# Information Collection and Processing Technology for Scenario Development in Uncertain Environments*

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**Abstract**

In this paper we outline an updated and improved original approach to scenario development in uncertain environments. Research objective is to devise a technology enabling analysts and decision-makers to develop possible scenarios in uncertain environments based on all available data. The method we suggest is based on hierarchic decomposition of a specified main goal or problem. Our key finding is the step-by-step procedure, allowing users to implement the original technology, i.e., collect information, process it, develop scenarios, and rate them according to their likelihood. Technology implementation is further facilitated by original decision support software prototypes.

**Keywords**

decision-making support system, scenario, uncertain environment, hierarchic problem decomposition, expert estimation

## 1. Introduction

### 1.1 Scenario as a decision option

Scenario analysis represents one of the key sub-domains of decision-making support. Decision as a general concept can be defined as a choice of one or several options from a set of available alternatives. Decision alternatives might include

- specific objects (such as a car or a piece of property to buy, a university to enter),
- projects or sets of projects to support and fund (competition-winning projects; first five/ten projects in the overall rating; project rating leaders, among which a limited funding volume should be distributed),
- strategies (i.e. patterns of allocation of limited resources among projects), and
- scenarios to anticipate and prepare for.

In the context of the present research a scenario is some certain outcome or course of events, according to which decision-makers should plan their future actions.

### 1.2 Features of decision problems in uncertain environments

Uncertain environments (sometimes called weakly structured or weakly formalized subject domains) are determined by a large number of interconnected factors of both qualitative and quantitative

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nature. These factors do not do not have established benchmarks or measurement units. Information on such environments, as well as objects, and criteria of their evaluation is, usually, incomplete or dispersed across various sources. A huge proportion of this information is unavailable for public access and can be retrieved only from narrow-profile specialists, i.e. experts [1].

If some decision or situation directly depends on "tangible" quantitative criteria, such as income or economic effect, then it can be formally described based on available data, expressed in specific numeric values. If a decision is a repeated one (such as annual budget planning or acceptance of students into an educational institution), then the technology for decision-making in such cases can be based on the experience of previous similar decisions, potentially, with minor corrections.

At the same time, decisions to be made in uncertain environments are unique, and call for consideration of large numbers of factors, that are hard to quantify.

The listed features complicate the process of decision-making in uncertain environments at different managerial levels. Examples of uncertain environments range from education sphere and community-level planning to national foreign policy, security domain, and even space industry.

Moreover, at each new managerial level the responsibility of the decision-maker for decision's outcome, associated risks, and the "price of a wrong decision" are increasing. Therefore, in order to make competent, informed, and well-substantiated decisions, all available information on particular uncertain environment should be taken into account.

As a result of scarcity of information, mentioned above, in uncertain environments expert knowledge often becomes the main source, aggregator, and "filter" of this information. Additional means, which can be used by experts, analysts, and decision-makers, include open sources [2, 3] (for instance, Internet media and social networks [4]) content-monitoring data [5], and artificial intelligence (AI) tools [6]. At the same time, lack of information on respective objects and factors complicates the usage of AI as a credible information source or aggregator.

Finally, in order to ensure credibility of decisions made based on available information, in addition to the information itself (including both quantitative and qualitative data, expert data, and information from open sources), efficient formal procedures are required to process it.

These considerations firmly place the tasks of scenario development and analysis in uncertain environments within the decision-making support paradigm.

### 1.3 Problem description

The problem addressed in our paper is the development of a technology allowing decision-makers and analysts to

- formulate possible scenarios,
- rate them according to likelihood,
- determine the most probable scenarios among them, and
- work out respective recommendations for planning of future actions.

Our current research is mainly targeted at such complex domains as national security environment and foreign policy. The problems analysts and decision-makers need to address in these particular uncertain environments are also quite complex.

That is why the approach we suggest for scenario analysis in these domains is based on hierarchic problem decomposition, expert methods, and available scenario generation techniques [7]. Presently, the technology is implemented within the special decision support software prototypes and used to generate scenarios across various threats and players.

## 2. Overview of existing approaches

### 2.1. Available methods and techniques

Extensive research on development of decision-making support techniques for uncertain environments was being conducted during the last few decades. It makes sense to provide a brief

quick overview of several approaches devised within this period.

Due to the features of uncertain environments, outlined in the introduction, it is impossible to come up with any analytic expression of a value function, according to which decision options could be compared. Thus, it is problematic to use approaches from optimization and multi-attribute utility theory (MAUT) [8] as basis of scenario development technology.

Almost all approaches, devised for decision-making support, were based on preliminary hierarchic decomposition of some main criterion, which defined the quality of decision options. Most of these approaches were implemented in the form of respective software products and applications, as demonstrated in [9].

Chronologically, the first method, developed for choice, ranking, and sorting of decision options was ELECTRE [10]. The key result of the method's work is the ranking of a set of alternatives, estimated according to multiple criteria of different weights. Alternative $A_i$ dominates over $A_j$ in the aggregate ranking if a set of criteria, according to which $A_i > A_j$, is representative enough. This ordering of alternatives is defined by special consistency and inconsistency indices, introduced by the method's authors. ELECTRE method is targeted at one-level hierarchies of criteria (i.e. graphs including some main criterion and its immediate descendants), while its outcomes heavily depend on threshold values of consistency and inconsistency indices, set by the decision-maker.

The analytic hierarchy method (AHP) in its initial form [11] was designed for construction of alternative ratings according to a set of evaluation criteria. That is, just like ELECTRE method, it was intended for one-level hierarchies. Its later modification, the analytic network process (ANP) [12], implies that criteria might form both hierarchic and network structures. The key features of AHP/ANP family of methods are:

- usage of a special multiplicative preference scale of 5 or 9 grades with respective verbal equivalents (from "weak" preference (grade 2) to "very-very strong preference" (grade 9)) for pair-wise comparisons of criteria and alternatives;
- usage of eigenvector method for calculation of criterion and alternative weights (priorities) based on pair-wise comparison matrices (PCM);
- usage of a special consistency ratio and empirically calculated threshold values of this indicator for defining a PCM's credibility.

AHP is one of the most widely used decision-making support method in the world. Numerous examples of its application for solving of decision problems across various uncertain environments can be found in the proceedings of the international symposium for the AHP (ISAHP) [13].

The next method we would like to mention is TOPSIS [14]. It is intended for ranking or rating of alternatives according to a set of criteria (again, forming a one-level hierarchy). Once all alternatives have been estimated according to all criteria, ideal worst and best alternatives are constructed. These alternatives combine the worst and best mono-criterion estimate values, respectively. Then, the rating of actual alternatives is constructed based on their distance from the two ideal ones.

PROMETHEE\GAIA method [15] allows users to build either partial or complete ranking of alternatives according to a set of criteria, which form a single-level hierarchy. Somewhat similarly to the aforementioned ELECTRE method, alternatives are ranked based on analysis of ratio between positive and negative preference flows. These flows, in their turn, reflect the ratios between aggregate multi-criteria estimates of alternatives. Problems, to which the method is applied, include selection of alternatives, prioritization, resource allocation, as well as decision-making in conflict situations where parties pursue opposite goals.

DEMATEL [16] technique is also used in multi-criteria decision support. It is intended to solve a specific problem within the multi-criteria choice – definition and quantitative evaluation of connections (influences) between criteria from a given set.

The method of complex target-oriented dynamic evaluation of alternatives (MCTDEA) [17] was developed simultaneously with other methods listed in this sub-section. The very name of the

method implies that its main task is to evaluate alternatives according to a hierarchy of criteria, subjected to a certain main goal (MG). This goal is, usually, formulated by the decision-maker (or a team of experts) as some global criterion. The key features of the MCTDEA are as follows:

- Evaluation of alternatives and projects is conducted within certain time frames (i.e., project implementation duration and delays are taken into consideration; these intervals are defined based on available information or through expert estimation);
- Criteria hierarchy, usually, features more than one level; it can include feedback edges and cycles. On the one hand, this feature additionally complicates the look of the value function, while on the other – it allows users to tackle more complex problems;
- A set of original methods has been developed in order to improve the credibility of the final outcomes (as we've explained in the introduction, specific form of the method's results depends on specific formulation of the problem).

## 2.2. Similarities and differences

Our brief overview of the key available methods and techniques shows that their common features are:

1. Usage of expert data as a source of knowledge on a given subject domain: this feature results from uncertainty and lack of available deterministic information, specific to environments we are dealing with;
2. Usage of analytic decomposition principles, graph theory, and hierarchic approach: the knowledge base (KB) on a given subject domain is a weighted graph, consisting of interconnected criteria, factors, or sub-goals, characteristic to the domain in the context of some specific MG.

Features, pertinent to specific technologies, allow us to build their simplified classification, presented in Table 1.

Strategic planning technologies, based on MCTDEA, allow for a group of experts to work remotely using the interface of the respective DSS [18]. Some software products and solutions, using other methods (such as AHP/ANP [19, 20] and TOPSIS [21]) also provide such an opportunity. Therefore, these are rather hardware-oriented than algorithmic solutions, so it does not make sense to use them as a separate criterion for our classification of decision support technologies.

**Table 1**
Classification of Decision Support Technologies for Uncertain Environments

| Technologies and methods | Information sources | | | Complexity of the KB (hierarchic decomposition) | | | | Problems solved | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Experts | Open sources | Survey data | 1 level | > 1 levels | Network | Network with cycles | Ranking, rating | Resource allocation, strategic planning | Information operation counteraction, conflict resolution | Prediction (including scenario development) |
| ELECTRE | + | - | - | + | - | - | - | + | - | - | - |
| AHP | + | - | - | + | + | - | - | + | + | - | - |
| ANP | + | - | - | + | + | + | - | + | + | + | - |
| TOPSIS | + | + | - | + | - | - | - | + | - | - | - |
| PROMETHEE \GAIA | + | - | - | + | - | - | - | + | - | - | - |
| DEMATEL | + | - | - | + | + | + | + | + | - | - | - |
| MCTDEA-based technologies | + | + | + | + | + | + | + | + | + | + | + |

It should be noted that not just MCTDEA-based technologies can be used for more diverse and complex problems. For instance, combinations of AHP/ANP with other algorithmic solutions are used for resource allocation in Decision Lens software [9, 19], while TOPSIS [21], ANP or DEMATEL [22] can use input information from any sources. However, it is only in combination with additional algorithmic solutions, that approaches, featured in Table 1, can be utilized for resource allocation or scenario development. Moreover, MCTDEA has been initially developed for complex target-oriented

program formation [17], which makes this approach more universal and creates a foundation for more extensive usage of respective technologies.

Having conducted this brief analysis of available approaches, we suggest using the MCTDEA as the basis of our scenario development technique.

## 3. Scenario development technology

### 3.1. Technology outline

The original scenario development technology combines usage of expert knowledge, enhanced by additional tools, such as large language models (LLM) [23], content monitoring [3], and AI tools, with the principles of hierarchic decomposition of some MG, specific to a given uncertain environment.

The outline or flow-chart of the technology is presented on Figure 1.

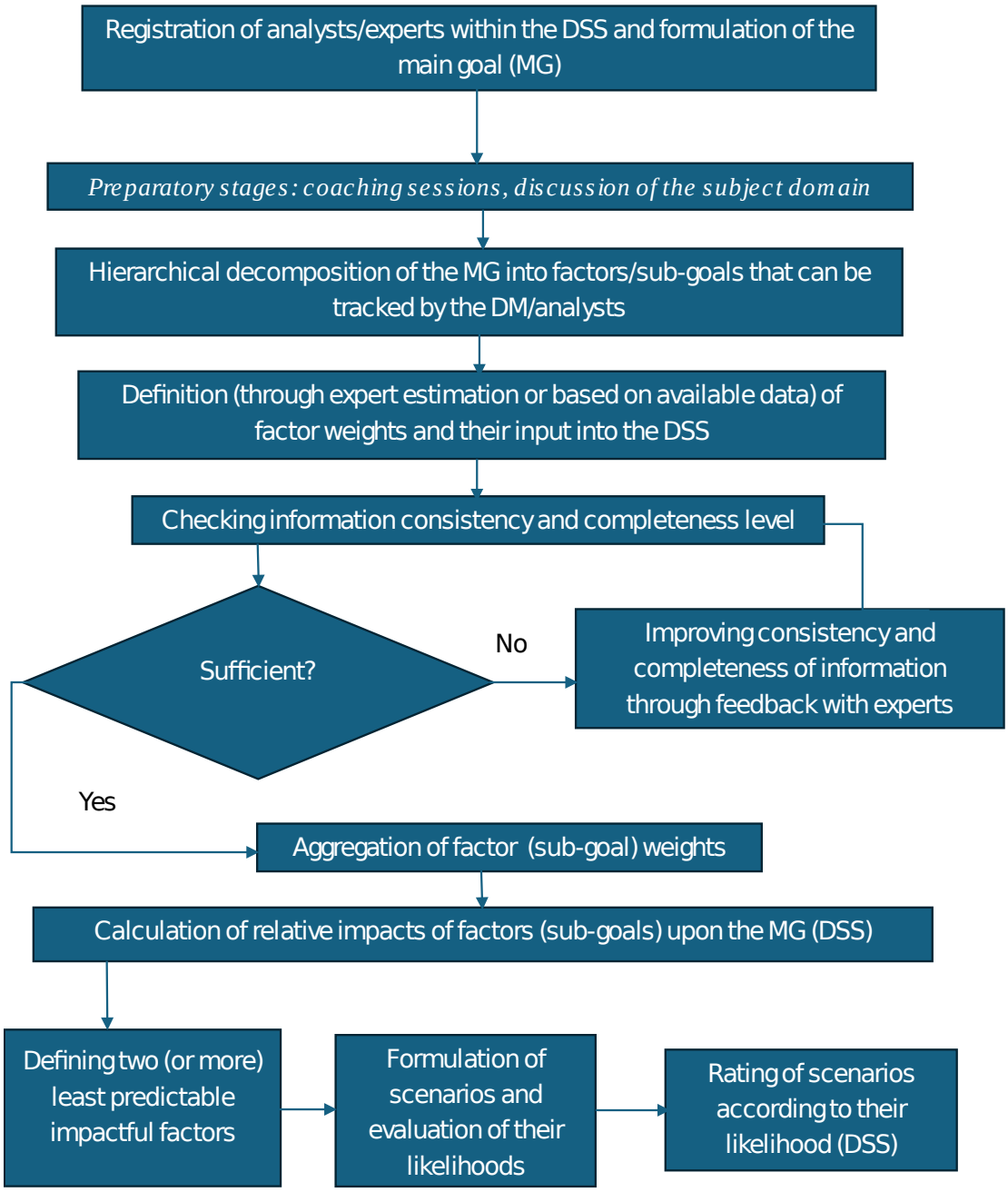



**Figure 1:** Flow Chart of the Scenario Development Technology.

All the listed steps of the technology are automated using original decision support software [18]. In the next subsections we will address each step of the scenario development process in greater detail.

### 3.2. Registration of experts and formulation of MG or problem

In contrast to previous technologies developed by the authors, within scenario development technology, the MG or problem is formulated by a whole team of competent experts or analysts, and not just by a single decision-maker, expert session organizer, or stakeholder.

Initially, the expert session organizer creates a topical expert session, specific to the subject domain (such as security environment) within the decision support system (DSS) and invites experts to register within the system. Experts register within the DSS and join the expert session in remote mode.

All registered expert session participants (usually, working in remote mode) are suggesting their formulations. At this step the inbuilt generative AI tool can be used by experts to provide detailed explanations for each of them. When the process of MG formulation input is complete, experts vote for the best formulation. Based on results of this voting, the formulations are rated and the best formulation is selected by the DSS and confirmed by the expert session organizer.

### 3.3. Hierarchic decomposition of the MG into sub-goals, factors, or criteria

At this step the MG or problem is decomposed by the experts into sub-coals or sub-criteria. Each expert suggests formulations of sub-goals and their detailed explanations. Again, experts select the best formulations of sub-goals of the MG by voting for them using the DSS interface.

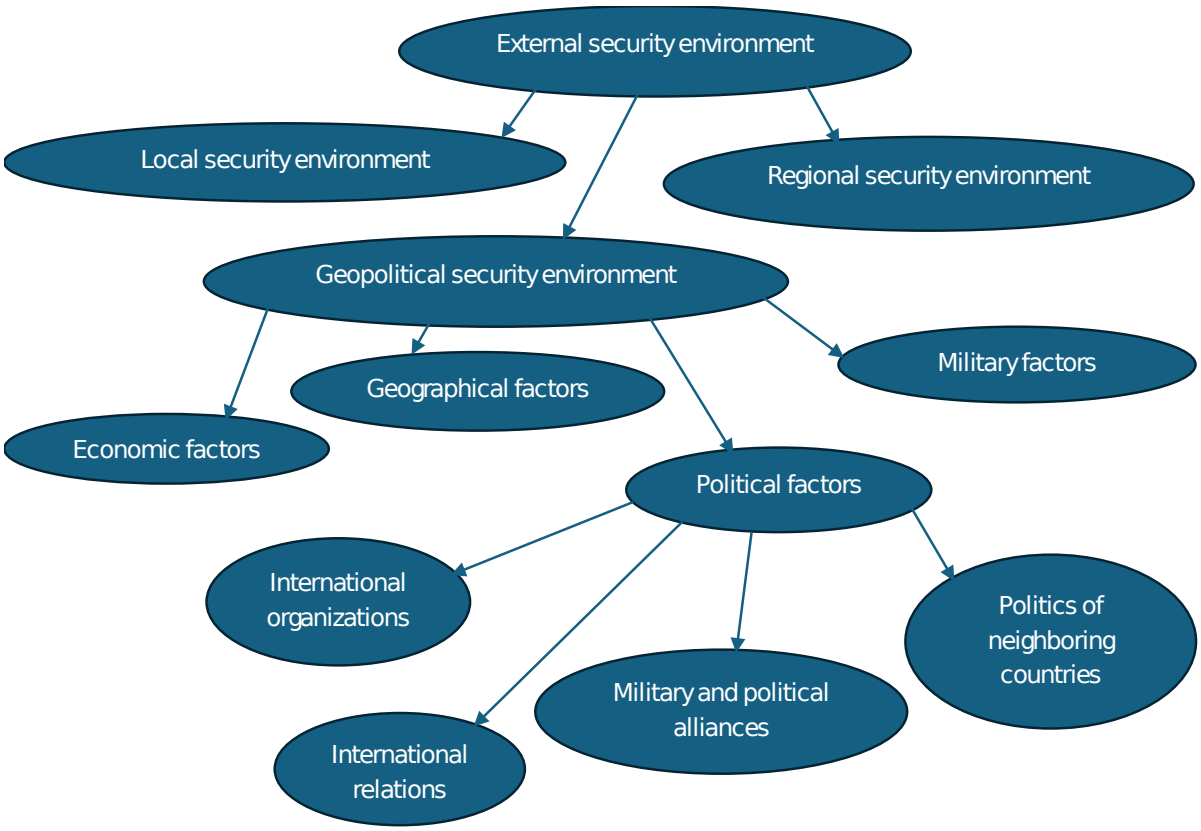



**Figure 2:** Subject Domain Decomposition Example.

The top-level sub-goals of the MG, usually, represent the spheres or aspects of activity within the given subject domain. For instance, according to [7], security might involve political, economic,

strategic, and technological aspects. An illustrative example of subject domain decomposition is provided on Figure 2.

Each sub-goal is further decomposed into more detailed sub-goals down to the "atomic" level which can be directly traced by analysts. Due to psycho-physiological constraints of human mind [21, 22], the number of sub-goals of each goal within the hierarchy should not exceed $7 \pm 2$.

During formulation of the MG and its sub-goals, experts have the opportunity to use AI tools, content-monitoring tools [3], and LLMs [23].

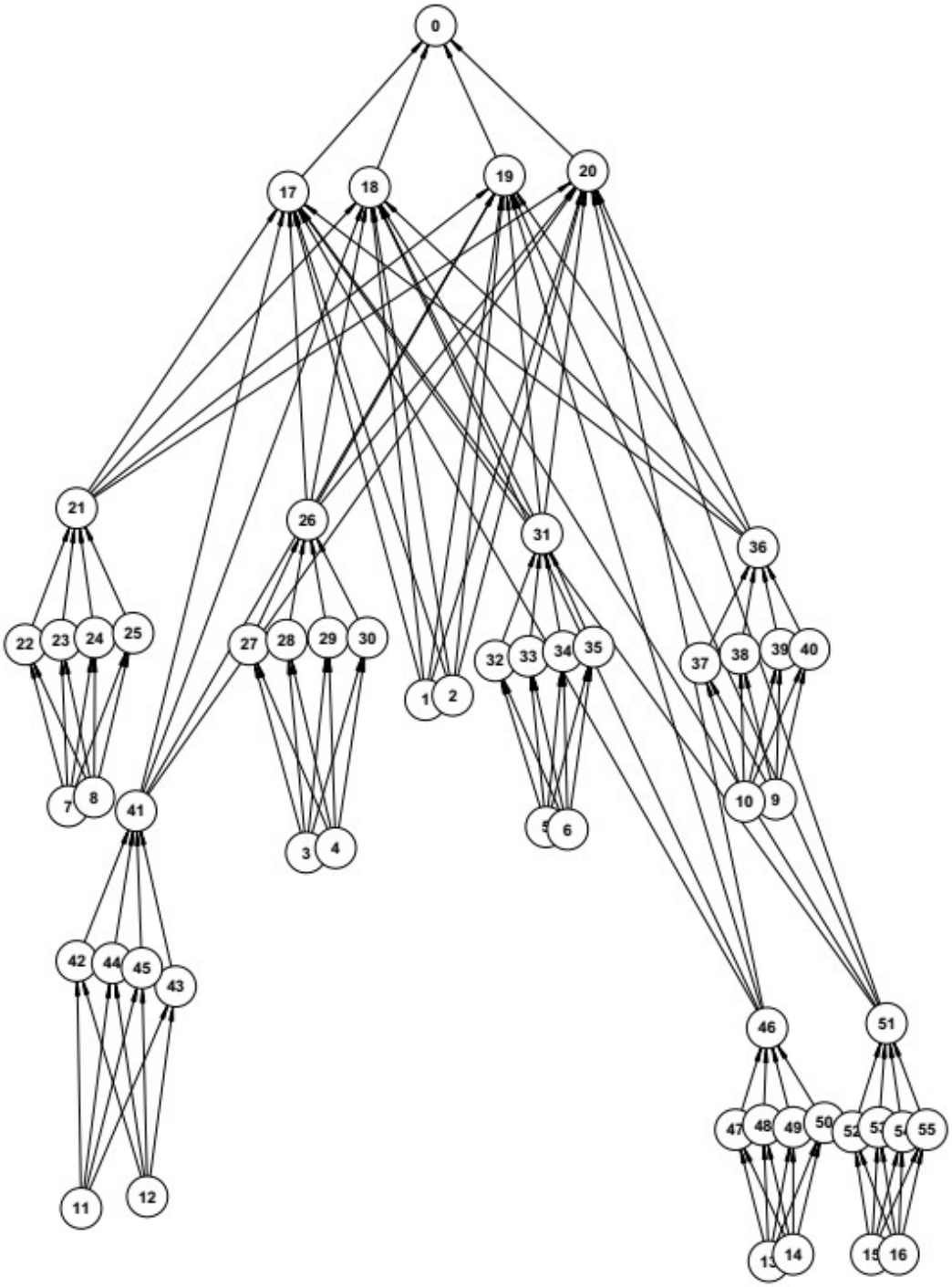



**Figure 3:** Example of a Hierarchy of Factors.

The result of this step is a hierarchy of sub-goals or factors, which significantly influence the MG, and, possibly, each other. That is, in the general case, the resulting hierarchy might have a network structure and even include feedback cycles. An example of a complete hierarchy of factors, built by experts using the DSS, is shown on Figure 3.

### 3.4. Definition of sub-goal weights

Weights of sub-goals (i.e., priorities [11]) are estimated by experts using either direct estimation or pair-wise comparison methods. If weights are input by experts through direct estimation, then they are subsequently normalized. If they are input using pair-wise comparison of criteria or sub-goals of a given goal in the hierarchy, then they can be calculated using one of the available methods, such as eigenvector [11, 12], geometric mean [26], logarithmic least squares [27], or combinatorial method [28].

At this step it is important to take consistency and completeness of expert estimates into account:

- Inner consistency of pair-wise comparisons implies that pair-wise comparisons of a group of sub-goals or criteria, should be transitive and not contradict each other. For example, if, according to some expert, criterion A is 2 times more significant than B, and B is 2 times more significant than C, then A should be 4 times more significant than C.
- Mutual consistency of expert estimates implies that estimates provided by different experts should not contradict each other. For example, if in a group of 4 experts 2 experts consider criterion A is 2 times more important than B and 2 remaining experts suggest the opposite, then the group members should be asked to reconsider their judgments.
- Completeness of estimates implies that these estimates should comprise a connected preference structure, allowing the DSS to build an overall rating of alternatives being compared. For example, in order to build a rating of 3 alternatives A, B, and C based on their pair-wise comparisons, at least one expert in the group should provide a comparison of each pair of alternatives: AB, AC, BC.

If expert estimates are not sufficiently consistent and/or complete, then respective feedback procedures should be organized [28 - 30]. That is, experts should be asked to provide missing estimates and reconsider their judgments, if they are not sufficiently consistent.

When providing the estimates, each expert should have an opportunity to choose the scale, which corresponds to his/her level knowledge of the subject domain [31]. For example, the least detailed pair-wise comparison scale is ordinal scale, while the most detailed one is the above-mentioned scale of 9 grades. Expert group members, providing more detailed estimates, are considered more competent during aggregation of estimates provided by the group.

When the estimates of all sub-goals or sub-criteria of a given goal from the hierarchy provided by expert group members are sufficiently consistent and complete, they are aggregated. During aggregation of these estimates, competence level of every expert is taken into consideration.

If some data on previous decomposition of a similar problem is available, then weights can be derived from this data, either directly, or using cardinal (ordinary or logarithmic least squares [27], group data handling [32]) or ordinal ([33]) factorial analysis methods.

Definition of sub-goal weights is performed top-to-bottom. That is, weights are calculated for immediate descendants of every goal in the hierarchy graph, starting from the MG level and ending with the lowest level of the hierarchy, where goals have no descendants.

As a result of this step, all edges of the hierarchy graph are assigned weights.

### 3.5. Calculation of impacts

Impacts of each sub-goal or factor upon the MG are calculated “bottom-to-top” by the DSS. Impact of each factor upon the MG can be calculated if the hierarchy graph has the structure of a tree, network, or network with cycles (as shown in [17]).

The weighted hierarchy of factors, complete with impacts, is the KB, describing the given uncertain environment in both qualitative and quantitative terms, from the standpoint of the MG, formulated on step 1 above.

### 3.6. Rating of factors and formulation of scenarios

All lowest-level factors in the hierarchy are rated according to their impact upon the MG. Out of each group of these "atomic" factors, two most unpredictable and influential ones are selected by the experts (analysts). These are chosen as "drivers" [7] behind the future scenarios.

Based on each pair of drivers, four potential scenarios are constructed. Scenarios are formulated based on the assumption that each driver reaches either the highest or the lowest extreme. In [7] this approach is called "alternative future analysis".

In the context of our target environments, each group of 4 scenarios, usually, reflects some specific threats or potential actions of some global or local political players. Figure 4 illustrates an example of 4 scenarios based on a pair of driving factors.

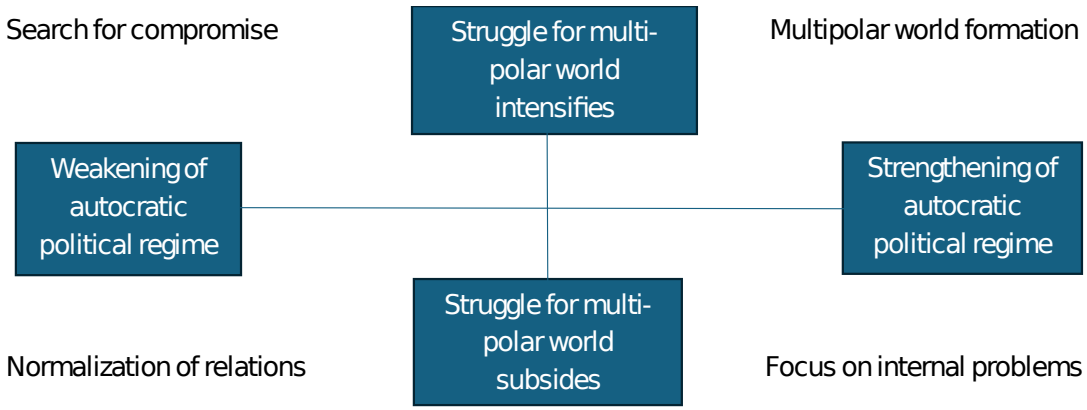



**Figure 4:** Example of 4 Scenarios Based on a Pair of Driving Factors.

### 3.7. Evaluation of scenarios

Experts (analysts) evaluate the likelihood of 4 scenarios within each group and prepare their detailed verbal descriptions. Ratings and descriptions of potential scenarios are the final outcome of the technology. An example of scenario likelihood ratings built by experts within the DSS is shown on Figure 5.

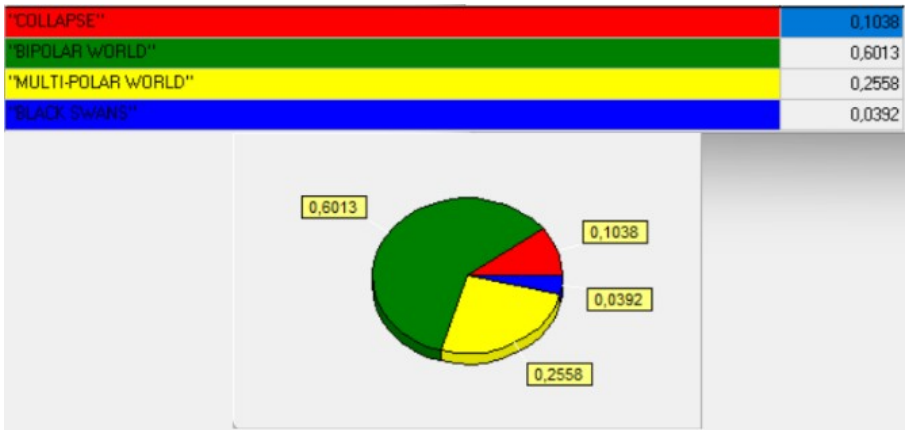



**Figure 5:** Example of a Rating of Scenarios.

Based on the rating of 4 scenarios and their analytical descriptions, further actions should be planned by decision-makers.

### 3.8. Discussion and further research

It should be noted that scenarios can be formulated based on each pair of unpredictable factors. So, if we have $n$ driving factors, then the total number of possible scenarios which can be generated is

$$N = 4 \times C_n^2 \quad (1)$$

Scenarios from this set can be further rated based on the impacts of their driving factors.

Additionally, it might be possible to introduce some intermediate scenarios, lying between the 4 "extreme" ones, if we allow the driving factors to assume some values between extremes. That is, according to the approach, outlined in [7], the drivers can only assume extreme values (say, -1 or 1), while in practice the set of these values can include other values from within this range (such as -0,5; 0; 0,5 and others). However, in this case the number of scenarios based on a pair of driving factors will dramatically increase.

## 4. Conclusions

We have outlined an original technology allowing decision-makers and analysts to collect and process information for scenario analysis in uncertain environments. The original approach combines expert methods, hierarchic decomposition principles, and available scenario analysis techniques. The main limitation of the technology results from extreme complexity of the subject domains, in which it is to be applied. As the number of involved experts and analyzed factors grows, the KB becomes harder to store and modify. Also, with addition of each new pair of driving factors, the number of scenarios to be analyzed increases combinatorically. The technology provides an essential decision support tool for national security and foreign policy specialists.

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## Declaration on Generative AI

The authors have not employed any Generative AI tools.

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