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Fuzzy Inference System and Fuzzy Neural Inference System Applied to Risk Matrix Classification in Projects

Sistema de Inferência Fuzzy e Sistema de Inferência Neural Fuzzy Aplicados à Classificação de Matrizes de Risco em Projetos

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ABSTRACT

Projects are essential for organizations to transform strategies into results, but uncertain events can impose risks to achieve a certain objective. Risk management aims to support an organization in deciding how to deal with risks, prioritizing them through the application of Risk Matrices (RMs). RMs or Probability and Impact Matrices is used to support decision-making, helping management to classify and prioritize risks to decide which will be ad-dressed, monitored, or tolerated. RMs are supposedly easy to build and explain, but according to the literature they may contain uncertainties. To deal with uncertainty, it is recommended to apply a Fuzzy Inference System, based on Fuzzy Set Theory (FST) or a Fuzzy Neural Inference System with the presence of an artificial neural network. Thus, the aim of this paper was to develop and apply a Fuzzy Inference System (FIS) and a Fuzzy Neural Inference System (FNIS) in the classification of MRs in projects to reduce uncertainty. The analysis of the results indicated that the application of the two systems resulted in a continuous classification rule by smoothing the boundary areas between each of the RM classes, reducing uncertainty and improving risk classification. Both systems showed good results in reducing uncertainty. However, the results obtained with FNIS were more consistent. The main contribution of this work lies in the possibility of improving the decision making by reducing the uncertainty present in RMs.

Keywords: Risk Matrices; Projects Risk; Risk Classification; Fuzzy Inference System; Fuzzy Neural Inference System

RESUMO

Projetos são essenciais para que as organizações transformem estratégias em resultados, mas eventos incertos podem impor riscos para atingir determinado objetivo. A gestão de riscos visa apoiar uma organização na decisão de como lidar com os riscos, priorizando-os por meio da aplicação de Matrizes de Risco (MRs). MRs ou Matrizes de Probabilidade e Impacto são usados para apoiar a tomada de decisões, ajudando a gestão a classificar e priorizar os riscos para decidir quais serão abordados, monitorados ou tolerados. MRs são supostamente fáceis de construir e explicar, mas de acordo com a literatura eles podem conter incertezas. Para lidar com a incerteza, recomenda-se a aplicação de um Sistema de Inferência Fuzzy, baseado na Teoria dos Conjuntos *Fuzzy* (TCF) ou um Sistema de Inferência *Neural Fuzzy* com a presença de uma rede neural artificial. Assim, o objetivo deste trabalho foi desenvolver e aplicar um Sistema de Inferência Fuzzy (SIF) e um Sistema de Inferência *Neural Fuzzy* (SINF) na classificação de MRs em projetos, para reduzir a incerteza. A análise dos resultados indicou que a aplicação dos dois sistemas resultou em uma regra de classificação contínua ao suavizar as áreas de fronteira entre cada uma das classes de MR, reduzindo a incerteza e melhorando a classificação de risco. Ambos os sistemas apresentaram bons resultados na redução da incerteza. No entanto, os resultados obtidos com SINF foram mais consistentes. A principal contribuição deste trabalho reside na possibilidade de melhorar a tomada de decisão reduzindo a incerteza presente nos MRs.

Palavras-chave: Matrizes de Risco; Risco de Projetos; Classificação de Risco; Sistema de Inferência *Fuzzy*; Sistema de Inferência *Neural Fuzzy*

INTRODUÇÃO

The use of Artificial Intelligence (AI) in operations management represents a significant field of research. AI’s ability to evolve solutions, address uncertainty, and perform optimization contributes to mitigating new challenges faced by operations management Baruah and Kakati, 2020). In this context, improving project management remains a primary concern of researchers and managers. Project managers face a variety of difficulties in managing projects, including project life cycle, external dynamic environment, management process complexity, uncertainties, costs, and risks of projects (Kerzner, 2013; Liu, 2015).

Risk management in project management is widely recognized as necessary to deal with project uncertainty. Due to its importance in the literature on project risk management. Risks are events which may affect the success of a project. Risks have two dimensions: the degree of uncertainty and impact on objectives (Hillson, 2009; Creemers, et al., 2014; Qazi, et al. 2016).

Projects are characterized by being subject to risks, on the other hand, they are also essential to implement organizational strategies, as an important piece to companies’ growth.

Thus, decisions on how to deal with project risks are key to the success of businesses (Knezevic et al., 2018; Gonçalves, et al., 2023).

Considering the two dimensions of risk, the probability and the impact, probability is generally used to describe the degree of uncertainty of events, while impact is most often used to describe the effect on the objectives of the project (Wideman, 1992; Montibeller, Winterfeldt, 2015).

The combination of the different degrees of intensity of these two dimensions allows to classify each risk on a qualitative scale as high, medium, or low. Thus, the higher the risk, the greater the urgency to address it, or the greater the resources required to mitigate it (Ball, Watt, 2013).

Risk management is characterized by a sequence of activities that begins with planning, followed by risk identification, qualitative and quantitative analysis, monitoring and control (Project Management Institute, 2017).

Risk Matrices (RMs) or Probability and Impact Matrices is used to support decision-making, helping management to classify and prioritize risks to decide which will be addressed, monitored, or tolerated (Cox, 2008).

The studies of Cox (2008), Ni, et al. (2010), Markowkski and Mannan (2008), Duijim (2015) and Jordan, et al., (2018) have shown that RM is widely applied, but it also has certain weaknesses, especially when the situation to be considered is not clear due to uncertainties arising from limited knowledge or lack of information.

RM displays the aggregated notion of risk through a graph, representing two dimensions, probability and impact organized into discrete categories, which can be described in IF-THEN rules (Markowski, Mannan, 2008).

RM allows the visualization of the two dimensions of risk, probability and impact, enabling communication between project team members and establishing a standard for decisions to be taken within pre-established criteria. However, it can present problems, as the values of each axis can become vague and imprecise (Goerlandt, Reiniers, 2016; Hong, et al., 2020) and subject to classification errors (Cox, 2008; Baybutt, 2015; Hsu, et al., 2016).

In search of alternatives to deal with this situation, Markowski and Mannan (2008) evaluated the use of the Fuzzy Set Theory (FST) in the elaboration of RM for risk classification in chemical processes. Smith, Siefert and Drain (2009), Levine (2012), Hsu, et al., (2016) and Hong, et al., (2020) also recommend that MR uncertainty be treated with FST.

According to Zadeh (1965), FST or Fuzzy Logic (FL) can work with uncertainty and inaccuracy and solve problems where there are no defined limits and precise values. Fuzzy Inference Systems (FIS) are based on the FST, on the IF-THEN fuzzy rules, and on the fuzzy reasoning process. FIS have been used in many areas, including data stream classification, monitoring ecological, decision on freeways, automation, pattern recognition, robotics, time series, decision-making, performance risk assessment in public–private partnership projects and risk matrices (Markowski, Mannan, 2008; Ježková, et al., 2017; Gu 2023, Sedighkia, Datta, 2023; Vechione, Cheu 2022; Chen, et al., 2020).

Javaheri, et al., (2023) presented an overview of the future perspectives of applied FL in the detection of attacks and network traffic anomalies. Pravena and Prasanna (2022) performed research on fuzzy-based game theory approaches to supply chain uncertainties in e-commerce applications.

Some techniques, when applied to solve real-world problems, have their own computational characteristics, which fit only a specific set of problems. We can illustrate this behavior by analyzing Artificial Neural Networks (ANNs) and FIS. Although ANNs have the ability to detect patterns, classifying and grouping, they are not efficient to explain how these patterns are detected. On the other hand, FIS deals better with imprecision and is able to clarify decision-making, managing to explain the pattern found through its set of rules.

ANNs and FL can be associated, generating a Fuzzy Neural Inference System (FNIS), including in the same model the treatment of the uncertainty of FL with the ability to learn and generalize the knowledge learned from an ANN (Wang, et al., 2014).

Artificial Neural Networks (ANNs) have applications in all aspects of science and have been used in many business applications over recent decades (Tkáč, Verner, 2016; Sermpinis, et al., 2019).

ANNs are models built of simple processing units called artificial neurons that calculate mathematical functions. They are particularly efficient for mapping the input and output of nonlinear systems and for parallel processing and simulating complex systems. Moreover, they are able to generalize the results obtained to previously unknown data, producing coherent and appropriate responses to patterns or examples that were not used in the training set. One widely used ANN architecture for classification is Multilayer Perceptron (MLP). An MLP consists of a set of units (nodes or neurons) that make up the input layer, one or more hidden layers, and an output layer, where the input signal propagates layer by layer. These structures can learn by example and perform interpolation and extrapolation of what they have learned through a learning algorithm (Haykin, 2001).

Thus, the aim of this paper was to develop and apply a Fuzzy Inference System (FIS) and a Fuzzy Neural Inference System (FNIS) in the classification of MRs in projects to reduce uncertainty. FIS and FNIS have been successfully used to solve problems in several areas of knowledge such as medicine, industry, business, control and automation, information security, agronomy and academic applications, among others.

LITERATURE REVIEW

Risk Matrices

According to Wideman (1992), many projects fail to achieve their goals due to unforeseen events. There is a need to address uncertainty in the decision-making process using project risk management, as it may cause harm when neglected. (Nozick, et al., 2004; Sharma, Gupta, 2012).

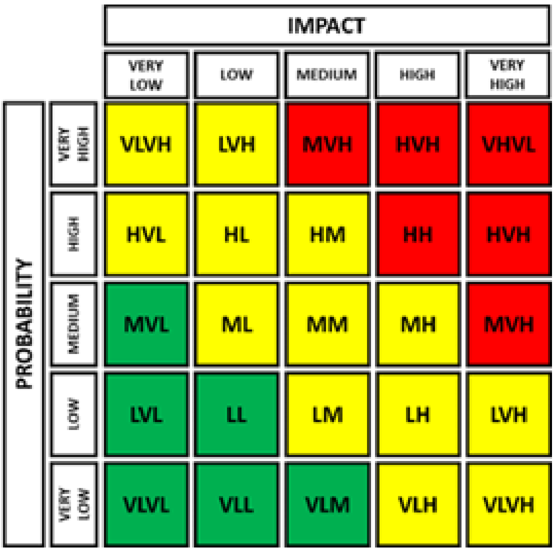
Although there is a correlation in using risk management tools and the successful achievement of a project's goals and performance (Del Cano, La Cruz, 2002); the adoption of risk management tools is not as common as it should be, contributing to many failures in projects (Raz, et al., 2002).

This scenario can be attributed to a lack of preparation and excessive optimism about the results of the project, which are manifestations of the cognitive biases reported by Montibeller and Winterfeldt (2015), Ball and Watt (2013), and Smith, et al., (2009), negatively influencing the risk analysis. The first step for risk management is the planning of the processes that will be employed in controlling. Next, the risks must be identified, mapped, and characterized. This set of risks will be further analyzed qualitatively and quantitatively, following a scale of priorities.

After these analyses, a risk response plan should allocate resources to enable measures to properly address risks. Finally, risks are continuously monitored during project implementation to control action outcomes, external environmental impacts, and eventual new risks (Project Management Institute, 2017).

A RM shows the aggregate assessment of risk through a graphical representation of its two dimensions: probability and impact. The RMs may vary in the number of rows and columns and the colors of the prioritization zones according to Cox, 2008 and Ni, et al., 2010, as shown in Figure 1.

Figure 1: Risk Matrix 5×5.



Source: Adapted from Cox (2008)

A traditional RM uses discrete consequence, probability, and risk categories, which can easily be described in IF-THEN rules (Markowski, Mannan, 2008). Figure. 1 shows a five-row, five-column RM (RM 5×5) with a gradation ranging from very low to very high for both impact and probability. This two-dimensional assessment is used to "plot" each risk in an RM, with high / medium / low zones. These zones are often colored following a traffic-light-like convention, with red being used for high-priority risks that needs to be addressed urgently, yellow designating medium-priority risks to be monitored, and a green zone containing low priority risks (Hillson, 2009).

The application of the RM requires the use of discrete categories. Although it is understood that any risk assessment that are not purely based on the assessment of mathematical consequences requires the use of subjective analysis, especially for their impacts, the discrete categories approach is being criticized (Cox, 2008). Therefore, the issue is not just a problem of the RM application, but also of a previous handling of the probability and the consequences of adverse events that are inaccurately assessed.

In some cases, due to the non-repetitive characteristics of projects, subjective risk assessments are necessary because of the lack of statistical data to estimate the probability of an event based on the frequency these events. Categorization may be necessary, for these cases it is recommended to use numerical scales, without much granularity, as they are less subjective. Impact categorization may require inherently subjective judgments, reflecting the evaluator's personal degree of risk aversion or arbitrary decisions about the extent of multiple small and frequent events.

Cox (2008) states that the need for such judgments and their potential for inconsistencies shows that RMs can be filled in many ways. Thus, RM represents the combination of factual data on risk, its position means the perception of risk, and its consequent classification corresponds to the decision on how the risk should be treated, allocating resources to mitigation (red area), monitoring (yellow area) or acceptance (green area).

Cox (2008) also indicates the importance of considering the context of qualitative analysis in projects, as it makes possible to identify and assess risks in a preliminary way that establishes a level of priority, so a consistent analysis can be performed over the prioritized risks.

Markowski and Mannan (2008) evaluated the use of Fuzzy Set Theory in the elaboration of risk applied RMs in chemical processes, proposing FRMs. An RM displays the overall notion of a risk portfolio through a chart, characterizing its two dimensions, probability, and impact, employing discrete categories that can be described in the IF-THEN rules. It is considered that research that apply systems to reduce the uncertainty contained in RMs are welcome because they can improve decision making in organizations.

Fuzzy Logic

Fuzzy Logic (FL) can work with uncertainty and inaccuracy to solve problems where no clear limits and precise values exist (Ježková, et al., 2017). This concept allows the creation of mathematical formulations that may characterize the uncertainty in parameters involved in the risk analysis method (Markowski, Mannan, 2008).

FIS are based on Fuzzy Set Theory, fuzzy IF-THEN rules, and fuzzy reasoning processes. In a fuzzy set, the inclusion of an element in a set is linked to an association function of a linguistic term (high, low, medium) and a membership function, which gives each object a degree of association that varies between 0 and 1 (Ježková, et al., 2017).

The formal definition of a fuzzy set is an extension of the classic set definition of a classic set: if X is a collection of objects generically denoted by x, then a fuzzy set A in x is defined as a set of ordered pairs (Ježková, et al., 2017), according to equation 1:

$$\mu A = \{[x, (x)] \mid x \in X\} \quad (1)$$

Where $\mu A\ (x)$ is called membership function (FP of fuzzy set A). FP maps each element of x with a member-ship degree between 0 and 1. Thus, x is called the speech universe. An IF-THEN rule takes the form "if x is A, then y is B," where A and B are linguistic values defined by sets in the description universes of x and y. The linguistic values x and y belong respectively to the sets of linguistic variables x and y. Normally, the proposition "x is A" is called antecedent, while the proposition "y is B" is called consequent.

In many cases, the conditional rule "if x is A then y is B" is abbreviated as follows.: $A \rightarrow B$. From the expression $A \rightarrow B$, several operators can be formed to calculate the binary fuzzy relation $R = A \rightarrow B$. Thus, R can be seen as a fuzzy set defined by a two-dimensional PF, according to equation 2:

$$\mu R\ (x,y) = f(\mu A(x),\mu B(y)) = f(a,b) \qquad (2)$$

With $\mu A\ (x) = a$, $\mu B\ (y) = b$, where the function f is called the fuzzy implication function. This function transforms the degrees of association from x to A and y to B from (x, y) to $A \rightarrow B$.

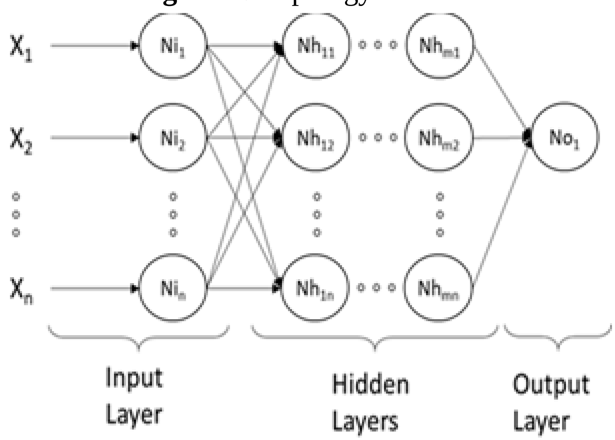
The IF-THEN fuzzy rules and their relationships, together with the compositional inference rule (Zadeh, 1965), form the basis of the fuzzy reasoning framework, which is the basis of FIS. The IF-THEN rules and the fuzzy inference engine produce fuzzy output. This fuzzy set can be converted through a defuzzification engine to an exact number that best represents it.

Multilayer Perceptron

Multilayer Perceptron (MLP) represents a set of units (nodes or neurons) that outlines the input layer, one or more hidden layers, and an output layer, where the input signal propagates through the ANN layer by layer. The topology of a MLP consists of the following information: total number of layers; number of neurons in the input layer; number of neurons in the hidden layer(s); and number of neurons in the output layer (Haykin, 2001).

In Figure 2, the basic structure of the MLP with N input layer neurons (sensory neurons), hidden layer neurons, and a single output neuron is presented (No1).

Figure 2: Topology of the MLP



Source: adapted from Haykin (2001).

The training algorithm used in a MLP is that of backpropagation, which works as follows: first, one is presented to the network input layer, and this pattern is then processed layer by layer until the output layer provides the processed response, fMLP calculated, according to equation 3:

$$f_{MLP}(x) = \varphi\left(\sum_{i=1}^{Nom} v_l \cdot \varphi\left(\sum_{j=1}^{Nem} w_{li} + b_{10}\right) + b_0\right) \quad (3)$$

Where vl and wlj are synaptic weights, bl0 and b0 are its the biases, and φ is the activation function, commonly specified as the sigmoid function. The purpose of the training process is to choose appropriate parameters to minimize a predetermined cost function. This function is dependent on the desired response yi and, if there is an error, it is calculated. The function of the sum of the most usual quadratic error is presented, according to equation 4:

$$E(X) = \sum_{i=1}^{N} \frac{1}{2}\left[f_{MLP}\,(x_i) - y_i\right]^2 \quad (4)$$

The calculated error is backpropagated from the output layer to the input layer and the weights are adjusted and processed, the weights are adjusted during the training process by error backpropagation. This process runs until a minimum error is obtained (Haykin, 2001).

The error backpropagation algorithm used in the MLP determines its variations in synaptic weights, minimizing the error obtained in the output through learning by training data. For this, the algorithm is based on the descending gradient method, which, given a measure of the error, seeks to modify the set of weights wij, reducing the error in the steeper direction of the defined surface in space w.

The descending gradient algorithm establishes changes in weights wij by an amount Δwj proportional to the error gradient. This algorithm calculates the errors in the intermediate layers, thus enabling the adjustment of the weights by backpropagation, proportionally to the values of the connections between layers.

A MLP trained with the backpropagation algorithm performs a nonlinear input and output mapping. An important question about the backpropagation algorithm is the training stop criterion. In absolute terms, the final solution will occur for the performance index (global error) equal to zero or within a very small value (Haykin, 2001; Lecchi, et al., 2022).

Artificial Neural Networks and Fuzzy Logic

Several hybrid architectures can derive from the combination of a FIS and an ANN, such as, for example, a Fuzzy Neural Inference Systems (FNIS) in which several ANNs are used in parallel to determine the FIS inference rules or NeuroFuzzy Inference Systems (NFIS) that employ a trained ANN to find a linear combination of the input variables that match the output variable. FNIS and NFIS are, in essence, SIF's parameterized through adaptive learning from a training database (Jang, 1993).

Several authors have tried to gather the association of FL and ANNs potentialities to the resolution of problems in different areas of knowledge. Some examples like pattern recognition (Kwan, Cai, 1994), anomaly classification and detection (Meneganti, et al., 1998), sales forecast (Kuo, Xue, 1999), bank credit rating (Malhotra, Malhotra, 2002), mapping mineral potential (Porwal, et al., 2004), adaptive load balancing based on delay-sensitive Internet applications (Chimmanee, et al., 2005), projects in the construction industry (Cheng, Tsai & Sudjono, 2010), solving civil engineering problems (Knezevic, et al., 2018), malware classification (Shalaginov, Franke, 2017), analysis of sentiments in texts (Nguyen, et al., 2018), medical diagnosis (Perova, Bodyanskiy, 2017), and Biology (Zamirpour, Mosleh, 2018). Rajab and Sharma (2018) review on the applications of neuro-fuzzy systems in business. Škrjanc et al. (2019) researched about the evolution of approaches involving distortions and neuro-fuzzy for grouping, regression, identification, and classification. Souza (2020), Shihabudheen and Pillai (2018) and Kar, et al., (2014) performed a wide literature review on hybrid methods applying ANN with Fuzzy Logic, considering techniques, applications, and future trends, concluded that this specific field of research is particularly promising in terms of the contribution to applications in progressively more areas of knowledge, along with the evolution of the techniques.

A FNIS has the characteristics of fuzzy logic in dealing with uncertainty and the ability to learn and generalize the knowledge learned from an ANN MLP type. Such a system follows the universal approximation theorem, i.e., it can correctly approximate nonlinear functions

(Wang, et al., 2014). This system is characterized by being a FIS, the inputs and outputs of which are crisp numbers. The FIS is coupled to an ANN, which adjusts the results of the inference system to the target data. However, the outputs are processed by input fuzzification, and inference rules based on defuzzification.

METHODOLOGY

The review of the literature on RM shows that there are several studies that seek to identify and reference the uncertainty inherent to the application of RMs and focus on proposing solutions within a traditional perspective. A second stream of research is focused on the use and application of FST to address this uncertainty.

This paper proposes an improved view in relation to the work of this second group by the association of ANNs with FIS. Therefore, the following experiments were built to allow a comparative assessment of the studied methods, including traditional RMs, in order to visualize the inherent characteristics of each method and how each method can contribute to reduce the uncertainty of the RMs. The experiments were divided in data preparation and modeling, performed in two phases, experiments with FIS and experiments with FNIS.

Data Preparation

Four data groups were generated for the experiments using a random function. In the first group, named ALE, random numbers were generated, without correlation between them, where ALE_PROB is the risk probability and ALE_IMP the risk impact. ALE_RISK is the risk, which is defined by the product of probability and impact. Similarly, the second group named POS was obtained, in this case the impact POS_IMP is positively correlated with the probability POS_PROB, i.e., POS_IMP = POS_PROB and then POS_RISK was calculated by multiplying them. The third group NEG was obtained analogously, using NEG_IMP = 1 – NEG_PROB. Finally, the fourth group POS_NEG where half of the data was generated using the formula POS_NEG_IMP = POS_NEG_PROB and half with POS_NEG_IMP = 1 – POS_NEG_PROB. Each data group was composed with 1000 instances.

With the help of a spreadsheet, each of the data for PROB and IMP were classified in a RM 5x5, and the classification colors distributed according to Figure. 1. In the spreadsheet, red color cells were classified as 1, yellow as 2, and green as 3. The results of these classifications were stored in the variables: ALE_CR55; POS_CR55; NEG_CR55; and POS_NEG_CR55. Table 1 presents the generated data groups, and their respective description are consolidated.

Table 1: Data groups used in the study.

Components		**Description**
[ALE_IMP, ALE_PROB]	ALE_RISK ALE_CR55	The data [ALE_IMP] and [ALE_PROB] are uncorrelated as they were generated completely independently. [ALE_RISK] is the result of their multiplication and from RM5×5 the rating [ALE_CR55].
[POS_IMP, POS_PROB]	POS_RISK POS_CR55	Data [POS_IMP] and [POS_PROB] are positively correlated [POS_RISK] is the result of their multiplication and from RM5×5 the rating [POS_CR55].
[NEG_IMP, NEG_PROB]	NEG_RISK NEG_CR55	Data [NEG_IMP] and [NEG_PROB] are negatively correlated. [NEG_RISK] is the result of their multiplication and from RM5×5 the rating [NEG_CR55].
[POS_NEG_IMP, POS_NEG_PROB]	POS_NEG_RISK POS_NEG_CR55	The data [POS_NEG_IMP] and [POS_NEG_PROB] are negatively and positively related in a 50% split of the data. [POS_NEG_RISK] is the result of their multiplication and from RM5×5 the rating [POS_NEG_CR55].

Source: Authors.

It is important to note that all _RISK data in experiments refers to the real value of each risk, and all _CR55 data is its classification according to the rules learned from the adopted RM 5x5.

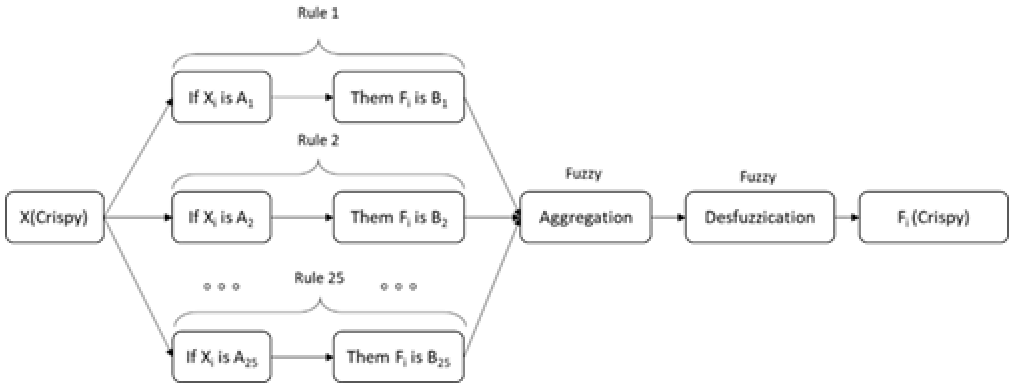
Conducting The Experiments

Before starting the procedures, the necessary tools were prepared for its execution. MATLAB software version R2014a was employed using an Intel® Core™ i7-6500DU CPU @2.5Ghz processor computer with 16GB of RAM. FIS was built into the Fuzzy Toolbox module, which was also employed in FNIS. In FNIS, the data were also processed in the Neural Net Fitting Toolbox module. The experiments were divided in two steps: step 1 will use FIS and step 2 will present experiments with FNIS.

In step 1, experiments with FIS were built using PROB and IMP data as inputs. Each instance of the groups was associated with membership functions corresponding to each of the RM5×5 cells, i.e., very high (VH), high (H), medium (M), low (L), and very low (VL), which were associated with Gaussian functions. Inference rules were extracted from each of the RM5×5 cells for a total of 25 rules, one for each matrix cell. A Mandani inference and defuzzification system was used by the centroid method (Jang, et al., 1997).

For each set of probability and impact of the ith risk, [PROBi, IMPi] was classified according to the values of the RM inference rules; each cell of the Aj RM was converted to an inference rule, which results in Bl. The result is the crispy F55 i value, which is the fuzzy corresponding risk of Ri = PROBi × IMPi. The general scheme of the inference process is presented in Figure 3.

Figure 3: Diagram of the inference process in FIS.



Source: Authors.

In the proposed system, X is a composite matrix of probability and impact for each group. Table 2 shows the structure and the variables generated for each data set.

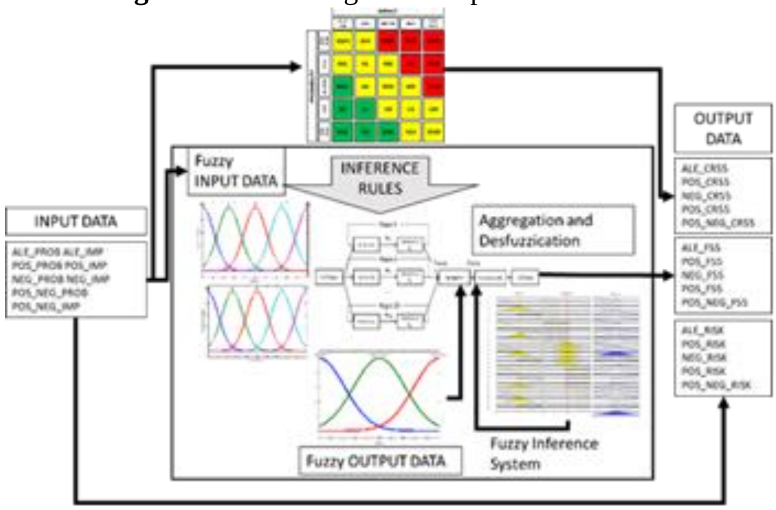
Table 2: List of FIS inputs and outputs.

FIS input	FIS output
[POS_IMP, POS_PROB]	POS_F55
[NEG_IMP, NEG_PROB]	NEG_F55
[POS_NEG_IMP, POS_NEG_PROB]	POS_NEG_F55
[ALE_IMP, ALE_PROB]	ALE_F55

Source: Authors.

In Figure 4, the block diagram of the experiments with FIS is presented.

Figure 4: Block diagram of experiments with FIS.



Source: Authors

In step 2, experiments with FNIS were built employing the same elements of FIS: (i) Gaussian membership functions; (ii) Mandani inference system; and (iii) centroid defuzzification. At this stage, FNIS output data were processed in a two-layered, three-neuron MLP, which had training. Table 3 shows the structure and the variables generated for each data set.

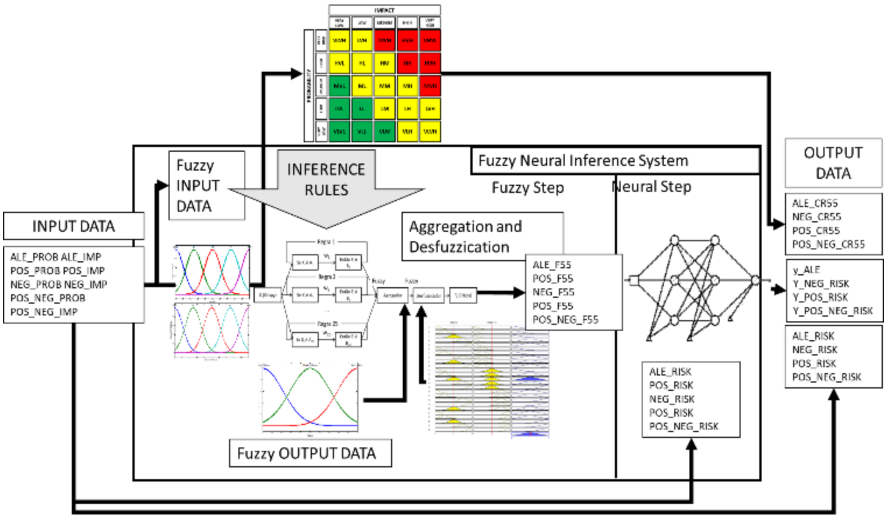
Table 3: List of FNIS inputs and outputs.

FNIS input	Intermediate data FNIS	Output (FNIS)
	POS_RISK	(training)
	NEG_RISK	
	POS_NEG_RISK	
	ALE_RISK	
[POS_IMP, POS_PROB]	POS_F55	*y*_POS
[NEG_IMP, NEG_PROB]	NEG_F55	*y*_NEG
[POS_NEG_IMP, POS_NEG_PROB]	POS_NEG_F55	*y*_POS_NEG
[ALE_IMP, ALE_PROB]	ALE_F55	*y*_ALE

Source: Authors

In Figure 5, the block diagram of experiments with FNIS is presented.

Figure 5: Block diagram of experiments with FNIS.



Source: Authors.

FINDS AND DISCUSSION

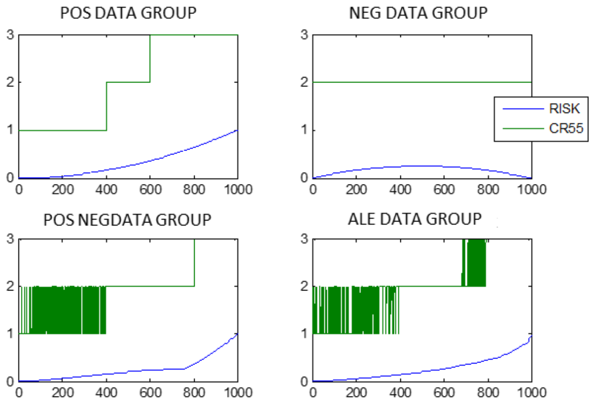
This section is organized as follows. For each dimension, the empirical results are first presented including relevant quotes. Theoretical propositions are then formulated, and the findings are then compared to literature.

Results and Analysis

The dataset was analyzed according to each data group, following the preprocessing sequence, the results and experiments with FIS, and the results and experiments with FNIS. The inference system outputs were compared to evaluate the effects of the experiments on the input data.

Following the sequence proposed above, the dataset was initially prepared to the experiments. The results of this preparation are presented in Figure 6, where each chart refers to the RISK item of each instance in each of the generated data groups. All charts were sorted based on the RISK variable of the scope.

Figure 6: Charts with results of data preparation (in each chart, the data prepared for variable RISK and CR55 are presented).

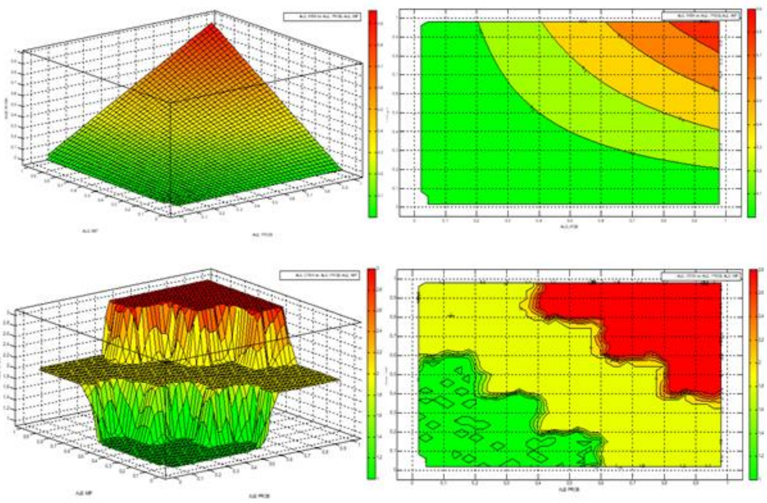


Source: Authors.

An important aspect to note is that in the data groups where behavior is correlated (POS and NEG), the classification results are more stable and follow the evolution of the RISK variable. In the dataset where data correlation is weaker, there is greater instability, and classification (CR55) does not follow the same growth direction as RISK in some zones. This means that the use of a rating matrix can be misleading, as a numerically higher risk can be ranked lower than a numerically lower risk, which is an inconsistency of the RMs.

To further illustrate this, in Figure 7, the charts of ALE_IMP × ALE_PROB × ALE_RISK and ALE_IMP × ALE_PROB × ALE_CR55 are presented, as well as their respective contour maps.

Figure 7: At the top are the response surface ALE_IMP × ALE_PROB × ALE_RISK and its outline map at the bot-tom ALE_IMP × ALE_PROB × ALE_CR55.

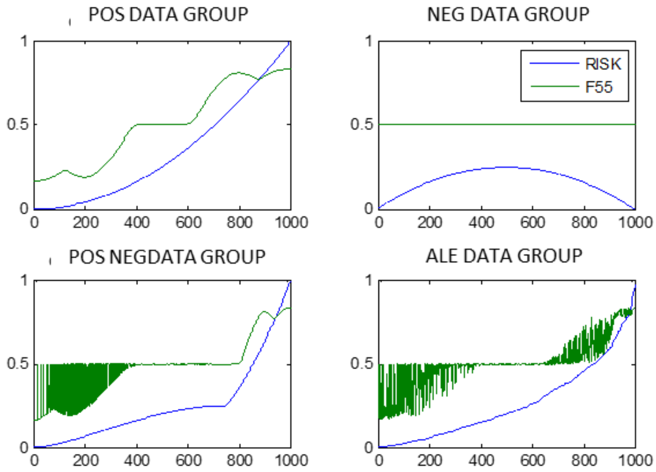


Source: Authors.

Figure 7 shows that RM can be understood as a simplification of the contour map of the response surface of the RISK function borders between each of the possible classes. Thus, numerically close values for risks may have different classifications.

The results of the FIS application (step 1 in section 3.2) are presented in Figure 8, where F55 represents the output of FIS, which were sorted according to the respective FIS variable value of each instance in each data group.

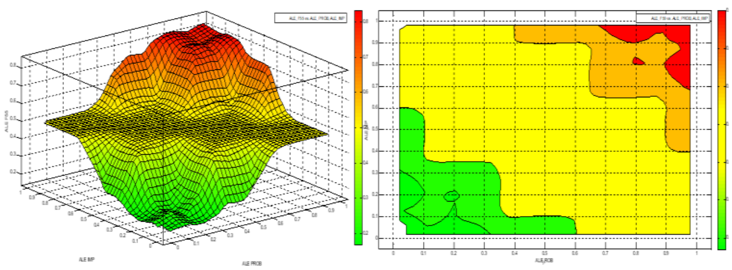
Figure 8: Results of experiments with FIS (in each chart, data are presented comparing the RISK variable and the output of FIS F55).



Source: Authors.

The use of FIS resulted in a system that has an adherence to RM and the effect of inference rules. It still presents some problems like the lack of consistency with the RISK variable. The data from the POS database indicate a different result from the others, as they make it possible to differentiate risks in each of the classification zones. However, when applying FIS in the POS_NEG, ALE bases, there is an instability in the results, which may affect the risk classification. The NEG base, on the other hand, maintains its characteristic of not generating differences between risks. In Figure 9, the response surface and contour map for ALE_IMP × ALE_PROB × ALE_F55 are shown.

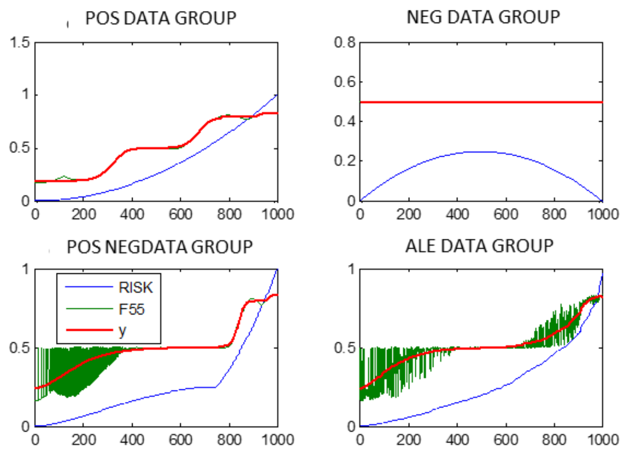
Figure 9: Response surface and contour map for ALE_IMP × ALE_PROB × ALE_F55.



Source: Authors.

The first chart in Figure 9 shows that FIS has helped to attenuate variations between values, the zone classified as 2 in the inference rules in FIS is still different from the shape of the response surface (RISK), being closer to that in RM. To eliminate inconsistencies that still exist in the FIS output, FNIS was used, whose outputs are shown in Figure 10 (step 2 in section 3.2).

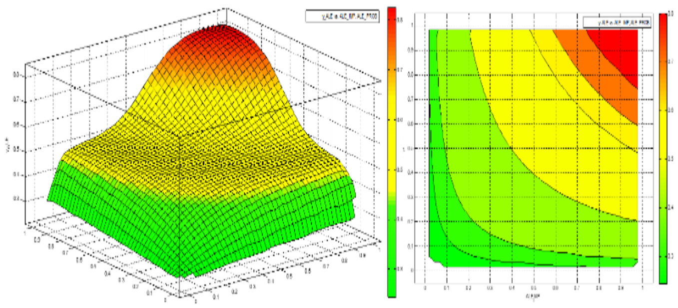
Figure 10: Results of experiments with FNIS.



Source: Authors.

The charts in Figure 10 show the results of the application of FNIS and reveal that nonlinear functions were obtained for each of the data groups, which allows to classify each of the risk instances generated, without the inconsistencies observed in the application of RMs and FIS. Figure 11 illustrates the response surface and contour map of the FNIS for the ALE data group (ALE_IMP × ALE_PROB × y_ALE).

Figure 11: Response surface and FNIS contour map for ALE data group (ALE_IMP × ALE_PROB × y_ALE).



Source: Authors.

About the analysis of the results, it is highlighted that the results obtained with the application of the FNIS were more stable, even in conditions with random data as in the ALE and POS_NEG groups. The contour map illustrated how the result of the FNIS is a continuous function, which allows classifying each instance of the risks generated. As a result of the inference rules extracted from the RM, the risks are weighted and quantified, allowing the person responsible for the project to clearly seek the risks that will impact their results.

Thus, risks classified as high on the MRs need to be prioritized according to the red zone on the contour map, which coincides with the red zone on the MRs. In the same context, the yellow zone, whose classification is medium, is related to the risks where the decision maker hesitates and normally chooses to wait. Finally, the green area, with a low rating, indicates where the risk is minimal or negligible.

It is noteworthy that in RM, the classes are discrete, that is, the changes between classes are abrupt and values very close to the risks can be classified differently. With the application of the FNIS, these categories become continuous, making the categorization process between close values less subject to sudden changes and still respecting the inference rules extracted from the RMs.

The results obtained show both techniques have advantages when compared with traditional RMs. Especially when it is possible to evaluate errors in the classification and the occurrence of tiles in a large quantity of risks. Furthermore, FNIS have proven to be more efficient in avoiding risk tiles and can be used to create risk ranking according to the risk rating of an RM.

CONCLUSION

In this paper, two systems for classifying RMs with the objective of reducing the uncertainty contained in the matrix were developed and applied: Fuzzy Inference System and Fuzzy Neural Inference System. The results showed that the rules extracted from the RMs, applying FIS and FNIS can generate continuous functions that allow classification, useful for risk prioritization. It was also verified that the risk classification, through discrete indicators obtained as MRs, can generate inconsistencies in the creation of rankings. Computational experiments were able to produce a function that reflects how the decision maker should prioritize which risks need to be mitigated, monitored, or ignored.

RM presents an approximation of the risk function, which can be handled by the decision maker, facilitating the risk classification process. However, this approximation results in loss of information quality, mainly at the border between the areas. The use of the FIS made it possible to obtain a function that smoothest these contour lines between the areas of the MR classes, but some inconsistencies were still observed in the results. With the use of the FNIS, however, the functions obtained were consistent with the MRIs and with the risk functions.

Such results have a direct impact on the reduction of uncertainty in the results of the MRs, avoiding classification errors verified in the application of traditional methods. Another contribution is the possibility of classifying risks without the occurrence of ties between the values, which makes the decision-making and prioritization process difficult, especially in sets of large numbers of risks. The results encourage further studies, employing other machine learning algorithms in the treatment of RMs, as well as evaluating their classification performance in real cases of project risk.

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