Extended Fuzzy Methods in Risk Management

M. Takács

Óbuda University, John von neumann Faculty of Infromatics, Budapest, Hungary
University of Novi Sad, Hungarian Language Teachers Training Faculty, Serbia
takacs.marta@nik.uni-obuda.hu
takacs.marta@magister.uns.ac.rs

***Abstract*—In the paper a system construction of the risk management principle is given where the system parameters are represented with fuzzy sets, and the grouped risk factors' values give intermitted result in the approximate reasoning. The experimental application is related to the stroke risk factor calculation.**

I. Introduction

Risk management modeling as a complex, multi-parametrical problem is one of the main research fields in the world today, from the micro-communities, families to the macro society structures and global phenomena of nature monitoring. Statistical methods-based reasoning models in crisis situations need long-time experiments and enough reliable data elaborated by experts. Additionally, they are time- and computing-demanding. The problems to be solved are full of uncertainties, and complexity of the systems increases the runtime factor of the decision process. Considering all those conditions fuzzy set theory helps manage complexity and uncertainties, and represents the inputs and outputs of the model in an emphatic form. The relationship between risk factors, risks and their consequences are represented in different forms, but in [1] a well-structured solution, suitable for the fuzzy approach is given. A risk management system can be built up as a hierarchical system of the risk factors (inputs), risk management actions (decision making system) and direction or directions for the next level of risk situation solving algorithm. A possible preliminary system construction of the risk management principle can be given based on this structured risk factor classification and on the fact, that some risk factor groups, risk factors or management actions have a weighted role in the system operation. The system parameters are represented with the fuzzy sets, and the grouped risk factors' values give intermediate result [2]. Considering some system input parameters, which determine the risk factors' role in the decision making system, intermediate results can be weighted and forwarded to the next level of the reasoning process.

Fuzzy set theory has gained recognition in a number of fields in the cases of uncertain, or qualitative or inguistically described system parameters or processes based on approximate reasoning. It can be successfully applied with numerous reasoning-based systems while these also apply experiences stemming from the fields of engineering and control theory.

In terms of architectures of the hierarchical systems, they are models of complex, multilayer, and multi-criteria systems, i.e. the cognitive [3] maps ontology [4] are often used models. A further possibility is for the system to incorporate the mutual effects of the system parameters with the help of the AHP (Analytic Hierarchy Process) methods [5].

Risk management as a complex system full of uncertainties and vagueness in its preliminary form contains the identification of the risk factors of the investigated process, and the representation of the measured risks is a good example for all the previously described issues. The system can be enlarged by monitoring and review in order to improve the risk measure description and decision system. The models for solving are knowledge-based models, where linguistically communicated modeling is needed, and objective and subjective knowledge (definitional, causal, statistical, and heuristic knowledge) is included in the decision process.

Considering all these conditions, fuzzy set theory helps manage complexity and uncertainties and gives a user-friendly visualization of the system construction and working model. Fuzzy-based risk management models assume that the risk factors are fuzzified (because of their uncertainties or linguistic representation); furthermore the risk management and risk level calculation statements can be represented in the form of *if premises then conclusion* rule forms, and the risk level calculation depending on measured input risk factors' level, or the output decision (summarized output) is obtained using fuzzy approximate reasoning methods. The model, known from the engineering applications is the Mamdani approximate reasoning model, which is able to manage risk level calculation.

The input risk factors can mostly be grouped, the groups can be weighted, and the mutual effects of the factors are thus represented in a block diagonal matrix. As the risk management system in its preliminary form contains the identification of the risk factors of the investigated process, the representation of the measured risks, and the decision model, the model construction is based on those steps.

One of the key issues in this modeling is the scaling of the quantitative input parameters of the reasoning system in their own universe. If they are qualitative parameters, scaling and decisions are often made on the basis of the ordinal ranking of humans, hence the qualitative nature of the decision process. This is important not only because scaling follows the characteristics of the real state space, but also from the point of view of applied mathematical models, as certain models apply operator families defined on a finite universe. Results in cognitive psychology have pointed out the importance of bipolar reasoning in human cognitive activities [6], but in terms of the possibility and fuzzy applications these scales are usually unipolar.

II. System construction

Considering the complexity of the risk management systems and the hierarchical or multilevel construction of the decision process and the grouped structural systematization of the factors can be introduced. This approach allows the possibility of gaining some subsystems, depending on their importance or other significant environment characteristics or on laying emphasis on risk management actors, is a possible way to manage the complexity of the system. Carr and Tah describe a common hierarchical-risk breakdown structure for developing knowledge-driven risk management, which is suitable for the fuzzy approach [1].

The preliminary fuzzification of the input risk factors have respect on objective and subjective related to the input parameters universe, and can be represented by membership functions defined on the unipolar, bipolar or qualitative scales. But after the first level of the decision making processes the inputs for the next level, as the outputs from the previous decision level, can be represented as the values on the [0,a] real number subscale, because for the users the decision and reasoning process is hidden, and depends on the experts, who have knowledge about the risk assessment problem and also about tools and mechanisms, which are applied by the risk level calculation. The final result, let us suppose the general risk level in the investigated risk assessment environment, of the complex decision making process should be represented on the scale, which is acceptable and recognizable for the final users. Considering the conditions, it can be reasonable to incorporate as the simplest possible fuzzy set theory based reasoning model, giving more emphasis on the input factors' scales and membership representations and on the user-friendly visualization of the system construction and final conclusion.

In the risk assessment projects, recently managed by the author of this article, this approach was applied in a very effective way, using the hierarchical or multilevel construction of the decision process, based on the Mamdani-type fuzzy reasoning model, the grouped structural systematization of the factors, with the possibility of gaining some subsystems, depending on their importance or other significant environment characteristics or on laying emphasis on risk management actors.

A. *Risk management model - generally*

The definition of the risk is given as the adverse consequences of an event. Events and consequences are full of uncertainty, and inherent precautionary principles, such as sufficient certainty, prevention, and desired level of protection. The steps of the problem solving can be defined as follows: the risk factor identification, the qualitative or quantitative description of their effects on the environment, the development of response actions to these risks, and if possible, to risk control in the future, trying to increase the effects of them.

For the transparency of the modeled risk management system it is possible to group and rank the risk factors, and to find the priorities of them. Reasonable risk factor choice and classification can be based on the severity of the hazard, probability of the risk, current knowledge regarding the hazard and the risk, availability of suitable hazard control and elimination methods or cost of such control or elimination methods. Further indicators of the ranking are: the nature and extent of the risks, the degree and category of risk, the likelihood of the risks materializing, the potential impact on the further connected events, and the cost or benefit of controls in relation to the identified risks.

The risk event determinates the necessary actions to increase the negative effects. Actions can be described by the ‘if … then’ type rules. The rules can have AND or OR relationship, described with the appropriate operation. If the model is a fuzzy based model, those operators can be represented by the t-norms and conorms, or conjunctive types and disjunctive types of uninorms respectively. Input Risk Factors (RF) grouped and assigned to the current action are described by the Fuzzy Risk Measure Sets (FRMS).

FRMS contains fuzzy rule base system and the method of approximate reasoning. With the output those components frame one unit in the whole risk management system, where the items are attached and grouped on the principle of the timescheduling, significance or other above-mentioned criteria. Based on the main ideas from [1] a risk management system can be built up as a hierarchical system of the risk factors, scaled on their universe and represented by membership functions covering over all possible qualitative or quantitative values appear in the application. The membership functions can be represented based on the experts' experiences, statistical distribution or others. Risk management actions and direction or directions for the next level of risk situation solving algorithm represent the decision making system. Actually, those directions are represented as the intermediate risk factors for the action on the next level of the risk management process. It is reasonable to use the scale of unit real interval to this intermediate values, because the weighting of the subsystems can be more controlled by the gaining multiplayer from the interval [0,1], namely the product of the intermediate value and gaining factor still stay on this unit scale, and fire the next level input scales.

The quantitative input system parameters (at the firs level of the hierarchies) are represented with fuzzy sets usually scaled in its naturally measured interval (such as the age of the pipeline section in the case study). Using the grouped, naturally scaled risk factors as the input at the first level of decision algorithm, the output risk level from the interval [0,1] is the calculated inference risk level for the mentioned risk factors group. The outputs of the first level risk inference systems are inputs for the second (or higher level) of reasoning process, and scaled on the unit interval, can be represented with the simple membership functions as ‘low’, ‘normal’, ‘high’, and other in the rule premises of the further decision process level, and they are suitable for further adjustment. [7].

The hierarchically structured risk assessment model with possible weighted factor groups can be involved in a fuzzy logic (FL) based inference mechanism environment, for example Mamdani-type, which adaptation in the previously presented system is based on the long time experiences from engineering applications.

B. B. The Mamdani-type fuzzy reasoning model

In the Mamadani-based fuzzy approximate reasoning model (MFAM) the rule output $B_i(y)'$ of the i-*th* rule if x is A_i then y is B_i in the rule system of n rules is represented usually with the expression

$$Bi'(y)= \sup_{x\in X}(T(A(x),T(Ai\ (x),Bi\ (y)))) \qquad (1)$$

where $A'(x)$ is the system input, x is from the universe X of the inputs and of the rule premises, and can be scaled, as it was described in the previous section. The y is from the universe of the output (in the multilevel decision making system it is the input universe of the next level in the decision process, i.e. the intermediate value universe). All outputs inside the hierarchical system can be scaled in the simplest form, but in the final rule system the output, for example, the general risk level for the monitored risk assessment system, should be represented in the recognalizable form for the final user (in the case study it is a ranking value of the pipeline reconstruction urgency).

The consequence (rule output) is given with a fuzzy set $B_i'(y)$, which is derived from rule consequence $B_i(y)$, as an upper bounded, cutting membership function derived of the $B_i(y)$. The cut, *DOF* is the generalized degree of firing level of the rule, considering actual rule base input $A'(x)$, and usually depends on the covering over $A_i(x)$ and $A'(x)$, i.e. on the ***sup*** of the membership function of $T\ (A'(x),A_i\ (x))$.

Rule base output, B'_{out} is an aggregation of all rule consequences $B_i'(y)$ from the rule base. As aggregation operator usually S conorm fuzzy operator is used.

$$B'_{out}\ (y) = S(B_n'(y),S(B_{n-1}'(y),S(....,S(B_2\ '(y),\ B_1'(y))))).$$

If the crisp MFAR output y_{out} is needed, it can be constructed as a value calculated with a defuzzification method. If the basic expectations of this fuzzy decision method are satisfied, then the B'_{out} rule subsystem output belongs to the convex hull of disjunction of all rule outputs $B_i(y)$, and can be used as the input to the next decision level in the hierarchical structure without defuzzification. Two important issues arise: the first is, that the B'_{out} is usually not a normalized fuzzy set (should not have a kernel). The solution of the problem can be the using of other operators instead of tnorm or minimum in Mamdani approximate reasoning process to calculate expression (1). The second question is, how to manage the weighted output, representing the importance of the handled risk factors group in the observed rule base system.

The solution can be the multiplication of the membership values in the expression of B'_{out} with the number from [0,1].

III. The Application: The Brain Stroke Risk Calculation

Health is commonly recognized as the absence of disease in the body. The fundamental problem with using probability–based statistics for patient diagnosis and treatment is the long time statistical data collection, complex calculation process and the elimination of the real-time human experience (at the actual medical examination) [8]. The influence of human perception, information collection, experiences involved in diagnosis and therapy realizes support the main fact, that patients are unique. Medical staff has various levels of expertise and the perceptions are often expressed in language. Diagnosis and treatment decisions are determined factors which are either unknown or are not represented within the framework of probability based statistics.

As it is stated in the information brochure published for patients by the University of Pittsburgh Medical Center, the risk factor in health diagnostics is anything that increases chance of illness, accidents, or other negative events. Stroke is one of the most important health issues, because it is not only a frequent cause of death, but also because of the high expenses the treatment of the patients demands. Stroke occurs when the brain's blood flow stops or when blood leaks into brain tissue [8]. The oxygen supply to a part of the brain is interrupted by a stroke, causing brain cells in that area to die. This means that some parts of the body may not be able to function. There are a large number of risk factors that increase the chances of having a stroke. Risk factors may include medical history, genetic make-up, personal habits, life style and aspects of the environment of the patient.

This classification is suitable for grouping the factors, but further different aspects can be applied for grouping. One of them is the classification depending on possibilities of the elimination. Some risk factors cannot be reversed or changed. They are uncontrollable. But some of the risk factors can get rid of, like smoking, for example. There are other risk factors that patient cannot get rid of, but can control, like diabetes.

In regard to the theoretical introduction, in the present application a restricted risk factors set is used. The factors are classified in the next *events* – groups (all of risk factors and theirs values are represented with fuzzy membership values)

- medical history (heart attack, previous stroke, …)

- genetic make-up and personal habits (diabetes, obesity, Heart and cardiovascular Disease,…)

- life style (stressed life, smoking, coffee, alcohol and drug use, Lack of Physical Activity, …)

- aspects of the environment (social-financial situation, living environment,…).

This classification is constructed on the first level of stroke risk evaluation. Grouping physiological events (medical history, genetic make-up and personal habits) and personal controllable events (life style and aspects of the environment) in the separated next level actions, we have two inputs on the final level of actions: summarized physiological factors and summarized personal controllable factors. The final output is the global stroke risk factor based on hierarchically investigated elementary risk factors.

The risk calculation actions are the if…then… rules regarding to the input variables of the current action level. The outputs at the actions are calculated using Mamdani type reasoning method, the crisp outputs are achieved with the central of gravity defuzzification. The complex risk calculation system is constructed in Matlab Fuzzy and Simulink environment.

It can be considered, that different events or risk factors have different impact on the stroke occur. Very often the

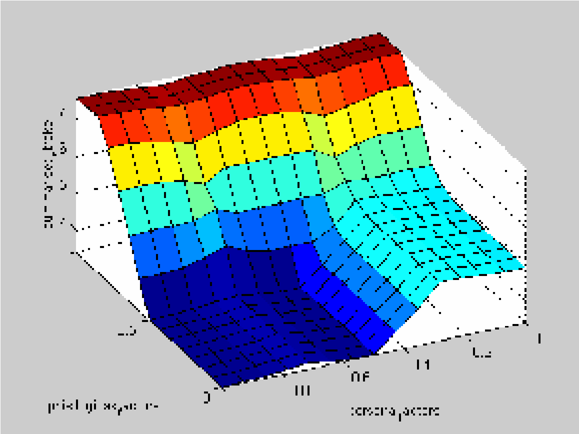

Figure 1. The summarized risk factor' decision surface

sex or age of patient affects the illness significantly. In this experimental system these factors will be the input variables of the system, by which some of the risk factors or events will be gained before the transmission to the next level of action.

Figure 1. shows the final risk level calculation surface.

IV. Conclusion

In the paper a preliminary system construction of the risk management principle is given based on the structured risk factors' classification and on the fact, that some risk factor groups, risk factors or management actions have a weighted role in the system operation. The system parameters are represented with fuzzy sets, and the grouped risk factors' values give intermitted result. Considering some system input parameters, which determine risk factors role in the decision making system, intermitted results can be weighted and forwarded to the next level of the reasoning process. The experimental application is related to the stroke risk factor calculation. In the diagnostic application field, further investigations will be focused on the different grouping of the risk factors and monitoring of the differences or effectiveness of different cases. The article also has given an overview of the scaling of the universe of the risk management systems' input parameters, which can be well-managed in a fuzzy environment. From the point of view of scaling several types of scaling can be defined. There are a number of issues to be further developed. One of these tasks is the fine tuning of the hierarchical and other multilayer systems in such a way, so that the scaling between the layers will better follow the operation of the system. In terms on fuzzy ontologies, this would be of utmost importance.

Acknowledgment

This work was supported by Óbuda University and Vojvodina Secretary of the Science and Technological development (title of the project: Mathematical Models for Decision Making under Uncertain Conditions and Their Applications).

References

[1] J.H.M Carr,. A. Tah, A fuzzy approach to construction project risk assessment and analysis: construction project risk management system, Advances in Engineering Software, Volume 32,Number 10, October 2001 , pp. 847-857.

[2] M. Takács, Extended Fuzzy Methods in Risk Management, Proc., of 14th WSAES International Conference on Applied Mathematics, ISBN 978-960-474-138-0, pp. 300-304.

[3] B. Kosko, "Fuzzy cognitive maps", in Int. J. of Man-Machine Studies, 24, 1986., pp 65-75.

[4] B. Neumayr, M. Schre, "Comparison criteria for ontological multi-level modeling", presented at Dagstuhl-Seminar on The Evolution of Conceptual Modeling, Institute für Wirtschaftsinformatik Nr. 08.03, Johannes Kepler Universität Linz, 2008.

[5] L. Mikhailov, "Deriving priorities from fuzzy pairwise comparison judgements", Fuzzy Sets and Systems, Vol. 134, 2003., pp. 365-385.

[6] D. Dubois, H. Prade, "Bipolar representations in reasoning, knowledge extraction and edcision processes", in Proceedings of RSCTC'2006. , 2006., pp.15-26.

[7] M. Takacs, "Multilevel fuzzy model for risk management", Proc. of 7th International Conference on Computational Cybernetics, 2009., pp. 153- 156

[8] C. M. Helgason, T. H. Jobe1, Stroke is a Dynamic Process Best Captured Using a Fuzzy Logic Based Scientific Approach to Information and Causation, IC-MED, Vol. 1, No. 1, Issue 1, Pp.:5-9.