Analysis of NON-factors in innovative project management

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Abstract

The specificity of innovative projects to create domestic high-tech products often leads to the fact that the information used to support management decisions does not possess such properties as completeness, consistency, accuracy, reliability. As a result, project management is carried out in conditions of uncertainty. Therefore, a large number of factors that could cause the project failure can't be taken into account when planning. As a solution to this problem, it is proposed to identify and analyze NON-factors that are sources of project risks and do not have one of the properties of classical knowledge models. For NON-factors' identification, it is suggested to use a neural fuzzy classifier, which subdivides them into categories. The selection of tools for analyzing NON-factors is advisable to take into account the Hartley emergence indicator: in the case of low value, it is proposed to use a fuzzy inference according to the Mamdani algorithm, otherwise – fuzzy pyramidal networks.

Keywords 1

Project management, NON-factors, emergence, neural fuzzy classifier, fuzzy pyramidal networks

1. Introduction

Currently, one of the priorities of state policy is to intensify activities to create domestic high-tech products, which will not only solve the problems of import substitution but also have competitive advantages in the global market. However, in modern economic realities, the implementation of such projects is highly risky due to the following factors:

- innovative nature of high-tech products (less than 10% of such projects reach commercialization);
- high requirements for resource support (material and technical, financial, personnel, information, etc.);
- long period of project implementation.

Experience shows that the success of such projects largely depends on the quality of planning processes, which are based on the results of analyzing information on their internal and external environment. This fact determines the relevance of organizing an effective system of information support of management processes, which will be the basis for supporting decision-making at all stages of an innovative project.

At the same time, the uniqueness of high-tech projects practically does not allow the formation of a sufficient amount of statistical information, which will be the basis for making timely and justified management decisions. Another factor that negatively affects the success of such projects is the long period of their implementation, which in combination with a large number of participants can lead to serious, difficult to predict changes in the internal and external environment.

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The foregoing allows us to conclude that the management of large innovative projects to create domestic high-tech products is carried out in conditions of information uncertainty due to the lack of "qualitative" (in particular, complete, reliable, accurate, consistent) data on their participants and the external environment.

In these conditions, to effectively support decision-making, it is proposed to use an approach based on the NON-factors analysis, which today is considered one of the key directions of developing artificial intelligence.

2. Different approaches to the definition of NON-factors

The term "NON-factor" was first introduced by A. S. Narinyani in the 1980s to describe "partial knowledge" as an integral element of the real Knowledge System [1]. It was used to denote a set of factors that have a negative assessment in natural language and deny one of the basic properties of "classical" formal systems (accuracy, certainty, completeness, consistency, unambiguity, etc.).

As a result of longitudinal research on this topic, A. S. Narinyani proposed the following stratification of NON-factors: basic (underdetermination, inaccuracy), systemic (ambiguity, fuzziness), classifiers (incorrectness), meta NON-factors (immensity) [2, 3].

The concept of NON-factors gained popularity only at the beginning of the 21st century when artificial intelligence methods began to be actively used to analyze real systems and support managerial decision-making. To date, several dozen works have been published on this topic. They describe various tools for analyzing NON-factors and consider the issues of their practical application for various subject areas [4, 5].

Naturally, the choice of a method of modeling NON-factors depends not only on the subject area but also on the way of their determination. In the Russian literature, there are several approaches to the definition of NON-factors, often significantly different from the founder of this concept.

For example, A. N. Borisov identified only three NON-factors: unknown, unreliability, ambiguity [6]. However, the factor "unknown" refers to complete ignorance, i.e. it is not included in the system of knowledge about the object or process under investigation.

G. V. Rybina proposed four NON-factors such as uncertainty, underdetermination, imprecision, fuzziness [7]. However, in practice, it is rather difficult to identify which factors are uncertain and which are underdetermined.

Yu. R. Valkman offered the classification in the space of "NON-factor – investigated object – modeling method". He identified universal (common to all subject areas) and special (specific only to a specific area) NON-factors and proposed methods for their modeling [8].

The approach proposed by Tarasov V.B. deserves special attention. He divides the NON-factors into two large classes: informational factors (incompleteness, uncertainty, inaccuracy, fuzziness, inconsistency) and factors of developing the complex system (irreversibility, nonequilibrium, instability, nonlinearity, openness) [9].

The choice of approach to the definition of NON-factors depends on the specifics of the considered subject area and the set scientific and practical task. So, in the process of project management, special attention should be paid to informational NON-factors (incompleteness, inaccuracy, underdetermination, fuzziness, inconsistency).

3. Choice of tools for identifying NON-factors in project management

The basis of decision support for managing innovative projects to create high-tech projects is the analysis of information coming from the various elements of their internal and external environment.

The internal environment of such innovative projects is formed by its direct participants (developers and executors), which are influenced by various factors of the external environment. As a result, the number of factors that have a different impact on the effectiveness of project implementation can be quite large.

In this regard, the task of identifying factors that can seriously affect the effectiveness of the implementing project to create high-tech products becomes especially urgent.

Figure 1 shows a conceptual model for the analysis of NON-factors used to support decision-making in project management.

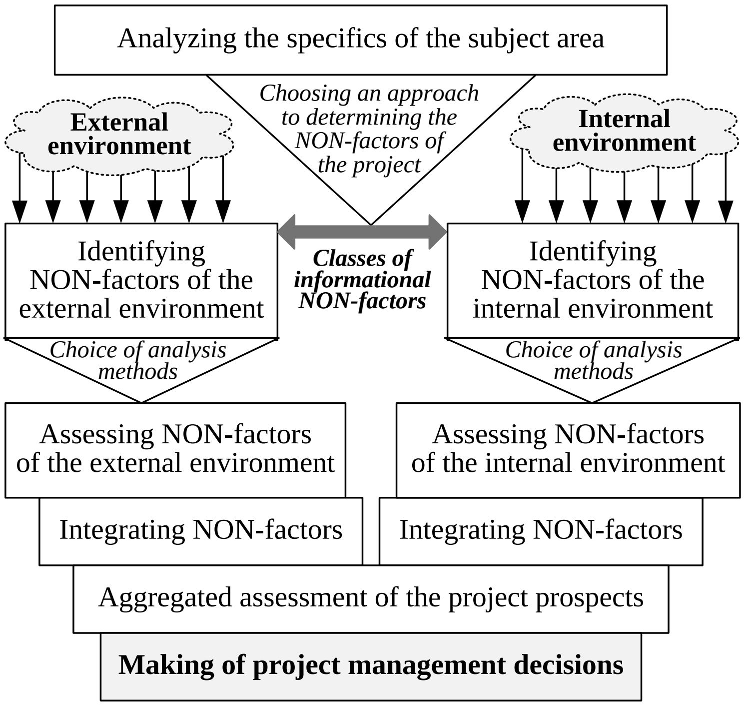

Figure 1: A conceptual model for the analysis of NON-factors in project management

The first stage of the model for analyzing NON-factors that can negatively affect the project effectiveness is their identification, which is associated with the construction of a classifier that assesses the significance of various factors of the internal and external environment in conditions of information uncertainty.

Due to the lack of "qualitative" statistical information for implementing this stage, it is advisable to use data mining, which allows working both with quantitative characteristics and linguistic description of the factor in natural language.

As a tool for solving this task, we can offer a neural fuzzy classifier that combines the advantages of artificial neural networks and fuzzy inference algorithms and relies on the base of fuzzy production rules [10].

To identify NON-factors of the internal and external environment of the innovative project, it was proposed to use a neural fuzzy classifier, consisting of five layers.

The input of this classifier (elements of the first layer) receives expert assessments of the significance of the NON-factor for project management, volume and quality of the available information about it.

The elements of the second layer implement activation functions for fuzzy production rules that assess the impact of the analyzed NON-factor on the project using the linguistic term sets specified by the Gaussian function.

The elements of the third layer perform minimization over all input values (i.e., they implement the operation of fuzzy logical "AND"). The output of the layer is the degree of fulfillment of each fuzzy production rule.

The elements of the fourth layer aggregate the results of executing fuzzy production rules (i.e., the operation of fuzzy logical "OR" is performed).

At the output of the classifier (the fifth layer), the degree of belonging of the considered NON-factor to various classes is formed.

Figure 2 shows an example of the structure of a neural fuzzy classifier used to identify NON-factors affecting an innovative project.

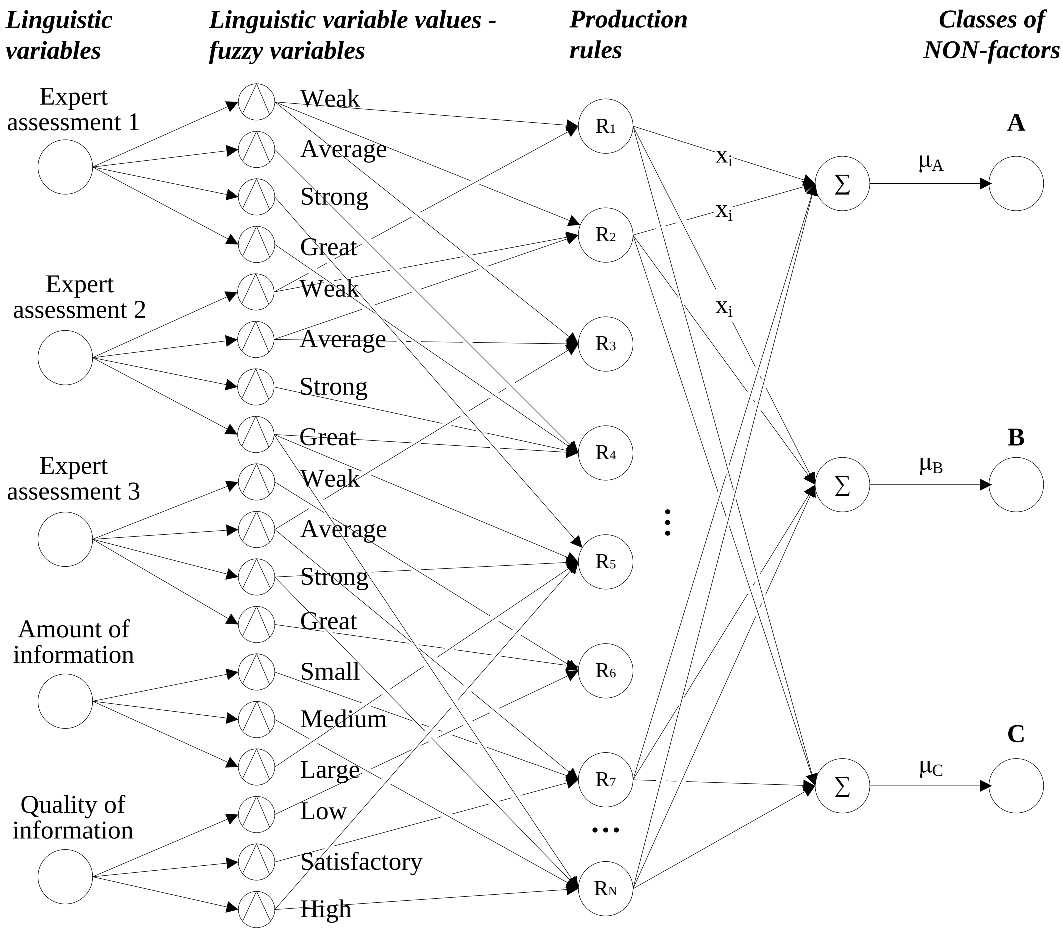

Figure 2: The structure of the neural fuzzy classifier used to identify NON-factors

The next stage of the model presented in Figure 1 is the assessment of NON-factors identified in the internal and external environment of the project to create high-tech products.

One of the important aspects that must be taken into account in the process of assessing the NON-factors is that they can lead to negative consequences for the project, both individually and in combination.

So, in the case of the NON-factors' triggering in combination, the property of emergence will manifest itself. It consists of the appearance of new properties in a complex system due to the interaction of its subsystems.

In project management, NON-factors can be considered as sources of risk situations. As a consequence, the project risk can be considered as a result of the emergence of the systemic effect of a set of NON-factors.

The Hartley emergence coefficient can be used to assess the systemic effect of the occurrence of several NON-factors. A detailed description of the procedure for its calculation is given in [11]).

The obtained values of the emergence coefficient can be used to select methods for assessing NON-factors that affect project implementation.

So, if the value of the Hartley coefficient is not high, then the project risk is caused either by one NON-factor or by their simple combination. In this case, Mamdani fuzzy inference can be used. It allows getting the aggregate possibility of a risk situation as a result of the triggering of several NON-factors.

If the Hartley coefficient has a high value, then it is necessary to combine the identified NON-factors into a single investigated system. In this case, it is advisable to use a more complex approach, since the total project risk may have properties that are absent in each of the combined NON-factors. Fuzzy pyramidal networks can be proposed as a mathematical apparatus for such a combination. Their detailed description is given in [12].

At the next two stages of the model for analyzing NON-factors that affect the implementation of the innovative project to create high-tech products, the results of assessing the identified factors are combined:

- at the third stage, the results of assessing the NON-factors identified within the various classes are integrated, separately for the internal and external project environment;
- at the fourth stage, the obtained results are aggregated.

The operations of combining the results of assessing the identified NON-factors are performed using fuzzy logical inference according to the Larsen algorithm, which is characterized by increased calculation accuracy.

4. Conclusion

It seems that the proposed approach to assessing the prospects of innovative projects to create domestic high-tech products, based on the identification and analysis of informational NON-factors, will allow timely identification of risk situations that can have an extremely negative impact on the project results.

Integrated use of data mining methods (in a particular, neural fuzzy classifier, fuzzy pyramidal networks, fuzzy logic algorithms) allows us to successfully process information that does not have one of the properties that characterize its "quality" (completeness, accuracy, certainty, consistency).

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