APPROACHES TO THE CONSTRUCTION OF CONTINGENCY RESPONSE SYSTEMS FOR STRUCTURALLY COMPLEX SYSTEMS UNDER UNCERTAINTY

Alexander V. Bochkov, PhD
20 (bld. 8) Staraya Basmannaya Str.,
105066, Moscow, NIIgazeconomika

E-mail: a.bochkov@gmail.com

ABSTRACT

An approach is presented to developing contingency response control for structurally complex systems (e.g., Gazprom gas pipeline network) based on a hierarchy model for calculating the integral index for multi-criteria selection of system evolution scenario. A qualitative methodology (based on the pairwise comparison method and the analytic hierarchy process) is proposed to define the contribution of lower level indicators (impact factors) requiring minimum baseline data on a ranked factor. An initial description is presented of an architecture prototype of expert-analysis system.

Keywords: structurally complex system, uncertainty, impact factor, pairwise comparisons, analytic hierarchy process, expert method.

1. Introduction

The contingency approach has been known since the late '60s of the last century. It is closely linked to the system approach, and attempts to incorporate its various specific approaches, emphasizing an integral connection between managerial functions [1]. This suggests that there must exist clear-cut management performance criteria that take into account relationships between social and economic factors and match the scope of tasks handled at all levels of management; in other words, there must exist a contingency response system (CRS) for managing a facility, process etc.

The main facilities in the gas sector that form a structurally complex system and require a CRS to be developed are gas transmission pipelines (GTPs) of gas transport system (GTS). The total length of Gazprom GTPs is more than 155 thou. km. For a GTS, a CRS will make it possible to boost the effectiveness of decision-making in maintenance and repair activities, of the determination of the safe operation life of gas pipelines, the frequency of preventive maintenance, etc., and will make it possible to improve the practices and methodologies of comprehensive analysis and forecasting of the technical condition of system facilities.

2. Research Approach

This paper discusses a CRS development approach that is based on a hierarchical model for computing the integral index for multi-criteria selection of system (target) evolution scenario.

The first stage covers the formation of a full set of indicators (impact factors) of specific physical nature. This is followed by expert construction of functions for converting the values into a dimensionless scale ranging from zero (when an indicator signals a negative critical value) to unity (when the indicator signals an optimum). Most often, the conversion functions are set in a table; sometimes, with a graph.

Expert construction normally involves quantitative assessment of the impact of technological, environmental and operational factors on the probability of impairment of integrity, stability and survival of a system, using a purpose-built system of weighting factors and estimates of impact factors that characterize the relative contributions to system stability impairment from each group of factors and individual factors within groups. An example of a hierarchical impact-factor system used in the methodology for expert assessment of local intensity of accidents in GTP sections [2-4] is given in Fig. 1.

A description of a specific task of plotting functions for converting the actual values of impact factors to an appropriate weight is provided in a number of papers (cf., e.g., [5] and [6]).

Let us assume, for example, that $F(t) = P(T < t)$ is a function that converts the actual value of a factor to its weight; T is a random value of the factor under discussion. Let us designate on the y-axis n intervals where the target factor is expected to change [12].

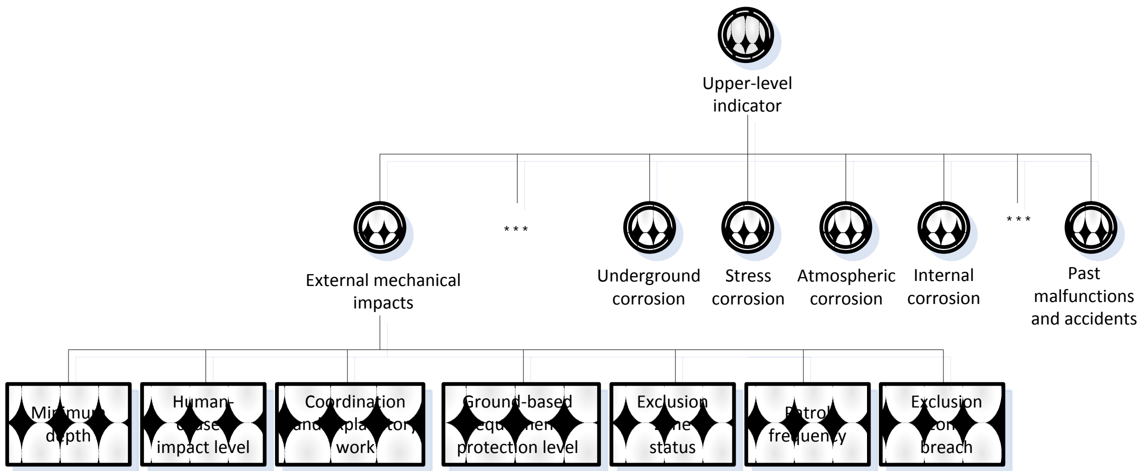


Figure 1. Hierarchical system of groups of factors affecting the local intensity of accidents in GTP sections (with only one group of factors itemized)

An arbitrary value of the factor from a parent population and falling into z th ($z = 1,2,...,n$) interval (its possible value) may have a varying impact on the integral index of upper level. The true value of the factor is linked to its discrete value via the ratio $t = t_0 + \Delta t \cdot z$, where t_0 is the value of the factor with the maximum weight; Δt is the step value of the factor corresponding to the discrete value.

Then the continuous random variable T of the factor value with the probability density function $f_T(t)$ is equal to the discrete random variable Z defined by the bar chart $\tilde{f}_Z(z)$. The reverse is also true, i.e., when defined in any way, the discrete random variable Z can be linked to the continuous random variable T. The aim of expert analysis is to obtain a pattern for converting the actual value of the factor to its weight.

The task of obtaining the bar chart $\tilde{f}_Z(z)$ can be accomplished by the pairwise comparison method based on a qualitative attribute with a quantitative assessment of preferences (analytic hierarchy process). The procedure is detailed in [12].

Because neither the Saaty method (paired comparisons) nor the pairwise comparison method has a clear-cut physical interpretation or affords interpretation of the obtained estimates q as subjective probabilities [6], which makes it difficult to use the nomenclature and mathematical apparatus well developed in the probability theory and mathematical statistics for further processing of the results obtained, it is proposed to supplement the method with a fuzzy model [7].

Let us introduce (by analogy with [12]) the following fuzzy variables:

– “possible value of impact factor” (main[1]) – for estimating the probability of the actual value of an impact factor falling in a specific interval, i.e. the probability density function $f_T(t)$;
– “anticipated average value of an impact factor” – for estimating the average of the actual value of an

[1] There may be also be introduced auxiliary fuzzy variables for solving specific tasks, such as calibration (updating the parameters of the distribution obtained using the first fuzzy variable), assessment of the accuracy of expert analysis, etc.

impact factor t_{cp};

– “the most probable value of an impact factor” – for assessing the distribution mode.

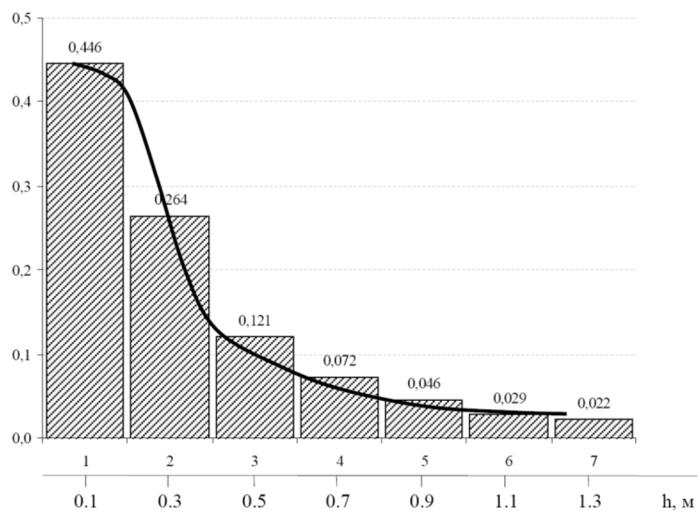
The processing of the pairwise comparison matrix yields the membership function $\mu_Z(z)$ of the impact of the value of the target factor on the value of upper level index for the fuzzy set $\tilde{Z}$, whose meaning is formalized with a fuzzy variable called “impact factor value”. The membership function is formed by membership degrees, which we will assume to be the components of the normalized maximum eigen vector of the pairwise comparison matrix. Let us interpret this function as a bar chart $\tilde{f}(z)$ of the observed random variable of the factor value's impact on the value of upper level index, which includes the accuracy of the expert estimate thereof [12].

Example 1. Suppose an expert is invited to identify the pattern of conversion of the actual value of a factor such as “the minimum depth of underground gas pipeline” from the group of “possible mechanical impacts from third parties” in order to determine the corresponding weight of the factor in 7 intervals of underground gas pipeline depth. It is required to determine the pattern and parameters of the shape of the likely distribution of possible weights of the target factor.

Solution. The pairwise comparison matrix B of the expert's judgements concerning the impact of the factor value on the value of the upper level index is presented in Fig. 2a.

	1	2	3	4	5	6	7
1	1	9	9	9	9	9	9
2	1/8	1	9	9	9	9	9
3	1/9	1/9	1	6	6	5	4
4	1/9	1/9	1/6	1	3	4	5
5	1/9	1/9	1/6	1/3	1	3	3
6	1/9	1/9	1/5	1/4	1/3	1	2
7	1/9	1/9	1/4	1/5	1/3	1/2	1

(a)



(b)

Figure 2. Pairwise comparison matrix of expert judgements concerning the distribution of the target factor's possible weights (a) and bar chart of the distribution of possible weights (b)

The processing of this matrix by the approximation method [9] yields the components of the normalized eigen vector q_z, which are interpreted as the relative weights (probabilities) of the average impact of the factor value on the value of the upper level index, i.e. the bar chart $\tilde{f}(z)$ (see Fig. 2b).

The average actual value of the impact factor affecting the value of the upper level index is computed from the formula (25) to yield $\tilde{t}'_{cp}$ = 0.336 metre. This value can be used as a characteristic of the average weight of the target factor, i.e. the risk is measured in terms of the value of the impact factor weight corresponding to the actual value of the impact factor equal to $\tilde{t}'_{cp}$.

The pattern of an a priori dependence of the distribution of the target factor's possible weights on the pipe depth to match the expert-produced bar chart can be determined by the method of moments using the system of Pearson curves [8].

The values of the coordinates of the dependence obtained in the form of the bar chart $f_T(t)$ (Fig. 2b) in the Pearson diagram are $\beta_1 = 2.244$ and $\beta_2 = 4.536$, and therefore the expert-produced dependence of the "minimum GTP depth" impact factor value weight on its actual value is smoothed by a distribution from the family of J-shaped beta distributions.

Not infrequently, primary indicators initially have an appropriate expert assessment that provides an opinion on the item (process evolution avenue or scenario) proposed to the expert for analysis. For example, an expert may believe that the target YeSG [Unified System of Gas Supply (USGS)] facility has no other nearby facilities capable of causing an accident (such as artillery shell dumps), and his estimate in terms of the indicator under discussion is 1. Another expert may believe with respect to the same situation that the nearby chemical fertilizer factory is a fire and explosion hazard and the flying projectiles (in the event of a major accident at this factory) are capable of damaging, for example, the LNG tanks, and his estimate of the same indicator will be 0.3. In this case it will be necessary to analyze both scenarios. It is unacceptable to keep only the best or worst estimates in the system because this creates a large combinatorial set of options and suboptions for analysis. To limit the number of options to be compared, they must be grouped (aggregated), as already mentioned earlier.

Here there are two extreme alternatives.

A) it is believed that an evolution scenario for a system (target) is "bad" if it already has at least one significant fault – the evaluation logic "AND" is applied: "for a good aggregate estimate of y it is necessary that all estimates of the indicators x_n used for the estimate of y to be computed be good (i.e. close to unity)". In the final analysis we obtain pessimistic (understated) estimates of options (facilities), and the integral index is conventionally computed from the formulas: $y = \prod_{n=1}^{N} x_n$ or $y = \min\{x_n\}$;

B) it is believed that an option can only be "bad" and must be rejected when any and all indicators are "bad" – with logic "OR" applied. The outcome is optimistic (overstated) estimates of options (facilities): $y = 1 - \prod_{n=1}^{N} (1 - x_n)$ or $y = \max\{x_n\}$. Most often, options are assessed based on a compromise solution for computing the value of y, whereby each of the indicators estimated contributes to the convolution in terms of its "weighting factor"[2]: $y = \sum_{n=}^{N} \beta_n \times x_n ; \sum_{n=}^{N} \beta_n = 1$. In practical economic applications of multi-criteria choice ("to build or not to build a facility", "to enter or not to enter into a contract with a given supplier", "to implement or not to implement a given innovation"), experts "tend" to show bias since improving the integral characteristic y in terms of this or that indicator x_n in practice means cash infusions aimed at improving the option (target) in terms of the indicator x_n. In practice, the aforementioned formulas are quite sufficient for the first stages of criterion convolution automation procedures. However, the convolution logic is more complex than a simple combination of assertions "AND" and "OR". The proposed approach uses for the convolution of indicators of an integral estimate for a target a multiplicative convolution for computing the values of y : $(1 + \alpha \times y) = \prod_{n=1}^{N} (1 + \alpha_n \times x_n)$.

It, when the sum $\sum_{n=1}^{N} \alpha_n$ is near zero, yields a linear convolution $y = \sum_{n=1}^{N} \beta_n \times x_n = \sum_{n=1}^{N} \left(\frac{\alpha_n}{\sum_{n=1}^{N} \alpha_n} \right) \times x_n$ At large positive values of α_n, logic "AND" is applied: $y \cong \left(\frac{1}{\alpha} \right) \times \prod_{n=1}^{N} \alpha_n \times \prod_{n=1}^{N} x_n$. For all values of the

[2] The responsibility of estimating the contribution of weighting factors should be given to other experts in an attempt to mitigate the experts' tendency to reinforce their own estimates of targets (options).

parameters α_n close to (-1), we have logic "OR": $y \cong 1-\left(\frac{1}{\alpha}\right)\times\prod_{n=1}^{N}\left(1-\alpha_n \times x_n\right)$. The theory of multi-criteria utility functions states that the normalizing factor α exists and is the only one for any set of values of the parameters α_n, each of which exceeds the value of (-1). Normalization is necessary in order that the indicator y could be, similar to the parameters x_n, aggregated further with the help of experts who are system analysts of an interdisciplinary level. And finally, at the third multilevel stage, analytical experts agree and obtain estimates at all levels of hierarchy (iterative stage).

Usually, the estimates of targets are sorted in ascending order so that they are at variance with the opinions of any expert at any level, apart from the opinion of "one" expert whose bias has ("accidentally") slipped to the very top while significant factors were "fighting each other". A schematic diagram of multi-criteria expert analysis of options for assessing complex systems (facilities, processes) is a network-oriented graph without cycles with one or several "children", i.e. the peaks of upper levels, which is defined by a system of certain rules and has three types of indicators: primary indicators, zero-level estimates, higher-level estimates [3]

$$\underbrace{N_{child} = f\,(N_{parent\ 1}, \ldots, N_{parent\ k})}_{\text{ultimate list}},$$

where f is the convolution.

The primary indicators have numbers (for example, from 1 to 1000) and are described by the following parameters: name, value, unit of measurement, date, author, facility. Zero-level estimates are derived from primary-level indicators by convolution. A zero-level indicator may have only one predecessor; it inherits the primary indicator's parameters such as number, author, facility and date. Zero-level indicators are dimensionless and assume values [0,1]; they are characterised by parameters such as convolution function and conversion parameters. The convolution function for primary indicators is of various types: uniform convolution or expert estimate (assigned by expert manually) (Fig. 3, left).

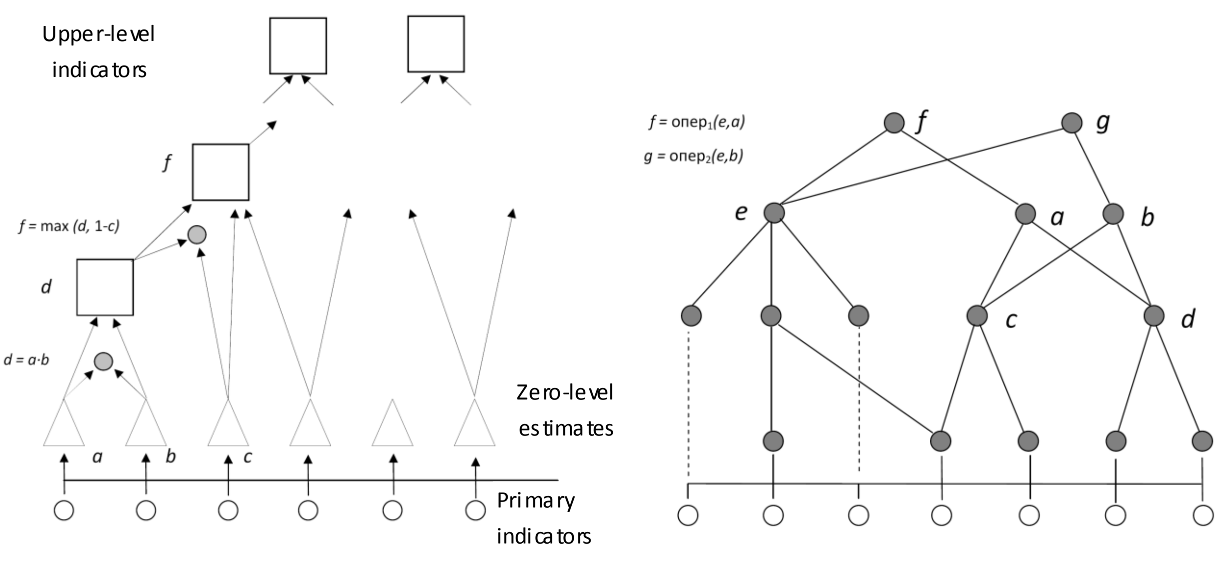


Figure 3. Example of a network and example of convolution

Higher-level estimates are obtained by convolution of any number of zero- or higher-level indicators. Indicators above zero [level] are numbered in the order of their appearance in the system. Estimates above the zero level are characterised by the following parameters: name, author, type of convolution, and input

[3] The system may also provide for the use of the so-called integral index, which combines two (or three) upper level indices.

values. An example of convolution is shown in Fig. 3 (right), where it is assumed that a and b are various versions of convolution c and d; therefore, when taken with e, they yield f and g.

Therefore, an LPR [decision-maker (DM)] receives a graphic and convenient analysis tool, which implements the principle of “traffic lights”. Red colour of upper level indicator (integral index), obtained by convolution of primary indicators – signal from DM that it necessary to analyze the causes of such behaviour of the system (facility, process) and a trigger action for the implementation of control or corrective measures.

Contingency control procedures can be logically developed by building the so-called fuzzy contingency systems. Fuzzy logic can be used in them to formalize fuzzy concepts based on their semantics and will enable effective processing of qualitative information on a par with definitive quantitative data. The variety of environments in which a system (project, facility) can exist dooms any attempt at a direct description of all of their diversity together with the rules for adequate response in critical and emergency situations.

Fuzzy, underformalized rules give an obvious advantage because they turn out to be considerably fewer in number. Moreover, the use of fuzzy logic for assessing situations that develop and for making inductive inferences in the models for controlling complex systems and facilities makes it easier to solve problems such as communication with DM using a profession-oriented language, and storage, accumulation, and processing of qualitative information. Just like in the theory of contingency control, centre stage is taken by the concept of a contingency as a set of values of attributes that describe the condition of the control target at a certain point in time.

The key assumption is that all possible conditions of the control target can be described by a set of generic situations, each of which is a group of linguistic values of attributes.

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