Organizational Risk Assessment using Adaptive Neuro-Fuzzy Inference System

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Abstract— *In this paper a fuzzy model based on Adaptive Neuro-Fuzzy Inference System (ANFIS) is introduced for calculating the level of risk in managerial problems. In this model, affecting factors on the level of risk are considered as inputs and the level of risk as the output. Using the fuzzy model, the risky condition changes smoothly in a fuzzy environment as it is the case in the real world; while in classic models, we may have some stepwise changes in the state of the system caused by an infinity small deviations in input parameters. The main advantage of the introduced model is that for continuous values of input factors, the counters of risk surface represent a more realistic behavior for different systems. The model is designed for a system of three inputs (probability, impact and ability to react) and one output (risky situation). The ability of using historical data as well as experts' knowledge and flexibility of adaptation to unusual risky situations are some benefits of the introduced model. This model which is originally used in strategic management system to analyze the external environment and the level of threats can also be used in contingency management for incidents (CMI) or as a tool for Comprehensive Emergency Management Program (CEMP). The strategic Risk of Roche is considered as the bench mark for comparing the difference between fuzzy and classic systems.*

Keywords— Risk assessment, Adaptive Neuro-Fuzzy Inference System, Risk Counters, Impact, Ability to react,

1 Introduction

Risk management has many applications in different fields such as financial management, industrial engineering, military and manufacturing systems as a Meta-disciplinary field. Companies and organizations have to monitor, scan and investigate the environmental factors and to update their strategic plans based on the level of recognized threats to select appropriate policies and strategies for reducing the risks. There are several steps for implementation of global risk management, starting with risk identification and calculation of its level for taking an appropriate decision. One of the most important sub-processes for this purpose is the methodology of calculation of risk and comparison of risky factors to determine the priorities. Considerable quantitative models have been introduced for this purpose in literature, where it is tried to calculate the level of the risk, which is simply defined as the rate of threat or future deficit of any system imposed by controllable or uncontrollable variables (Chavas, 2004; Doherty, 2000). Several factors such as probability of occurrence, impact, severity and ability to react are introduced as effecting factors on the risk. Then it is tried to find the mathematical relation between affecting factors and the value (level) of the risk (McNeil and Frey and Embrechts 2005; Li and Liao, 2007). The concept of risk is considerably wide. It can contain strategic, financial, operational or any other type of the risk. Based on literature review, the models which are mostly used in different fields of risk analysis can be classified to three types:

a) Data oriented models
b) Analytical models
c) Models based on judgment

Although it should be mentioned that this classification is not only related to Risk analysis, but in general it can be applied to system identification tasks.

a) Data oriented models:
In these models the structure is not needed to be known and the only important issue is the system's behavior. Some of the features of this type of models are: dependence to historical data, being behavioral, and storing experience and knowledge, based on the recognition of the input and output patterns of the system. Artificial intelligent models such as ANFIS and Neural Networks as well as statistical methods by concept of math average approach can be classified as this type of models. The more the number of the historical data is, the more reliable the models and their results would be. Figure 1 presents this type of model which is considered as a black box.

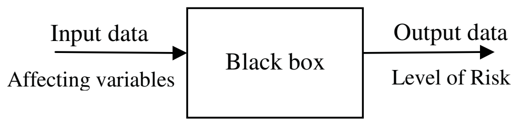


Figure. 1. Data-based System as a black box

This black box shows that there is no information on the analytical model of the system. It means that the relation among the variables as well as the way they affect each other is still unknown for user.
b) Analytical models.
In these systems it is possible to design a homomorphous model based on the system analysis process and structure of the problem. Being structure-based, analytical and independent from the data, are some of the features of this class of models. Many of the existing mathematical models,

ISBN: 978-989-95079-6-8

System Dynamics and a variety system analysis models are included in this class (Marrison2002). In this type of systems the structures must be recognized. It means that components and their relations must be identified to develop the analytical model. Figure 2 represents the concept of a structure based system. As it is mentioned the component and their relations must be recognized for developing an analytical model of the system.

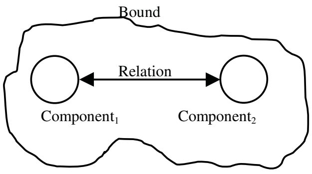


Figure. 2:. Structure-Based Systems (analysis)

For example if component$_1$ is Risk of investment when constructing a building, and component$_2$ represent the probability of earthquake in the region, the relation between them can be presented as :

Risk of investment=f (probability of earthquake)

Although it is a dream for researches to find an analytical model for such problems, however the major weakness of this kind of models is that they need precise data for modeling and the process of verification is considerably hard.

c) Models based on judgment

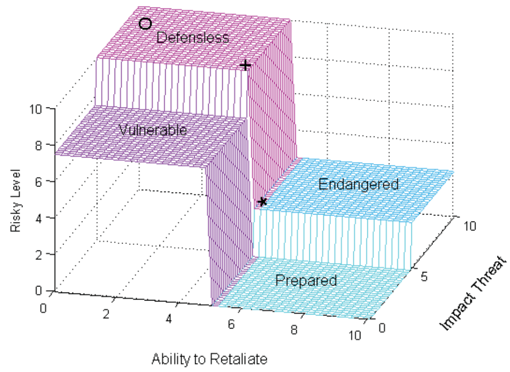
As it is mentioned, sometimes the first and second methods can not be used in real world problems. For example when the risk is based on the human behavior as a complex system, it is impossible for researches to find a pattern or mathematical model for it with available tools. So the judgment and knowledge of experts can help us to determine the level of risk and to find suitable solutions for risk management.

In this type of models, it is tried to overcome the major weakness of the first type consisting their uselessness in the case of no preexisting patterns. The growth of environmental dangers and the rapid increase of their variations as well as the increase of demand for such models by insurance companies have caused rapid and accelerated developments of such models (Roberets, 2005; Michael, 2004; Bernadell and CArdon and Coche and Diebold and Manganelli, 2004). This classification will help us to use the appropriate model in different situations.

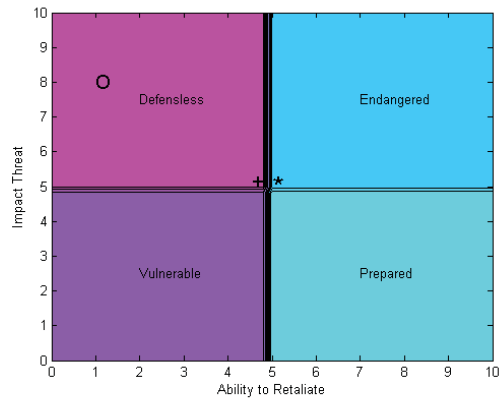
In this paper, the classic models of second type, commonly used in risk assessment of threats in strategic planning, are analyzed and criticized. Afterward a new model based on fuzzy inference is introduced for calculation of risk levels.

2. Problem Statement

Figure 3 shows a classic model of risk analysis. It consists of two factors: Impact threat and the ability to retaliate. In this model the risk value is classified in four groups. Each group represents a risky condition for the organization. During the implementation, first the opinions of the experts on the impact threat and the ability to retaliate are processed by means of any appropriate method such as group decision making, Delphi, …, and then the risky situation of organization is recognized. The distributions of the points with the same risk levels (contours of different levels) are also presented in Fig. 3(b), Points O and + represent the risky situation for two organizations with ability to retaliate and impact threats of (1, 8) and (4.9, 5.1) respectively.



(a)



(b)

Figure 3: (a) Risky situations classified in 4 levels, (b) counters

This model is very simple, but it has some structural drawbacks. For example the organization + which is in Endangered situation will change to completely opposite condition (Vulnerable) point(*) with infinity small deviations (A-da) in ability to retaliate. Also because of its geometrical structure, this model suffers from the lack of considering additional parameters such as ability to react.

Another method which has gained more attraction in the risk analysis literature is the model based on the linear combination of ability to retaliate and impact threat as:

$$Risk = (\text{ability to retaliate}) \times (\text{impact threat}) \qquad (1)$$

Figure 4 represents a practical continuous increasing surface (levels), instead of stepwise levels for risk values. Two particular levels are shown by the cutting planes K1 and K2. Positions O, + and * are also presented in this figure. Figure 4(b) shows some contours of risky surface. As it is seen, in this model any small change in the values of probability and severity will cause a very small deviation in its risky level of organization. Also sometimes the risky level remains unchanged. This model is more realistic than the one

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presented by figure 3. However, it also has its limitations for real world applications because it simplifies the complicated relation between different factors that affect the risky conditions of organizations to a simple multiplication of two factors (ability to retaliate and impact threat).

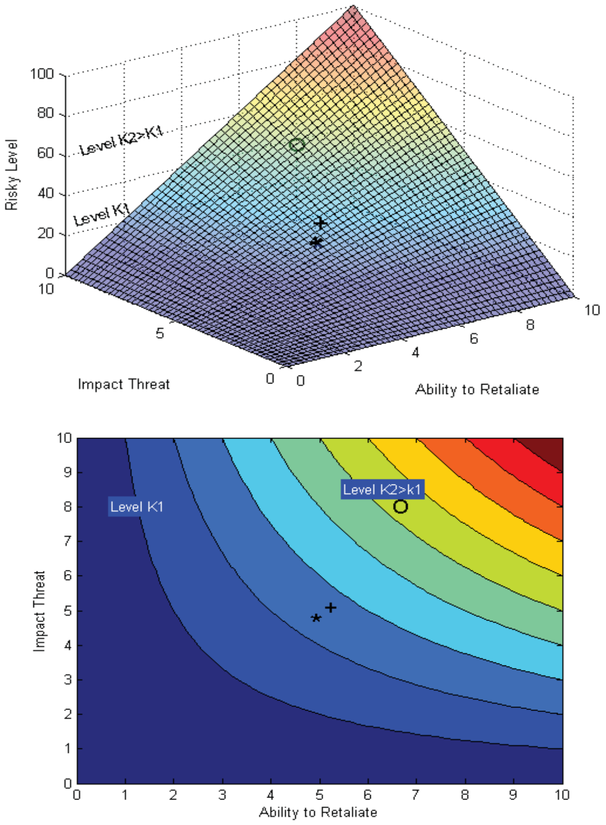


Figure. 4: Continuous surface for risk levels and counters

These kinds of models suffer from some weaknesses such as considering the relation between variables as a linear relation. Also when the number of inputs increases, the complexity of the system will increase dramatically while the accuracy of the model will decrease. Moreover due to inflexibility of the model, it can not be improved considering our experiences based on real world situations or the growth of experts' knowledge.

Hence we can formulate our problem as an input output system by:

$$R=F\ (X) \qquad (2)$$

Where X is the set of input variables which affect the level of the risk, R is the level of the risk and F(.) is a nonlinear function (Kreinovich and Nguyen, 2000).

The problem here is to find an appropriate solution by which the level of risk of the system (Organization) can be determined in complex situations when there is no access to all data, or the historical data is useless.

In this paper we try to develop a rule based model by using fuzzy inference system.

3. Fuzzy model

Fuzzy inference systems (FIS) are rule-based systems with concepts and operations associated with fuzzy set theory (Zadeh, 1965) and fuzzy logic (Ross, 2004; Mendel, 2001). These systems are mappings from an input space to an output state; therefore, they allow constructing structures that can be used to generate responses (outputs) to certain stimulations (inputs), based on stored knowledge on how the responses and stimulations are related. Sometimes this knowledge is obtained by eliciting information from specialists, in which case these systems are known as fuzzy expert systems (Takács, 2004). A fuzzy system also can be created to mach any set of input-output data. Adaptive Neuro-fuzzy Inference System (ANFIS) is one of the well known methods for creating Input-Output based models. (Krus , Gebhart and Palm, 1994). ANFIS only support Sugeno systems (Sugeno, 1985) subject to the structure of the system such as unit weight for each rule. Since its introduction, ANFIS has successfully been proved in many engineering applications (Jang, 1993). Another common denomination for FIS is fuzzy control systems (see for example (Mendel, 2001)).

FIS are usually divided in two categories (Mendel, 2001; Takagi and Sugeno, 1985): multiple input, multiple output (MIMO) systems, where the system returns several outputs based on the inputs it receives; and multiple input, single output (MISO) systems, where only one output is returned from multiple inputs. Since MIMO systems can be decomposed into a set of MISO systems working in parallel, all that follows will be exposed from a MISO point of view (Mamdani and Assilian, 1999).

FIS suffers of adjusting the linguistic knowledge of the expert with available data; so in this paper a fuzzy model based on ANFIS is introduced for calculating the risky situations of organizations by considering different factors such as probability, Impact threat and ability to retaliate (Nguene and Finger, 2007; Hyo and Hyun, and Yoon, 2002). This model is developed in three phases. To clarify the process of modeling in different phases a benchmark case study adopted from "strategic management by Rowe, et all" (Row et all, 1999) is used as a test example.

Phase 1: Data generation

The expert s' judgments may be extracted by means of different group decision making methods. Our experience in this work shows that the Delphi method as well as Nominal group is more practical. In case there are hard data as a result of historical behavior, a similar methodology can be used. By the way combination of hard data and information extracted from expertise can be used to develop first table which is necessary for next step.

Table 1 shows the set of generated data for test example.

Table.1

Probability	Impact	Ability to React	Risk (Vulnerability)
1	10	4	7.5
0	0	10	0
.5	5	5	1
1	5	5	3
.2	5	2	0
.8	2	8	5
.4	7	3	1

ISBN: 978-989-95079-6-8

1	0	5	0
.7	8	2	4
.8	8	7	2
.2	9	5	.5
.2	3	5	0
.7	10	3	4.5
.5	10	2	2.5
.5	10	10	0
1	8	0	10
1	2	8	.5
.6	10	4	3
.1	2	6	0
.3	6	8	0

Phase 2: Rule making

In this step the Adaptive Neuro-Fuzzy Inference System (ANFIS) is used for generating the rules.

Figure 5 Shows the surfaces of the rule base system adapted for the data of table 1 with:

numMFs = 25

mfType = gaussmf

epoch_n = 20

After constructing rule-base surface the model is improved by investigating the critical states (which are not approved by expert or when there is illogical behavior). Then by adding more rules or by imposing some minor deviations to data set the final rules may be obtained as shown in figure.5. By this way any specific behaviors cause by unusual relation between some particular inputs and output of the system can be supported which is significant advantage benefit of introduced model compare to other model such as Neural Network.

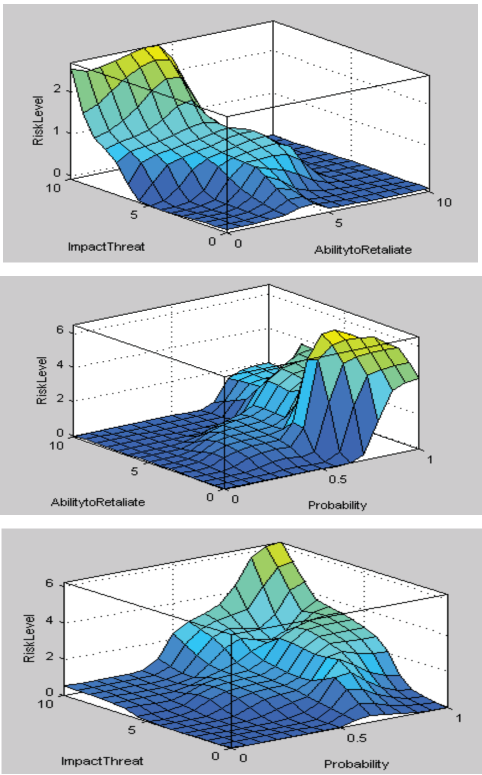
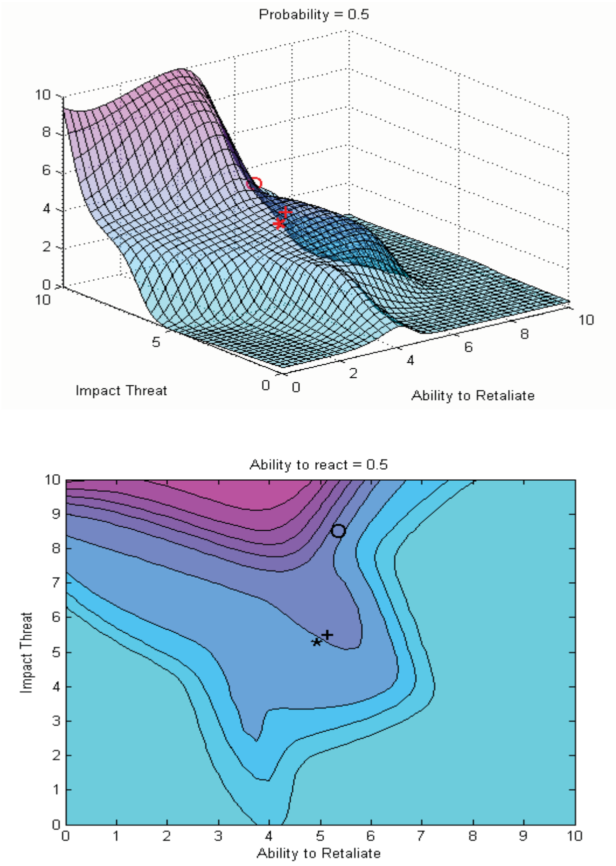


Figure.5: Surfaces of generated rules.

Phase 3. Implementation

This model is implemented to the simple example of section one to have an idea on the main difference between this method and the classic model. Figure 6 shows the surface and counters of risky levels of organizations +, and O. The results are shown for 50% of probability of impact to visualize the obtained results.



(b)

Figure. 6: (a) Risky surfaces, (b) counters for simple example

As it is seen, organization + which is appropriately Endangered situation will change to appropriately defenseless, point(*), with infinity small deviations (A-da) and (T-dt) in ability to retaliate and impact threat which is more realistic than the classic one.

The vulnerability analysis for Roche Company is also considered as a benchmark for implementing and comparing the obtained results with the classic methods. Figures 7 and 8 compare the results obtained by implementing the introduced model. Note that in the rest of paper only the surfaces and counters for probability of 50% are shown.

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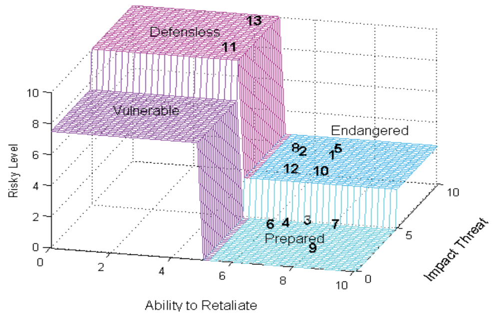
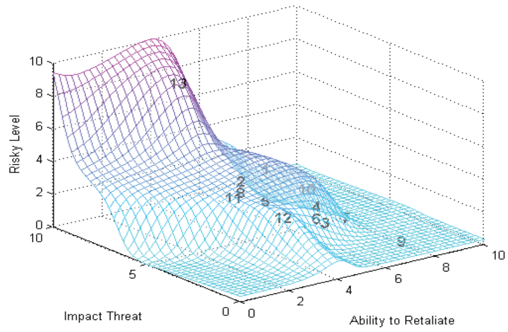


Classic



Fuzzy

Figure.7: application of classic and fuzzy models for vulnerability analysis of Roche Company

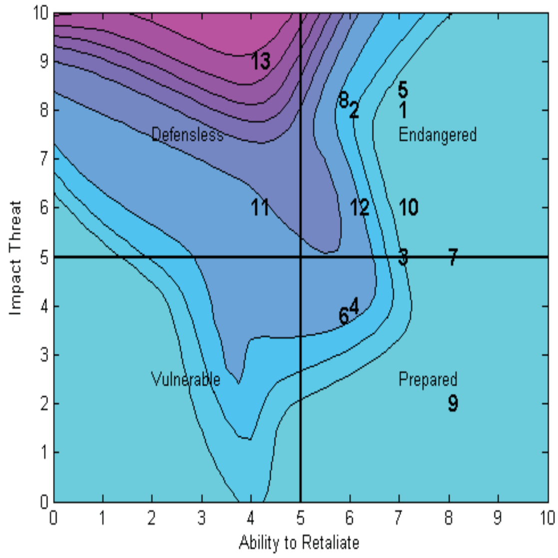


Figure 8: Risky levels of Roche by using classic and fuzzy models

Table 2 compares the results of this method by the classic one.

Table 2

Assumptions	Impact 0-10	Probability 0-1	Capability 0-10	Vulnerability Assessment Strategic management Approach	Vulnerability Assessment Classic	Vulnerability Assessment Fuzzy
1. Needs and wants served by products	8	0.7	7	Endangered	2.5	1.9960
2. Resources and Assets	8	0.6	6	Endangered	2.5	1.6119
3. Cost position relative to competition	5	0.4	7	Prepared	0	0.1490
4. Customer base	4	0.5	6	Prepared	0	1.9093
5. Technologies	8	0.4	7	Endangered	2.5	0.0446
6. Special skills	4	0.4	6	Prepared	0	1.1455
7. Corporate identity	5	0.5	8	Prepared	0	0.0298
8. Institutional barriers to competition	8	0.4	6	Endangered	2.5	0.8793
9. Social values	2	0.2	8	Prepared	0	0.0015
10. Sanctions, supports, and incentives	6	0.7	7	Endangered	2.5	1.7019
11. Customer goodwill	6	0.5	4	Defenseless	10	2.1834
12. Complementary products or services	6	0.3	6	Vulnerable	7.5	0.2943
13. Regulatory agencies	9	0.7	4	Defenseless	10	7.8129

It is seen that using the fuzzy method appropriate continues vulnerability levels are obtained to analyze the risky levels.

As it can be seen in Table.2 the Result of Vulnerability assessment by using Strategic management approach (as shown in fig.3) is stepwise and limited to 4 categories; hence the real value of risk is unclear. The second model (Classic Vulnerability Assessment) suffers from rigidity and can not be customized in different situations. So its efficiency can not be improved by considering available data and knowledge of experts. It is why in real world applications the decision Makers are not generally satisfied (trust the model) by the results obtained by this method.

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The introduced fuzzy based method overcomes the mentioned drawbacks. For example considering rows 1,2,5,8,10 in table.2, by using classical method as well as strategic management approach the same levels of risk are obtained for different assumptions where by using introduced method different level of risk is determined.

4. Conclusion

In this paper the fuzzy risk analysis procedure is compared with classic methods. It is demonstrated that the fuzzy analysis seems to be more reasonable and applicable because of its smoothness in calculating the risky situations. By fuzzy analysis the dynamic (time dependent) behavior of risk conditions can be defined and used for convenient and reliable decision makings. The model presented in this paper has some features as follows: a) Relations between variables in real life are nonlinear. Abstracting the situation and simplifying the problem to a linear model will cause the missing of some vital data where by utilizing the introduced model the relation between Risk and variables can be considered as a nonlinear function. b) Using FIS brings the advantage of developing and improving the model based on historical data. It is noted that the original model is constructed only based on the experts' knowledge due to lack of historical data. c) The model can be extended to be used for any number of inputs, where expanding the classic models to more inputs is not an easy task. d) This model considers probability as an input where other models usually solve the problem in a probabilistic environment. e) Any Specific behavior caused by unusual relation between some particular inputs and output of the system can be supported by imposing new rules to the model.

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ISBN: 978-989-95079-6-8