Performance Analysis on Health and Safety Issues of Companies from the Slaughterhouse Industry

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***Abstract* - The purpose of this article is to analyze the performance of companies in the slaughterhouse industry in health and safety issues. The research method is quantitative modeling. The main research technique uses a mixed method based on multi-attribute utility method (MAUT) and artificial neural networks (ANN). The research object is 34 slaughterhouse companies located in Southern Brazil. Then, we ranked the companies and modeled their decision trees using the MAUT method. From these results, neural networks were used to benchmark and compare the methods. This resulted in a linear equation that represents the closest solution to the ideal and percentage error in the decision tree's resolution. Thus, neural networks are most efficient, because they indicate which KPI's (key performance indicators) most influence the organization's performance. We numerically present the gain of information and the margin of error, concluding that some KPI's do not influence competitiveness without requiring controls. The academic and social contribution is that through the union of MAUT and neural networks we can measure the performance and select the main KPIs that need to be controlled for any type of industry.**

Keywords: Multi-attribute utility method; Artificial neural networks; Decision tree; Competitiveness, Performance.

1. Introduction

Competitiveness is the sum of all factors that determine a business' continued presence in a market. It also determines the profitability and helps to create the ability to adapt the production to the clients´ strategic requirements [1]. Therefore, the competitiveness in an industry reinforces vulnerable positions of companies and reduces exposure to the entrance of substitute products and services [2]. In industry, competitiveness determines the strength of a company; a well-defined strategy usually fosters competitive advantages to a company [3].

Assessing competitiveness is an important step in strategic management [6]. To assess the competitiveness of a company, we use key performance parameters (KPI) to help managers to improve productivity, quality, operational performance, and efficiency [7]. KPIs are defined by the strategic objectives of the company [8].

This study used data from the slaughterhouse industry. The industry suffers the consequences of accidents. Therefore, monitoring and controlling performance indicators related to health and safety can be relevant to competitiveness. The selection of KPI's is an MCDM (multi-criteria decision-making) problem [4], and adapting the workplace to a safer and healthier environment is a goal of slaughterhouses that wish to ensure competitiveness in the marketplace [5].

The structuring of the problem start with the construction of a cognitive map that provide the basis for understanding the problem and the variables that form the decision tree [9]. Our model uses KPIs and critical success factors (CSF), which are activities in which the company must succeed to transform strategies into results [10], [11]. Qualitative studies are especially important to better understand the CSF and also to understand how to make the tool [12], [13], 14]. Additionally, fundamental points of view (FPV) should be considered by decision-makers to help evaluate potential actions in competitive studies [15].

The purpose of this article is to analyze the performance of companies in the slaughterhouse industry in health and safety issues. To achieve this goal we used initially MAUT, that is an MCDM with a systematic approach for quantifying the preferences of an individual, based on the measurement of decision-maker preferences [16]. For the ranking of KPI's, solved by MAUT, we propose the use of a decision tree to quantify the global competitiveness rate for health and safety at a slaughterhouse company located in Southern Brazil. We numerically present the gain of information and the margin of error, so they indicate which KPI's most influence the organization's performance and what KPI's do not influence competitiveness without requiring controls. We used Artificial Neural Networks (ANN), as it can solve problems via continuous data processing, which is impossible in decision trees.

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2. Literature Review

2.1. Multi-Attribute Utility Theory (MAUT)

MAUT measures the utility of the alternatives offered to a decision-maker, according to his/her preferences, given by the utility function of Equation 1.

$$v(x_1, x_2, \ldots, x_n) = \sum_{i=1}^{n} v_i(x_i), \tag{1}$$

The function transforms the initial criteria expressed on the same scale, resulting in a ranking of alternatives that reflect the preferences of decision makers [16]. In practical cases, to accurately estimate the decision-maker preferences for each criterion, a given amount of data is necessary, which can difficult the evaluation process [17]. Additionally, MAUT does not consider the relationship between entries, making the reading of information incomplete and causing misinterpretations. To overcome such difficulties, we combined MAUT with ANNs.

2.2. Artificial Neural Networks (ANN)

In recent years, the use of ANNs has increased in the business environment [12], [18]. ANNs are a supervised machine learning algorithm [19] that creates connections between neurons, grouped in layers [20], with the ability to solve problems involving prediction, approximation, classification, and pattern recognition [21]. ANNs provide many advantages when compared to other decision-making models, particularly in the case of non-linear and complex data [22]. The advantage is due to the learning capacity of neural networks [23]. Figure 1 shows the architecture of a neural network: the input layer (X), composed of the neurons that receive the initial data; the hidden layer (H), composed of neurons that divide the problem into other smaller problems; and the output layer (Y), composed of computational neurons that label or classify the data [24].

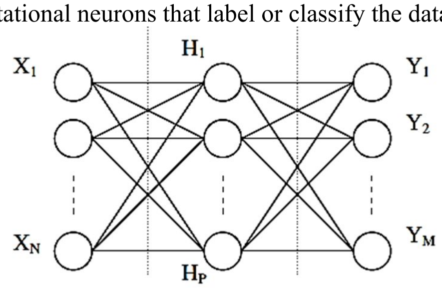

Figure 1. Representation of a neural network [23].

An ANN is an arrangement of connections between input and output layers, where each connection (i.e., node) is assigned a value representing the force of the connections. The network learns by iteratively adjusting weights to acquire a predictive capacity for an attribute, considering a class (i.e., output) as a function of the values of the set of input attributes [12].

Figure 2 represents a fundamental RNA, consisting of a set of neurons with synaptic weights, arranged in layers, that receive input information from the previous layers, which sums the products of each input by its respective weight, and an activation function, which limits the amplitude of the output value of the neuron [25].

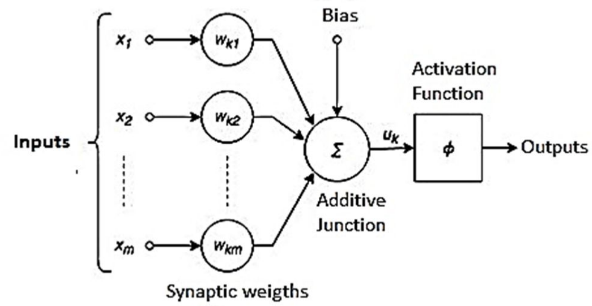

Figure 2. Model of an artificial neuron (24)

Neuron *k* can be represented mathematically by equations 2 and 3, *x*(1… *m*) represents the input values, *wk*(1… *m*) represents the synaptic weights, *bk* represents the bias setting, *uk* represents the output of the additive junction, *φ* represents the activation function, and *yk* represents the output [25].

$$u_k = \sum_{j=1}^{m} w_{kj} \cdot xj \tag{2}$$

$$y_k = \varphi(uk + bk) \tag{3}$$

We use the multilayer perceptron (MLP) neural network because it works with more than one hidden layer. Thus, it is the basis of other neural networks, as demonstrated in other studies [26], [27], [28].

2.3. Multilayer Perceptron

The MLP network is one of the most well-known types of RNAs that is adaptable to the analysis of organizational scenarios and was a universal approximation with the ability to relate and approximate input and output data [29], [30]. MLP is a universal approximation because it can be used in different domains and application areas, including simulation of phenomena and scenarios [31], [32], biological models [33], deep learning [34], modeling in different areas of knowledge [35].

An MLP consists of an input layer, one or more hidden layers, and an output layer. Figure 3 shows the structure of an MLP ANN. An MLP is appropriate when the relationship between input attributes and outputs are not clear [21]. In this article, an MLP is trained by a supervised learning algorithm using back-propagation.

2.4. MLP Training Algorithm

Back-propagation is the best-known learning algorithm for multi-layer training. It is an ANN method that can predict new data using learning and supervision of past data [36]. During the training phase, input data is presented to the ANN according to a certain ordination. All training data propagate forward to output, which is compared to the desired output. The comparison generates a value that determines the error used as feedback for connections, resulting in the adjustment of the synaptic weights of each layer in the opposite direction to the propagation of the training signals. MLP networks can predict performance and support managerial decision making regarding the definition of progressive performance goals in consecutive stages [37].

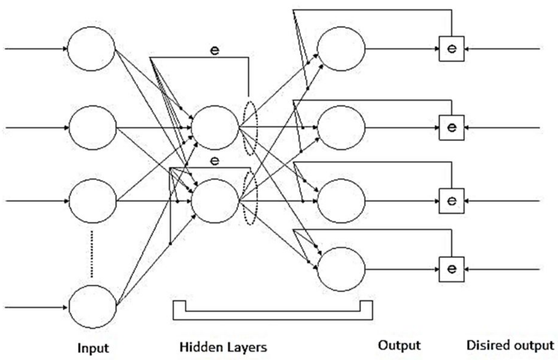

Figure 3. MLP network for weight adjustment [38].

The learning mechanism is an iterative sequential process that includes information feed-forward, error calculation, error back-propagation, and weight adjustment [37], [39]. The process is repeated until the first hidden layer is adjusted and the errors are back-propagated layer-by-layer with the corrections [40]. The learning rate should be comprised into limits, as it can cause instability if too high or too low [41], [42]. Free software packages can provide a basis for algorithms to make these simulations.

This article uses an open source project from the University of Waikato, the Waikato Environment for Knowledge Analysis (WEKA) [43]. WEKA is a machine learning environment that provides practical knowledge [44]. The tool is well-accepted in academic and business environments, justifying its success since 1992 [45].

3. Methodological Procedure: Five Stages

3.1. Survey Data

A survey of 34 companies in the slaughterhouse industry in Southern Brazil provided the data. Brazil is one of the largest meat producers in the world due to its favorable climate, territorial extension, investments in technology, and professional training, development of public policies, animal health control and food safety [46]. The industry generates 1,756 million direct jobs - more than 400 thousand of them in the refrigeration plants - totaling 4,155 million direct and indirect jobs. In 2015, exports reached 409.8 thousand tons of chicken meat until July, corresponding to circa 40% of global production. United States (28%), the European Union (9%), Thailand (4%) and China (4%) follows Brazil [47]. Islam [43] developed a similar work, based on a survey that aims to better understand how developing countries can increase the value derived from their fisheries resources.

However, the industry concerns on healthcare, environmental, and safety issues, that have motivated complaints by official entities. In recent years, the industry suffered with penalties that jeopardize competitivity [48]. The selection of Brazil can add new insights to the literature regarding emerging countries [50], [51]. Healthcare, environmental, and safety issues are emergent issues in studies on competition regarding the process industry [52], as well as the manufacturing [53] in developing countries.

MAUT has generated for each company a rate, which we call the Individual Competitiveness Rate (ICR) and serves as a basis for comparison between companies and to monitor the performance of each company. To establish the data necessary to calculate the ICR of the health and safety function of slaughterhouses, a decision tree was created, consisting of KPIs, CSFs, and FPVs. This decision tree assumes interdependence between the variables and allows calculating the replacement rates by the MAUT method.

KPIs correspond to the first level of the modeled decision tree. Therefore, a question was elaborated for each KPI, resulting in 33 questions on health and safety issues. Each question referred to the service level provided by the company to the described KPI, using a Likert scale with alternatives ranging from 1 to 4 (i.e., 1 = not attending, 2=attending a little, 3=attending and 4=completely attending). The Likert scale is 1-dimensional and considered one of the best-known methods for classifying opinions among a group of individuals [53].

Figure 4 shows the decision tree used for the calculation of the ICR.

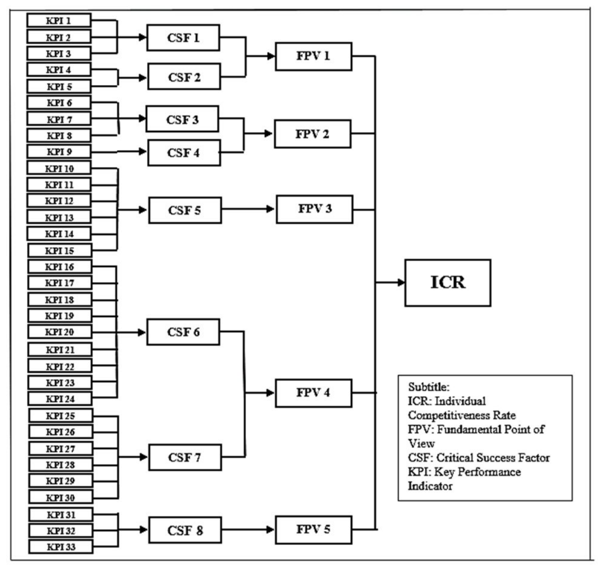

Figure 4. Initial Decision Tree.

3.2. Application of the MAUT method

To calculate an ICR for the health and safety issues of a slaughterhouse company using the proposed model, we shall calculate the individual replacement rates for KPIs, CSFs, and FPVs. Replacement rates are the values that quantify the respondents' preferences for each ICR and modeling level (i.e., KPIs, CSFs, and FPVs), according to Equations 4 and 5.

$$RR_{KPI} = \frac{KPI}{k} \tag{4}$$

Where:

RR_{KPI}: KPI replacement rate;

KPI: response value for KPI;

k: number of KPIs within the CSF.

$$RR_{CSF} = \sum_{1}^{n} RR_{KPI} * \frac{y}{w} \quad (5)$$

Where:
RR_{CSF}: CSF replacement rate;
n: number of CSF KPIs;
RR_{KPI}: KPIs replacement rate;
y: number of KPIs within the CSF;
w: number of KPIs within the FPV.

$$RR_{FPV} = \sum_{1}^{n} RR_{CSF} * \frac{w}{x} \quad (6)$$

Where:
RR_{FPV}: FPV replacement rate;
n: number of FPV CSFs;
w: number of KPIs within the FPV;
x: the total number of KPIs.

The Individual Replacement Rates of the FPVs allows obtaining the ICR of the companies (equation 7).

$$ICR = \sum_{1}^{n} RR_{FPV} \quad (7)$$

Where:
ICR: individual competitiveness rate;
RR_{FPV}: FPV replacement rate;
n: number of FPVs.

3.3. Application of the Neural Network

The data set obtained by the survey can be considered small to be applied to the neural network. Therefore, we need to maximize the training performance of the network.

The neural network was resolved using WEKA and the MLP algorithm. Using default mode, WEKA automatically selected the optimal number of hidden layers and nodes in each hidden layer. It also allows users to manually change the numbers of layers and nodes, as needed.

The input data for the neural network came from the survey KPIs; the network output attribute was the ICR value calculated for each company using the MAUT method. Thus, the modeling for the neural network consisted of 33 inputs and one output attribute, leaving the definition of the hidden layers for the WEKA to address. If a decision tree like the original proposal was used with the neural network, two hidden layers would be needed: one with 8 nodes and another with 5 nodes.

To solve these problems using neural networks, it is necessary to use one set of training data and another set for testing. In this article, the cross-validation mode, which simulates predictions of new objects by repeatedly dividing the original training dataset into training and validation objects [54] was used because the survey dataset was small to be divided into training and validation sets.

WEKA presents the results of neural network modeling in the form of weights and biases for each node. It uses the sigmoid function as the activation function. However, in cases where the modeled data have a linear behavior, the *S* values obtained via WEKA must be considered and modeled using a linear equation, as shown in Equation 9.

Therefore, to obtain the final mathematical equation for the network, we must make a correct arrangement of these constants (Equations 8 and 9). Figure 5 graphically represents the position of the weights and biases at each node, using a more simplified neural network with four inputs (i.e., x1, x2, x3, and x4), a hidden layer with two nodes (i.e., S1, S2), and one output (i.e., ICR):

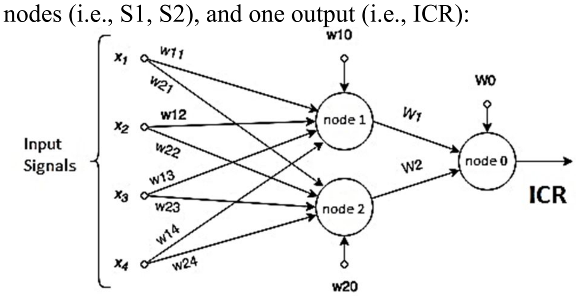

Figure 5. Representation of a neural network.

$$ICR = W0 + \sum_{1}^{n} W_n . S_n \quad (8)$$

Where:
ICR: Individual Competitiveness Rate obtained by the neural network;
W0: Linear Node 0 - Bias node 0;
W: Linear Node - Synaptic node weight;
S: Sigmoid Node - Result of S function.

For each node in the hidden layers of the neural network, the value of S is the result of the linear function described by S (equation 9):

$$S = w0 + \sum_{1}^{n} w_n . x_n \quad (9)$$

Where:
S: Sigmoid of the Node - the result of the linear function;
w0: Sigmoid Node 1 - Bias of node 1;
wn: Sigmoid Node n - Synaptic Weight of attribute xn;
xn: Values of x (KPIs).

The results obtained with the neural network equation were normalized between 0 and 1 and converted to the same scale of 1.0 to 4.0 of MAUT. When obtaining the equations corresponding to resolution, we also received the correlation coefficient and the equation error.

3.4. Optimization of KPIs

The reduction in the number of the KPIs necessary to achieve a similar response from the neural network was based on the gain of information that each KPI brought to the network. To obtain the gain of information, it was necessary to calculate the entropy, a measure of how uncertain the content of information is for a random variable [55]. Equation 10 shows the entropy calculation.

$$E\ (S) = \sum_{i-1}^{n} -p_i log_2(p_i) \qquad (10)$$

Where:
E (S): network entropy;
n: number of elements;
p: occurrence probability of the element p.

From the entropy concept, it is possible to calculate the gain of information for each KPI by equation 11.

$$G\ (S,A) = -E(S) - \sum_{Values\ (A)} \frac{|S_v|}{|S|} E(S_v) \qquad (11)$$

Where:
G (S, A): gain of information of the attribute A in function of the set S;
E (S): network entropy;
S_v: number of occurrences of element p in attribute A;
S: total number of occurrences in attribute A;
$E(S_v)$: individual element entropy.

The information gain is calculated, by WEKA, for each attribute, and the attribute with the highest information gain [56] is designated as the root node. After obtaining the gain provided by each KPI, tests are performed to reduce the number of KPIs used, keeping the error of less than 0.2.

3.5. Validation of KPI reduction

To validate the reduction of KPIs obtained from the neural network, ICRs were recalculated for each company using the MAUT method, establishing a new ranking for comparison. Thus, three rankings were obtained: the first by MAUT, the second using the neural network, and the third using MAUT with the optimized number of KPIs.

4. Results

4.1. MAUT method analysis

The initial research data submitted to MAUT analysis enabled the calculation of an ICR for each company that answered the survey. The ICR scale ranged from 1.0 to 4.0, according to the Likert Scale used in the survey, and the distribution of the KPIs in the decision tree presented in Figure 4 was used for the development of the calculations. Table 1 shows the ranking of companies. Company C28 obtained the highest ICR: 4.0. Company C21 obtained the lowest ICR: 2.545.

Table 1. Initial Ranking by MAUT method

Ranking	Company	ICR MAUT	Ranking	Company	ICR MAUT
1º	C28	4.000	18º	C9	3.121
2º	C01	3.636	19º	C23	3.091
3º	C18	3.545	20º	C10	3.061
4º	C30	3.455	21º	C15	3.061
5º	C04	3.424	22º	C3	3.000
6º	C06	3.394	23º	C26	2.970
7º	C12	3.333	24º	C7	2.939
8º	C20	3.273	25º	C29	2.939
9º	C32	3.242	26º	C17	2.909
10º	C33	3.242	27º	C34	2.909
11º	C16	3.242	28º	C22	2.818
12º	C14	3.182	29º	C24	2.758
13º	C11	3.182	30º	C2	2.727
14º	C13	3.182	31º	C31	2.667
15	C05	3.152	32º	C25	2.606
16º	C08	3.152	33º	C27	2.576
17º	C19	3.152	34º	C21	2.545

These rankings serve as the initial parameter. The MAUT results were used as input data for the neural network.

4.2. Manual analysis and parameterization of the neural network

In the first simulation, the decision tree solved by the neural networks presented itself differently from the initial decision tree. In the initial decision tree, each KPI exerted an influence on only one CSF; each CSF exerted influence only on one FPV, as seen in Figure 4. By proposing to optimize and validate this decision tree with neural networks, we obtained a model whereby each KPI exerts influence on all nodes of the hidden layer. Additionally, all nodes of the hidden layer influence the value of the ICR.
In the first simulation, the initial 33 KPI's were used, and the WEKA software was parameterized to consider two hidden layers, corresponding to the CSF and FPVs of the initial tree. That is, one layer had eight nodes and another layer had five nodes, with a learning rate of 0.3, and 500 iterations. Thus, the simulation presented a Pearson's correlation coefficient of 0.8327 and an error of 0.1898, according to WEKA.

4.3. Automatic analysis and parameterization of the neural network

In the second simulation, WEKA worked in automatic mode, with a learning rate of 0.3 and 500 iterations. Considering the 33 input KPIs, and the results of the ICR by the MAUT method as output parameters, WEKA presented a network with only one hidden layer with 17 nodes. Pearson's correlation coefficient, according to WEKA, increased from 0.8327 to 0.9393, and the error fell from 0.1898 to 0.1133. Pearson's product-moment correlation coefficient is a measure of the linear dependency between two random variables, where 0.9 indicates a very strong correlation [57].

4.4. The information gain calculation

After calculating the initial reference parameters, the information gain brought by the 33 KPIs for modeling by the neural network was calculated. This calculation was done by WEKA and so that we could verify how each KPI influenced the final ranking. The ranking of the KPIs by the gain of information is shown in Table 2:

Table 2. KPIs information gain ranking

Rank	KPI	Information Gain	Ranking	KPI	Information Gain
1º	KPI17	1.704 +/- 0.056	18º	KPI5	1.208 +/- 0.094
2º	KPI28	1.619 +/- 0.073	19º	KPI3	1.213 +/- 0.121
3º	KPI16	1.601 +/- 0.063	20º	KPI25	1.211 +/- 0.093
4º	KPI12	1.478 +/- 0.085	21º	KPI1	1.199 +/- 0.083
5º	KPI9	1.413 +/- 0.067	22º	KPI8	1.199 +/- 0.088
6º	KPI30	1.409 +/- 0.042	23º	KPI13	1.179 +/- 0.050
7º	KPI21	1.405 +/- 0.050	24º	KPI29	1.176 +/- 0.074
8º	KPI4	1.409 +/- 0.062	25º	KPI19	1.142 +/- 0.066
9º	KPI22	1.340 +/- 0.101	26º	KPI33	1.132 +/- 0.069
10º	KPI6	1.315 +/- 0.053	27º	KPI20	1.116 +/- 0.072
11º	KPI15	1.303 +/- 0.073	28º	KPI27	1.124 +/- 0.068
12º	KPI2	1.285 +/- 0.111	29º	KPI18	1.089 +/- 0.093
13º	KPI10	1.279 +/- 0.125	30º	KPI7	1.081 +/- 0.075
14º	KPI23	1.283 +/- 0.101	31º	KPI24	1.033 +/- 0.057
15	KPI14	1.234 +/- 0.091	32º	PI32	0.791 +/- 0.050
16º	KPI11	1.207 +/- 0.066	33º	KPI31	0.475 +/- 0.059
17º	KPI26	1.211 +/- 0.074			

In Table 2, it is possible to observe all the 33 KPIs and the respective information gain of each. With this data, it is possible to recalculate the neural network by removing the KPI's with less information gain and by observing that the error is not greater than the initial network.

4.5. Neural Network and Decision Tree Optimization

For optimization purposes, the last eight KPI's of the information gain ranking were removed from the neural network calculation. The margin of error given by WEKA was nearly the same: an error of 0.1545 against 0.1133 of the initial network. When removing more than eight KPI's, the error became greater than 0.2, stipulate limit for this search, making the network less than totally reliable.
Figure 6 presents the network obtained with WEKA in automatic mode. The network presents a learning rate of 0.3 and 500 iterations, with the 25 KPIs having the highest information gain as inputs, a hidden layer with 13 nodes, and the value of ICR as an output.

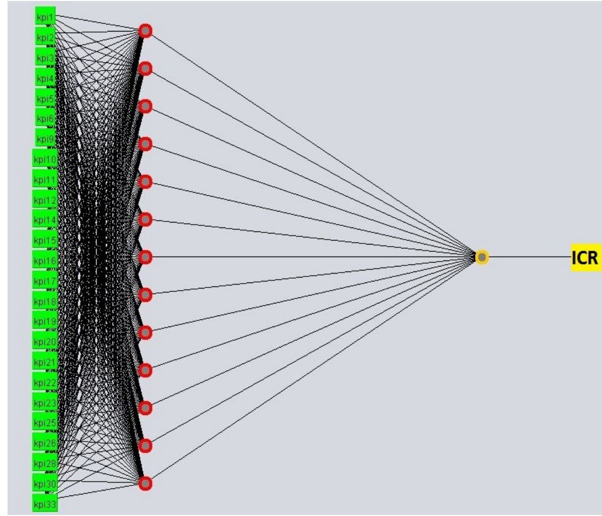

Figure 6. Perceptron Neural Network Decision Tree

Knowing the KPIs that can be removed without significantly changing the results of the companies' ICRs, the decision tree for the MAUT method can be redesigned, reducing the KPIs from 33 to 25. Figure 7 shows the reduced network.

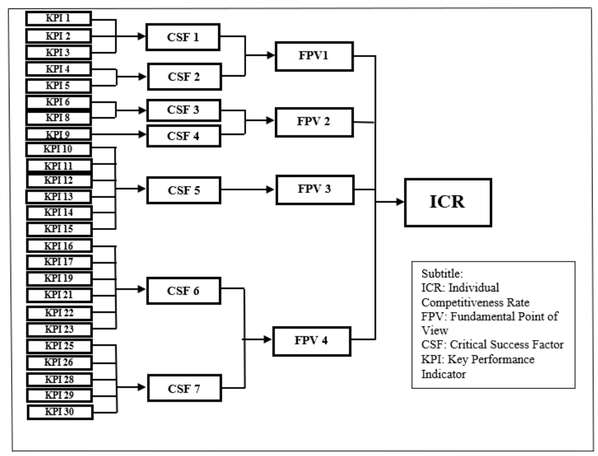

Figure 7. New Decision Tree

From the 25 KPIs with the greatest information gain, it is possible to simplify the decision tree and therefore increase its reliability. This implies that the control of KPIs in companies can be simplified and become more effective, contributing to increased competitiveness.

4.6. Compared Analysis

To corroborate the results, Figure 8 compares the three set of rates.

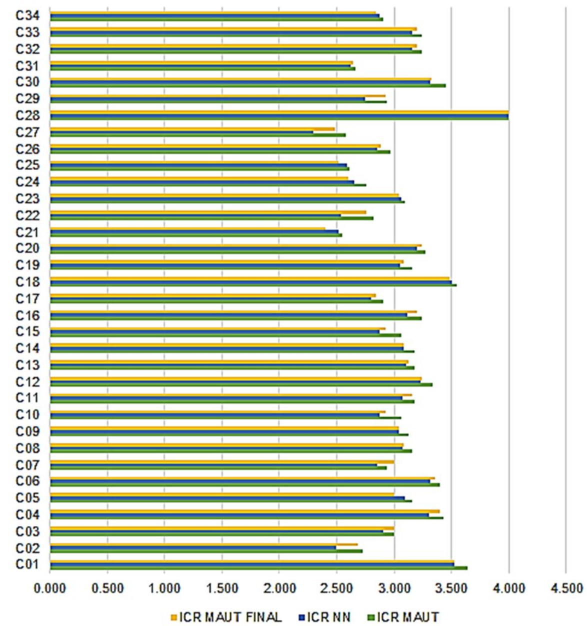

Figure 8. Comparison between ICRs

The standard deviation obtained between the ICRs calculated by the initial and final MAUT method was 0.3212, and the highest variation between the ICRs by the MAUT method was in Company 24, which initially had ICRs of 2.758 and, in the end, 2.600. When establishing a ranking of the companies that followed the two ICRs calculated by MAUT, the positions of 10 companies were the same, and the others changed one or two positions in relation to the initial calculation by MAUT.

5. Conclusion

The study ranked 34 companies according to 33 KPI's of competitiveness, comparing the results and concluding about the information that each method could provide. MAUT is a method of analysis used to rank variables already consolidated. However, with this work, it was feasible to show, with real data, that it is possible to refine the results and numerically present the error and the weight of the information. This was made possible through the application of neural networks. The initial results obtained by MAUT were used as the basis for the neural network calculations. Without these initial data as bases, the tests to arrive at the optimized decision tree would have been random.

By observing and comparing the proposed neural network with 25 KPIs and the new initial decision tree, each KPI influences all nodes of the hidden layer in the neural network. This is different from the decision tree used for resolution by the MAUT method, where each KPI influences only one CSF of one intermediate layer. Optimizing the decision tree, calculating of the obtained error, and ensuring precision are advantages of our neural network approach.

WEKA provided advantages, such as obtaining the equation for the calculation of the ICR of each company and the information gain each KPI brought to the modeling. It also made it possible to exclude and include variables reflected in the decision tree optimization.

Additionally, with neural networks, a company can focus on the KPIs that influence the results, thus facilitating improvements and avoiding improvements in areas that will not significantly increase competitiveness. Our future work will apply these procedures to other business areas to simplify monitoring and control via KPIs. Other multi-criteria analysis methods may be used as input parameters for neural networks. Additionally, in the future, we intend to refine error levels and training rates of neural networks in applications similar to those described this article.

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