Uncertainty Resolution with Fuzzy Inference System Approach towards Stress, Anxiety, and Depression

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Abstract: - There is indisputable proof that stress, anxiety, and depression significantly and negatively impact people's well-being. Recently, problems with stress and sadness have frequently resulted in a variety of chronic health concerns or even mortality. It is important to remember that stress, anxiety, and depression are all dangerous and closely associated. According to a proverb, "Life is 10% what you experience and 90% how you respond to it." This suggests that how we react to and equally manage whatever happens to us depends on how we respond to it. Several unknowns make the condition more ambiguous, such as diverse symptoms and different underlying causes of health disorders. Fuzzy can benefit medical professionals, experts, hospitals, drugs, etc. by handling the ambiguity and uncertainty of such vast amounts of data on people in these circumstances. To solve so many ambiguities, gaps in knowledge, or imprecision, fuzzy logic is frequently used. The current experiment applies a fuzzy method with fuzzy logic in R to develop a fuzzy inference system for pattern identification and classification to increase performance. This focuses on creating a fuzzy rule foundation, model, and inference for the study of data related to stress, anxiety, and depression. The results show that using a fuzzy inference system for uncertainties aided in making decisions that could have resulted in more serious problems if not handled on time. This study should only be used to observe the symptoms and causes of stress, anxiety, and depression; it should not be used to treat the identified health problems. Hospitals are the best places to solve problems.

Key-Words: - Stress, Anxiety, Depression, Fuzzy Inference System, Fuzzy Inference Model, R

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1 Introduction

The impact of stress and anxiety on depression, or depression and anxiety on stress, is one of today's most pressing issues [1], [2]. According to information about stress, anxiety, and depression, stress and anxiety can lead to depression, and they can sometimes show and share the same symptoms. Stress and anxiety can hurt both physical and mental health, whereas depression is more harmful and has a significant negative impact on both physical and mental health. Stress and anxiety can make it difficult to maintain positive habits or coping strategies, while depression symptoms can be severe. Stress, anxiety, and depression can all have an impact on one's mood and irritability. They can also have an impact on appetite, sleeping habits, and the ability to concentrate [3].

To address this issue, medical practitioners must be able to make an informed decision about how stress, anxiety, and depression will be detected through symptoms and causes. As a result, we require a model that can handle this. To handle the situation, the researcher employs fuzzy logic or a fuzzy inference system.

Fuzzy logic is an effective method for mapping an input space to an output space [4]. The concept of fuzzy logic is easy to understand, the mathematical concepts that underpin fuzzy reasoning are very simple and easy to comprehend, fuzzy logic is very flexible, it has a tolerance for inaccurate data, and it is also based on natural language. A model based on fuzzy logic will be generated from a system that can predict the actual problem.

The researcher created a Fuzzy Inference System or a Fuzzy Inference Model to obtain more refined classification and patterns in data, as well as a specific impact value for uncertain data spread. Once established, fuzzy variables and rules can be easily seized and applied repeatedly to obtain further suitable and bug-free technical solutions.

Fuzzy rule-based systems use fuzzification, inference, and composition procedures to evaluate linguistic if-then rules. They produce fuzzy results which usually have to be converted into crisp output. To transform the fuzzy results into crisp, defuzzification is performed.

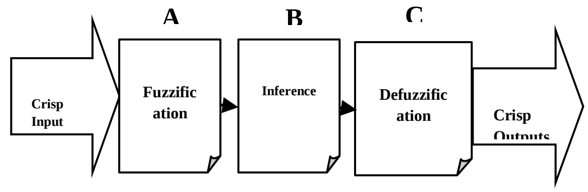

Fig. 1: A fuzzy Inference System Model

A. **Fuzzification** is the process of transforming measured input values into fuzzy membership functions. A membership function is a curve that defines how each point in the input space is assigned a membership value ranging from 0 to 1. Membership functions come in a variety of shapes, including triangular, trapezoidal, piecewise, Gaussian, bell-shaped, and others.
B. **Inference** is an if-then rules that can be used to infer multiple input and output variables. Because the rules are based on word descriptions rather than mathematical definitions, fuzzy logic can typically define any relationship that can be described with linguistic terms. This means that fuzzy logic can be used to describe and control nonlinear systems.
C. **Defuzzification** is the process of converting internal fuzzy output variables into crisp values that can be used. It is carried out after the inputs have been evaluated and applied to the rule base. Defuzzification frequently employs the centroid calculation method.

Fuzzy logic, originally conceived as a way to represent intrinsically vague or linguistic knowledge, is one of the research fields involving Artificial Intelligence - AI. It is based on fuzzy set mathematics. The combination of fuzzy logic and expert systems results in fuzzy inference. Other models frequently employ a large number of parameters, making modeling a difficult and time-consuming task. Fuzzy rule models are regarded as adequate tools for representing uncertainties and inaccuracies in knowledge and data. Without a precise quantitative analysis, these models can represent qualitative aspects of knowledge and human inference processes. There are at least five reasons why models based on fuzzy rules may be justified:

It includes:

1. They can be used to describe a wide range of nonlinear relations;
2. They are simple because they are based on a set of local simple models;
3. They can be interpreted verbally, making them similar to AI models;
4. They make use of information that other methods cannot, such as personal knowledge and experience.
5. The fuzzy approach has a significant advantage over other indices because it can expand and combine quantitative and qualitative data.

2 Related Literature

[5] presented an artificial intelligence approach for predicting different types of accidents in an uncertain environment (from fatal to minor). In the paper, author put those accidents in the workplace are a random phenomenon, but wise investment in various attributes such as health care, safety training, tool and machinery upgrades, and expenses on safety equipment and tools may lead to a reduction in the accident rate. The relationship between accident type and investment is difficult to establish because they do not adhere to any predictable rule and instead associate in a non-linear fashion. In such a case, fuzzy logic assisted in efficiently mapping inputs and outputs for the inference engine, allowing various types of accidents to be predicted. The prediction of various types of accidents assists managers in developing organizational policies to improve safety performance. As well [6] investigated how climate change and hydric stress were limiting clean water availability. Furthermore, stated that overexploitation of natural resources had resulted in environmental imbalance. They predicted that decisions regarding the management of hydric resources would have a significant impact on the economy and the future environment; they used indicators as a good alternative for evaluating environmental behaviour as well as a management tool, as long as the conceptual and structural parameters of the indicators were respected. The influence and consequences of environmental problems were studied using fuzzy logic. The need to combine different indicators was mentioned as one of the many reasons for using fuzzy logic in complex situations. The most significant advantage of using fuzzy logic to develop environmental indicators was that it combined different aspects with far more flexibility than other methods, such as binary indices of the type "acceptable vs. unacceptable."

[7] proposed a weather prediction model for testing that used a neural network and a fuzzy inference system (NFIS-WPM) to predict daily fuzzy precipitation given meteorological premises. The model was divided into two parts: the "fuzzy rule-based neural network," which simulated sequential relationships among fuzzy sets using an artificial neural network, and the "neural fuzzy inference system," which was based on the first part but could learn new fuzzy rules from previous ones using the algorithm they proposed. The model has been improved with NFIS-WPM (High Pro) and NFIS-WPM (Ave). When considering the benefits, it was well known that the need for accurate weather prediction was obvious. However, the overzealous pursuit of accuracy in weather

prediction renders some "accurate" prediction results meaningless, and the numerical prediction model was frequently complex and time-consuming. They made the predicted outcomes of precipitation more accurate and the prediction methods simpler by adapting the novel model to a precipitation prediction problem, which would occupy large computation resources, be time-consuming, and have a low predictive accuracy rate. In the end, they were able to produce more accurate predictive precipitation results than traditional artificial neural networks with low predictive accuracy.

[8] researched the use of fuzzy logic in solving production problems using the Tsukamoto and Sugeno methods. They resolved to determine the production of woven fabric when using three variables as input data in the study (stock, demand and inventory of production costs). The study consisted of four steps: solving the problem of woven fabric production using the Tsukamoto method, fuzzifying the input variable into a fuzzy set, processing the fuzzy set data with the maximum method, and defuzzifying the output into a firm set using a weighted average method. The Sugeno method solved the production problem almost identically to the Tsukamoto method; the only difference was that the system output was a constant or a linear equation rather than a fuzzy set. The distinction between the Tsukamoto Method and the Sugeno Method was based on the outcome. The results showed that the analysis's direct comparison with the original data in the company could conclude that the product obtained by processing data using the Tsukamoto method using the Weka rules was the method that was closest to the truth value.

In 2018, [9] conducted a study on performance appraisal, which was the systematic assessment of employees' performance to understand their abilities for future development. The approach adopted for the evaluation of teaching staff performance focuses on areas like Teaching, Learning, Extension, Research, Publication etc. which were fuzzy concepts that could be captured in fuzzy terms. Using MATLAB, a fuzzy inference system was created for teaching staff performance appraisal. The research developed the mappings from performance factors to incentives.

Also, [10] investigated three mathematical procedures for estimating the parameters of the weight-length relationship in Cichla monoculus: least squares ordinary regression on log-transformed data, non-linear estimation using raw data, and a combination of multivariate analysis and fuzzy logic. Their goal was to find a different approach that took into account the uncertainties inherent in this biological model. Non-linear estimation produced more consistent estimates than least squares regression. Their findings also showed that consistent estimates of the parameters could be obtained directly from the centres of mass of each cluster. The intervals obtained with the fuzzy inference system, however, were the most important result.

Similarly, [11] conducted research in which two simpler types of fuzzy inferences, triangular and trapezoidal fuzzy numbers, were combined with the centre of gravity defuzzification technique to develop two methods for assessing human skills. The applications of those two fuzzy numbers to assessing student skills and football player performance were presented, with their findings illustrated. The advantages and disadvantages of the two methods were also discussed leading to analogous conclusions about their usefulness. In the same vein, [12] discovered that the decision-making environment frequently encountered complexity during its processes, particularly in the context of multidisciplinary scientific research. They observed that the integration of fuzzy networks and Z-numbers was distinguished by their dependability and transparency mostly in engineering, computing, finance, astrology, and other fields. However, the method they proposed was unique and novel.

They used a fuzzy inference system because it provided some interesting insights into dealing with information reliability and transparency in a Z-hesitant fuzzy network decision-making environment; fuzzy networks have functionality under rule bases of fuzzy systems that were recognized by their transparency and precision. To assimilate decision information towards alternatives, the proposed method employed a fuzzy network with the incorporation of hesitant fuzzy sets. As a real-world problem for the validation and applicability of the proposed method, a case study of stock evaluation assessed by several decision-makers was used. The performance of the proposed method was assessed using Spearman's rho correlation. The results demonstrated that the proposed method outperformed the established method when additional dominant features were taken into account.

Recently, [13] investigated the COVID-19 Pandemic. Various parameters, such as different symptoms, existing health conditions, age, diagnosis level, and significant uncertainties, were used to make the condition more ambiguous. After implementing an experiment with a Fuzzy Inference System for pattern identification and classification using a fuzzy approach with Fuzzy Logic in R to improve performance. The purpose of the research was to create a Fuzzy Rule base, Model, and Inference for COVID-19 data analysis.

Table 1: Symptoms of stress, anxiety and depression

Serious	Difficulty breathing, Panic attacks, Blurred eyes sight or sore eyes, Sleep problems, Fatigue, Muscle aches and headaches, chest pains, high blood pressure, indigestions or heartburn, lingering low, Chronic fatigue, Sadness, Hopeless mood, more irritability, Feeling of guilty, Worthlessness, Helplessness, Restlessness, Pessimism, Loss of interest, Frequent anger
More_Serious	Nervousness, Fear, Irritability, Sense of dread, doom or panic, Persistent fatigue, brain fog, Headache, Muscle tension, Nausea, Diarrhea
Most_Serious	Emptiness, Changes in appetite and weight, Difficulty in concentration or making a decision, Thoughts of suicide, death or dying

Table 1 categorizes stress, anxiety, and depression symptoms into three categories: Serious, and More_Serious and Most_Serious. Based on the literature used by the researcher to compile and collate the information.

Table 2: Causes of Stress, Anxiety and Depression

Serious	1. Feeling under lots of pressure 2. Facing big challenges in life

	3. Having overwhelming responsibility 4. Having no control over the outcome of a situation 5. Working longer than normal time Financial problems
More_Serious	1. Taking alcohol and drugs 2. Consumption of caffeinated teas 3. Self-medication 4. Taking too many weights loss supplements
Most_Serious	1. Experiencing traumatic or stressful events 2. The death of a loved one 3. Having a medical problem 4. Having blood relatives who have had depression

Similar to how the information in table 2 categorized stress, anxiety, and depression causes into three categories: Serious, More_Serious and Most_Serious. In light of the literature, the researcher employed Serious, More_Serious and Most_Serious to gather and organize the data. The categorization is based on the causes' arrangements.

3 Materials and Methods

In this study, a fuzzy inference system with two inputs and one output was utilized to simulate stress, anxiety, and depression.

3.1 Analysis of Input Constraints or Parameters

Table 3: Parameters Assumption Case

Parameter Name	Parameter Type	Total Number of Membership Functions
Symptoms	Input	Serious, More_Serious, Most_Serious
Causes	Input	Serious, More_Serious, Most_Serious
Likely_Health_Challenge	Output	Stress, Anxiety, Depression

As shown in Table 3, it is suggested to construct the FIS (Fuzzy Inference System) with various two input parameters and one output parameter as a potential health challenge to be recognized in people.

3.2 Rule Analysis

Instead of a binary classification of likely health challenge testing as only common or not common, likely health challenge of stress, anxiety, and depression varies on a scale based on symptoms and causes values. As a result, as shown in table 4, some important input variables identified as constraints to designing the rule base are symptoms and causes to get output variable likely health challenge. Different input degree value mixtures result in different output variable, which reflects Stress, Anxiety and Depression.

Table 4: Knowledge Base

Symptoms	Causes	Likely_Health_Challenge
Serious	Serious	Stress
More_Serious	More_Serious	Anxiety
Most_Serious	Most_Serious	Depression

3.3 Need for fuzzy logic

Different blends of Symptoms and Causes input constructions were passed as input constraints to the fuzzy function of the designed knowledge base of the fuzzy model, which inferred inputs using the knowledge base designed in the model for fitness of membership. Membership Estimated to generate linguistic output, fitness and defuzzied value was used.

3.4 Rules:

If [Symptoms] is Serious && [Causes] is Serious, Then Likely_Health_Challenge is Stress

If [Symptoms] is Serious && [Causes] is More_Serious, Then Likely_Health_Challenge is Stress

If [Symptoms] is More_Serious && [Causes] is Serious, Then Likely_Health_Challenge is Stress

If [Symptoms] is Serious && [Causes] is Most_Serious, Then Likely_Health_Challenge is Anxiety

If [Symptoms] is More_Serious && [Causes] is More_Serious, Then Likely_Health_Challenge is Anxiety

If [Symptoms] is Most_Serious && [Causes] is Serious, Then Likely_Health_Challenge is Anxiety

If [Symptoms] is More_Serious && [Causes] is Most_Serious, Then Likely_Health_Challenge is Depression

If [Symptoms] is Most_Serious && [Causes] is More_Serious, Then Likely_Health_Challenge is Depression

If [Symptoms] is Most_Serious && [Causes] is Most_Serious, Then Likely_Health_Challenge is Depression

As input value passed accordingly membership fitness function was applied.

3.5 Variables:

Symptoms (Serious, More_Serious, Most_Serious)

Causes (Serious, More_Serious, Most_Serious)

Likely_Health_Challenge (Stress, Anxiety, Depression)

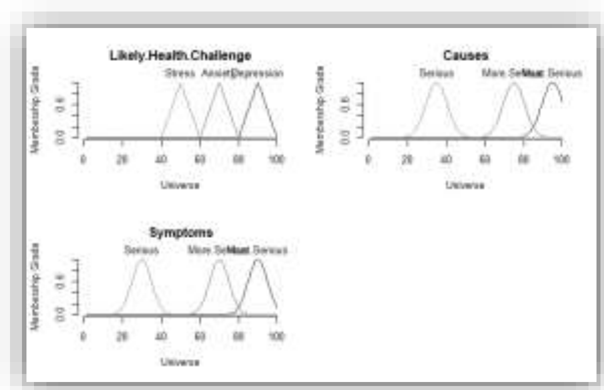

Fig.2: Model plot

The outcome of the plot in fig.2 showed the membership functions of the two inputs as well as the output. Symptoms showed Serious, More_Serious and Most_Serious members. Likewise, Causes showed the same members; finally, the output plot of Likely_Health_Challenge with Stress, Anxiety, and Depression members was shown.

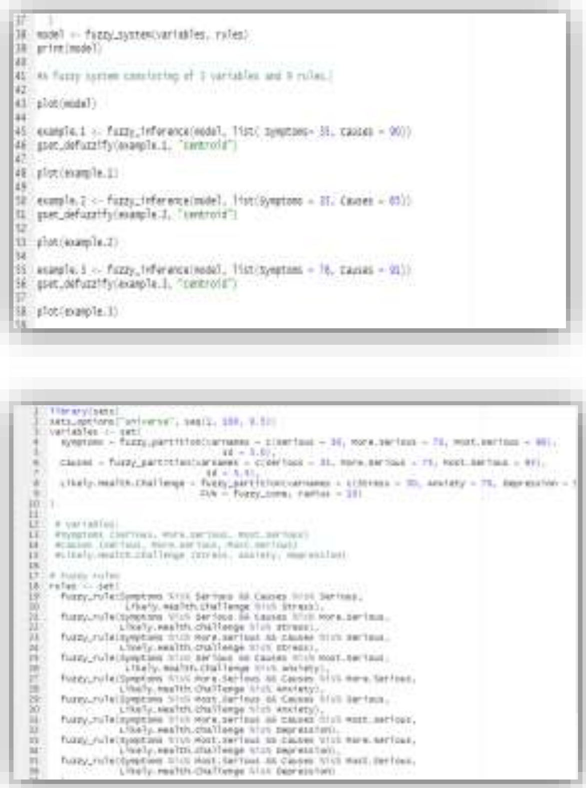

Fig.3: Screenshot of the r code

Fig.3 showed the coding of the model in R Language

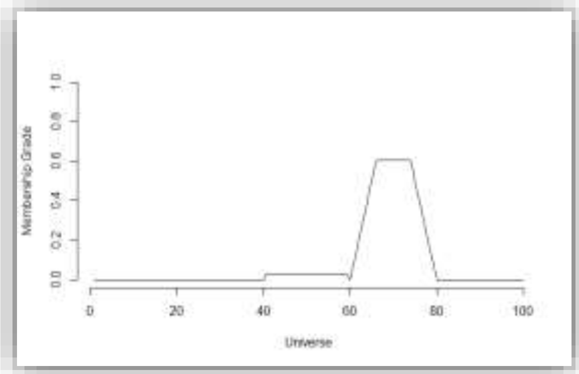

Fig.4: Example1 plot

Example1 plot from fig.4 was used to test/evaluate the model. When it was tested using the below code:

```
example.1 <- fuzzy_inference(model, list( Symptoms= 35, Causes = 90))

gset_defuzzify(example.1, "centroid")

plot(example.1)
```

The result of 68.93963 was given which was equivalent to deciding that the likely health challenge is Anxiety

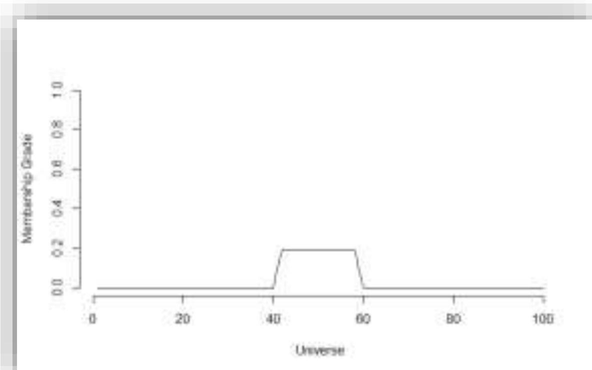

Fig.5: Example2 plot

Example2 plot from fig.5 was used to test/evaluate the model a second time. When it was tested using the below code:

```
example.2 <- fuzzy_inference(model, list(Symptoms = 35, Causes = 65))

gset_defuzzify(example.2, "centroid")

plot(example.2)
```

The result of 50.00004 was given which was equivalent to deciding that the likely health challenge is Stress

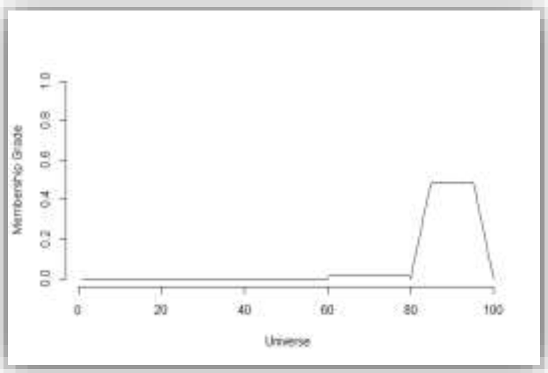

Fig.6: Example3 plot

Similarly, the Example3 plot from fig.6 was used to test/evaluate the model the third time. When it was tested using the below code:

```
example.3 <- fuzzy_inference(model, list(Symptoms = 76, Causes = 91))

gset_defuzzify(example.3, "centroid")

plot(example.3)
```

The result of 89.2586 was obtained which was equivalent to deciding that the likely health challenge is Depression

4 Results and Discussion:

Traditional approaches to dealing with uncertainty and solving such ambiguous problems include binary values (Boolean Logic) and general statistical measures of central tendency. It also has limitations in dealing with linguistic issues and estimations. Fuzzy logic is a multi-value solution for dealing with uncertainty with different partitions, sub-ranges, or interval classes. So Fuzzy can deal with linguistic variables by converting linguistic data to numeric classes and then back to linguistic data. This binary classification can be represented in binary form with 1 and 0. However, stress, anxiety, and depression cases cannot be treated and handled using the same set of treatment and care actions. People with stress symptoms can have a gradation between 0 and 1 as Serious, More_Serious and Most_Serious using fuzzy to infer cases using a classification rule set.

By dealing with incompleteness, imprecision, and incompleteness, fuzzy can produce a more precise set of values identifying its class. For this purpose, the investigator devised fuzzy ranges for degrees of membership to acquire resemblance through fuzzified patterns for a variety of input value degrees.

Initially, all relevant input parameters were studied, analysed, and identified as important factors influencing stress, anxiety, and depression. The identified parameters are pre-processed data with crisp results that were used to experiment with different machine-learning implementations and evolutions. As a result, Symptoms and Causes have been accepted as input constraints for fuzzy implementation. The researcher created these input constraints in the fuzzy model with different variable partitions, as in the case of the Symptoms constraint Serious, More_Serious, Most_Serious. Sub-ranges were denoted by the numbers 0, 0.50, and 1. Likewise, other constraints were classified for interval ranges marking to improve impact output variable classification from extreme outcomes to closely associated outcome classes. The degree of membership for input fitness for all different input parameters is validated in contradiction of the stated knowledge base or rule base for different combinations customized in model design.

The result of fuzzified inference was transformed to a specific value using centroid defuzzification. This specific outcome was divided into three categories for likely health challenge research: Serious, More_Serious, and Most_Serious. As a result, the fuzzy function accepts pre-processed input parameter values. This fuzzy model generates a fuzzy Output parameter that evaluates the likelihood of a health challenge.

Finally, there are some limitations to the current study. To begin, the study looked into uncertainty resolution using a Fuzzy Inference System Approach to Stress, Anxiety, and Depression. The study only applied to uncertainty, not to the treatment of any identified health problems. Second, the study only employed a fuzzy inference system. It might be worthwhile to replicate similar inquiries using a different approach in future studies.

5 Conclusion

The investigator investigated and developed a strategy for stress, anxiety, and depression data in the research work. Normalization, fuzzy classification for pattern and certainty analysis; graphical relative analysis, Coefficient of relationship which aided in analysis in form relevance analysis, classification, prioritization, and grouping to assist individuals in society in observing their health status once they experience any of the symptoms and causes and in decision making to advise relatives on necessary actions to be taken when such health challenges arise.

References:

[1] Cownley, Sarah (2021). How Stress and Depression Are Connected and the Strategy That Can Help You Cope, www.How Stress and Depression Are Connected and the Strategy That Can Help You Cope (belmarrahealth.com)

[2] Sharma, T; Banerjee, K; Mathur, S & Bali, V (2020). Stress Analysis Using Machine Learning Techniques. International Journal of Advanced Science and Technology, 29(3), 14654-14665

[3] Pingle, Y (2020). Evaluation of Mental Stress using Predictive Analysis. International Journal of Engineering Research & Technology (IJERT). NTASU -2020 Conference Proceedings

[4] Kusumadewi. S, Purnomo, H., Fuzzy Logic Application for Decision Supporters, Yogyakarta: Graha Ilmu, 2010.

[5] Beriha, G.S; Patnaik, B; Mahapatra S.S & Padhee, S (2011). Assessment of safety performance in Indian industries using fuzzy approach. Expert Systems with Applications (2011), doi:10.1016/j.eswa.2011.09.018

[6] Lermontov, André; Yokoyama, Lidia; Lermontov, Mihail & Machado, Maria Augusta Soares (2011).A Fuzzy Water Quality Index for Watershed Quality Analysis and Management, Environmental Management in Practice, 387-410

[7] Lu, Jing; Xue, Shengjun; Zhang, Xiakun; Zhang, Shuyu & Lu, Wanshun (2014). Neural Fuzzy Inference System-Based Weather

Prediction Model and Its Precipitation Predicting Experiment, Atmosphere 2014, doi:10.3390/atmos5040788

[8] Tundo & Enny Itje Sela (2018). Application of the Fuzzy Inference System Method to Predict The Number of Weaving Fabric Production, IJID International Journal on Informatics for Development, (1), 21-29

[9] Bhosale, G.A. & Kamath, R. S. (2013). Fuzzy Inference System for Teaching Staff Performance Appraisal, International Journal of Computer and Information Technology, 2(3), 381-385

[10] Bitar, S. D; Campos, C. P & Freitas, C. E. C (2016). Applying fuzzy logic to estimate the parameters of the length-weight relationship, http://dx.doi.org/10.1590/1519-6984.20014

[11] Voskoglou, Michael Gr(2018). Application of Fuzzy Numbers to Assessment of Human Skills, Punjab University Journal of Mathematics (ISSN 1016-2526), 50(2)(2018), 85-96

[12] Yaakob, Abdul Malek; Shafie, Shahira; Gegov, & Abdul Rahman, Alexander Siti Fatimah (2021). Z‑Hesitant Fuzzy Network Model with Reliability and Transparency of Information for Decision Systems, International Journal of Computational Intelligence Systems (2021) 14:176 https://doi.org/10.1007/s44196-021-00029-6

[13] Manisha Shinde-Pawar, Jagadish Patil, Alok Shah, Prasanna Rasal, Development of Fuzzy Inference System for Covid-19 Data Analysis, J Pharm Negative Results 2022;13: 693-699

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Muraina, Ismail O coined the title, collected the data and carried out the analysis and discussion.
Aiyegbusi, Edward A reviewed the literature and wrote the conclusive part of the manuscript. The final draft of the manuscript was read and collated by the authors.

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