ADAPTIVE NEURO-FUZZY MODEL FOR THE CONTROL SYSTEM OF THE CLINKER GRINDING PROCESS IN BALL MILLS IN CEMENT FACTORIES
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MODEL ADAPTIV NEURO-FUZZY PENTRU SISTEMUL DE CONTROL AL PROCESULUI DE MACINARE A CLINKERULUI IN MORILE CU BILE DIN FABRICILE DE CIMENT

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ABSTRACT
The main goal of this study was to create a model for the development of a decision support system for the cement grinding process in ball mills, including the data acquisition, processing and analysis subsystems, based on intelligent hardware and software technologies. The paper presents a model based on the techniques proposed and developed with the application of fuzzy logic and artificial neural networks. The simulation results of the proposed models in the Matlab environment are also presented. Testing and verification of data obtained with the proposed inference model were performed by comparing with experimental data.

REZUMAT
Scopul principal al acestui studiu a constat în realizarea unui model de dezvoltare a unui sistem suport de decizie pentru procesul de măcinare a cimentului în morile cu bile, inclusiv subsistemele de achiziție, prelucrare și analiză a datelor, bazate pe tehnologii hardware și software inteligente. Lucrarea prezintă un model bazat pe tehnicile propuse și dezvoltate cu aplicarea logicii fuzzy și a rețelelor neuronale artificiale. Sunt prezentate și rezultatele simulărilor modelelor propuse în mediul Matlab. Testarea și verificarea datelor obținute cu modelul de inferență propus au fost efectuate prin comparare cu datele experimentale.

INTRODUCTION
The realities are such that there are specific industrial processes that can be characterized by a certain degree of uncertainty in the decision-making process. The basic problem in the automation of industrial processes is the acquisition and structuring of data for the purpose of training intelligent systems. The procedure for training decision systems requires a fairly large volume of data, and the effectiveness of this training directly depends on the quality and quantity of data used. If, under the conditions of the continuous production process, the amount of acquired data is not a problem, then ensuring its quality depends directly on the qualification and experience of the human operator. It should be noted that specific industrial processes can be characterized by the variation of their parameters throughout the technological process. Thus, the task of intelligent decision-making systems consists in making decisions that would ensure the precision of the parameters of the production process within the limits specified by the quality requirements. Insufficient data on the state of the technological process can cause a drastic decrease in the accuracy of quality parameters.

The hypothetical-deductive methodology was used in the research works. The argumentation for the use of this method emerges from the experimental nature of the studied processes and from the possibility of experimental verification of the correctness of the hypotheses and assumptions formulated during the research process. As part of the research, the analysis of the collected statistical data was carried out, with the aim of generalizing the studied process. The elaborated researches are based on mathematical analysis, numerical methods, the theory of fuzzy sets, the theory of artificial neural networks, data acquisition techniques and the design of numerical circuits (*Amaral et al., 2022*).

The capacity of high-tech computer to process large amounts of data quickly provides researchers with a unique occasion to study problems that are too expensive, time consuming, or practically impossible to approach. In this way, researchers can obtain optimal answer that justify experimental reality within a reasonable amount of time. The term adaptive system refers to an interdependent system composed of interconnected entities that cooperate to adapt and self-organize to environmental conditions. Studies in the field of adaptive hardware architectures offer a variety of new solutions and means of addressing different problems related to the methods of organization and efficient operation of systems. The basis of adaptive hardware systems is the collaborative functional components or entities. The system adaptation process can be done through software or hardware. Software adaptation can generally be achieved through a functional change at the application level. Hardware adaptation, as opposed to software adaptation, represents a more profound change in the internal organization of the computing architecture of an embedded system.

Ciobanu and Scrieru, (*2016*), proposed the application of the fuzzy regulation method for the automated control of the wastewater treatment process. In order to obtain a quasi-optimal regulation, a classic PID controller was used and then the Fuzzy controller was implemented in which they were included in the rule base with compound premises, which reflect a situation composed of two variables that simultaneously act on the wastewater flow and its variation to determine the amount of recycled sludge. *Vikram*, (*2014*), presents the results of designing and analysing the functioning of one fuzzy logic control system on the compressor motor of the air conditioning system to control its speed. Analysis was performed using simulations in Simulink. The comparison with a classic bipositional model used in the experiments shows that the energy saved is significant, between 36.29 and 41% for different operating regimes. *Carbune V.,* (*2020*), presents some innovative solutions in the form of embedded hardware systems for use in the research and development of intelligent decision support systems. Intelligent, reconfigurable command and control solutions in the microwire casting process are presented, which have been designed as a flexible set of tools that can be reconfigured for new conditions or even new industrial processes. *Taylan and Karagözoglu,* (*2009*), present in their research a new approach in the design of a FIS based on neural networks to evaluate the school results of students. They mention that fuzzy systems have achieved admirable results in solving various classes of problems. The method they developed uses a neural network augmented fuzzy system to improve some of its characteristics, such as the ability to change or be changed easily according to the situation, rapidity and ability or willingness to change in order to suit different conditions, known as the adaptive inference system (ANFIS).

The aim of the work incorporate the development of new system for prospect the knowledge of the human expert, the development of adaptive neural network controller for the research of the process of making important choices and the construction of a computer program that can arrange and sort large amounts of data, and take important decisions based on the data in industrial applications. The following research objectives are derived from the proposed purpose: a) Examining of the general aspects of self-organizing neuro-fuzzy systems; b) Research, elaboration and growing or becoming stronger or more advanced of decision support procedure and rules under conditions of uncertainty; c) Designing adaptive hardware and software architectures for hybrid decision-making systems.

MATERIALS AND METHODS

Recent progress in the field of artificial intelligence and the optimization of computational software techniques have opened up new opportunities for researchers in the field. The learning methods are based on such paradigms of intelligent computing as: artificial neural networks, decision trees and neuro-fuzzy systems, which are successfully applied to solve various problems in different fields (*Amaral et al., 2022; Ciobanu and Scrieru, 2016; Vikram 2014; Cărbune, 2020; Taylan and Karagözoglu, 2009; Baqui, 2012*).

Since cement crushing systems are nonlinear and time-varying MIMO (Multiple Input Multiple Output) systems, fuzzy logic controllers appear to be in the greatest measure the choices for controlling these. By the same token, considering the human perception of the composition and dimensions of the material is vague and subjective, the theory of fuzzy logic is well suited to describe it linguistically according to the state of the variables dependent on the mineral composition.

The knowledge inference mechanism is the basic element of an expert system that ensures the knowledge process by applying reasoning rules and strategies on the basis of facts. Knowledge is based on three fundamental concepts *(Stefenon et al., 2020; Taylan, 2006)*:

1. Facts – represent primary information that describes the elements of the domain;
2. Rules – describe how facts can be used;

3. Reasoning strategies – describe how the rules can be used.

Knowledge processing involves the definition of storage structures and processing methods, which ensure the realization of reasoning. As a result, specific structures are used for the storage and use of knowledge *(Lin and Lee, 1991).*

The inference mechanism in a fuzzy system consists of three stages. In the first step, the numerical values of the inputs are mapped by a membership function according to the degree of membership in the respective fuzzy sets. This operation is called fuzzification. In the second step, the fuzzy system evaluates the inference rules according to the weights of the inputs. In the third step, the resulting fuzzy values are transformed back into numerical values. The given operation is called defuzzification (*Ciobanu and Scrieru, 2016; Carbune, 2020; Taylan and Karagözoglu, 2009; Freksa, 1994; uk.mathworks.com*).

A fuzzy logic way is used to achieve the desired set of rules based on the input and output data sets and the membership functions. To generate the ANFIS structure, we need to specify the cluster radius, which indicates the extent of influence of the cluster. Consider a collection of n data points $\{x_1,...,x_n\}$ in an M-dimensional space. Since each point is a candidate to be the centre of the cluster, the density measure of the data point xi is defined by the equation (*Taylan and Karagözoglu, 2009*):

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{(r_a)^2}\right) \tag{1}$$

where, r_a is a positive constant. Data points near the first x_{c1} cluster centre will have significantly reduced density measures.

In principle, the shape of the membership functions is less important than the number of curves and their placement (*Taylan, 2006*). We proposed the form of sigmoidal and three-curve/segment membership functions to adequately cover the required range of input values. In analytical form, it is presented as follows:

$$\mu(x; a_k, c_k) = \frac{1}{1+e^{-a_k(x-c_k)}} \tag{2}$$

where, to define the parameters of the member function, a vector of the form $[a_1\ c_1\ a_2\ c_2]$ is created. Membership values are calculated for each input value in x.

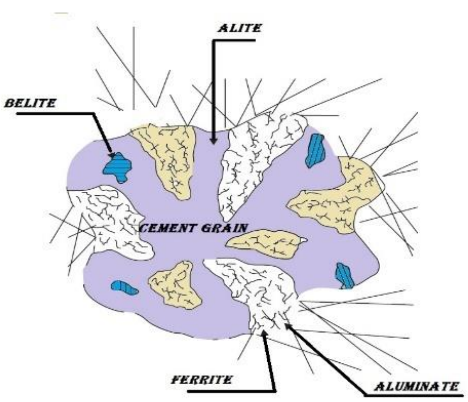

Fig. 1 – The chemical composition of the clinker
(adapted from *Schumacher and Juniper, 2013*)

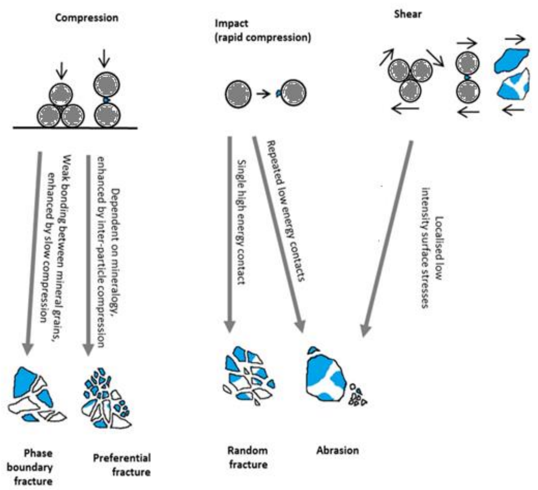

Fig. 2 – Mechanisms of particle breakage - the links between contact events (force application) and the result of breakage (adapted from *Litlle et al., 2017*)

Portland cement is a fine powder produced by grinding Portland cement clinker (more than 90%), a limited amount of gypsum (dehydrated calcium sulphate - $CaSO_4 \cdot 2H_2O$, which controls the setting time) and other minor constituents that can be used to vary the properties of the final cement (*Schumacher and Juniper, 2013*). Portland cement clinker is a sintered material (granules with a diameter of 5–25 mm) produced by heating a homogeneous mixture of raw materials in a furnace to a sintering temperature of about 1450 °C for modern cements. The resulting clinker is made up of four main minerals, which mostly give resistance to crushing, presented in Table 1 (*Labahn and Kohlhaas, 1983*). Figure 2 shows the mechanisms of breaking particles - the links between contact events (force application) and the result of breaking *(Little et al., 2017).*

Table 1

Composition of cement granules by mass fraction (%)

% (mass)	Alite	Belite	Aluminate	Ferrite
	C3S	**C2S**	**C3A**	**C4AF**
maxim	**80**	**30**	**15**	**15**
minim	**40**	**0**	**7**	**4**
average	**60**	**15**	**11**	**8**

Following the study of the industrial cement grinding process in the ball mill led by an experienced operator, the idea of developing and implementing an intelligent fuzzy command and control system for the clinker grinding process in the ball mills was put forward. In order to estimate the possibility of achieving the control of the grinding process, the efficiency of the ordering process and the real-time control of the particle sizes, the approach that would use the intelligent techniques was proposed. Fuzzy logic methods and algorithms are implemented in command and control processes either separately or combined with other intelligent methods and techniques (*Cărbune, 2020)*.

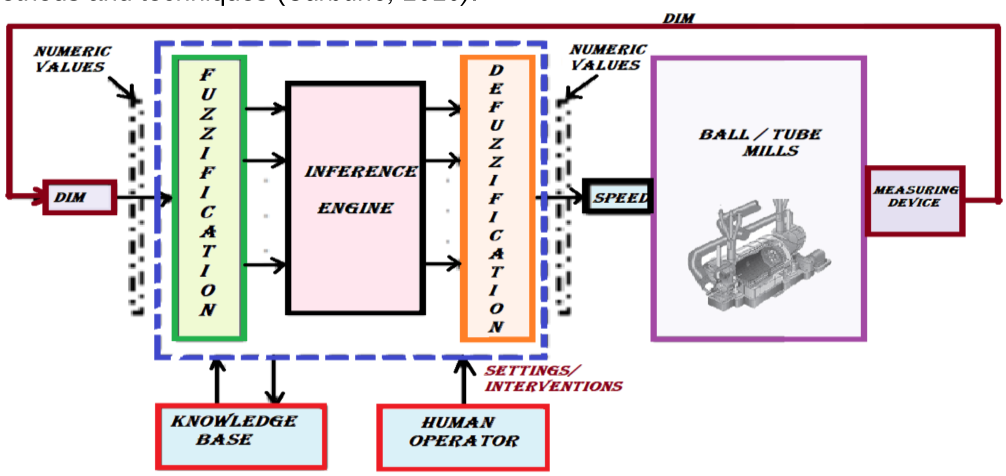

Fig. 3 – The structure of the intelligent command and control system of the grinding process

Practically, two grinding systems are used for the preparation of raw materials for the manufacture of clinker: wet and dry. In the dry system, the raw materials are dosed in the proportions necessary to obtain the desired chemical composition and supply either a rotary ball mill or a vertical axis (roller) mill. The raw materials are dried in advance with the residual process gases taken from the combustion furnace. The objective of the grinding process is for the bulk of the product to be smaller than 75 μm (*Schumacher and Juniper, 2013*). The product from the mill is pneumatically mixed to ensure that it has a well-homogenized chemical composition and is then stored in silos until needed. The fineness of the final product, the amount of gypsum added and the amount of additional additives are all varied to result in the desired quality of each of the final cement products (*Labahn and Kohlhaas, 1983*).

The conceptual structure of the intelligent fuzzy command and control system of the particle grinding process in the ball mill is presented in Figure 3. The system can have a fuzzy intelligent (or neural) control block in its composition. The connection between the control block and the technological system is made with the help of the data acquisition block. At the initial stage of knowledge base collection and testing, the presence of a human operator is required in the decision-making loop to control the comminution process and ensure particle quality parameters. Initially, the most important system variables that can be used in the control process were determined: Dim – particle size; SPEED – rotation speed of the ball mill. The SPEED control variable is an essential one in managing the grinding technological process. In figure 3 the intelligent control subsystem is represented with a block of fuzzy type. A special problem in the construction of fuzzy systems is related to the choice of membership functions (*Cărbune, 2020)*.

Experimental investigations were carried out on samples of Portland cement clinker with a medium phase composition: Alite - C3S 60%; Belite-C2S 17%; Aluminates C3A 10%; Ferrites 5%; CaO 1%. The phase composition was determined by X-ray diffraction. The grinding of the above-mentioned material was carried out on a steel ball mill (drum diameter 280 mm and height 120 mm), filled with steel balls, the diameter of which is 30 mm.

The number of revolutions of the mill was cc 72.5% of the critical speed, which ensures optimal conditions for reducing the size of the clinker grains. The chosen diameter of the mill reduces the risk of the material going up to the feed mouth. Experiments were performed with a mill loading of 55% balls and a particle loading of 100%. The grinding procedure was carried out in 15 batches, with and without chemically active substances, and the cement samples were collected at different time periods. Particle size distribution was determined with the Mastersizer 2000E laser by sieving for 60 seconds. Figure 4 shows the cumulative size distribution curves according to the mass fraction of particles larger than the mesh size of the sieve (passing through the sieve). The data were classified into three groups as follows:

- data for training the model "Prob87", "Prob88", "Prob89" and "Prob95";
- data for testing the "Prob97", "Prob98", "Prob113" and "Prob114" model;
- data for checking the model "Prob116", "Prob117", "Prob118" and "Prob119".

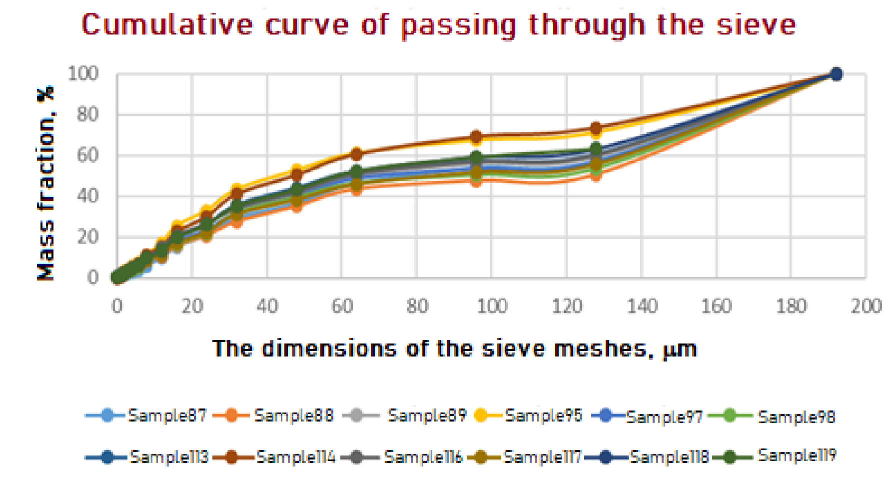

Fig. 4 – Experimental data – cumulative curves of mass fractions smaller than the mesh size of the sieve

The characteristic parameter (x_{50}) of the distributions was obtained by calculation with the weighted average method and is presented in Table 2:

$$x_{50} = \frac{\sum_{i=1}^{n} w_i \cdot x_i}{\sum_{i=1}^{n} wi} \tag{3}$$

where:

x_{50} = weighted average; n = number of terms to be averaged; w_i = weight of fraction i; x_i = average particle size of fraction w_i.

Table 2

Characteristic size x_{50} [µm] of distributions by particle size

Sample	**87**	**88**	**89**	**95**	**97**	**98**	**113**	**114**	**116**	**117**	**118**	**119**
$D_{50[\mu m]}$	66.1	118.8	174.9	119.9	59.3	104.9	127.7	97.3	64.1	94	118.5	92.2

The study of the material's resistance to size reduction based on the obtained values, i.e. the existence of the Rehbinder effect, clearly shows that the addition of chemically active substances does not significantly influence the size reduction rate. However, when the optimal ball mill operating conditions are reached, the chemically active substances become responsible only for the occurrence of the Rehbinder effect *(Little et al., 2017).*

RESULTS

In this study, three cluster centres were determined for the given 181 data set. The number of fuzzy rule sets would be equal to the number of cluster centres, each representing the cluster feature, as shown in figure 5. Fuzzy rules and fuzzy reasoning are the backbone of fuzzy inference systems, which are the most important modelling tools based on fuzzy sets (*Taylan, 2006*). Fuzzy reasoning is an inference procedure that derives conclusions from the set of fuzzy If-Then rules and known facts. Fig. 6 shows the reasoning procedure for a first-order Sugeno fuzzy model. Since each rule has a clear output, the total result is obtained by a weighted average, thus avoiding the time-consuming process.

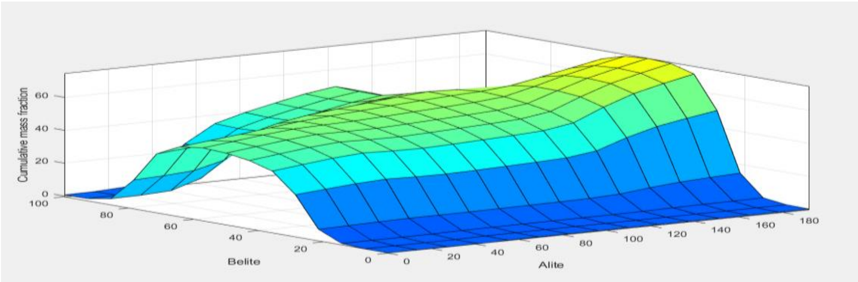

Fig. 5 - The control action surface after training the input data

The input parameters of the ANFIS adaptive inference system taken into account are the mineral compositions, Alite (C3S), Belite (C2S), Aluminate (C3A), Ferrite (C4AF), and the result is the "cumulative particle size distribution (DIM)". These imprecise attributes are called fuzzy linguistic variables and are used to characterize the chemical composition of the product. These linguistic variables are imprecise, vague and incomplete fuzzy terms. They are entered and expressed by fuzzy linguistic values, such as "unsatisfactory (A1), average (A2), good (A3)", as shown in Fig. 7.

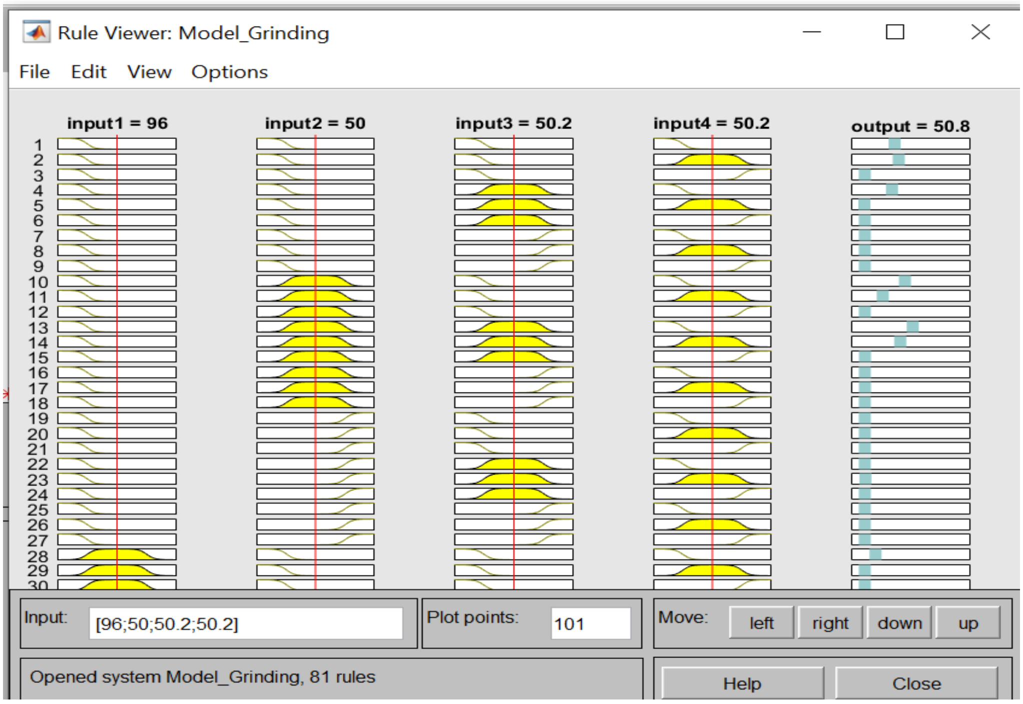

Fig. 6 - Fuzzy procedure for the Sugeno model of the output quantity

Fuzzy rules are mathematical relations that map input relations to output relations and are constituted by fuzzy linguistic variables and their term sets (*Taylan, 2006; uk.mathworks.com*). Fuzzy If-Then rules are known as fuzzy implications or fuzzy conditional statements which are widespread in our daily language expressions. Fuzzy rules are the backbone of an ANFIS model. E.g.: "IF the Alite fraction (C3S) of the slag is good and the Belite fraction (C2S) is medium and the Aluminate fraction (C3A) is medium and the Ferrite fraction (C4AF) is medium THEN DIM will be medium" is a complete rule that defines the relations between the input and output linguistic variables.

Rule 1: If C3S is A1 and C2S is A2 and . . . and C4AF is A2
Then f 1 = p1 C3S + q1 C2S + .. · + m1 C4AF + r1
Rule 2: If C3S is A2 and C2S is Ai and .. . and C4AF is A5
Then f 2 = p2 C3S + q2 C2S + · · · + m2 C4AF + r2
………………………………………………………………………

Rule n: If C3S is An and C2S is An and . . . and C4AF is An
Then f n = Pn C3S + qn C2S + · · · + mn C4AF + rn

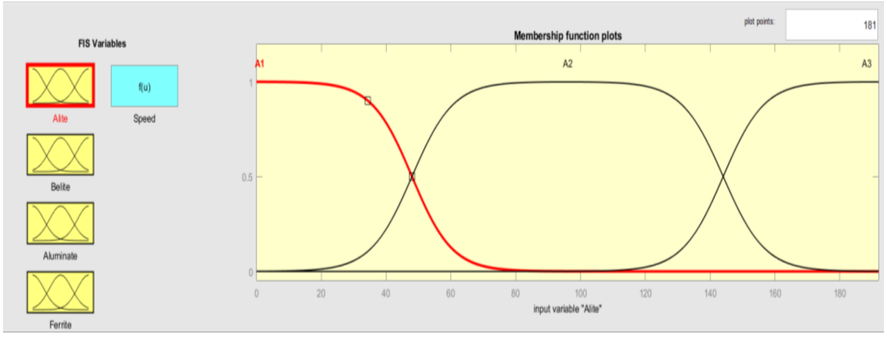

Fig. 7 – Adjusted member functions of the "Alite" input variable

Architecture of hybrid and adaptive learning neuro-fuzzy inference system. Figure 8 shows the architecture of the neural network structure. Calculating the parameters of the MF membership function (or fitting them) is facilitated by a gradient vector, which provides a measure of how well the ANFIS is modelled with the input/output data for a given set of parameters. Once the MFs are established, several optimization methods can be applied to adjust the parameters and reduce the error (typically defined by the sum of the squares of the difference between the actual-measured and desired outputs). The parameters associated with MF will change through the learning process *(Carbune, 2020; Taylan and Karagözoglu, 2009).*

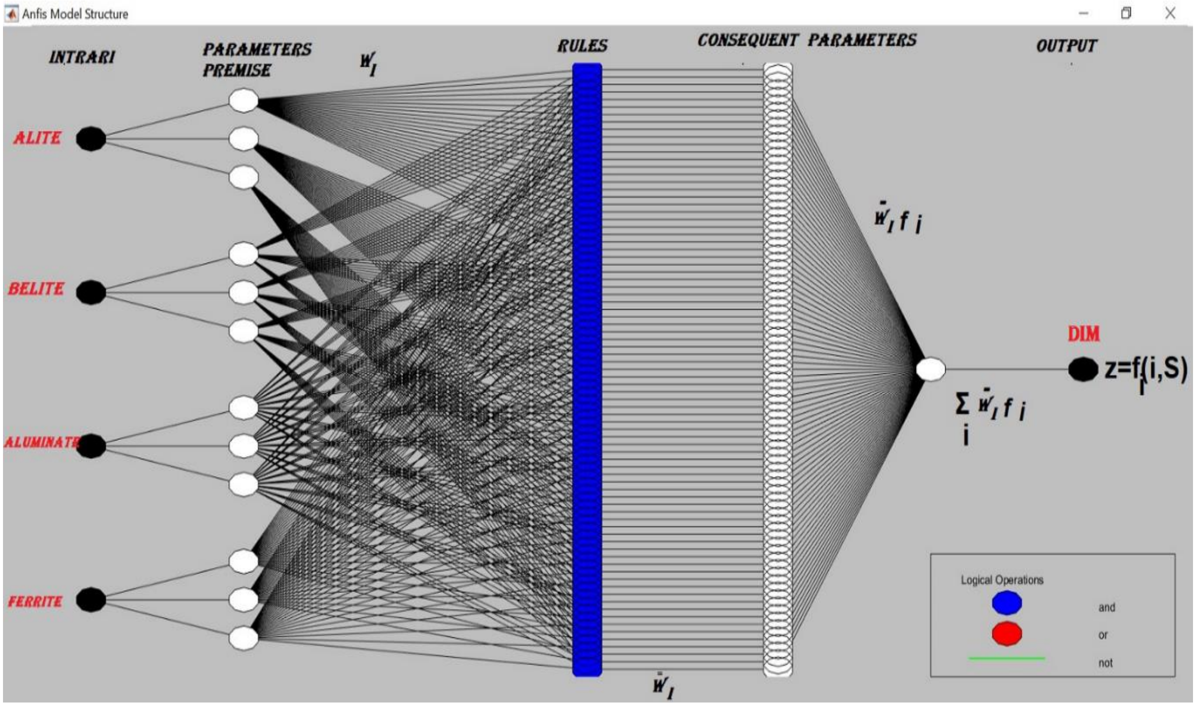

Fig. 8 – ANFIS architecture for a Sugeno fuzzy model with four inputs and one output

The only node in the last layer of the neural network is a fixed node, which calculates the total output as the summation of all input signals calculated by the equation *(Taylan and Karagözoglu, 2009):*

$$z = \sum_i \bar{w}_i \cdot f_i = \frac{\sum_{i=1}^{n} w_i \cdot f_i}{\sum_{i=1}^{n} wi} \tag{4}$$

From the ANFIS architecture shown in Figure 8, it is observed that when the values of the premise parameters are fixed, the total output can be expressed as a linear combination of the consistent parameters. In symbols, the output z can be rewritten as the equation:

$$\begin{aligned} z = {} & (\bar{w}_1.C3S) \cdot p_1 + (\bar{w}_1.C2S) \cdot q_1 + \cdots + (\bar{w}_1.C4AF) \cdot m_1 + (\bar{w}_1.)r_1 \\ & + \cdots + (\bar{w}_n.C3S) \cdot p_n + (\bar{w}_n.C2S) \cdot q_n + \cdots + (\bar{w}_n.C4AF) \cdot m_n + (\bar{w}_n.)r_n \end{aligned} \tag{5}$$

which is linear in the consistent parameters, p_1, p_2, q_1, q_2, r_1, and r_2.

To train the designed neural network, the hybrid optimization method was chosen, which uses a combination of back propagation and least squares regression to adjust the FIS parameters.

After the completion of the training process, the details about the status of this process and the accuracy of the neural network operation algorithm are presented. As a result of this stage, graphs are generated that describe the operation mode and performance of the developed artificial neural network (see figure 9).

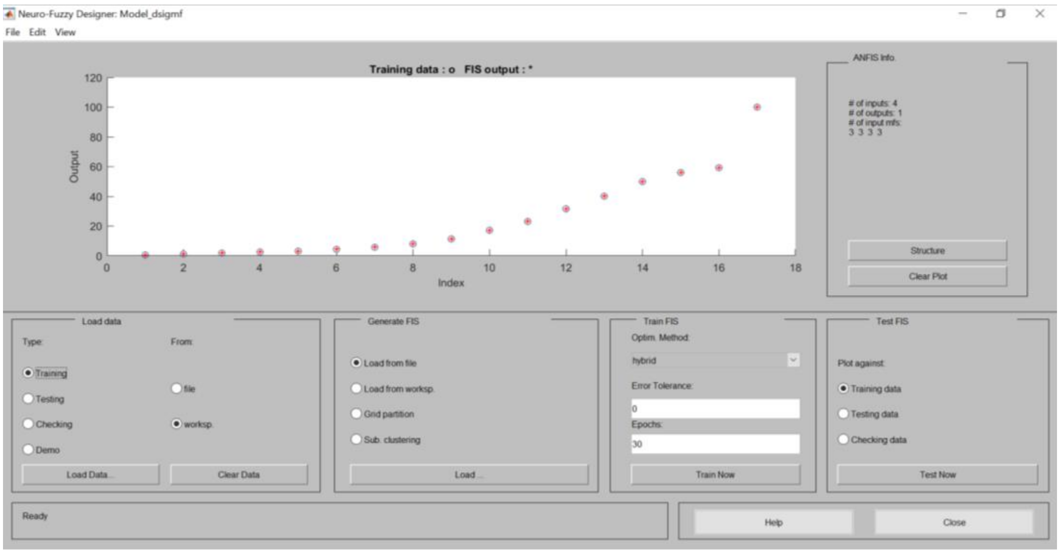

Fig. 9 - Displaying training data in the Neuro-Fuzzy Designer application

The neural network of the designed control system is made up of 193 nodes, with a total number of 453 parameters, of which 405 are linear parameters and 48 are non-linear parameters. For the 17 values of the training data, the network uses a number of 81 fuzzy rules.

Validate the model using the verification and test data set. Model validation is the process by which the input vectors from the input-output data sets are presented to the trained FIS model to see how well the ANFIS model predicts the corresponding data set of values of exit. When the test and training data are fed into the ANFIS adaptive interference system, it is expected that the selected FIS model has associated parameters such that there is minimal error between the model data and the test data. The basic idea behind using a test data set for model validation is that after a certain point in training, the model starts to overfit the training data set. The learning convergence and ANFIS parameters for the training and testing data sets can be seen in figures 10 - 12. The minimum error was 5.43506 e-05, and the final value was 0.000217096.

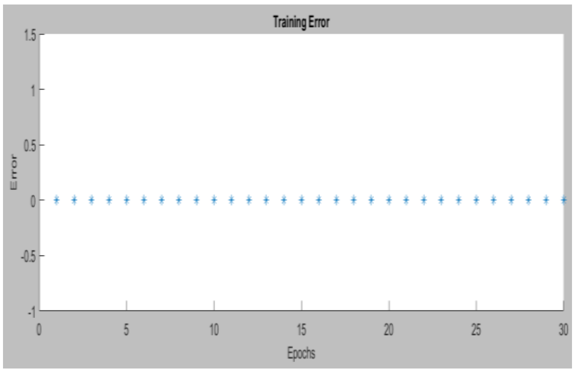

Fig. 10 – Convergence of learning for the training data set

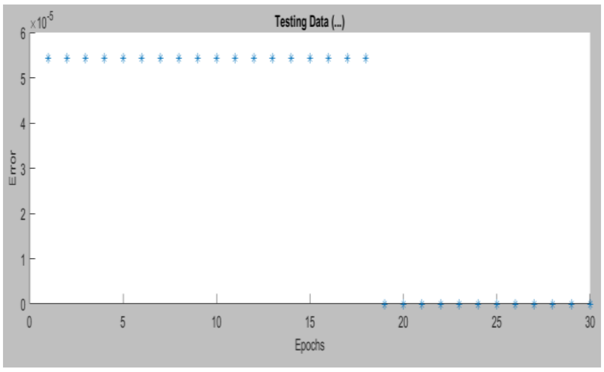

Fig. 11 – Convergence of learning for the test data set

In principle, the model error for the test data set tends to decrease as training occurs until the point where overfitting begins, and then the model error for the test data increases sharply. After loading the verification data set and choosing the variant in which ANFIS will generate a FIS with four inputs having 4 Linguistic Terms (a base of 81 rules), the convergent training of fig. 12. To eliminate this problem, as seen in fig. 13 -14, data are used to identify each input-output parameter used to check model validation. This data set contains all the necessary representative characteristics of the assessment tools. Note its output variable consisting of 17 different values (singleton), each of which is optimized during training. In this case, the linear option was chosen for the member function.

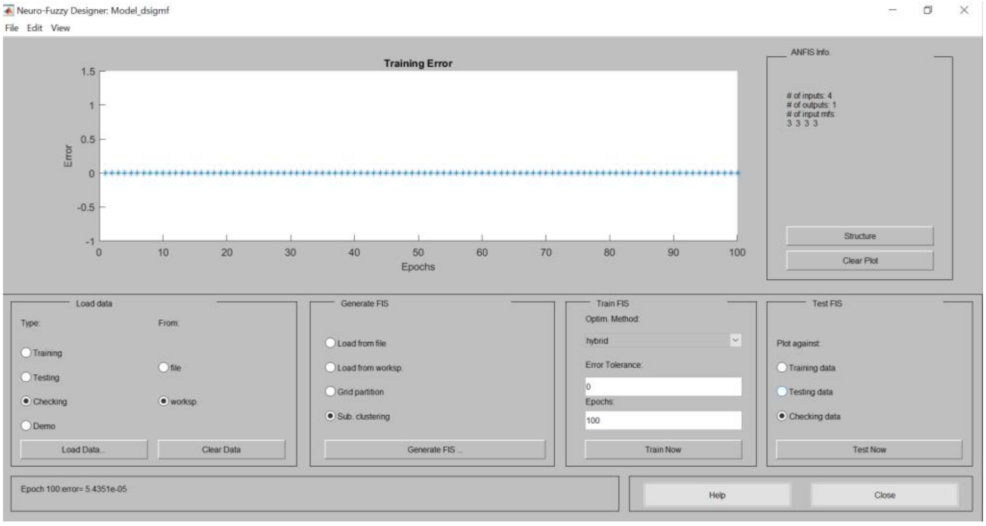

Fig. 12 – Convergence of learning for the test data set to validate the model

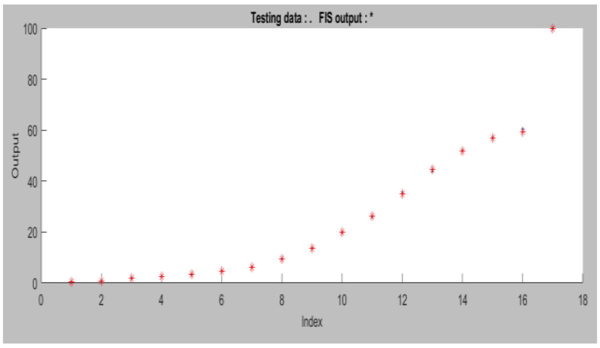

Fig. 13 – Testing the data obtained with the ANFIS model

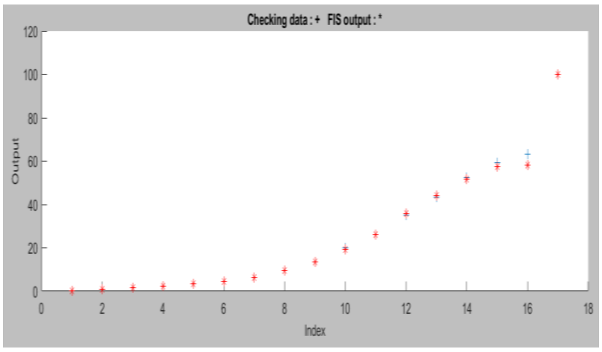

Fig. 14 – Checking the data obtained with the ANFIS model

As many authors have pointed out (*Baqui, 2012; Stefenon et al., 2020; Taylan, 2006; Lin and Lee, 1991; Elkan, 1994*), conventional system analysis techniques are not suitable to deal with a humanistic system, whose behaviour is strongly influenced by human judgment, perception and emotions. This belief gives rise to the concept of linguistic variables as an alternative approach to modelling human thought. Since the convergence errors are both very small, we assume that ANFIS has captured the essential components of the underlying dynamics, and the training data contains the effects of initial conditions that may not be easily explained by the essential components identified by ANFIS.

CONCLUSIONS

One reason for using fuzzy regulation is that it is more appropriate in regulating non-linear processes. If a fuzzy regulator or generally a non-linear one is in principle able to regulate a non-linear process, it is a problem that depends on the chosen inputs of the regulator. When controlling nonlinear processes, fuzzy controllers should outperform conventional controllers. This applies as long as we have additional knowledge about the nonlinearity of the process.

Clearly, we can argue that the information in a neuro-fuzzy control system is usually superficial, both statically and dynamically, but that the numerical parameters can be adjusted during a learning process, which implies a quick adaptation to environmental change and, consequently, to an obvious economic benefit.

A particularly important problem facing the design of an adaptive neuro-fuzzy inference system application is the choice of training, testing and validation datasets. The main way to improve the quality of neuro-fuzzy systems is to choose an appropriate training data set. The more we move from the representation of human knowledge about clearly delimited problems to the representation of concepts related to open domains, the more we will have to overcome certain rigidities of classical formal approaches. The great advantage of control systems with neural networks, the ability of machine learning, can be illustrated by the response of these controllers, very similar to that of much more complicated systems, justifying its choice for applications, considering the similar performances.

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