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Application of the fuzzy logic in the employees' wage quantification process

Aplicação da lógica fuzzy no processo de quantificação salarial de funcionários

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ABSTRACT

Fuzzy Logic was introduced in 1965 by Lofti Zadeh and aims at the analysis of linguistic variables and membership functions, allowing a subjective interpretation than the classical logical-mathematical models. This contribution uses a Mamdani inference model in the hypothetical application of fuzzy logic in a decision-making process in a human resources department. The possibility of a company determining the employee's wages in the hiring step is considered. The characteristics to be observed are the age of the candidate, classifying him in one of the following generations, baby boomer, X, centennials (Y) and millennials (Z), in addition to his experience and qualification, in years. Then, 21 valuation rules are considered as well in this calculation. Finally, some simulations are presented, with different input values for some candidates and their respective salaries, showing that the implemented tool can be very useful, providing a result free from any personal judgment of the HR analyst.

Keywords: Fuzzy Logic, Decision Making, Human Resources, Strategic Management.

RESUMO

A Lógica Fuzzy, ou Lógica Nebulosa, foi introduzida em 1965 por Lofti Zadeh e visa a análise de variáveis linguísticas e conceitos de pertinência, permitindo uma interpretação mais subjetiva do que os modelos lógico-matemáticos clássicos. Este artigo aborda, sob a ótica de inferência proposta por Mamdani, uma aplicação hipotética da lógica nebulosa em um processo decisório de um departamento de recursos humanos. Considera-se a possibilidade de uma empresa determinar o valor salarial de funcionários em fase de contratação. As características a serem observadas são a idade do candidato, classificando-o em uma das seguintes gerações, baby boomer, X, centennials (Y) e millenials (Z), além de suas, experiência e a capacitação, em anos. São consideradas 21 regras de valoração que determinam o quantitativo salarial (variável de saída) correspondente a cada candidato, as quais são as variáveis de entrada para o problema. Por fim, são apresentadas algumas simulações, com valores diversos de entradas para alguns candidatos e os respectivos salários, mostrando que a ferramenta implementada pode ser muito útil, fornecendo um resultado isento de qualquer julgamento pessoal do analista de RH.

Palavras-chave: Lógica Nebulosa, Processo Decisório, Recursos Humanos, Gestão Estratégica.

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1. INTRODUCTION

According to Rignel *et al* (2011), the principles of Fuzzy Logic were originally developed by Jan Lukasiewicz who, in 1920, worked with sets under an approach of degrees of pertinence allied to the concepts of Classical Logic. This idea supported Lofti A. Zadeh, in the 1960s, to publish for the first time a study on Fuzzy Logic.

Russ (1996) states that Zadeh assumed that many natural and commonplace rules could not be easily explained by users. As an example, for this observation, he cites the fact of touching a sponge over a sink, estimating how dry or wet it may be, without, however, quantifying how dry or wet. From this systematic approach it was possible to develop what is known today as Fuzzy Logic.

To make a parallel to Classical Logic, also known as Boolean Logic, which admits only true or false states, Fuzzy Logic deals with membership values that continuously vary between true or false, that is, between 0 (false) and 1 (real). According to Silva (2005), the membership value 0.5 represents a *half-truth* (or *half-false*), while 0.9 represents *almost true* and 0.1 represents *almost false*.

Meanwhile, probability theory dealt successfully in various areas of science, but when it came to complex problems where there is some uncertainty about the very design of the variables, it did not apply efficiently. At this point, it is necessary to make a counterpoint between the two areas: while probability theories deal with degrees of uncertainty and variability, fuzzy theories deal with aspects of subjectivity. To understand the difference, one can cite a vehicle that travels with an average speed, varying within a speed range. Despite the variability, the values are known. On the other hand, if measuring devices are not available, subjective and perceptual concepts of *very fast* and *fast* can be useful in modeling. Thus, the fuzzy theory allows, even if the quantitative values are not available, the elaboration of a model is possible. This even allows several systems that could not be built because they are abstract concepts, to be implemented.

In everyday life it is not uncommon to come across terms that facilitate the understanding of Fuzzy terms. For example, “the patient's health status is stable”, or “the task is partially completed”, indicate Fuzzy structures through the words “stable” and “partially”, as they are terms that quantify subjectively. Other terms that can be considered Fuzzy are "small", "dirty", "strong" or "weak", as they admit an implicit subjectivity, because, in traditional logic, it is difficult to establish a limit that considers how small, dirty, strong or weak (Klir, 1997).

Thus, according to Mukaidono (2001), an example of a fuzzy problem would be a variable *middle age* that starts at 35 years and ends at 55 years. By traditional logic, a 34-year-old can only belong to this middle-aged group after completing his 35th birthday, and a 56-year-old is not middle-aged. To clarify this issue of belonging and differentiation between the two approaches, Figure 1 presents a comparison between the definition of middle age in a conventional set and a Fuzzy set. The degree of belonging of a 25-year-old to the middle-aged group is much lower than that of a 45-year-old.

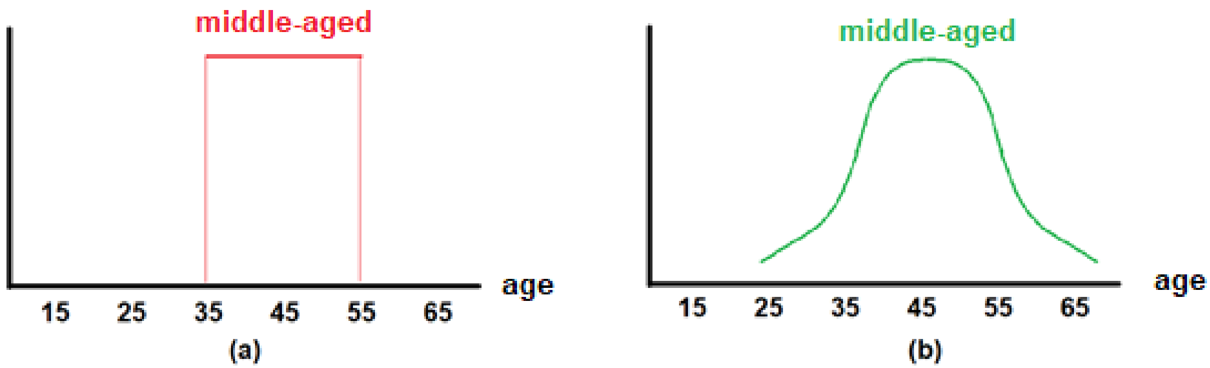

Figure 1. Middle-aged definition: a) conventional set; b) fuzzy set.

According to Wagner (2003), Fuzzy Logic facilitates the capture of subjective information, usually described in natural language, converting them into a mathematical model that can be properly manipulated. These possibilities allow, for example, the construction of fault monitoring systems considering extremely subjective aspects, as seen in BARELLA *et al.* (2019) and FREITAS *et al.* (2021).

Rignel, *et. al* (2011) describes that in classical logic a given element of the universe under consideration can only belong or not to a given set of this universe itself. However, Fuzzy sets allow each element to be determined a degree of (subjective) membership for a given set. In this way, there is not a limit that defines how a person is categorically low-income or high-income, being able to assume a certain low-income characteristic, and somewhat high-income, carrying the subjective characteristic of the evaluated context, not allocating it in a given set. at the expense of another.

Thus, in order to use Fuzzy Logic, two concepts are important to define: linguistic variable and membership function. According to Gonçalves (2007), a linguistic variable is one whose values assume the characteristics of Fuzzy sets and its function is to provide a systematization to approach complex or poorly defined phenomena. As an example, here the linguistic variable Professional Experience will assume the subjective values LITTLE, AVERAGE or A LOT (Figure 2).

Figure 2. Linguistic variable Professional Experience with fuzzy sets.

For Sandri (1999), the values for a linguistic variable can be sentences in a specific language, constructed from proper terms (little, medium, a lot, weak, strong, etc.), from logical connectives (not, and, or, etc), modifiers (a lot, a little, etc) and limiters.

The membership functions represent the degree of truth of a variable, but they can take different forms depending on the context in which they are inserted (Gonçalves, 2007). As an example, considering the linguistic variable Professional Training (in the range 0 to 15 years), it can assume the terms WEAK, AVERAGE and STRONG. Considering the subintervals for the terms, respectively, [0-5], [2-13] and [10-15] the membership function evaluates when a given corresponds to each of these intervals (Figure 3).

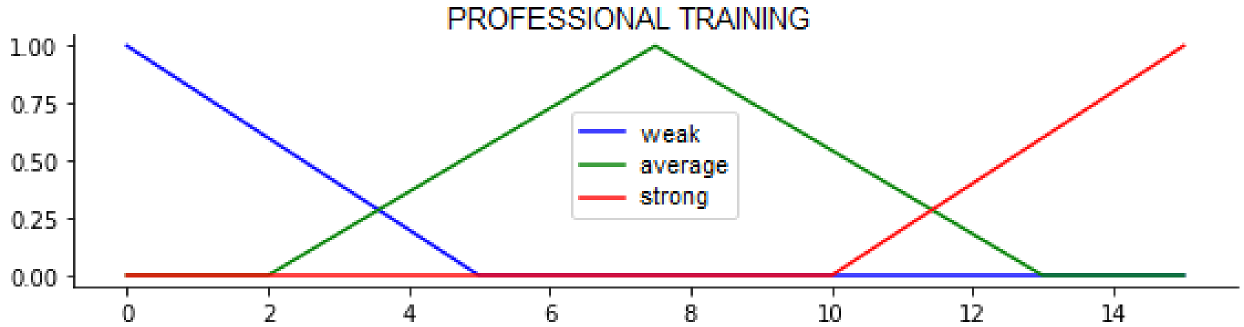

Figure 3. Linguistic variable Professional Training with fuzzy sets.

Thus, a person with one year of professional training has a membership function equal to 1 in the WEAK set, while this value decreases as time increases. A person with seven years of professional training is completely part of the AVERAGE set. Also, a person with

12 years of professional training has a small membership function in the STRONG set, but a person in the 14-year condition is considered totally and solely belonging to the STRONG set.

As previously contextualized, a subjective condition occurs when the individual needs to make a judgment so that the result is impartial. Even trying to be exempt in the decision-making process, some kind of bias can occur due to human factors.

In this way, this study aims to understand, through a hypothetical and simulated analysis, the determinations about the employee wage amount of candidates for a job position, based on three input variables: professional experience, professional training, and the candidate's age.

The entire decision-making process is driven by the application of Fuzzy Logic, through 21 previously defined weighting rules that will determine the salary of each employee who can be hired.

2. HUMAN RESOURCES MODELING

As previously presented, three input variables are considered, which were established according to the authors' experience and a local headhunter.

Professional Experience (x_exp) is defined in the range between 0 and 30 years, where 0 means that the candidate has no experience and 30 years represents the maximum experience considered in the career. In this field, previous jobs duly proven in the curriculum are considered.

Professional Training (x_cap) was defined in the range between 0 and 15 years, where similarly, 0 and 15 years correspond, respectively, to no training, and in the specific case, the counting of years of training is scored up to a maximum of 15 years. In this case, any courses, mini-courses, undergraduation, high school, etc. completed by the candidate are considered Professional Training. Only completion of primary education is considered 0.

The last input variable is based on the classification of generations, computed by the candidate's date of birth, considering 18 years as the minimum age and 75 years as the maximum age for hiring. These generations are called Baby Boomers for those born between 1945 and 1964, Generation X for those born between 1965 and 1984, Generation Y (centennials) for those born between 1985 and 1999, and Generation Z (millennials) for those born after 2000.

In this modeling step, it is necessary to divide the input variables, called linguistic variables, into their respective Fuzzy sets. This segmentation is performed considering the analyst's understanding of the characteristics of each subset.

In the case of Professional Experience, three subintervals are considered, LITTLE (exp_L), AVERAGE (exp_A) and A LOT (exp_H), as illustrated in Figure 2.

In the case of Professional Training, three subintervals are also considered, WEAK (cap_W), AVERAGE (cap_A) and STRONG (cap_S), as also already illustrated in Figure 3.

It was chosen for the age variable to use a concept of cultural generations due to the striking characteristics between the groups instead of the direct use of age. This feature provides heterogeneous Fuzzy sets ensuring similar behavioral profiles as well as facilitating the application of Fuzzy rules. The Generation variable took into account the Baby Boomers (ger_B), Generation X (ger_X), Generation Y (ger_Y) and Generation Z (ger_Z) denominations. However, to guarantee a flexible margin for the classification of the individual in a generation, two years were extended up and down in each generation group. For example, an individual is said to be Generation X if they are between 35 and 55 years of age. However, here the partition of the Fuzzy set considered the interval from 35 to 57 years for this generation (Figure 4).

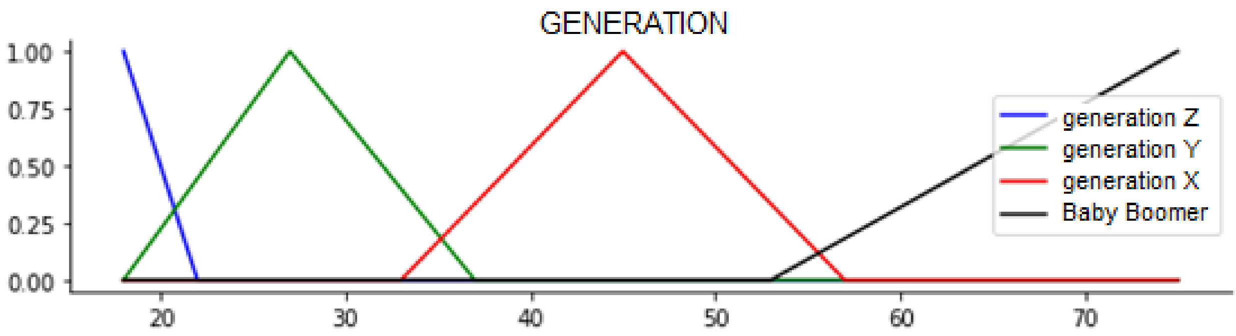

Figure 4. Linguistic variable Generation with fuzzy sets.

The output variable of the Fuzzy model, the employee's monthly wage varies from 1,000.00 to 5,000.00 BRL. This range was segmented into five Fuzzy sets called “very low” (sal_LL), “low” (sal_L), “medium” (sal_M), “high” (sal_H) and “very high” (sal_HH), as shown in Figure 5. It is important to mention that, like the input parameters, the salary values were established after consulting a local headhunter for a specific job position.

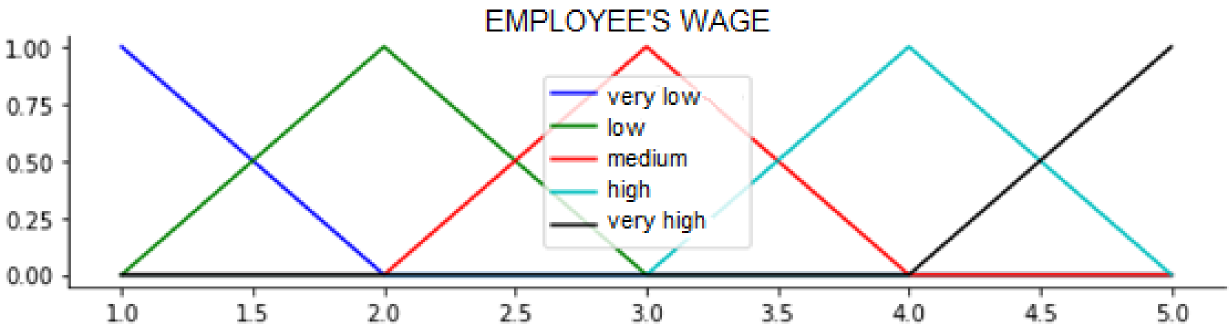

Figure 5. Linguistic variable Employee’s Wage with fuzzy sets.

As the intervals and their sets are defined, it is necessary to define the shape of the fuzzy sets, that is, the geometry of the area where the sets are included. The format of Fuzzy sets can be homogeneous or not, both in shape and scale. The most common shapes for each set are triangular, trapezoidal, unit impulse, stepwise, gaussian, or sigmoid.

In this model, all fuzzy sets adopted were triangular. The disadvantage of triangular sets is that it reaches its maximum truth value for only a single point, being more conservative. However, it is one of the most chosen forms for works in which more precise statistical information is not available for the well-delimited survey of fuzzy sets. Since the model built was based on only tacit knowledge of a professional in the field, and not on industry statistics, this type was chosen. Just clarifying the overlap of the sets, when looking at Figure 3, a candidate who has 11 years of Professional Training would have an assessment considered as AVERAGE and also as STRONG. In this way, the membership function weight via fuzzy logic, by a given proportion of inclusion in each of these sets to be considered.

After the fuzzification step of the input parameters, it is necessary to apply the fuzzy ruleset. In this step it is necessary to determine the rules of the decision-making process of the system. The rules here are constructed in the form *IF <condition1> AND <condition2> THEN <conclusion>*. The conclusion indicates the set to which the output variable belongs, within the fuzzy sets of this variable.

It can be noted that the greater the number of rules, the more difficult it is to know if they are adequate for the problem due to simultaneous iteration in the answer. Thus, the system must be calibrated in such a way that adequate responses are obtained during a test period. In this adjustment, the number of fuzzy sets per linguistic variables, their shapes and limits must be considered.

Once the membership functions and rules were defined, the fuzzy inference system was implemented via Python language, using the Maximum of Maximums method for the additive conjunction of the rules and the defuzzification was performed by the Centroid method.

The 21 fuzzy system rules used for inference are described in Table 1.

Table 1. Fuzzy rules for the model.

#	Fuzzy Rules
1	IF professional training is WEAK AND the professional experience LITTLE THEN the salary is VERY LOW
2	IF professional training is WEAK AND the professional experience AVERAGE THEN the salary is LOW
3	IF professional training is WEAK AND the professional experience A LOT THEN the salary is MEDIUM
4	IF professional training is AVERAGE AND the professional experience LITTLE THEN the salary is LOW
5	IF professional training is AVERAGE AND the professional experience AVERAGE THEN the salary is MEDIUM
6	IF professional training is AVERAGE AND the professional experience A LOT THEN the salary is HIGH
7	IF professional training is STRONG AND the professional experience LITTLE THEN the salary is MEDIUM
8	IF professional training is STRONG AND the professional experience AVERAGE THEN the salary is HIGH
9	IF professional training is STRONG AND the professional experience A LOT THEN the salary is VERY HIGH
10	IF professional training is WEAK and generation is B THEN salary is LOW
11	IF professional training is WEAK and generation is X THEN salary is VERY LOW
12	IF professional training is WEAK and generation is Y THEN salary is VERY LOW

13	IF professional training is WEAK and generation is Z THEN salary is LOW
14	IF professional training is AVERAGE and generation is B THEN salary is MEDIUM
15	IF professional training is AVERAGE and generation is X THEN salary is LOW
16	IF professional training is AVERAGE and generation is Y THEN salary is LOW
17	IF professional training is AVERAGE and generation is Z THEN salary is MEDIUM
18	IF professional training is STRONG and generation is B THEN salary is HIGH
19	IF professional training is STRONG and generation is X THEN salary is MEDIUM
20	IF professional training is STRONG and generation is Y THEN salary is MEDIUM
21	IF professional training is STRONG and generation is Z THEN salary is HIGH

3. RESULTS

With the problem implemented, with the fuzzy sets and the rules defined, the results of three simulations are presented. First, all candidates with random input variables are considered. For defuzzification step, the Mean of Maximum function was used for all cases.

Candidate A has 15 years of professional experience, 11 years of professional training and 34 years of age. The linguistic output and the inference of the membership functions are shown in Figure 6 and 7.

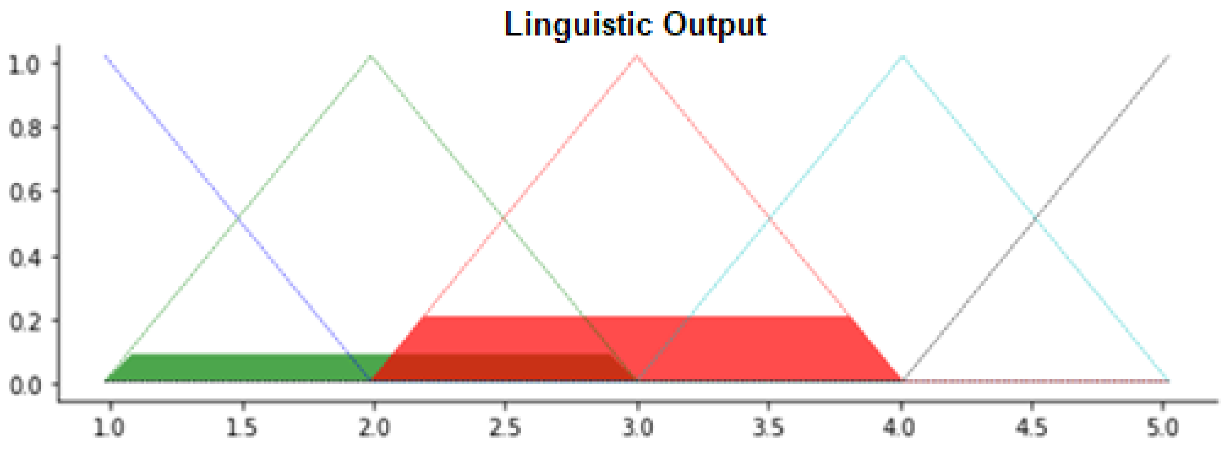

Figure 6. Linguistic output variable for Candidate A - Employee’s Wage.

As can be seen, the combination of the input parameters and the fuzzy rules, returned the sets LOW and MEDIUM for the output parameter. A real value is then calculated based on the centroid of the shapes, as shown in Figure 7.

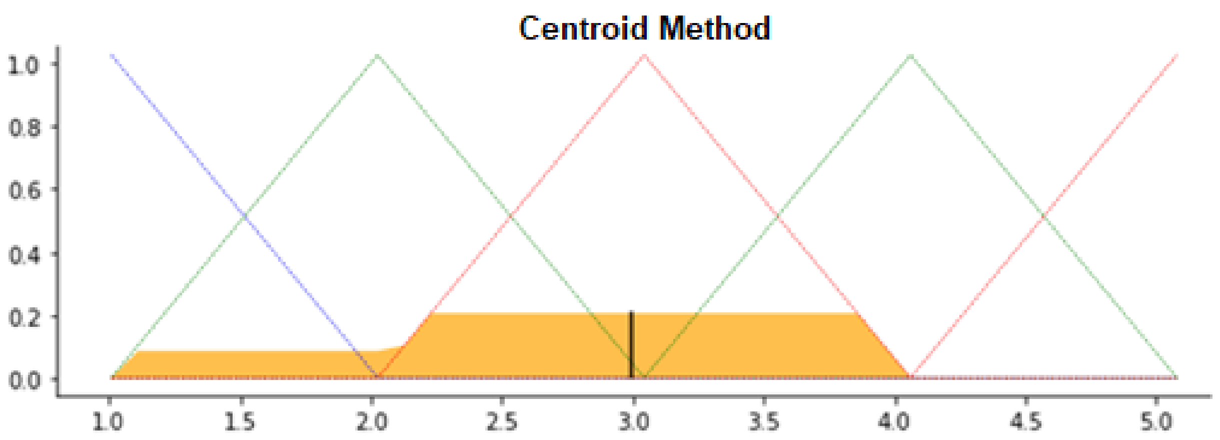

Figure 7. Centroid of the linguistic output variable for Candidate A.

As can be seen with the black bar indicating the centroid of the resulting figure, the employee's monthly wage is 2,950.00 BRL.

For a second example, candidate B has 5 years of professional experience, 10 years of professional training, and 45 years of age. The linguistic output and the inference of the membership functions are shown in Figure 8 and 9.

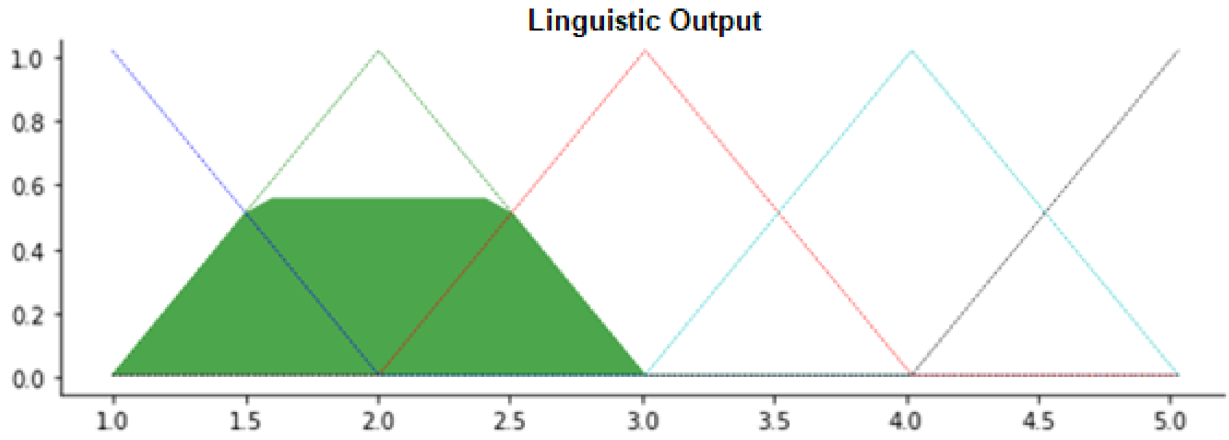

Figure 8. Linguistic output variable for Candidate B - Employee’s Wage.

As can be observed, the combination of the input parameters and the fuzzy rules returned only the set LOW for the output parameter. The real value is then calculated based on the centroid of this only set, as shown in Figure 9.

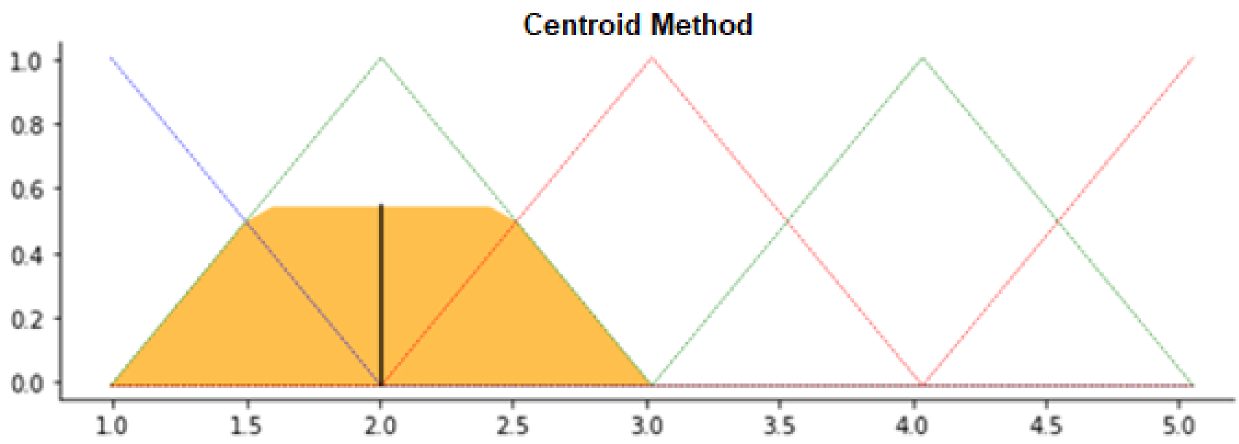

Figure 9. Centroid of the linguistic output variable for Candidate B.

As can be observed with the black bar indicating the centroid of the figure, the employee's monthly wage is 2,000.00 BRL.

Finally, candidate C has 24 years of professional experience, 3 years of professional training and 55 years of age. The linguistic output and the inference of the membership functions are shown in Figure 10 and 11.

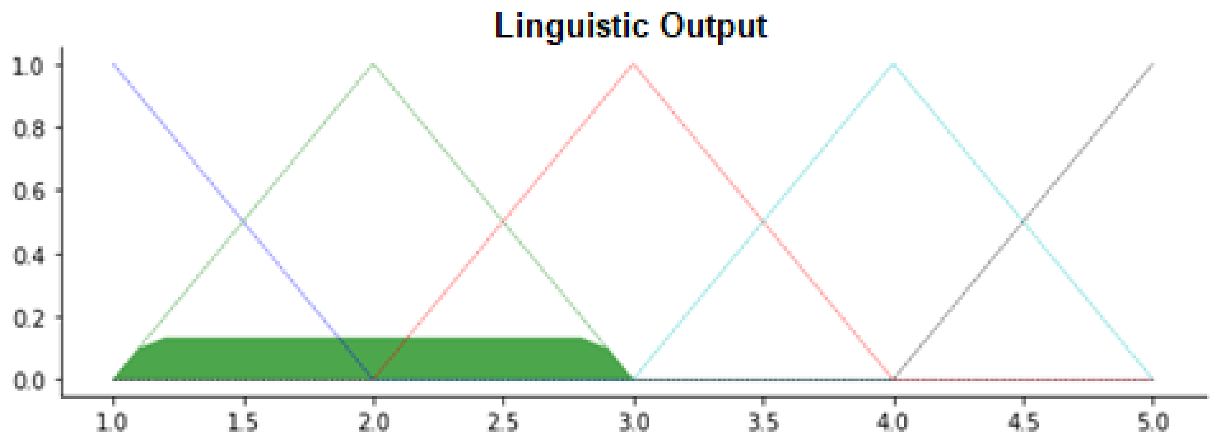

Figure 10. Linguistic output variable for Candidate C - Employee’s Wage.

As can be observed again, the combination of the input parameters and the fuzzy rules returned only the set LOW for the output parameter. The real value is then calculated based on the centroid of this only set, as shown in Figure 11.

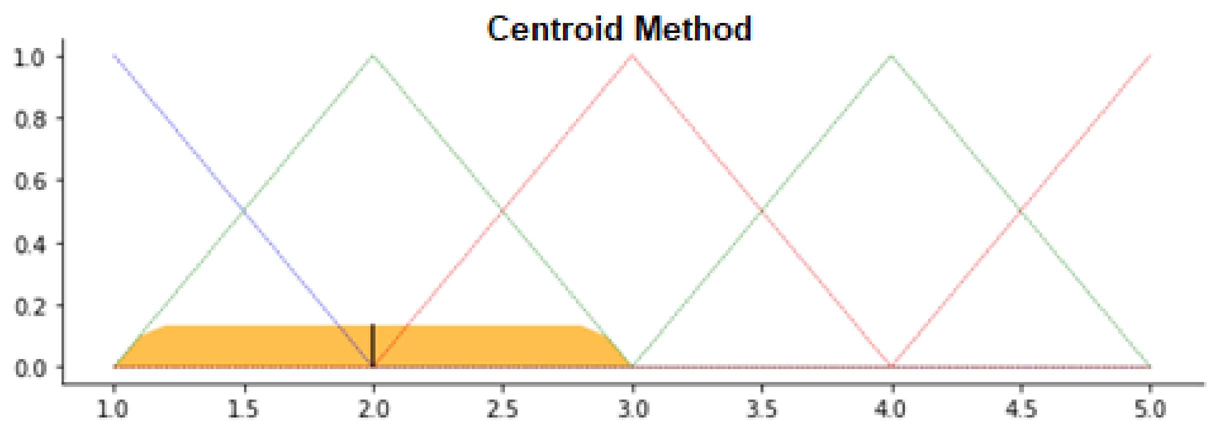

Figure 11. Centroid of the linguistic output variable for Candidate C.

This time the black bar has indicated the centroid of the figure at the same point, meaning the employee's monthly wage is 2,000.00 BRL.

In another simulation round configuration, three candidates were considered, but with the same age and professional training: 38 years old and 11 years old. However, different professional experience was considered: 4, 11 and 26 years. These results are presented in Table 2 considering the Mean of Maximum as defuzzification method.

Table 2. Simulation round with professional experience variation.

Professional Experience (years)	Professional Training (years)	Age (years)	Employee's Monthly Wage (BRL)
4	11	38	2,000.00
11	11	38	2,000,00
26	11	38	2,000.00

As can be seen, the applied rule set returns the same value for the three candidate conditions. To avoid this effect, an interesting situation was observed, because, in the defuzzification process, if the centroid function is used instead of Mean of Maximum, the salary value changes considerably to 2,593.56 BRL for the candidate with 26 years of experience. For the other cases, there was no change in the result. This aspect can be illustrated in Figures 12 and 13.

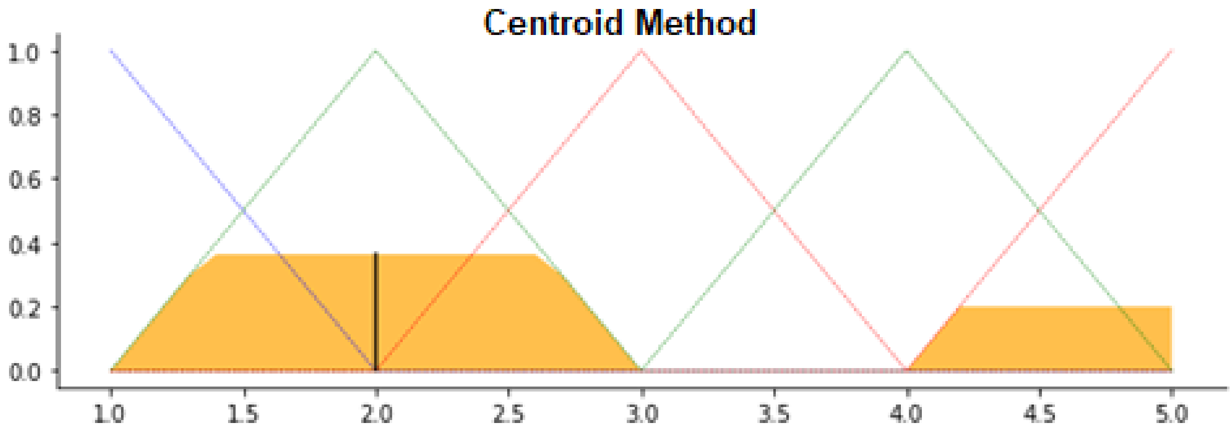

Figure 12. Candidate with 26 years of experience - Mean of Maximum method.

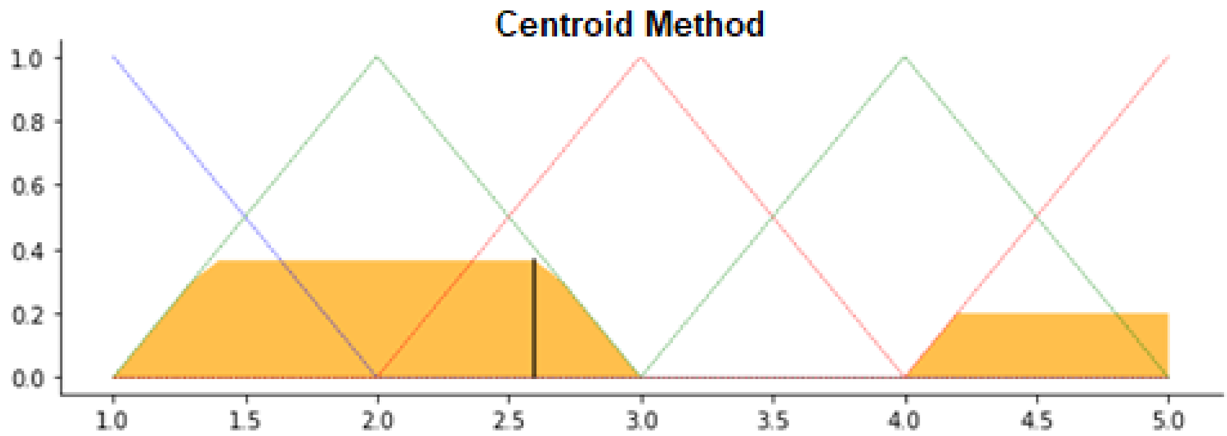

Figure 13. Candidate with 26 years of experience – Centroid method.

Subsequent test runs were used the Centroid method for the defuzzification process.

In another simulation round, also considering three candidates, candidates with the same professional experience and age were evaluated: 11 years of experience and 38 years. However, with different training time: 3, 9 and 14 years. The results are shown in Table 2.

Table 3. Simulation round with professional training variation.

Professional Experience (years)	Professional Training (years)	Age (years)	Employee's Monthly Wage (BRL)
11	3	38	2,000.00
11	9	38	2,000.00
11	14	38	3,000.00

In a last round of simulation, four candidates with the same professional experience and professional training were considered: 11 years in both. However, in this case the ages are different: 22, 35, 55 and 65 years old. The results are presented in Table 4.

Table 3. Simulation round with Age variation.

Professional Experience (years)	Professional Training (years)	Age (years)	Employee's Monthly Wage (BRL)
11	11	22	2,950.00
11	11	35	2,950.00
11	11	55	2,000.00
11	11	65	3,000.00

4. DISCUSSION

With the results obtained during the test rounds, it is possible to understand the need for calibration of the functions and methods used. Although fuzzy systems have the ability to model subjective aspects, their flexibility in defining fuzzy sets in different forms, homogeneous or heterogeneous, can build unrealistic solutions. Likewise, this combination with the defuzzification rules can further amplify a result for inappropriate solutions. Finally, it is important to analyze, evaluate and reevaluate constantly throughout the use of the fuzzy system, the set of inference rules. This set of rules is generally built based on the tacit knowledge of the analysts, and may cover only a part of the model's coverage domain. Thus, during the test rounds, it is necessary to evaluate the wide possibility of conditions that the model that will be put into use is exposed to.

By the trial-and-error process for the best combination of the output results in relation to the defuzzification method, the Centroid method was adopted.

Then, the first round of tests was performed again, showing no significant changes, indicating that the optimal conditions of the model were found for its use.

5. CONCLUSIONS

In this contribution, a possibility of application in fuzzy logic was presented for a human resources department to define employee salaries. The input variables of the model presented are the candidate's age, experience and professional trainings. For age, the classification by generations was used: baby boomer, X, centennials (Y) and millennials (Z) due to cultural particularities. Altogether 21 fuzzy rules were used to perform the inference in determining the employee's monthly wage.

After implementing the model, several rounds of tests were performed, simulating results for hypothetical candidate cases. Data were compared, especially on the use of defuzzification functions from the Fuzzy library, which may vary the results found.

There are several fuzzification and defuzzification methods that can be used to obtain a suitable model for the system. Thus, this calibration process, adjusting the possible functions and test runs become essential. Examples of fuzzification functions include triangular, trapezoidal, gaussian, among others. In the work, the variation of the output result due to the defuzzification method was pointed out. Here, triangular functions were used in the definitions of the fuzzy sets, while the defuzzification method, after trial and error, was adjusted to the Centroid method. It is important to point out that there are several alternatives to this method, such as the Bisector, Mean of Maximum, Minimum of Maximum and Maximum of Maximum.

In conclusion, it is possible to understand that Fuzzy Logic is an important auxiliary tool in the decision-making process of subjective aspects, especially in human resources departments. However, the construction of the rules must be carefully evaluated, as well as the use of mathematical models of fuzzification and defuzzification that can significantly influence the results.

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