific goal, and the approach taken depends on the extent of available knowledge within the modeling process. When reliable information about the sub-goal's effect is at hand, the PIF is calculated as the ratio of the achieved sub-goal's effect to the resources necessary to attain the super-goal, with both measured in the same units. In the opposite case (there is no reliable information about the effect of achieving the sub-goal or when the sub-goal is qualitative), expert evaluation methods are used to determine the PIF [10-14], in particular, group expert evaluation methods [15, 16].

Another property of influence is related to the necessity of modeling the system dynamically over a specific time horizon within the context of strategic planning. To realize such opportunities, each influence is marked by a temporal delay in its propagation. In the realm of strategic planning, experts ascertain this delay down to the nearest day (day/24 hours). By having information on the timing of impact propagation delays and project schedules, it becomes feasible to forecast the extent to which goals can be attained within distinct timeframes.

2.2. Group decomposition

In alignment with the system analysis approach, when solving complex problems, the process involves decomposition them into smaller components and subsequently synthesizing solutions. Similarly, the main goal is decomposed into sub-goals.

Any model creation involves simplification and neglect of some non-essential properties of the modeling object. Within the framework of the goal-based approach, this simplification consists in not taking into account minor connections between system components, i.e., when decomposing a certain goal, only the goals that have the most significant impact on achieving the decomposed goal are taken into account.

What impacts should be considered significant to be taken into account when building a model?

For this type of modeling, the rule is that the impacts of goals whose relative importance on the achievement of a particular goal does not exceed 1/10 (10%) of the total number of impacts are considered significant. If we follow this loose rule, then, as a consequence, the requirements for the reliability of the results in pairwise expert comparisons will be met, namely: the values of the compared alternatives in a pair should be of the same order [17] and the number of alternatives for comparison should not exceed 7±2 [18].

Due to a number of the above-mentioned features of the decomposition process, only some of the operations can be implemented using AI tools. We will describe the proposed possibilities of using these tools below.

There is probably no doubt that all available knowledge should be used to build a model of the subject domain. The question arises: is it possible to rely on the results generated by AI alone, without consulting experts, when decomposing? The answer, in our opinion, is related to a study conducted by the Delphi Group [19], which presents the distribution of knowledge used by organizations in their daily activities. The results of the study show that a significant share of knowledge (42%) is not described or registered anywhere and exists only in the minds of specialists. It is the existence of this informal knowledge that leads to the need to turn to experts, since this share of knowledge is not available to AI tools. Since one person, even a very qualified one, cannot possess all the knowledge in a certain area, it is advisable to use group expertise when building models that allow obtaining knowledge from a team of experts.

Group decomposition is an element of the process of building a domain model that allows a group of people with domain knowledge to decompose a certain goal by coordinating their ideas about the necessary conditions for achieving it (the impacts of sub-goals) and reaching a consensus. The choice to initiate this collaborative effort is generally made by a knowledge engineer when there is insufficient existing knowledge regarding the conditions required to achieve the goal being decomposed. It should be noted that at this stage, it is advisable for the knowledge engineer to use the capabilities of AI tools to deepen their own knowledge of the goal to be decomposed, but in no case should they rely entirely on the results of the decomposition obtained by AI tools. It is important that when modeling a subject domain, during decomposition, only the most important factors that have the greatest impact on the achievement of the goal being decomposed are taken into account, and the importance of the impact is not constant, but can change and depends on the context in which the decomposition is considered. Modern linguistic models of AI often include some substitution of concepts, namely, the frequency of occurrence of a certain concept in texts is compared to the importance of this concept. In general, this is not the case, and therefore, during decomposition, it is appropriate for a knowledge engineer to get a list of sub-goals that affect a certain goal just to make sure that the goal is decomposed into sub-goals. Lists of concepts generated by AI tools that can form the basis of the decomposition or complement it are useful, but the final list of the most important factors should be formed on the basis of collective experience and knowledge.

It should be noted that it is the completeness of the description of the subject domain model that largely ensures the adequacy of the model. AI tools, in this case, make it possible to ensure the completeness of the description of the modeled system.

The knowledge engineer manages the decomposition process, forming an expert group of specialists who are knowledgeable about the object of decomposition. The following main stages of group decomposition are worth highlighting:

– The process of generating a sub-goal list by an expert involves each participating expert creating a list of goals that they believe directly influence the goal to be decomposed. This list comprises goals (sub-goals) that exert a notable impact on the primary goal, as defined earlier. When composing this list, the expert first evaluates the existing hierarchy of goals to determine their relevance for inclusion in the list. By including a goal, the expert suggests that it significantly contributes to the decomposition of the main goal, thereby proposing the establishment of a corresponding link in the goal hierarchy. Subsequently, the expert formulates and adds any other goals they deem to have a substantial impact on the goal under decomposition. This process concludes upon the discretion of the knowledge engineer once a sufficient number of experts have created their sub-goal lists.

– Combining wording identical in content into groups. This stage is necessary because different experts usually formulate the same concept in different ways, and in the course of such an examination, identical formulations with different textual forms are accumulated. This task is related to the detection of text synonymy and can be solved with the use of neural network technologies. In addition, a linguistic generative AI model can solve this task quite successfully. This stage is still performed in a semi-automatic mode using AI tools under the control of a knowledge engineer. The result of grouping identical wording depends to a large extent on how accurately the knowledge engineer specifies the number of groups of identical wording in the AI tool's query. Without specifying the number of groups, experience has shown that the quality of combining wording into groups with identical content may be unsatisfactory. The result of this step is a list of goal statements that are identical in content and grouped together (a group may include a single, unique statement).

– Group consensus on the decomposition. Experts involved in the decomposition are asked to choose the best wording among the wording presented in each group, which is identical in content. At the initiative of the knowledge engineer, one of the implemented group selection methods can be used. This can be, for example, voting based on the competence of experts. It is not advisable to use AI tools to select the best wording from the available ones with the same content in a certain group, since writing a query to select the best wording according to a certain criterion is not a trivial task. The list of wording among which the expert has to choose the best in each group has also been supplemented with the option "None". When choosing "None", the expert is inclined not to include a sub-goal with such wording in the hierarchy and/or not to establish the impact of an existing goal on the one being decomposed due to its insignificance. In other words, the expert believes that the impact of a certain sub-goal can be neglected. The experts' work on the choice of wording is finalized at the initiative of the knowledge engineer if their assessments are sufficiently consistent1 and they reach a consensus. After that, the experts' preferences are aggregated. The result of this stage is a goal decomposition, which is a list of sub-goals with existing influences on the goal.

The decomposition conducted by the expert group is presented graphically as a subgraph within the overall goal hierarchy graph.

2.3. Model structure formation

The model structure of subject domain is built by sequential decompositions of the main goal and sub-goals until no more decomposition is possible. Goals not decomposed become projects.

The goal hierarchy graph is presented to determine model parameters. The knowledge engineer sets some known parameters. Other parameters like influence time lags are determined through group review by experts.

At the end of the process of building the model structure, the entire hierarchy of goals is presented to the knowledge engineer in the form of a graph (see Fig. 2).

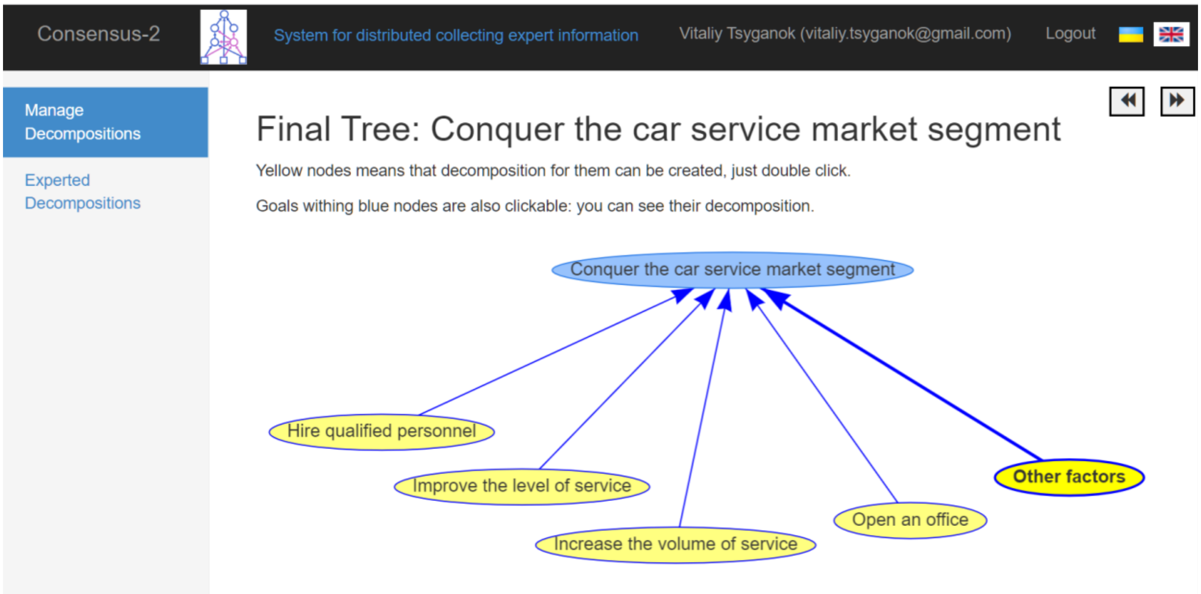

Figure 2: The screen form of Consensus-2 software system with an example of the goal hierarchy

2.4. Defining model parameters

Once the model structure is established, the next step involves defining its parameters. Among these parameters, some are decided by the knowledge engineer, as their values are clear and indisputable. The remaining parameters are determined by a team of experts, initiated by the knowledge engineer.

The knowledge engineer is responsible for assessing whether the influence on each goal is quantitative or qualitative, linear or subject to threshold effects, as well as determining the compatibility of sub-goals and whether the influence is positive or negative. As for the other parameters, the time delays associated with these influences are determined through a collaborative review process involving the same experts who previously conducted the group decomposition of the relevant goals.

As part of the technology for creating strategic plans in group examinations, methods for obtaining and processing expert opinions using pairwise comparisons, verbal scales of varying detail, feedback from the expert, etc. are widely used to determine the known unknown parameters of the model. All of these tools are designed to increase the reliability of expert opinions and, thus, to improve the adequacy of the models used for strategic planning. The technology of group construction of the subject domain model is implemented in the web- based software system for conducting examinations by distributed groups of experts "Consensus- 2" [20]. Now that the subject domain model has been built on its basis, it is possible to solve a number of decision support, forecasting and analytical tasks.

Such a wide range of tasks, including the construction of strategic plans, can be solved by the decision support system "Solon- 3" [9].

2.5. The Method of Goal Dynamic Evaluation of Alternatives

The Method of Goal Dynamic Evaluation of Alternatives (MGDEA) was originally developed to evaluate decision alternatives using a goal-oriented hierarchical model, as outlined in [21]. Subsequently, the method was enhanced to enable the evaluation of alternatives such as projects, measures, and decision variants when constructing strategic plans, as described in [22]. MGDEA is primarily designed for assessing decision alternatives within a defined time frame in Decision Support Systems (DSSs). This evaluation is conducted based on an expert-constructed subject domain model. MGDEA is particularly well-suited for deploying in moderately structured subject domains, which effectively capture the specific characteristics of a given subject domain.

In contrast to other existing methodologies, such as multi-criteria methods [22,23], which employ optimization techniques [24], MGDEA allows for the evaluation of diverse projects that defy a unified set of criteria. Additionally, MGDEA does not necessitate experts to comprehend the entire problem comprehensively; instead, it allows decision-makers to engage expert groups. During the model construction, each expert possesses complete knowledge of a specific aspect of the subject domain. Due to these attributes, MGDEA can be regarded as a foundational approach in the realm of expert decision support. The method facilitates the computation of ratings or estimates for decision variants, actions, measures, or projects based on a knowledge base.

At the core of MGDEA lies a generalized procedure for determining the degree of goal achievement within a hierarchy at a given moment in time (t). As stipulated in [21], assessing the achievement of a particular goal involves analyzing the accomplishment levels of its immediate sub-goals (for each alternative subset of compatible sub-goals). Thus, the degree of achievement, denoted as, $d_i(t)$, for the i-th goal at time t is defined by the following expression:

$$d_i(t) = \begin{cases} 0, & \text{if} \quad D_i(t) < T_i \\ T_i, & \text{if} \quad D_i(t) = T_i \\ f\big(D_i(t)\big), & \text{if} \quad T_i < D_i(t) < 1 - \sum_j \left|w_{ij}^{(k-)}\right|, \\ 1, & \text{if} \quad 1 - \sum_j \left|w_{ij}^{(k-)}\right| \le D_i(t) \le 1 \end{cases} \tag{2}$$

where $D_i(t) = \sup_k \sum_j w_{ij}^{(k)} d_j(t)$; T_i is the threshold for achieving the *i*-th goal; $f\big(D_i(t)\big)$ is a function of achievement degree of the *i*-th goal at moment *t*; $w_{ij}^{(k-)}$ is the PIF of the *j*-th goal in the *k*-th group of compatible goals, which has a negative influence on the *i*-th goal.

MGDEA serves to assess the rating or relative estimation of a decision option corresponding to the *l*-th goal within the hierarchy at a specific time *t*. Essentially, this involves determining the disparity between the achievement levels of the main goal, denoted as $d_0(t)$ under condition of full achievement of all goals that correspond to decision variants intended for comparison $d_i(t) = 1,\ i \in L,\ L = \{m..n\}$ and under the condition $d_i(t) = 1,\ i \in L\backslash\{l\},\ d_l(t) = 0$. In other words, the rating of a particular alternative (decision option) represents the difference in the main goal's achievement level with and without the influence of that specific alternative.

To expand MGDEA's functionality, it has been suggested to enhance the method by enabling the calculation of alternative ratings not only concerning their contribution to the attainment of the main goal but also regarding any chosen goal. This feature allows for the comparison of alternative decision variants' impacts on intermediate goals within the comprehensive domain model.

This process of calculating $d_i(t)$ which represents the achievement degree of the selected *i*-th goal at time *t*, unfolds as follows. In the goal hierarchy graph, one identifies goals that do not affect other goals within the hierarchy. This selection typically comprises projects and serves as the starting point for computing goal achievement degrees. Initial achievement values for these goals are set to 1 or 0, although intermediate values within the [0,1] range are also admissible to accommodate the partial execution of the project at a specific time – *t*. It is advisable to incorporate expert assessments of project implementation progress when evaluating intermediate states of the system model, especially when resources (funding) are partially allocated to projects.

It is important to note that, in general, the graph may lack vertices without incoming arcs. While this is improbable based on the model-building logic and was not addressed in [21], it is advisable to introduce a "Other factors" goal within the hierarchy, influencing all goals within the hierarchy whose achievement is inadequately determined by the available goals. By adhering to this recommendation, the initial set of goals for determining goal achievement degrees will never be empty, as it will include the "Other factors" goal, which has no dependencies. Subsequently, a set of goals is formed based on the direct influence of the goals from the previously established set. This set includes all goals that are directly influenced by the goals from the initial set, denoted by incoming arcs originating from the vertices in the initial set. Goals from the initial set may also be included in this group.

For every goal within the defined set, we compute its attainment level at time t. This computation entails a hierarchical traversal through the graph, starting from lower-level goals and progressing upwards to the main goal. In cases where the graph includes feedback loops (connections from higher-level vertices to lower-level ones), the iterative process of determining the goal's attainment level concludes when the absolute difference between the calculated achievement values for the selected goal in consecutive iterations (*x*) and (*x*+1) does not exceed the specified accuracy *ε*:

$$\left|d_i(t)^{(x)} - d_i(t)^{(x+1)}\right| \leq \varepsilon. \tag{3}$$

The accuracy of the calculations, represented by ε, as well as the planning period, are input parameters. Considering the nature of the tasks addressed by this DSS, time intervals are measured in days, making one day the minimum unit of measurement. The default planning period, defined in the form, designates the time interval for calculating the relative ratings of chosen projects. This value in days is computed based on the goal hierarchy graph while moving from lower-level vertices to upper levels, akin to the process for determining goal achievement degrees. It signifies the maximum duration for which changes in the relative project rating calculations no longer occur and is determined by summing the delays in influence propagation beyond this point.

MGDEA enables the computation of relative project ratings at any given time from the initiation of their implementation. However, these ratings only change at specific time points along the temporal axis. Therefore, it is suggested to identify these reference points in advance and not before each iteration. In contrast to the iterative approach proposed in [21] for determining the next moment of time $t^{(i+1)}$ for calculating goal achievement degrees:

$$t^{(i+1)} = \inf_{k,\ \tau_k \geq t^{(i)}} (\tau_k), k \in \{1,2, \dots, n-1\}, \tag{4}$$

where τ_k is the value of the delays of the influences of the goals in the hierarchy, which contains n goals, it is currently proposed to move from lower-level goals to upper level while calculating and adding to the list of all possible values of the delays of influences of the goals in the hierarchy. This progress unfolds in parallel with the evaluation of the main hierarchy goal's achievement level. In instances where hierarchical feedback loops exist, it continues until condition (3) is satisfied. Essentially, the creation of the list of goal influence delays occurs simultaneously with the calculation of the recommended planning interval, which spans the maximum of the calculated impact delays in the list.

2.6. Resource allocation

In the domain of strategic planning technology, it is essential, during its final phase, to outline a list of activities (projects) along with their financial support, with the aim of maximizing the achievement of the strategic goal within a given time frame while adhering to specified funding limitations. As previously demonstrated, MGDEA allows for the calculation of the extent to which the main (strategic) goal is reached at a specific time point based on the subject domain model and project implementation degrees. Therefore, the statement of the funding allocation problem is as follows:

What is given:

1. A set of projects $P = \{P_i\}, i = (\overline{1,n})$.
2. For each project P_i, the dependence function $S_i = f(R_i)$ of the degree of its implementation S_i on the amount of funding R_i is set (the function is shown in Fig. 1).
3. Algorithm for calculating the main goal's achievement degree based on vector of project implementation degrees $\overline{S}$: $E(\overline{S})$.

We should find:

vector $\overline{R_x}$, in which $E(\overline{S_x}) \to max$, under constraint $\sum_{i=1}^{n} R_i \leq R_T$, where R_T is the total program funding volume.

Optimal resource allocation issues are typically addressed through a variety of optimization methods, such as mathematical programming. However, this problem exhibits specific characteristics:

– Dealing with a model of a weakly structured system, wherein the goal function cannot be analytically represented; only its algorithmic representation exists, like an algorithm for calculating the main goal achievement degree.
– Utilizing subjective expert estimates as input data for model construction, which may lack strict accuracy. Therefore, the precision of resource allocation determination need not be excessively high; a reasonably good, rather than necessarily optimal, solution suffices.

To tackle this practical challenge, a transition from continuous-scale search to discrete-space search is recommended. This involves specifying the accuracy of resource allocation as part of input data, represented by a unit of financial resource discretization.

Considering the aforementioned features, evolutionary methods, essentially involving targeted random search variants, are suitable for problem resolution. Among these, a modified genetic algorithm (GA), initially proposed by Holland [25], is suggested. GAs are algorithms that find satisfactory solutions to analytically intractable or complex problems by iteratively selecting and combining parameters, similar to biological evolution. GAs operate with a population of individuals, each encoding a potential solution. Unlike many other optimization algorithms, GAs work with multiple solution variants simultaneously, improving adaptability through selection and reproduction.

The universality of GAs lies in the fact that only specific problem-dependent parameters, such as the fitness function and solution encoding, vary. Other steps are executed consistently for all tasks, making them highly adaptable to different problems. The fitness function for this problem is the main goal achievement degree function under predefined levels of project implementation. This function is already available and in use within the Solon 3 DSS in various modes, obviating the need for re-implementation.

Regarding solution encoding, the resource intended for allocation is initially discretized into elementary units, with the user defining the unit size. This practice aligns with the need for practical resource allocation precision, avoiding excessive rounding. A solution vector represents the resource allocation, where each element indicates the number of elementary units assigned to a specific project.

To calculate individual fitness values, the degree of implementation for each project under the specified funding level must be determined in advance. This involves using pre-entered data related to the resource requirements for full project implementation, minimum reasonable resource levels, and expected completion percentages under minimal funding (see Fig. 1).

The choice of GA operators and parameters poses some complexity in method implementation and usage. Selected operators include tournament selection, one-point crossover, mutation, and elitism.

Default input parameters include a population size of 50 individuals, a mutation probability of 0.05, and a GA termination condition of 50 generations with the same result. These parameters can be adjusted to suit the specific model effectively.

In summary, this study addressed the problem of rational allocation of limited resources among projects. Results, obtained with parameter fine-tuning, were consistent with those from the exhaustive brute-force method, verified on examples with a limited number of projects and elementary resource units.

3. Conclusions

The paper proposes to automate the process of group building of models of poorly structured subject domains based on the use of existing and developed knowledge-based methods for creating strategies.

It has been shown that the use of linguistic generative models of artificial intelligence at certain stages of modeling helps to increase the adequacy of the created models of subject domains and, thereby, improve the quality of recommendations generated by decision support systems. However, the use of artificial intelligence tools does not avoid the involvement of teams of experts in modeling subject domains. The theoretical foundations and methods for reliable acquisition and application of collective knowledge in various fields have been developed. This theoretical basis allowed us to come to the practical application of the created tools for strategic business planning in various fields.

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