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Fuzzy neural networks and neuro-fuzzy networks: A review the main techniques and applications used in the literature

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ABSTRACT

This paper presents a review of the central theories involved in hybrid models based on fuzzy systems and artificial neural networks, mainly focused on supervised methods for training hybrid models. The basic concepts regarding the history of hybrid models, from the first proposed model to the current advances, the composition and the functionalities in their architecture, the data treatment and the training methods of these intelligent models are presented to the reader so that the evolution of this category of intelligent systems can be evidenced. Finally, the features of the leading models and their applications are presented to the reader. We conclude that the fuzzy neural network models and their derivations are efficient in constructing a system with a high degree of accuracy and an appropriate level of interpretability working in a wide range of areas of economics and science.

1. Introduction

The performed of Intelligent models allow that standard human actions are simulated computationally. That facilitates decision-making in various contexts of industry, commerce, and the financial market. Models such as artificial neural networks get answers to challenges of classification of patterns, regression problems, image identification, problems related to the capital market, among others [1].

One of the problems in using this type of intelligent model is that its answers become complex to be explained in a way where people, other than of the artificial intelligence areas, can understand [2]. To make smart models outputs closer to expected in typical situations, the concepts of fuzzy systems have emerged. They allow us to bring the interpretability in the representation of the problems [3]. Seeking the coherent synergy between the training capacity of artificial neural networks and the possibility of representing the problems in a more interpretable way, models that use the best of both concepts to form hybrid models, called fuzzy neural networks or neuro-fuzzy models have been proposed [4]. These models have been present in the literature since the 1960s and have been acting dynamically and efficiently in solving various problems in our society [5]. The motivation for the development of these networks lies in its easy interpretability, being possible to extract net topology knowledge. These networks are formed by a collaboration between fuzzy set theory and neural networks allowing a wide range of learning abilities. They provide models that integrate the uncertain information handling provided by the fuzzy systems and the learning ability granted by the neural networks [6]. These networks are highly promising in various application areas, such as fuzzy clustering, modeling of nonlinear dynamic systems [7], to eliminate the vibration of large scale systems [8], or in the fault detections in the industry, among others.

Over the last few decades, fuzzy systems and their hybrid derivations can simulate the typical human reasoning ability in a computationally efficient way. An important area of current research is the development of such systems with a high level of flexibility and autonomy to evolve their structures and knowledge based on changes in the environment, being able to handle modeling, control, prediction and classification of patterns in a situation not stationary, susceptible to constant changes [9]. These models have been absorbing concepts of the evolution of neural network training and data processing to form highly accurate models to build systems based on rules, expert systems, classifiers, and universal approximators. This article intends to comprehension the methodology proposed by works so relevant to the literature, adding applications and techniques that improved the neuro-fuzzy network in the years 2000 and the last decade. This paper will also demonstrate the concepts and applicabilities of the hybrid models, like the works of Kar et al. [10], which focused on the presentation of a group of functionalities provided by fuzzy neural networks. This paper will also make a broad approach to hybrid models in their performance, but unlike the work of Kar et al. [10], Our primary focus will be on the characteristics of the various model architectures and structures having been defined in the context of NFNs and FNNs, leaving aside quantitative aspects on the number of publications in each journal or conference.

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The main highlight of this paper is a review of the leading models of fuzzy neural networks and neuro-fuzzy available in the literature with a focus on models that work in a supervised way during the training phase of the model. Their architecture, way of acting in solving problems, its components, and the training algorithms will be the target of this study. Therefore, this paper seeks to bring aspects of the timeline of the hybrid models of artificial neural networks and fuzzy systems, presenting characteristics of the presence and relevance of these models during the past, present, and future. Besides that, to describe the main techniques of data treatment in the model's input, as well to explain the constructed fuzzy neurons through the dataset characteristics used in the model. This paper will focus on the primary methods and training structures of the hybrid models and finally will present how they were applied to solve problems of different natures.

The paper is organized as follows: Section 2 clarifies the methodology used and the databases where the consultations were carried out on the articles used in this paper. Section 3 presents basic concepts about the hybrid models that are the subject of this review. In Section 4 are presented characteristics of the architecture of the models, methods of fuzzification and defuzzification, and training. In Section 5 will be presented examples of the applications and practices that use the hybrid models in solving general problems, and finally, in Section 6, the conclusions and future works are presented.

2. Materials and methods

This section presents the main content of this paper: an in-depth review of existing hybrid models, their training models, defuzzification and fuzzification techniques, together with an evaluation of the practical applications of the context model of science and research. All the works present in this article were obtained according to a well-thought-out taxonomy of research carried out in the area in the leading periodicals and scientific events related to the models that join artificial neural networks and fuzzy systems.

Initially, it sought to carry out a critical review work on the main bases of academic research. Along with this, a timeline has recovered the first existing hybrid models, in addition to highlighting their main techniques evolutions during the following decades.

The literature review approach necessarily contributes to the progress of the research to reveal the main trends and the history of the models. Essential characteristics of neural networks and fuzzy systems involving the concepts of hybrid models were reported in this article to facilitate the understanding of new researchers on critical themes for the construction of this type of model. In addition to presenting the concepts of fuzzy neurons, they were also part of this extensive research, highlighting the models and techniques in each of the decades covering the study.

The first search filter was performed in Google Scholar on the main keywords that guide the research: Fuzzy Neural Network, Neuro-Fuzzy, combined with the contexts evaluated within the article such as survey and review to identify the main revision work done in the literature, seeking to verify the approaches proposed previously.

When the objective of the search in the databases was to identify specific models for particular areas, the keywords were combined with other keywords such as health, industry, pattern classification, regression problems, time series prediction, among others. This type of search presents reliable sources of research, identifying even the leading scientific periodicals and events that deal with the themes.

The search for specific journal articles was conducted using a keyword search of the electronic library database. The literature review was done from the electronic library, such as ScienceDirect-Elsevier[1]; IEEE Xplore Digital Library,[2] Springer Online Journal Collection[3], Multidisciplinary Digital Publishing Institute,[4] IOS Press Content Library[5] and other ancillary sources such as Researchgate and Google Scholar tools (more than 100 pages of articles with the theme). These databases were chosen in previous research on the subject, mainly because they are renowned groups in science and critically approach the revisions of articles submitted to their journals and academic events.

In May 2019 the researches by the main themes resulted in the approximate results listed in Table 1 where we highlight the searched topics: "Fuzzy Neural Network" (FNN), "Fuzzy Neural Network Survey" (FNNS), "Fuzzy Neural Network Review" (FNNR), "Neuro-Fuzzy" (NFN), "Neuro-Fuzzy Survey "(NFNS)", Neuro-Fuzzy Review "(NFNR).

The main decisions were made according to the relevance of the paper (based on the number of citations and advanced training techniques), place of publication (with differential the form of a review of the papers), besides selecting articles in the main events of fuzzy systems, neural networks, and machine learning according to the Brazilian Scientific Quality Score, called quali-capes conferences. Academic events classified as A1, A2, B1, and B2 (the best scores according to Brazilian methodological definitions in 2019), were used in this paper. Another factor is the international relevance in scientific activities based on Journal Citation Reports (preferably those with the highest factor). As the main highlight, several papers published in the year 2018 and 2019 were chosen to highlight the main evolutions of studies in the area.

After the papers' selections, the most important ones for the science history were identified, those that acted in several areas of research, and also the number of scientific-based citations. Other outstanding factors also take into account the role of these models in solving problems of the most diverse nature, such as software development, problems in the industry, aspects of health, diseases, and the financial market. This paper also wishes to explore authors who stand out in different scientific production, using intelligent models to solve complex problems in various branches of science. These definitions helped to choose the current papers in the study.

Finally, the definitions of the methodology were chosen around 500 articles. Articles that did not have free versions for Brazilian universities were also disregarded of this work because they do not allow their full reading. The articles present in this study meet the methodological criteria listed above.

3. Basic concepts

This section will present basics concepts to the understanding of the relevance of works proposed in the literature on fuzzy neural networks, neuro-fuzzy networks, and other revisions proposed in the literature.

3.1. Related work

In the literature, the performed revisions of the hybrid approach on fuzzy neural network models were the highlight in the works of Buckley et al. [5] and Takagi [11]. These studies were

1 https://www.sciencedirect.com/
2 https://ieeexplore.ieee.org/Xplore/home.jsp
3 https://link.springer.com/search?facet-content-type="Article"
4 https://www.mdpi.com/
5 https://content.iospress.com/search

Table 1
Number of papers raised with keywords.

Electronic library	FNN	FNNS	FNNR	NFN	NFNS	NFNR
ScienceDirect-Elsevier	51.843	11.628	22.844	12.233	2.713	5.581
IEEE Xplore Digital Library	19.612	233	495	4.134	43	78
Springer Online Journal Collection	22.950	6.275	10.229	4.623	1.163	1.910
IOS Press Content Library	10.371	4.860	7.464	977	303	471
Multidisciplinary Digital Publishing Institute	30	0	0	118	0	0

carried out in the early 1990s, presenting advances and applicability of hybrid models in different scientific contexts. They were works that, for their time, helped area researchers to understand the origin, the present, and the future of these applications.

It should be noted that there are works of revision of concepts focused on specific areas or applications. The review made in Vieira et al. [9] presents neuro-fuzzy aspects with the principal focus on evolving systems. Works such as Mitra and Hayashi [12] describe the performance of hybrid models in creating fuzzy rules for soft computing. In the work of Moller [13], we can visualize a group of hybrid model works that have improved general aspects of civil, computing, and mechanical engineering. In the work of Kwan and Cai [14], an emphasis was given to models of fuzzy neural networks performed pattern classification. Recently a review of the neuro-fuzzy approach based on intelligent control was developed, highlighting the main contributions to this area [15]. Additionally, Knezevic et al. [16] present a study on the performance of smart models and fuzzy neural networks in solving civil engineering problems. It also is highlighted the paper of Sayaydeh [17] presented a review of pattern classification performed by a fuzzy neural network using the min and max techniques. An approach to neuro-fuzzy pattern classification was addressed in Pal et al. [18], and Mitra and Yoichi [12] explored a review of the approach in soft computing framework based on the concepts of fuzzy rules. These authors presented a survey in the 2000s on the significant works of hybrid models that addressed the knowledge present in the intelligent models that can be extracted from the problem dataset. As the main conclusion for that work, there were several approaches capable of extracting fuzzy rules to make problems more interpretable. This paper will also present models that generate fuzzy rule extraction but focus on models after the 2000s and the various forms of interaction between rules and the creation of expert systems. Recently, the papers of Mishra et al. [19] and Shihabudheen and Pillai [20] are made a focused review of neuro-fuzzy models and their applications to the academic community.

The study of Mishra et al. [19] highlights the main positive characteristics of the neuro-fuzzy models, the simple interaction of the problem's expert with the engineer of the system and the ability to represent knowledge through linguistic rules. However, it also highlights the model's difficulties are linked to its incapable of generalizing, that not robust about the topological system changes, beyond the dependence of a specialist on the subject to gauge the validity of the rules generated. In the review proposed by Shihabudheen and Pillai [20], the main focus is to approach neuro-fuzzy classifiers published between 2000 and 2017, different from this paper that will approach methods in distinct periods of science, with a particular emphasis on models published in 2018 and 2019. Recently a survey elaborated by Skrjanc et al. [21] shows the evolving hybrid models, that is, that has a direct relationship with the update and modification of the nature of the data submitted to the problem. The main focus of Skrjanc et al. paper was to present the relevant literature in classification, clustering, and regression problems when the nature of the problem evaluated is online and in real-time with the emphasis on models that use supervised training.

3.2. Artificial neural networks

Intelligent systems seek to simulate human behavior in models to solve everyday problems. In humans, the brain processes information in parallel, distributing tasks to nerve cells. It is made up of many nerve cells, where the neurons are the main structures responsive reactions to the stimuli of the environment. They are responsible for treating inducements, that is, processing signals from a chain of neurons or external situations. In its composition, the neuron presents dendrites, the axon, the cellular body, and the synapses. They receive incoming signals from other cells through the dendrites, process them in the cell body, and generate the output signals that are transmitted to other neurons through axons and their ramifications [22].

For Fausett [23], Artificial Neural Networks (ANN) are computational techniques that present a mathematical model inspired by the neural structure of intelligent organisms and that acquire knowledge through experience allowing tasks commonly practiced by intelligent beings to be performed in computational environments.

The history of the models involving the concepts of artificial neural networks begins with the human biological neuron modeling performed by McCulloch & Pitts [24]. In the late 1940s and 1950s, the several works of Hebb [25] and Rosenblatt [26] allowed machines to perform simulated human behavior, through a mathematical model. These works allowed the creation of one of the best-known models in the history of neural networks: the perceptron of supervised learning. Also worthy of note is the self-organization network model. After a significant hiatus in history, work has been prominent in the 1980s, especially with the backpropagation method introduced by [27].

Haykin [22] defines an artificial neural network composed of an input layer, one or more hidden layers, and an output layer. The network can be connected entirely, where each neuron is connected to all the neurons of the next layer, partially connected where each neuron is, or finally, locally connected, where there is a partial connection-oriented to each type of functionality. A set of data is required that contains patterns for training and desired outputs (in a supervised training case) to perform the training of a neural network. In this way, the problem of neural network training is summarized in an optimization problem in which we want to find the best set of weights that minimizes the mean square error calculated between the network outputs and the desired outputs.

Fig. 1 represents the architecture of an artificial neural network and its main elements. This example deals with the separation of two classes, where the orange values allow the classification of negative patterns and the blue values of the positive patterns. In the figure, it is possible to see how the input data connect in hidden layers (in this example, the model has three hidden layers), wherein any one of them there may be any number of artificial neurons. In these neurons, it is possible to verify how the learning and decision are made, allowing the model to classify the samples used in the example correctly. The union of the various neurons allows the answers to be the closest to the real ones.

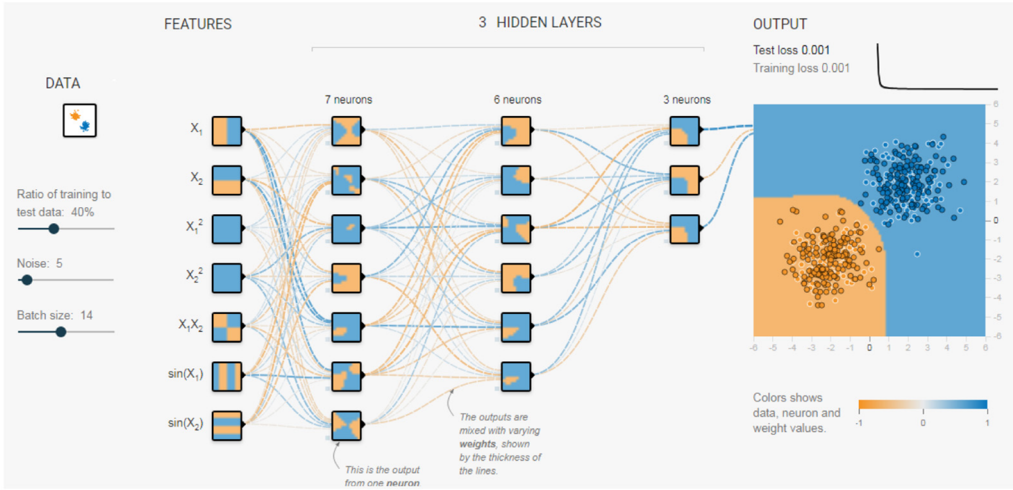

Fig. 1. ANN Feed Forward Network architecture.
Source: Adapted from: https://playground.tensorflow.org/.

3.3. Fuzzy systems

The fuzzy logic systems are based on fuzzy logic concepts, developed by Zadeh in 1965. His work was motivated because of the wide variety of imprecise information in making human decisions. Some problems cannot only be solved with classical Boolean logic. In some situations, only two values are insufficient to solve the problem [3]. Fuzzy techniques solve uncertainty in the resolution of complex problems dealing with the possibility of representing complex problems with more considerable variability of representations [28].

Fuzzy logic allows mathematics to be used to represent information in the field of vagueness to solve various problems. With fuzzy logic, it is possible to create systems that can perform a function approximation [29], mainly by the universal approximations theorem [30], that an additive system $\mathbf{F}$:$\mathbf{X} \rightarrow \mathbf{Y}$ approximates a function f: $\mathbf{X} \rightarrow \mathbf{Y}$ if $\mathbf{X}$ is a compact region and f is continuous [28]. This is because, in a fuzzy system, each rule represents a local model which is aggregated with other rules to provide a final model output.

The standard composition of a fuzzy system consists of four useful pieces: the fuzzifier, the fuzzy inference engine, the knowledge base, and the defuzzifier process. The linguistic values and crisp (numerical) data can be used as information for a fuzzy system. If crisp data are applied, then the inference process is preceded by fuzzification, which allows the creating of an appropriate fuzzy set to the nonfuzzy input. The contents of input variables are mapped into linguistic values of the output variable operating the appropriate method of approximate reasoning (inference engine) using expert knowledge, which is interpreted as a collection of fuzzy conditional rules (knowledge base). In an extension of the linguistic values, the numerical data may be required as the fuzzy system output. In the before-mentioned circumstances, defuzzification methods are used, which allow the crisp representative data to the resultant output fuzzy set. Useful employment of fuzzy systems includes problems for which the entire mathematical representation is unavailable, or where the usage of the precise (nonfuzzy) model is uneconomical or highly inconvenient [31].

For Pedrycz and Gomide [32], the use of fuzzy systems is necessary in cases where the classical approach becomes unfeasible for the resolution of a problem due to the nature of its complexity. The best-known methods are capable of making abrupt changes to solve problems due to the model simplification. However, the fuzzy systems have resources (membership functions, rules, and aggregation operators) that allow a more accurate approximation to the actual model, avoiding that the solution generated by the fuzzy system is different from the real model.

Another relevant concept in fuzzy systems is the fuzzy set. This type of element can be represented by a relation that evaluates a range of a target variable of the problem [28], such as the height of a plant, which can vary from zero to 15 m, like any other tree. These membership functions are generally defined as linear, triangular, Gaussian, trapezoidal, sigmoidal, among others [28].

Finally, Pedrycz and Gomide highlight operations involving fuzzy logic, identified as t-norms (a generalization of the intersection of fuzzy sets) and s-norms (a generalization of the union between fuzzy sets) [32].

3.4. Fuzzy sets

Distinct of the classical sets, the fuzzy set introduced by Zadeh in [33], can be defined as an smooth set, where the transition between whether or not to belong to an assessed set occurs gradually rather than abruptly. By defining a fuzzy set A in a universe of discourse $\mathbf{X}$ we are characterizing a membership function A that realizes the association of each element x any, where $x \in \mathbf{X}$, with a membership degree $A(x)$ that belongs to the interval between zero and one, and can be represented by $A(x) \in [0, 1]$. This fuzzy set A in $\mathbf{X}$ can also be represented by a set of ordered pairs in the form of $(x, A(x) \ \mid x \in \mathbf{X})$ [28].

Some techniques rely on the data to construct the fuzzy sets that partition the sample space. In general, these fuzzy sets are triangular, Gaussian, trapezoidal, among others [32]. Fuzzy sets can represent a set of ages of people who responded to an opinion poll. The concept of the young or older may vary depending on the distribution of the data or human perception.

Fig. 2 presents an exemplified set of ages, where three fuzzy sets were applied. Within the context of ages, it can be affirmed that the first fuzzy set represents the age of young people, the second of mature people, and finally, the third represents the age of the old. It is also verified that if more fuzzy sets were used to describe this set of ages, the intervals of representation would be different, and one more characteristic would be added to evaluate the age of the people.

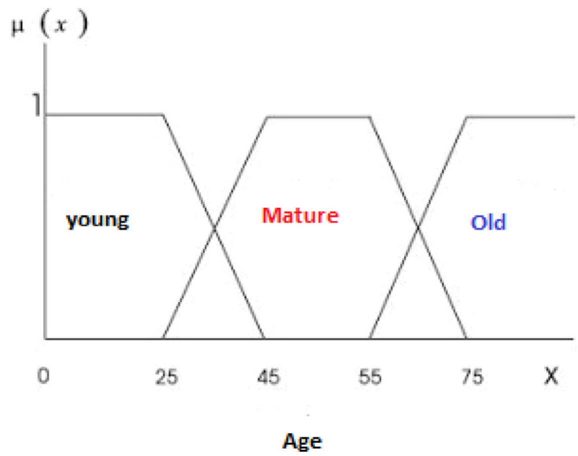

Fig. 2. Example of fuzzy sets representing an age group.

3.5. Fuzzy neurons

Logical neurons are functional units that add relevant aspects of processing with learning capacity. They can be seen as multi-variate non-linear transformations between unit hypercubes.

According to Lin et al. [4] numerous models of neurons have been proposed, but their classification is divided into three distinct types, varying according to the use of fuzzy logic concepts in the construction of their structure:

(a) Fuzzy neurons with non-fuzzy inputs combined with fuzzy weights (Type I).

(b) Fuzzy neurons with fuzzy inputs that are combined with fuzzy weights (Type II).

(c) Fuzzy neurons described by fuzzy rule if-then (Type III).

Type I neurons are those where the input of the model are real numbers, and the connection weights are fuzzy sets, called fuzzy weights. Therefore, for n non-fuzzy inputs $x_1, x_2, \dots, x_n$ there are n fuzzy sets A_i, $i = 1, \dots, n$, where weights are exchanged for operations with membership functions, also known as fuzzification operations. The result of each fuzzification operation, denoted by $A_i(x_i)$ is the membership degree of the input x_i in the fuzzy set A_i [4]. The mapping of a type I neuron is $NT_1 = \mathbb{R}^n \rightarrow [0, 1]$ defined as follows:

$$NT_1(x_1, x_2, \dots, x_n) = A_1(x_1) \otimes A_2(x_2) \otimes \cdots A_n(x_n) \quad (1)$$

where the aggregation operator $\otimes$ can be any aggregation mechanism such as *min*, *max*, or any *t-norm* or *s-norm* operators [28], but they are constant, that is, the same for each antecedent.

Type II neurons, called NT_2, are very similar to type I neurons, except for the inputs and the outputs that are fuzzy sets. Each of the non-fuzzy inputs X_i is composed with its respective fuzzy weight A_i through a weighting operator '#' (the multiplication between two fuzzy sets, fuzzy compositions, among others). The result of this weighting is another fuzzy set $X_i' = A_i \# X_i$, $i = 1, \dots, n$. All fuzzy sets X_i' are then associated through an aggregation operator $\otimes$ to produce the fuzzy set of output **Y**. The mapping of neuron NT_2 is $[0, 1]^n \rightarrow \times [0, 1]$ and can be described in mathematical form according to Eq. (2) below [28].

$$\begin{aligned} X_i' &= A_i \# X_i,\ i = 1, 2, \dots, n \\ Y &= NT_2(X_1', X_2', \dots, X_n') = X_1' \otimes X_2' \otimes \ldots \otimes X_n' \end{aligned} \quad (2)$$

Finally, the fuzzy neurons are denoted as Type III (NT_3) fuzzy rules represented by the *if-then* form, according to the fuzzy rule:

$$NT_3 = IF\ X_1\ AND/OR\ X_2\ AND/OR\ \dots\ X_n\ THEN\ Y \quad (3)$$

Nevertheless, unlike type I neurons, the aggregation mechanisms can be different between the rule antecedents, sometimes acting with t-norms, sometimes with s-norms. Where X_1, X_2, X_n are the inputs and **Y** is the output of the fuzzy neuron.

In the fuzzy rules, the antecedents (X_1, X_2, X_n) and the consequent ones (**Y**) are related through the fuzzy sets $(X_1', X_2' \dots, X_n')$. A fuzzy relation (R) can expand the concepts of fuzzy sets for a multi-dimensional universe. This relation represents the notion of partial association between the elements of the universes. A fuzzy rule can be analyzed as a fuzzy relation of the form R: $X_1' \times X_2' \times \cdots \times X_n' \times \mathbf{Y} \rightarrow [0, 1]$ where $R\,(x_1, x_2, \dots, y)$ represents the degree of association between the antecedent and consequent variables [6].

In general, these fuzzy relations can be composed by operators of set theory and can vary according to the choice of t-norms and s-norms. The two most important types of fuzzy relationships are compositions of the sup-t and inf-s type. These relationships define membership functions between two distinct universes evaluated (e.g., **X** and **Y**). Therefore a type III fuzzy neuron can also be described by a fuzzy relation R, for example, [6]:

$$R = X_1 \times X_2 \times \cdots \times X_n \times Y \quad (4)$$

In this case, a set of inputs of a type III neuron and the rule of compositional inference adopted in the problem result in an output represented by a type of fuzzy composition (e.g., a sup-t or inf-s composition).

For this neuron, the inputs can be both fuzzy or non-fuzzy, and a fuzzy type III neuron with non-fuzzy inputs can be seen as a particular case of this fuzzy neuron. Hybrid models with the type III neurons enables the creation of an architecture for extraction rules from training data [34].

When types II and III work in synergy, there arise derivations of neurons that are called fuzzy logical neurons. Initially, they were proposed by Pedrycz [1] and can process the aggregation of inputs with weights of connection w_i, differing from type III because they have weights associated with each of the inputs x_i. Thus the logical neuron performs mapping in the space formed by the Cartesian product between the input space and the space of the weights in the unit interval, i.e., $\mathbf{X} \times \mathbf{W} \rightarrow [0, 1]$ [28].

Noteworthy is the fuzzy logic neurons of the AND type (s-norm is used for ponderation and aggregation operator is a t-norm) OR neuron (t-norm is used for ponderation and aggregation operator is s-norm) [1], unineuron [35] (using the concepts of uninorm [36] to perform the aggregation of inputs and weights) and nullneuron [37] (uses nullnorm [38] concepts to perform neuron operations).

4. Fuzzy neural networks and neuro-fuzzy networks

The computational intelligence area presents remarkable advances in the development of techniques and models that simulate processes and systems, with emphasis on artificial neural networks, fuzzy systems, and their hybrid models, with a significant amount of new applications being proposed in the literature. One of the primary goals of computational intelligence research is to create and model computational systems that emulate specific human characteristics, such as learning, intuition, logical reasoning, classification, and regression [22].

The work of Aliev et al. [39] highlights that there are two distinct strategies in the academic literature. The first approach is neuro-fuzzy systems, whose primary task is to process mathematical relationships. Many papers, combine features of neural and fuzzy approaches into neuro-fuzzy systems. The second method is fuzzy neural systems to process both numerical (determination based) information and knowledge-based data represented as fuzzy numbers.

Fuzzy neural networks (FNN) are neural networks of fuzzy neurons. According to Pedrycz, these networks have as main characteristic the synergic collaboration between the fuzzy theory and neural networks, generating models that integrate the treatment of the uncertainty and interpretability provided by fuzzy systems and the learning ability provided by neural networks [6].

On the other hand, a Neuro-Fuzzy Network (NFN) [40] can be defined as a fuzzy system that is trained by an algorithm provided by an intelligent model. Given this analogy, the union of the neural network with the Fuzzy logic comes intending to soften the deficiency of each of these systems, making us have a more efficient, robust, and easy to understand system [28,41,42].

The fuzzy neural networks can be classified as to how their neurons are connected. This form of connection defines how the signals will be transmitted on the network. In general, there is feedforward where the fuzzy neurons are grouped in layers, and the signal travels the whole network in a single direction, usually from the input of the model to its output generating an expected result. Fuzzy neurons in the same layer that do not have a connection and their networks are also known as nets without feedback [43].

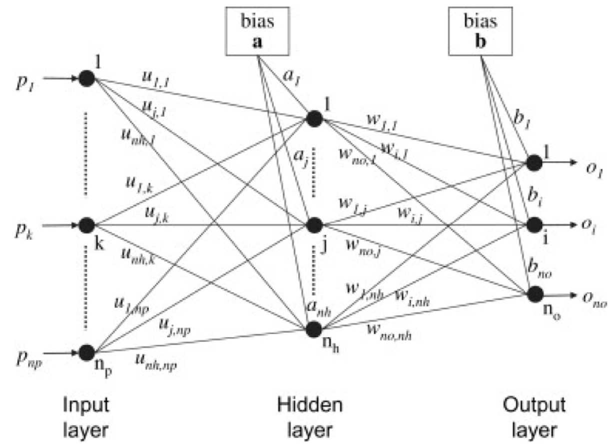

Fig. 3. Fuzzy neural network for multiclass problem [79].

4.1. FNN And NFN architecture

The architecture of hybrid models of neural networks and fuzzy systems have several characteristics. In general, each layer is responsible for a task to be performed, allowing the models to have a more dynamic way of solving problems. In general, architectural models of hybrid networks follow the similar organization of neural network models, so that they can be organized feedforward, where there are layered neurons. In it, the signal travels the network in one direction from input to output. Neurons in the same layer are not connected.

Just as there are recurrent networks, which have the output of some neurons feeding neurons of the same layer (including itself) or previous layers, the signal travels the network in two directions, has dynamic memory, and the ability to represent states in dynamic systems [44].

The type and quantity of layers in the architecture of hybrid models can vary based on the problem complexity. They have several functionalities to perform the tasks. The more traditional models have one or two layers hidden in their structures. They may be responsible for the process of fuzzy inference, rule-making, fuzzification, or defuzzification of data. Each layer has precise functions about its performance in the model, but in general, the first one is responsible for the fuzzification process and the last one responsible for the final answers of the model. Some of these layers may represent fuzzy inference systems or a neural network of aggregation.

The first layer of these models can perform fuzzification, organization of training samples, selection of samples, or bias identifications. The last layer presents the final outputs of the model, and the hidden layers may have a more significant variation in their quantity. It can be responsible for the creation of fuzzy rules, processing of model responses, degrees to which output membership functions are matched by the input data, defuzzification, among others. The number of layers and their functions is defined in order to meet and solve the problem's complexity.

After conducting the research, it was found that some authors count the input layer, and others do not consider it to count for the final number of layers in the hybrid models. In this case, this review paper will consider the input layer of the models as one of the layers belonging to the model when procedures are carried out, such as feature selection or another method that precedes the fuzzification processes, amount others.

For example, the first layers of the two or three-layer-model are responsible for the fuzzification process, the hidden layer, when existing, performs the aggregations of the input of the first layer, and the third layer is responsible for the defuzzification. Models with these characteristics have been proposed since 1975 [45], where the traditional neurons were modified by fuzzy versions of the neurons of Mc Culloch and Pitts [24]. They reappear in hybrid models in the year 1992 [46], allowing new models also to be proposed during the 90s to deal with various problems such as those related to construction, finance, pattern classification, the approximation of functions and identification of gases. It can be highlighted as models belonging to this group of characteristics like the model proposed by Blake et al. for hardware implementations of fuzzy systems [47]. Other examples were an FNN built with triangular fuzzy weights [48] and models proposed by Blanco et al. to the identification of fuzzy relational equations [49].

Other examples are Buckley et al. [50], Kuo and Xue [51], Kuo et al. [52], Simpson et al. [53], Ishibuchi et al. [54], Feuring [55], and a short term load forecasting created by Bakirtzis et al. [56]. Also, the detection of anomalies by Meneganti et al. [57] and gas sensing model proposed by Vlachos and Avaritsiotis [58] were models that exemplify those concepts.

In the decade of 2000, the models of two or three layers were destined for diverse tasks. Algorithms of clustering, together with new techniques of fuzzification and defuzzification, were incorporated into this group of intelligent models. The fuzzy c-means proposed by Bezdek [59] was used extensively from the 2000s to find the fuzzy sets of input data. The simple linear neuron made up most of the models studied, mainly because most of the models were time-series predictors and fault-diagnosis. Finally, many models were used in tasks related to the manipulation and control of robots. In this type of network, we also used several training contexts based on genetic algorithms, evolutionary, evolutionary, and based mainly on the technique of backpropagation and gradient descent. They illustrate this group of models in Table 2.

Lastly, in the last years, the three-layer fuzzy neural network attempt to solve unbalanced problems (where a group of samples is present in a majority of the experiment), binary pattern classification, time series prediction, water, and rain, as well as models focused on the capital market. Of the models and hybrid applications developed in the last decade stand out in Table 2. Fig. 3 present a model of fuzzy neural networks having three layers, where the first two layers of the models is a fuzzy inference system, and the last layer of the model can act as a classifier or as a universal functions approximation.

The models that use four layers in their structure have several functionalities for this extra layer. Some models have more than

Table 2
Models and applications. Three layers.

Models and applications	References
Years 2000	
Fuzzy regression	Aliev et al.[60]
Time series Forecasting	Liao et al [61] and lemos et al. [62]
Automatic detection of epileptic seizure	Subasi et al. [63]
Fault diagnosis and detection	Zhang et al. [64], Caminhas et al. [65]
Robot manipulators	Gao et al. [66] and Er and Gao [67]
Type 2 Models	Rutkowska [68]
Box and Jenkins Gas Furnace	Hell et al. [69]
Wind power forecasting	Pinson and Kariniotakis [70]
Fuzzy Cognitive Maps	Hengjie et al. [71]
Last decade	
Pattern Classification problems	Souza et al. [72–76], Duan et al. [77]
Regression Problems	Souza [78]
Water level	Alvisi and Franchini [79]
Fault detection	Serdio et al. [80]
Type 2 Models	Castillo et al. [81] and Gaxiola et al. [82]
Pricing fixed income options	Maciel et al. [83]

one hidden layer, or they make an auxiliary input or output layer to handle the data obtained by the network. In the research carried out, these models were appreciated in the middle of the 90s, where it is possible to emphasize that the most used training algorithm was the backpropagation create by Rumelhart et al. [27], and the purpose of the model was to be a function approximator or a model to diagnostic of failures. To exemplify these models stand out the works of Zhang et al. to fault diagnosis [84], the model of Chen et al. [85], the Wang et al. capable of acting as a universal approximation [86] and, finally the model of Lin et al. [87] which operates for PM2.5 Prediction.

From the 2000s onwards, many four-layers models were used as universal approaches to dynamize tasks linked to various contexts in industry and economics. In this period, the models that generate fuzzy rules for the construction of expert systems and several fuzzification techniques were used, such as the Semi-closed fuzzy set concept [88], B-spline membership functions [89]. Examples of four-layer models in the 2000s are the networks listed in Table 3.

Eventually, four-layers-models in the health area were proposed by Perova and Yevgeniy [106], aiding in rapid medical diagnosis beyond the work of Gao [107] that among its layers there is an inference system with rules if/then. The models of Mumtaz et al. [108], Shalbaf et al. [109] and Chimmanee et al. [110] uses adaptations concepts for training in neuro-fuzzy approaches. Fig. 4 presents an example of fuzzy neural networks with four layers.

Models with more than five layers have been developed since 1996 with the proposed network in Zhou et al. [111]. In 1998 a five-layered evolutionary model created by Kasabov and others [112] used online training to perform the identification of phonemes. Finally, in 1999, Figueiredo and Gomide [113] proposes the modeling and design of fuzzy systems using five-layer neuro-fuzzy networks.

In the early 2000s, models with five layers worked in several areas of problem-solving, such as time series prediction, robot control, and synthesizing processes using online training concepts, backpropagation, data clustering using fuzzy c-means, among others. The models proposed in Oh et al. [114], Kasabov et al. [115] are examples. The Dynamic fuzzy neural network proposed by Wu et al. [116], the robot manipulators for geometrically unknown objects created by Kiguchi et al. [117], the model of Er et al. [118], a model created for PID controller for plants [119], and subsequently, the models proposed by Kasabov et al. [120,121] are highlighted.

In the late 2000s several models with five layers were proposed to verify water quality [122], noise controls in various

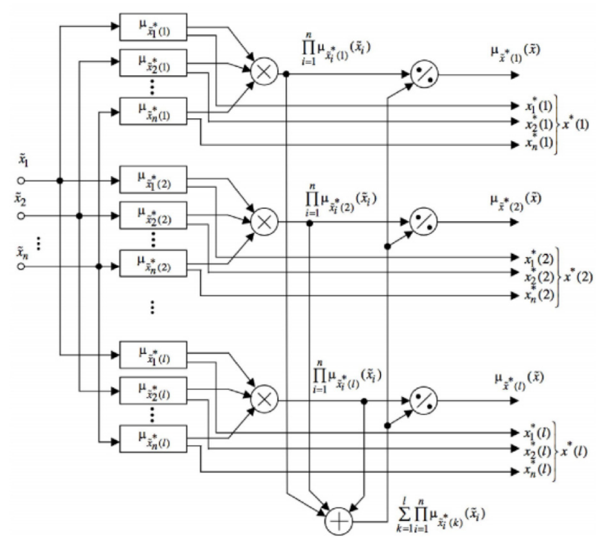

Fig. 4. Autoassociative neuro-fuzzy [106].

industrial processes [123] and [124], online time series forecast [125], which may involve problems where elements in time are critical to context analysis. Also noteworthy are models that act on the predictions of financial markets [126] and aspects related to the stock exchange like the model proposed by Li et al. [127]. Ultimately, stand out models that perform pattern classification. Exemplify, models are belonging to the highlighted period following Zhao et al. [128], Lin et al. [129], Leng et al. [130] and finally Leite et al. [131].

In the last decade, models with five layers were proposed to act to regression problems, time series predictors, and to classify patterns in related problems. There were models developed proposed in Aliev et al. [132], or the model that applies to dynamic system processing created by Juang et al. [133]. Other examples, such as the identification of dynamic systems elaborate by Lu et al. [134] and Leite et al. [135], have problem-solving efficiency in the industries. A model that uses Correlated-Contours Fuzzy Rules for Function Approximation made by Ebadzadeh and Salimi-Badr [136], and adaptative neuro-fuzzy model created by Asemi et al. [137]. Other models with five layers or more: Ay et al. [138], Azimi et al. [139], Kisi et al. [140] and Zhang et al. [141]. Recently, a paper about decoupling control for the wastewater treatment process [142] was studied through a recurrent fuzzy neural network. At the same time, a multiobjective

Table 3
Models and applications. Four Layers.

Applications	References
Years 2000	
Direct adaptive control	Da and Song [90]
Fuzzy identification	Yu and Li [91]
PID controllers	Ho et al. [92]
Automatic generation of fuzzy rules	Wu et al. [93,94]
Time Series Forecasting	Ballini et al. [95]
Mineral potential mapping	Porwal et al. [96]
Last decade	
Predicting evolving chaotic time series	Xing et al. [97]
Control for a constrained robot	He and Dong [98]
Structural damage detection	Jiang et al. [99]
Active power filter	Fei and Wang [100]
Fault-tolerant aircraft	Yu et al. [101]
Reinforced or Recurrent hybrid model	Kim et al. [102], and Yen et al. [103]
Energy aware clustering scheme	Robinson et al. [104]
Machine Monitoring	Ting et al. [105]

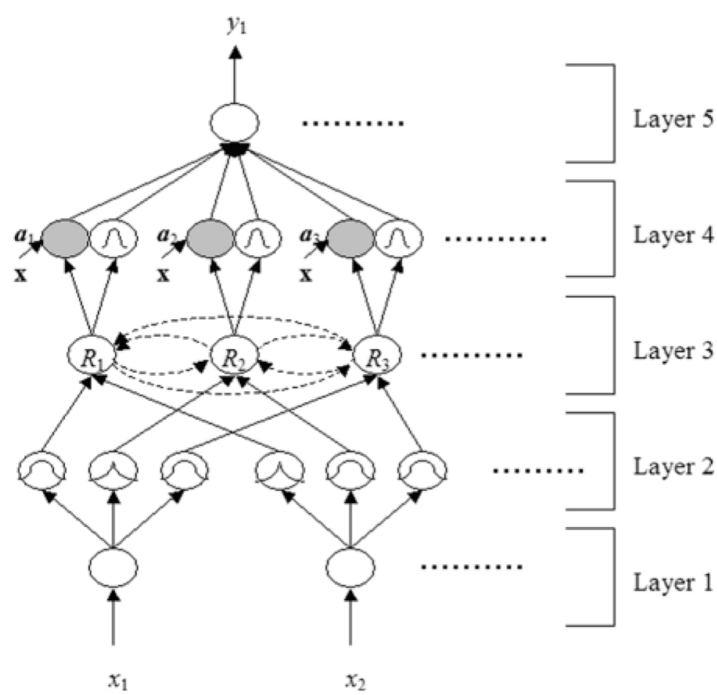

Fig. 5. Structure of Adaptative fuzzy neural network [129].

controller in a fuzzy neural network for the same objective has created by Han et al. [143]. Fig. 5 presents an example of a five-layer fuzzy neural network architecture.

4.2. Fuzzification techniques

This step is crucial for hybrid models. The choice of the number of membership functions or the technique can affect performance characteristics and even the interpretability of the results. This process allows the creation of regions in the decision space, formed by fuzzy functions that can be triangular, trapezoidal, or Gaussian [144].

For Ross [144], fuzzification is the stage at which fuzzy sets with their respective domains model system inputs. It is at this stage that the great importance of specialists of the phenomenon to be modeled is justified. Thus, even if the input is crisp, it will be fuzzified by its characteristic function. A typical example is taking the height of a group of people and proceeding with the property of interpretability.

This step is the first action in the concept of fuzzy inference. In this process, fuzzy rules are constructed with the chosen fuzzification process, allowing the results to be interpretable and logical, especially if there is the aid of a specialist. This process is based on the analysis and definition of fuzzy rules and the region's resulting determination for the problem. In general, these rules are conditional (IF B is C THEN Z is J) or nonconditional (B is C). To verify the importance and the representativeness of a rule, we highlight aggregation operations (calculates the relevance of a given fuzzy rule for the analyzed problem) and the composition (derives the influence of each rule on the output variables) [28].

Some techniques are used to perform fuzzification processes in hybrid models of neural networks and fuzzy systems. The papers of Er et al. [118] and Yu and Yan-Qing [126] uses algorithms based on genetic concepts. Genetic algorithms seek the optimization of evolution-inspired tasks that incorporate a potential solution to a specific problem (in a chromosome-like structure) and apply selection and cross-over operators to these shape structures to preserve critical information about solving the problem [145].

Table 4
Models and applications using ANFIS.

Models capable of generating fuzzy rules	
Applications	References
Short-term load forecasting	Papadakis et al. [147]
Forecasting stock market	Li and Xiong [127]
PID controller for plants	Shen [119]
Pattern Classification problems	Souza et al. [72,74,75]
Time Series Forecasting	Souza and Bambirra [76]
Regression Problems	Souza [73]
Prediction of Breast Cancer	Silva Araujo et al. [148]
Predict absenteeism at work in companies	Araujo et al. [149]
Diagnosed of Autism in Adults	Guimaraes et al. [150]
Treatment of Cryotherapy and Immunotherapy	Araujo et al. [151]
SQL Injection	Batista et al. [152]
Business Failure Prediction	Chen [153]
Customer Satisfaction for New Product	Jiang et al. [154]
Software Effort Estimation	Souza et al. [155]

A model that is used for fuzzification is the ANFIS model proposed by Jang in 1993 [146], where its versions can generate membership functions that are equally or differently spaced. Several works such as this use this approach, as in Table 4, allowing the data set to be partitioned in a grid format, allowing for inferences and interpretability about the dataset studied.

Several fuzzy neural networks use fuzzy concepts to perform granularization of the input space: stand out models using Axiomatic Fuzzy Set [77], fuzzy backpropagation system [56], Fuzzy finite Automation [45]. Other examples are Fuzzy I/O controllers [50], Fuzzy Delphi [51,52] (The two models act with the same problem, but they differ by the architecture and the way of updating the weights), vector-based fuzzy structures [64, 117], fuzzy cognitive structures and label [71,112]. The concepts of fuzzy hyperboxes proposed by Leite et al. [53,135] and the performed using the commonly used methods for dividing multi-class classification problems: OAA (one-against-all) and OAO (one-against-one). Consequently, two models are introduced to Priyandoko: OAA and OAO based neuro-fuzzy classifiers [156].

A few papers address the data clustering to perform the fuzzy step of the process. The networks use in their first layers the concepts of clouds in Rosa et al. [157,158]. General clustering methods were used in Pedrycz [46], de Campos Souza et al. [159], and Ballini et al. [95]. Evolutionary and self-organizing clustering [83,111,113,120,160–163] were used in a bunch of models. The concepts of Wavelets [103,134], concepts of radial base function in Real-coded [128] also have highlighted. Also finally stand out models that use clustering methods commonly applied in the literature, such as the fuzzy c-means (like in the models proposed by Lemos et al. [62,164]) and its various forms: Hybrid identification create by Oh et al. [114], for approximation capabilities using uninorm [165] and nullnorm [69]. A dynamic Evolving Fuzzy Neural Networks proposed by Kasabov and Song [121], a classifier with self-organizing properties [166] and Reinforced hybrid interval FNN created by Kim et al. [102] were examples of relevant models that use different fuzzification techniques. In this approach, the parameters obtained by the clustering methods are used to construct neurons with membership functions. Fig. 6 exemplify the fuzzy c-means results in the data clustering, and Fig. 7 explains the granular process.

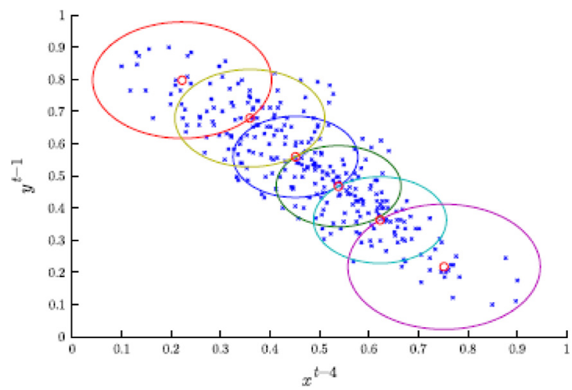

Fig. 6. Clustering approach by Fuzzy C-means [167].

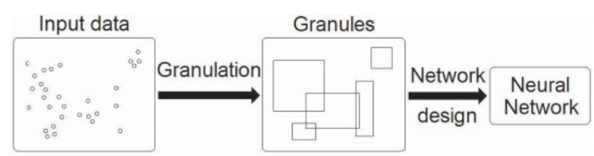

Fig. 7. Granular process [135].

4.3. Defuzzification techniques

When the problem's variables are transformed into decision regions and interpretable elements, they aid in the construction and interpretation of fuzzy rules. In this context, for the hybrid model to be able to produce responses consistent with the context of the problem, the defuzzification process must be carried out, which is nothing more than transforming the resulting region of the problem into values for the output of the problem. This step consists of the union of the inference system and the expected response of the model. For Ross, some techniques are commonly applied to perform the defuzzification process, such as the centroid technique, first of maxim, middle of maximum, and the maximum criterion [144].

There are recent models proposed by Kumar et al. that use the Crisp Gain technique as a defuzzification technique [168]. Fig. 8 presents relevant characteristics of the defuzzification process, highlighting the possible results obtained varying according to the applied technique.

4.3.1. Centroid

The centroid is the most popular method of defuzzification. This standard technique calculates the centroid or center of gravity (COG) of the area under the membership function. This technique has a stable and monotonous characteristic [169].

4.3.2. Center of area

A fast method because it needs only simple operations, the center of area (COA). This method determines the center of area of the fuzzy set and returns the corresponding crisp value [169].

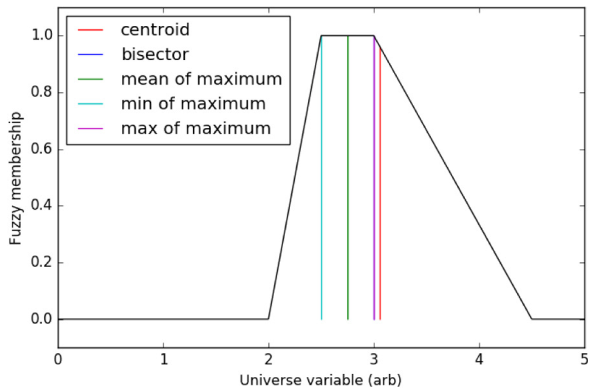

Fig. 8. Example of defuzzification methods.
Source: Available in: pythonhosted.org.

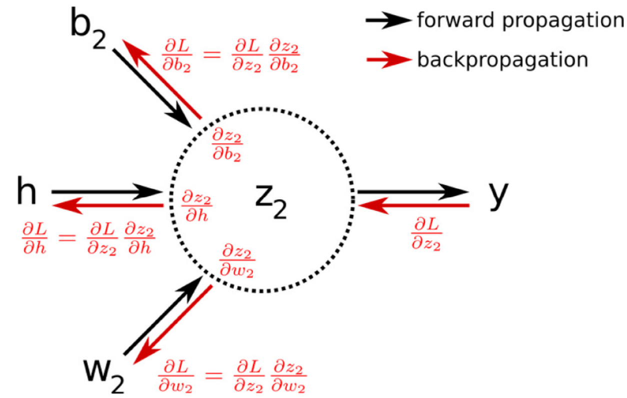

Fig. 9. Backpropagation.
Source: Available in: https://qwertee.io/blog/an-introduction-to-backpropagation/.

4.3.3. Maxima methods

There are different maximum methods with different conflict resolution strategies for multiple maxima, for example, first of maxima (FOM), last of maxima (LOM), an average of maxima (AOM), and center of maxima (median). These techniques seek to adapt the answers about the area of the pertinence functions adopted in the fuzzification phase. Maxima methods are section invariant, arithmetically compatible, and exclusive. Some of them are consistent, monotonous, linear, offset invariant, scale-invariant, or compatible with the maximum [169].

4.4. Training algorithm

This section presents algorithms that are commonly employed in the training of hybrid models based on neural networks and fuzzy systems. In general, the algorithms act in existing parameters in the architecture of the models allowing the answers to be adapted to the purpose for which they are intended. Here are some of the analytical techniques researched.

4.4.1. Backpropagation

The most popularly used training algorithm in fuzzy neural networks and neuro-fuzzy models is backpropagation proposed by Rumelhart et al. [27]. This approach is a technique that goes through the network structure and updates the fundamental parameters for the performance of the model through mathematical techniques based on derivatives. It is an efficient technique in the supervised training of models where its primary objective is to optimize the weights so that the intelligent model can learn to correctly map the inputs to the outputs, in other words, we want to find a set of weights that minimizes the output of the loss function, or network error. This technique uses two steps: Forward Pass and the Back Forward pass. These approaches propagate the calculations of the model to obtain the answers, allowing the return step to identify the error of the expected output with the calculated output, and the adjustments in the synaptic weights are performed to obtain better answers. Fig. 9 shows the backpropagation scheme where $\frac{\partial L}{\partial \lambda_n}$ is the gradient and $\lambda = \text{h, b, w, z n} = 1, 2$.

Hybrid models that use these techniques to update weights and/or other parameters of the network are in Table 5.

The gradient descent is an optimization algorithm used to minimize some function by iteratively moving in the direction of the steepest descent of the problem, widely known in academic society. This technique uses backpropagation to execute its tasks. This optimization method seeks to find a local minimum using the gradient descent to look in the hypothesis space for the best weights' vector. This method determines a vector of weights, which minimizes the training error of the model, starting with an initial vector of arbitrary weights and modifying it repeatedly in small steps allowing the vector of weights to be changed in the direction that produces the significant drop along the error surface [170]. The paper of Shi and Masaharu [171] present a review of gradient descent methods in Neuro-Fuzzy algorithms. Fig. 10 shows the general functioning of the gradient descent algorithm to minimize the error by seeking a local minimum.

Hybrid models that use this technique has listed in Table 5.

4.4.2. Extreme learning machine

ELM (Extreme Learning Machine), proposed by Huang et al. is a learning method developed for single-layer feedforward neural networks (SLNFs) that are being widely used in hybrid models, where random values are assigned to elements of hidden layers (weights and biases). The weights of the output layer of the models are estimated analytically using the least-squares concepts [180]. This type of parameter definition allows the training time of models to be smaller, even less complicated than models that are trained with backpropagation (due to the need to update the internal parameters according to the error of the model output). As a disadvantage, ELM-trained models can suffer from overfitting in training, allowing intelligent models to be influenced by training patterns, generating responses with a high percentage of error. A hybrid model algorithm with ELM differs from conventional feedforward networks due to the dispensability of adjusting the hidden layer parameters, which usually occurs by backpropagation, generating the delay in training if the adjustment rate is far from ideal, which may be composed of neurons randomly defined and independent of training patterns [180].

The hybrid models trained with ELM have existed since the late 2000s with an emphasis on a model built by Sun et al. [181] and Lemos et al. [62] model. During the last years, some models update synaptic weights for the neural network of hybrid modeling, such as proposed by Lemos et al. [182] and [164], evolving models for time series forecasting of by Rosa et al. [183], binary pattern classification problems proposed by Souza [72], Souza and Oliveira [75] and Souza et al. [74]. A model that uses Or Neuron for Time Series Forecasting created by Souza and Bambirra [76] and a pruning model proposed by Souza [73] use the ELM concepts do define weights to link the second layer and the output layer of the models. The model created by Rosa et al. that realized volatility forecasting with jumps [157] and system

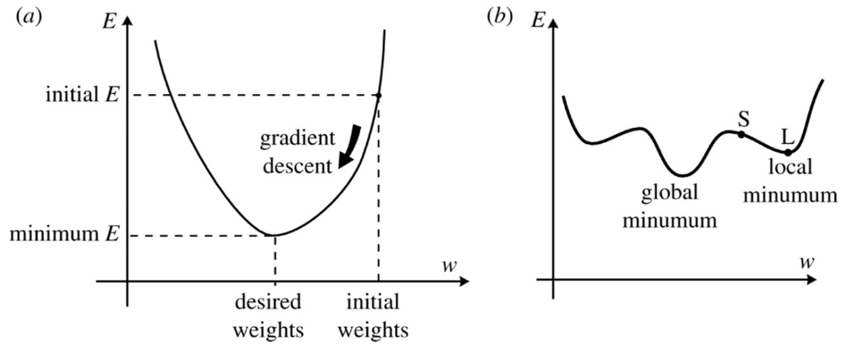

Fig. 10. Gradient descent.
Source: Available in: royalsocietypublishing.org.

Table 5
Models and applications.

Models	References
Backpropagation	
Triangular fuzzy weights	Ishibuchi et al. [48]
Identification of fuzzy relational equations	Blanco et al. [49]
Structural damage detection	Jiang et al. [99]
Sales forecasting	Kuo and Xue [51]
Fault diagnosis	Zhang and Morris [84]
Predictive control for industrial process	Lu and Tsai [124]
Fuzzy weights and fuzzy biases	Ishibuchi et al. [54]
Control of uncertain systems with time delays	Chen et al. [85]
Industrial robot manipulators-application	Kiguchi and Fukuda [172]
Gas Sensing	Vlachos and Avaritsiotis [58]
Function approximation	Wu and Er [116]
Prediction system for sintering process	Er et al. [118]
Interpretation based on fuzzy inference	Rutkowska [68]
Direct adaptive control	Da and Song [90]
Adaptive EEG-based alertness estimation	Lin et al. [129]
System Identification	Leng et al. [130]
Fuzzy modeling	Horikawa et al. [173]
Numerical prediction of Time Series	Hengjieet al. [71]
Gradient Descent	
Fuzzy identification	Yu and Li [91]
Class of interval type-2	Castro et al. [174]
Forecasting	Silva et al. [175], Bakirtzis et al. [56], Li and Xiong [127], Hell et al. [69]
Fuzzy identification	Yu and Li [91]
Identification and predictive control of dynamic systems	Lu [134]
Adaptive feature selection	Silva et al. [176]
Nonlinear process	Ballini et al. [95]
Fault detection of dynamic systems	Caminhas et al. [177]
Real-time nonlinear modeling of a twin rotor MIMO	Silva et al. [178]
Classification and prediction	Mascioli and Martinelli [179]
Function approximation and classification type systems	Gao et al. [107]

modeling [158] uses ELM with an evolving approach. Finally, the models created by Rong et al. [184] and Souza et al. [78] operating with function approximation, classification problems, and regression problems, respectively.

4.4.3. Genetic Fuzzy neural networks

Genetic Algorithms are global optimization algorithms, based on the mechanisms of natural selection and genetics that work with the coding of the set of parameters and not with the parameters themselves. They employ a parallel, structured but random search strategy, working with a population rather than with a single point, which is directed towards reinforcing the search for "high aptitude" points, that is, points at which the function a to be minimized (or maximized) has relatively low (or high) values [145].

Mitchell explains that they use cost or reward and non-derivative information or other auxiliary knowledge in addition to using probabilistic and non-deterministic transition rules. They are based on biological evolution and are capable of identifying and exploring environmental factors, enabling them to converge to optimal or approximately optimal solutions at global levels [145]. In the model proposed by Dahal et al. [185], a genetic algorithm is used to identify the fuzzy rules in network architecture.

The training of the hybrid model creates in Kisi et al. [140] uses genetic algorithms to update parameters in its six layers of architecture.

Zhang and Zili [186] use AutoRegressive with exogenous input (ARX) with the nonlinear Tanh function in the Takagi–Sugeno (T–S) type fuzzy, and a genetic algorithm makes adjustments in the model architecture. A trained neuro-fuzzy approach with genetic algorithms was used for modeling and control of dynamic systems in Farag et al. [187]. The fuzzy neural network model acts to product form design using genetic algorithms in training the

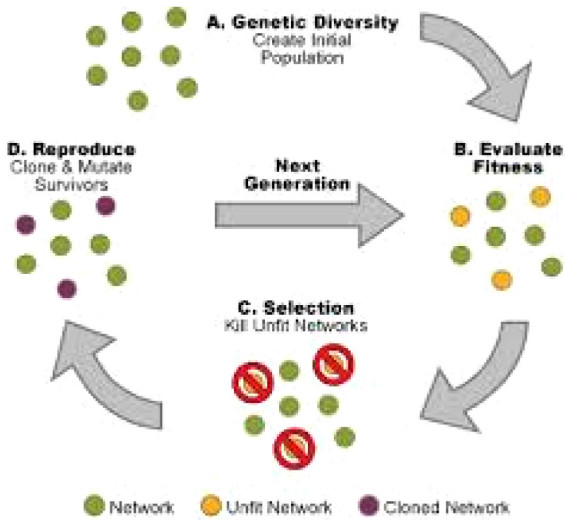

Fig. 11. Genetic algorithm.
Source: Available in: https://quantdare.com/ga-to-define-a-trading-system/.

main attributes in the network of Hsiao and Hung-Cheng [188]. Other models can be seen in the review carried out by Cordon et al. [189]. Fig. 11 shows an example of the operation of a genetic algorithm in the definition of neurons of an intelligent model.

4.4.4. Evolving and on-line algorithm

Intelligent evolving systems, according to Kasabov and Dimitar [190], are based on online machine learning methods for smart hybrid models. These systems are characterized by their ability to extract knowledge from data and adapt their structure and parameters to better suit to changes in the environment [191].

Angelov et al. [191] explain that they are formed by an evolving set of locally valid subsystems that represent different situations or points of operation. The concepts of this learning methodology make it possible to develop unsupervised clustering algorithms capable of adapting to changes in the environment as the current knowledge is not sufficient to describe such changes. According to Angelov et al. [192], fuzzy evolutionary systems are based on the process of evolution of individuals throughout their life; specifically, the process of human learning, based on the generation and adaptation of knowledge from experiences.

The evolving models, which alter parameters as they update new training inputs, can be exemplified by the hybrid models listed in Table 6. Comprehension surveys on these models can be found in [21]. Other examples can be seen at Lin et al. [193] and a neuro-fuzzy approach by Vahedi et al. [194]. A self-constructing neural fuzzy inference network (SONFIN) is a hybrid model that works with online training in areas such as chaotic series prediction, Dynamic System identification, Water Bath Temperature Control, and others [195]. In Gu et al. [196], a novel self-boosting algorithm for structure and parameter-optimization is proposed, and in Gu et al. [197] a zero-order evolving intelligent system (EIS) is presented. Perova and Bodyanskiy have created a model capable of obtaining Fast medical diagnostics [106]. Malcangi et al. [198] created an evolving model capable of recognition and removal of artifactual beats in continuous recordings of seismocardiogram. Finally, Souza et al. [199] have constructed a hybrid model of fuzzy neural networks where fuzzification of the model is performed by a fully-data driven algorithm for binary pattern classification.

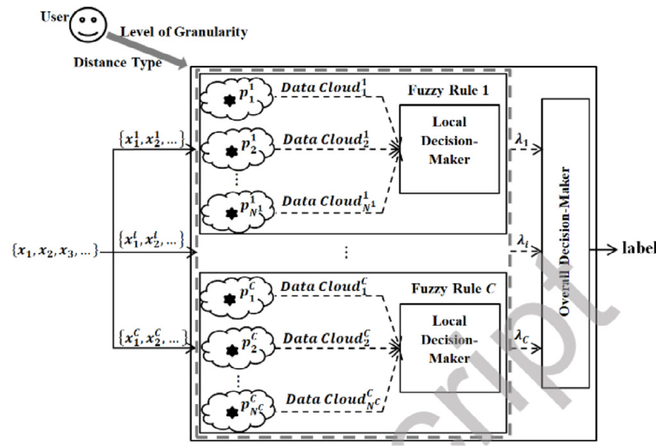

Fig. 12. Self organizing model [201].

In Fig. 12 is presented a scheme on the operation of the decision of a model where the user influence is fundamental [200]. This model is an enhancement of another hybrid model called AnYa that is seen as a generic multi-input-multi-output (MIMO) modeling framework that is able to process data clouds not having a fixed apriori distribution, including fuzzy rules and neural networks.

Most machine learning techniques work offline, that is, always being considered a fixed structure. However, some methods and algorithms need a continuously changing learning. Generally speaking, online learning allows a new sample or dataset submitted to the model to work with an instant analysis of the model's architecture or hyperparameters, allowing for instant changes and adaptations [202].

Thus the models gain in the efficiency of their adaptability the nature of the problems, maintaining resolution efficiency of actions. The online nature of the training allows the model to have no worse performance in cases of so-called data shifts and/or drifts [200].

Hybrid models that present this type of training: Kasabov [120], Leng et al. [203], Pinson, and Kariniotakis' online model [70] that can predict the risk of wind power forecasting. Finally, online models can also work on the efficient detection of robot trajectories, as found in Bencherif and Chouireb [204].

4.4.5. Evolutionary algorithm

Genetic algorithms and genetic programming [205] are based on the evolutionary process that occurs in populations of individuals and use operators based on the concepts of selection, crossing, and mutation of chromosomes as adaptive mechanisms.

These models stand out by using techniques to update parameters using the dataset itself or procedures based on the theory of evolution. The models that use genetic training can be exemplified by Blake et al. [47], by Zhao et al. [128], by Gao and Er [88], the model proposed by Aliev et al. [60], by Chaves et al. [122] and finally, the recent model created by Kim et al. [102]. The model called LNFF created by Ranjan and Prasad [206] uses an evolutionary model to perform classification tasks and Feature extraction using semantic processing.

4.4.6. Deep learning

The hybrid models also advance in the use of new forms of training, mainly using the concepts of deep-learning. Deep-learning is a sub-category of machine learning, which addresses deep training opportunities with the use of neural networks. This

Table 6
Evolving and evolutionary hybrid models.

Models that evolve with training	
Applications	References
Active noise control	Zhang et al. [123]
System identification	Aliev et al. [39]
Load forecasting	Liao and Tsao [61], Hell et al. [207]
Nonlinear functions approximated	Wang and Li [208]
Time Series Forecasting	Kasabov [120], Hu et al. [209], Lughofer et al.[210]
Hybrid financial prediction	Yu and Zhang [126], Maciel et al. [83]
Active power filter	Fei and Wang [100]
Fault-tolerant aircraft control	Yu et al. [101]
Concept drifts	Pratama et al. [211], Lughofer et al.[212,213]
Function approximation and classification problems	Rong et al. [184]
Control for a constrained robot	He and Dong [98]
Modeling nonlinear systems	Han et al. [214], Lin et al. [215], Zhao et al. [216]
Control of wastewater treatment process	Tang et al. [217]
Fault Detection	Silva et al. [218], Costa et al. [219]
Modeling biodiesel synthesis	Tang et al. [220]
Non-stationary dynamic system	Rocha et al. [221]
Cost estimates in construction industry	Cheng et al. [222]
Intrusion detection	Toosi and Kahani [223]
Brain Dynamics in Predicting Driving Fatigue	Liu et al.[224]
Adaptive Feature Selection	Silva et al. [225]
Black-Box Modeling Based on Instrumental Variable	Rocha and Serra. [226]
Liquid Desiccant Air Conditioning	Jiang et al. [227]
Classification problems	Wang and Lee. [228]
Dynamic systems identification	Lin et al. [229]
System and Second-Order System Identification	Lin et al. [230]
Web News Mining	Zain et al.[231]
Control	Ferdaus et al. [232]
Visual Inspection (with Classification)	Lughofer et al.[233]

training is used to improve many tasks in the computational environment, such as speech recognition, vision, and natural language processing [234]. This subject has quickly become one of the most sought after and studied within modern science.

Deep Learning is an automatic learning technique that teaches computers to learn based on examples submitted to the evaluation of a model and is considered a specialized form of machine learning. In general, a computer algorithm learns to perform classification tasks directly from images, text, or sound. Deep Learning requires large amounts of tagged data and requires significant computational power, usually performed in parallel computing. It performs the learning of a model so that later it can decipher the natural language or inference about the problem. It lists terms and patterns to put meaning and solve the problem effectively.

The term "deep" usually refers to the number of layers hidden in the neural network. Traditional neural networks contain only two or three hidden layers, while deep nets can have up to 150. Deep Learning models are trained through the use of extensive marked data sets and neural network architectures that learn directly from the data, without the need for manual extraction of resources [234].

Because it is a well-explored topic in the world of artificial intelligence, hybrid models also use deep-learning concepts to perform various tasks. The models that use these concepts perform data classification [235] in the model proposed by Deng et al. Situations of daily life in the big cities were also approached with hybrid models and deep-learning as in the traffic incident detection model proposed by El Hatri and Boumhidi [236]. Prediction of lung tumors proposed by Park et al. [237], inspections for text sentiment analysis [238] created by Nguyen et al. detection of cyberattacks, especially multiple malware attacks by Shalaginov and Franke [239] moreover, benchmark datasets and an industrial case were used by Suhang et al. [240] are examples of hybrid models with this approach. Recent models propose the use of neuro-fuzzy models to simulate human characteristics in image recognition. Angelov and Gu have proposed an example of this type of architecture [241]. Already Gu and Angelov [242] have constructed a semi-supervised hybrid model for image classification, and Gu et al. [243] have devised a model for dealing with classifier for remote sensing scenes.

4.4.7. Other methods

The training in intelligent models involves regularized, pruned, and updated approaches. In general, these methods act in the regularization of models allowing the answers to be closer to the real one. Pruning methods eliminate unneeded neurons or connections in the network, allowing architectures to be leaner and more cohesive, reducing complexity and improving model outputs.

The models proposed by Han and Qiao [244] and Leng et al. [245] act to increase the structure of the network and to prune it when necessary. That allows the model to be adaptive and grow or decrease in complexity to improve responses. The models proposed in Shann and Fu [246], Souza [73], Dash et al. [247] and Leng et al. [203] use structures with many primary neurons and apply techniques based on techniques that eliminate less significant neurons. The model proposed by Kasabov and others [112] discards old neurons in the model architecture. Genetic algorithms are also used to eliminate neurons less relevant to the model, as suggested in Ishigami et al. [248], Tung and Quek [249], and Leng et al. [130]. Already as regularized models, stand out the models that use the concept of least-square linear regression problem and replications proposed by Bach [250]. The models proposed by Souza et al. [72,74–76] use the Bolasso (bootstrap-enhanced least absolute shrinkage operator) to accomplish the elimination of less significant neurons to the problem. This regularization allows less significant neurons to have zero weight and does not interfere with model outputs.

In new propositions of Azimi et al. models training approaches based on stochastic processes perform parameter updates of a five-layer ANFIS network [139], and in Han et al. [254] uses an optimization Method for improving generalization performance in hybrid models. In that paper, it is proposed as a method to

Table 7
Pattern classification models.

Models	
Applications	References
Synthetic patterns using clustering techniques.	Simpson [53]
Synthetic dataset	Pedrycz [46], Rutkowska [68], Leite et al. [135], Zhou and Quek [111]
Iris and/or Wine Dataset	Leite et al. [131], Mascioli and Martinelli [179] Nauck and Kruse [251], Sun and Jang [252]
Diverse dataset-UCI Machine Learning Repository	Duan et al. [77], Souza [72], Souza et al. [74], Souza and Oliveira [75], Lin et al. [253]
Ionosphere dataset	Mitrakis et al. [166]

estimate and improve the generalization performance of FNNs and can minimize the structural risk by balancing the empirical risk and the complexity of the candidate structures. In the model of Camci et al. [255], an FNN uses a particle swarm optimization-sliding mode control to is used in an aero robot responsible for inspecting rice farms. In the paper of Wang [256] the concepts of fuzzy cellular neural networks are used to solve time-varying coefficients and proportional delays using differential inequality techniques, and in Lin and Chin [257], Wang et al. [258], Yen et al. [103], Lin et al. [259] and Zhao et al. [260] uses a recurrent approach.

A neuro-fuzzy model proposed by Ichihashi et al. [261] introduced an incremental method of inducing fuzzy decision trees with linear programming for maximizing entropy. In another recent work, Bayesian techniques are used by Altilio et al. in a neuro-fuzzy approach to generate sparse models [262]. In the paper of Zamirpour and Mosleh [263], a new training model for fuzzy neural networks based on the human brain was created and was named fuzzy emotional neural network. Fortified Offspring Algorithm has developed by Qaddoum [264] using fuzzy c-means, principal component analysis, and evolutionary algorithm for classification problems. In Tagliaferri et al. a fuzzy neural network uses to carry out its principal activities, the concepts of fuzzy relations with truth values in a suitable algebraic structure [265]. Intelligent hybrid models also utilize Reinforcement learning by integrating the integration of two models capable of constructing a fuzzy control system through a reward/penalty signal [266].

Hybrid models have the advantage, in comparison to powerful neural network training models, of generating fuzzy rules that can be interpreted as linguistic variables of the problem [267]. However, it should be noted that due to the relevance and complexity of this topic, this survey will not address these aspects in detail. Therefore, to consult on the interpretability of hybrid models, the surveys of Shukla and Tripathi [268], Adadi and Mohammed [269], and Guillaume [270] are advised.

5. Fuzzy neural networks applications

This section will be presented hybrid models in their various forms of representation of human characteristics in the construction of expert systems in the industry, health, and the financial area.

5.1. Pattern classification

The pattern classification is a methodology used by the intelligent models to identify similar characteristics in a group of samples seeking to label it according to the inferences made. In this context, we seek to determine if a new sample will belong to a group of characteristics or another context evaluated. Pattern classification problems involve binary problems, where there are only two possible classifications. This type of problem is present in situations where the evaluation of whether or not to be in a state is fundamental, such as sick and healthy, right and wrong, or even industry evaluations as a fit or unfit product. There are also models where classification involves multiple labels, allowing more distinct types of groups to be identified [271].

Stand out as example models that perform pattern classification, the ones presented in Table 7.

These models solve problems related to the bases commonly used by the scientific community that is available in repositories like UCI Machine Learning Repository [272,273], or applied research in jobs and routines of industries and people. In the paper proposed by Tseng and Hu [274], they seek to solve a significant business classification problem: Bankruptcy prediction. Also, in Singh et al. [275], a neuro-fuzzy system is suggested for rule-based classification, and the novelty lies in the way significant linguistic variables using dynamic clustering. In Ranjan and Prasad [206], an FNN is used for text classification using an entropy-based feature selection approach for selects required keywords and reduces the dimension of the search space. The model recently proposed by Souza et al. operates in the binary pattern classification using the concepts of nullneurons and fuzzification algorithms based on the data density [276].

Fig. 13 presents a synthetic database with two classes and how a hybrid model can find a solution to classify the two categories.

5.2. Regression problems

Regression problems consist of a process to estimate a functional relationship between the variables analyzed in a problem. It allows the relevance of independent variables to be evaluated in a dependent variable. It aims to be able to define an equation that represents the analyzed phenomenon. This behavior can be linear, quadratic, exponential, among others. The hybrid models work with elements that favor the determination of these factors through internal connections between the neurons of the model. Intelligent models using neural networks can act as linear regression models because they identify the correlations between the elements of the problem [285]. Examples of fuzzy neural networks and neuro-fuzzy models acting as regressors are those listed in Table 8.

To demonstrate how intelligent models perform the function approximation through linear regression models, Fig. 14 represents the result of an estimate of values of a predictor model.

5.3. Time series prediction

It is possible to define a time series as a set of data observed and ordered according to time parameter and with serial dependency (schedules, daily, weekly, monthly, quarterly, or annual.). Models that are intended to solve time series problems work with approximate results, as well as the regressors, but the form and the sequence of how the events happen are a preponderant factor in the analysis.

Models that propose to solve time-series problems validate their proposals through tests with the Box–Jenkins gas-furnace

Table 8
Regrassion models.

Models	
Applications	References
Non-linear function approximation problem.	Blake et al. [47], Wu et al. [93]
Synthetic dataset	Ishibuchi et al. [48], Blanco et al. [49]
	Zhao et al. [128], Buckley and Hayashi [50]
	Wang et al. [86], Figueiredo and Gomide [113]
	Wang and Li [208], Ishibuchi and Nii [277]
Nonlinear Dynamic System Identification	Leng et al. [130]
Diverse dataset-UCI Machine Learning Repository	Souza et al. [78,159]
Plants and Non Linear Plants	Ho et al. [92], Ballini et al. [95]
Effort Forecasting in Software Development	Souza et al. [155], De Campos Souza et al. [278]
Google stock tracking	Ebadzadeh and Salimi-Badr [136]

Table 9
Time series forecasting models.

Models	
Applications	References
Economy and finances.	Yu et al. [126], Maciel et al. [83], Malhotra and Malhotra [279]
Forecasting stock market	Li and Xiong [127], Atsalakis and Valavanis [280],
	Chang et al. [281], Garcia et al. [282],
	Kuo et al. [283]
Monthly temperatures of weather times series	Silva et al. [176], Pinson and Kariniotakis. [70]
	Nauck and Kruse [251], Sun and Jang [252]
Short term load	Bakirtzis et al. [56], Papadakis et al. [147], Liao and Tsao [284],

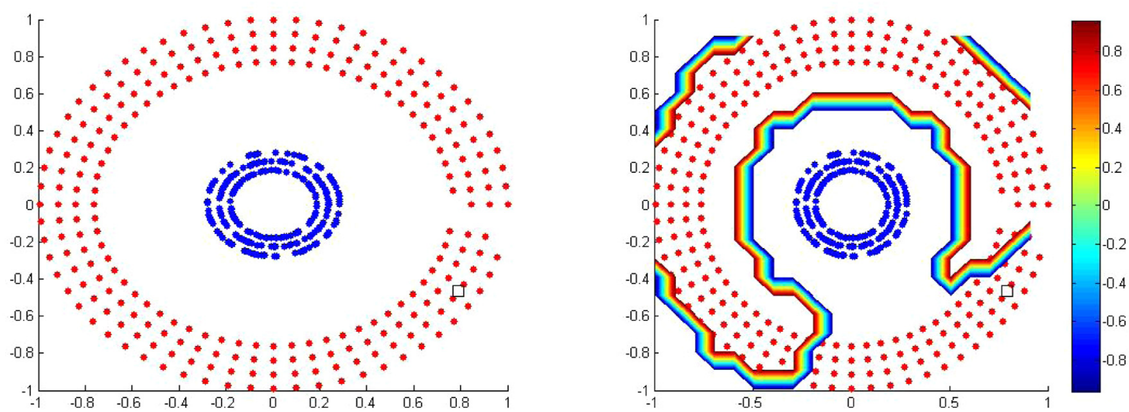

Fig. 13. Pattern classification example.

dataset [286]. In the work of Xing et al. [97], the hybrid model is responsible for predicting chaotic series using the concepts of the DENFIS algorithm. Fig. 15 presents the resolution of a fuzzy neural network for the Box–Jenkins gas furnace problem. Models that act with this problem are exemplified by the eX-uninet model proposed by Bordignon et al. [165], Silva et al. [175] and Huang and Pedrycz [287] obtained excellent results in the prediction of the time series.

Table 9 presents some models that act for time series forecasting solve-problems.

Others propose generalist models, which can adapt to any problem where time is a crucial factor in predicting a value. It should be highlighted the architectures of Hell et al. [69], Bordignon and Gomide [288], Kasabov and Woodford [162], Hengjie et al. [71], Leite et al. [289], Lemos et al. [62,164], Rosa et al. [157], Souza and Torres [76], Castro et al. [174], Deng and Wang [125], Oh et al. [114], Gao and Er [88], Aliev et al. [39], Juang et al. [133], Chaves and Kojiri [122], Kasabov [115,121], Silva et al. [290], Yoon et al. [291], Mans and Tonshoff [292], Shi et al. [293] and the model proposed by Vlasenko et al. [294].

In the work of Meng et al. [295], the periodicity impulses and time-varying delays and in Terziyska et al. [296] the model can capture uncertain variations in the data space. In Han et al. [254] a fuzzy neural network is used for financial Time-Series, and in [297] a fuzzy neural network is evaluated with mainly two problems of time series applications: the Mackey Glass Chaotic Time-Series prediction problem with different sets of parameters and levels of noise and the ECG heart-rate Time Series monitoring problem. In Wu and Er [116] and in the model proposed by Kasabov [120], an FNN also works with the Mackey Glass problem. In the model proposed in Lohani et al. [298] an adaptive neuro-fuzzy model is used for hydrological time series modeling, and a weighted evolving fuzzy neural network is used for monthly electricity demand forecasting [299] was proposed by Chang et al. Another model act in Chaotic Time-Series prediction [300] and sales forecasting [301].

5.4. Faut detection

The detection and diagnosis of failures can be based on models, which represent the physics of the process, constructed from knowledge acquired directly from experts or data. This type of activity performed by intelligent models facilitates the dissemination and organization of techniques that assist in predicting problems arising from machine or process failures [302] and the early mechanical failure [303].

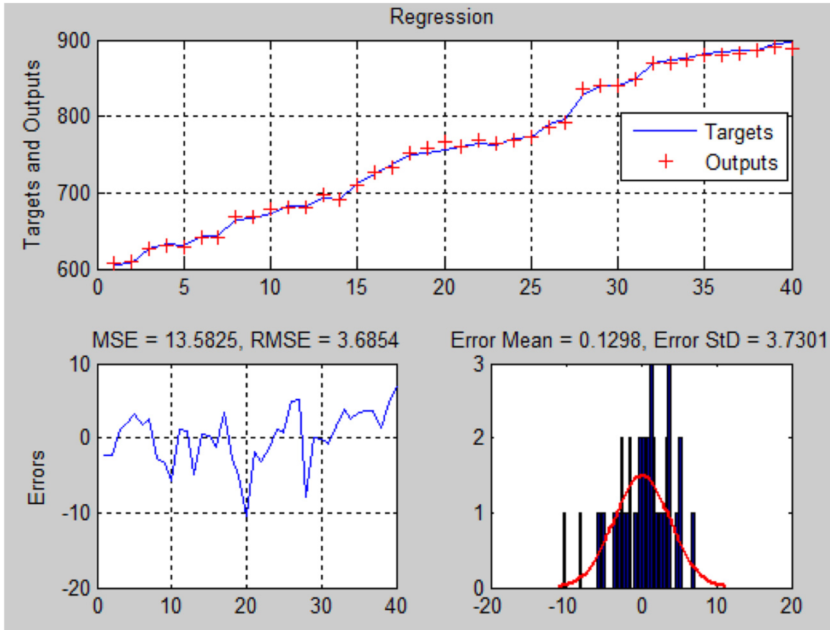

Fig. 14. Results obtained by a fuzzy neural network in a linear regression problem [78].

Photovoltaic systems are also the subject of researches of models to predict system failures [304]. Several forms of the ANFIS model were proposed to predict multiple classifications of faults within the context of photovoltaic systems, and a fuzzy neural network based on PCA–BDA was introduced to the failure detection method int that context [305].

The fuzzy neural networks and other hybrid models were applied in the prediction of failures in works such as those in Caminhas and Takahashi [65], Meneganti et al. [57], and in Subbaraj et al. that acts in the diagnosis of a pneumatic valve in cement industry [306]. An evolving approach [218] acts on predicting system failures, demonstrating that various techniques can work to build hybrid model architectures to work with failures. Wang and Keerthipala [307] create a neuro-fuzzy model to fault classification for transmission line protection.

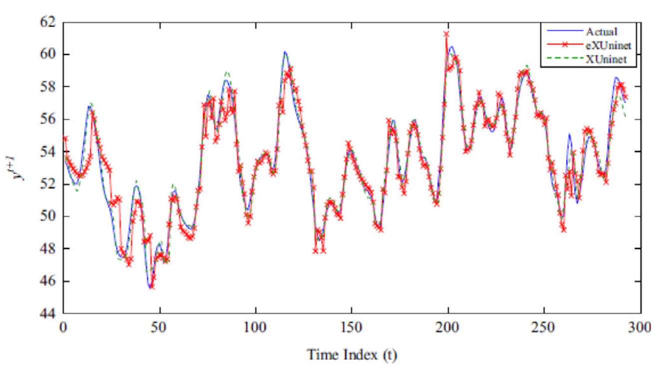

Fig. 15. Box–Jenkins gas furnace identification [165].

5.5. Industry problems

Industry across the globe requires tracking processes linked to various factors that affect productivity and the way mechanical work on production lines. Hybrid models work to be predictors of situations that hurt people and products in the industry. Stand out models that perform monitoring of machines [105], industrial processes in civil engineering [308], industrial processes model [124] and plants with underdamped responses [119].

Another models can act in non-linear PI controller [309]), systems control [85,91,134], noise detection and control [90, 123,310], robots controllers (Intelligent position/force [117,172], adaptive control of robot [66], robust adaptive control [67,98]). Approaches based on control for industrial robot manipulators [103], a Flexible Robotic Manipulator [311,312] mobile robot navigation [313], voice-controlled robot systems [314]) can be highlighted.

Actuators in energy filters by Fei and Wang [100], mineral mapping proposed by Porwal and Carranza [96], automatic steering system of agricultural machinery by Duau et al. [315], support pressure zones in coal mines created by Yu and Li [316], modeling material properties [317], sliding-mode position controller for induction servo motor drive [318] also to be act in general industry-problems. In Efitorov and Dolenko [319], an adaptive neuro-fuzzy model is used to classify the measurements of chemical sensors confined concrete [320].

The paper of Aengchuan and Phruksaphanrat [321] brings a comparison of several forms of hybrid architecture to act in the resolution of inventory control problems, and Acikgoz and others [322] evaluate the dynamic performance of three-phase AC–DC PWM rectifier.

In the paper of Azimi et al. [139], ANFIS-based architectures and firefly algorithm (FA) [312] training, are developed to work with hydraulic forecasts and [323] using a fuzzy neural network for estimation of saturated hydraulic conductivity. Ali et al. [324] works in the Optimization of the PV model for DC–DC converter systems. Fuzzy neural networks may also act in the control and decision-making part on the maintenance of a petrochemical plant [325] and paper of Rameshkumar and Mayilsamy [326] used a neuro-fuzzy model to reduce the tar content and particulate in producer gas and for prediction of the gas utilization Ratio [327]. In the construction industry, fuzzy neural models aid in the calculation of fire resistance of reinforced concrete columns [328], and a model is proposed by Ma et al. to use the fuzzy neural network for architectural foundation selection [329]. The work proposed in [330] performs the comparison between neuro-fuzzy approaches and other intelligent models for the prediction of residual welding voltages.

Lastly, the work performed by Tavakoli et al. [331], the fuzzy neural network models are based on static synchronous series control. The proposal is interesting because there are no neurons initially in the structure because they are automatically created according to the demand needed to solve the problem. Han et al. [332] develop an intelligent control, and the model still uses the pruning technique used to guesstimate the damping ratio of oscillations to mitigate the inter-area oscillations in interconnected power systems. In Deng et al. [333], the risk evaluation model of Highway Tunnel portal construction is approached. A neuro-fuzzy model was the subject of an experimental study for the semi-active magnetorheological elastomer base isolation system [334].

5.6. Problems in the health area

The health area uses several hybrid solutions using neuro-fuzzy or fuzzy neural network models to solve problems. The hybrid model proposed in [335] and Ozbay et al. [336] act in the area of biomedical in the resolution and identification of problems related to the electrocardiogram. Also, a human cognitive status monitoring system for drivers [337] proposed by Lin et al. helps in the monitoring of drivers evaluating their mental conditions during the car's direction. The hybrid network of Ando et al. [338] performs actions to identify lymphoma through gene expression. In the proposal made by Perova and Bodyanskiy [106] an evolutionary neuro-fuzzy hybrid system Takagi–Sugeno–Kang was proposed to assist medical diagnoses, and a regularized fuzzy neural network was used to improve the predictive ability of smart algorithms used in mobile devices to detect autism in children [339] and diagnosed of Autism in Adolescent [340] and adults [150] who ask a set of questions on their mobile phones.

Also, the network of [341] acts in the resolution of problems connected to the brain–computer interface. In health care, stand out models that assist in predicting behaviors of patients on little-known diseases. The model of Ahmed works with a neuro-fuzzy model for classification of Crohn's Disease (CD) [342] and in paper proposed by Guimaraes et al. [343] the fuzzy neural network operates in the construction of expert systems aimed at the prediction of breast cancer. In Abiyev et al. [344] it is also introduced a model of fuzzy neural networks capable of predicting breast cancer, but using images. The model performs a binary classification on the characteristics present in a sick person and a healthy person.

A neuro-fuzzy model is used for heart disease diagnosis based on multiple kernels learning [345]. In the paper of Ranjan et al. [346] a fuzzy neural network act to Detection in Sleep EEG Signal, and in Chang et al. [347] a fuzzy-brain-based deviation detector was built and finally in the work of Guimaraes and others [348] hybrid concepts of fuzzy neural networks were used to assist in the construction of systems specialized in the treatment of immunotherapy. Junio Guimaraes et al. [349] also addressed predictions of treatment of warts through cryotherapy and immunotherapy techniques using a pruned fuzzy neural network by F-scores. Neuro-Fuzzy approaches are used for Shalbaf et al. [109] monitoring the depth of anesthesia and a new temporal mining system is known as FTCM (Temporal Cognitive Diffuse Map), which defines a mechanism of discrete temporal extension and complete fuzzy inference of the FCM acts in the prediction of health data [350]. A neuro-fuzzy technique combined with the concepts of PCA [351] was developed for the creation of expert systems for predicting people with diabetes [352]. The prediction of Acute Myeloid Leukemia Subtypes Based was addressed in the paper by Roy et al. [353] using a hybrid approach of neuro-fuzzy and artificial neural networks.

Alzheimer's problems have also been predicted through pattern classification using intelligent hybrid models in [354]. In the paper of Leng et al. [355], the motion feature quantization of athletic sports training is the goal and in Souza et al. [356] a fuzzy neural network was applied to assist in the identification of cognitive and motor problems in children. Finally, the fuzzy neural network was used to improve the accuracy of classification of data from medical care [357] and Silva et al. [148] used a regularized fuzzy neural network based on logical neurons and an extreme learning machine to build a specialist system to aid in the treatment of breast cancer based on Resistin, Glucose, Age and BMI.

5.7. General problems

Other models of fuzzy neural networks and of neuro fuzzy models are used to driver control [129,358], vehicle control [359], non linear control [360–362], non linear systems dynamics [363], feature selection [225], input selection [364]. Examples like a neuro-fuzzy approach created by Jiang et al. [365] to simulating the peak particle velocity in rock blasting projects, the risk of fraudulent financial report [366], time-varying delays [256, 367] and identification of black plastics [368] are effective with that problems solving. Another approaches: product form design [188], forecasting tropical cyclones [369], hydrometeors [370], PM2.5 Prediction [87], fast target maneuver detection [371], powerful emitter identification [372], control of wastewater treatment process [217], soft soil foundation settlement in Guangxi granite area [373], prediction of monthly inflow [320], river flood [374], water level forecasting [375,376], modeling approach to real time streamflow [377], water quality [378], China's water quality [379] precipitation forecasting [380], forecast of rainfall and temperatures in a Brazilian state using satellite data [381], wastewater treatment [142], marine biological enzyme fermentation process [382] wind speed [383], speed control system [384], air pollution modeling in Athens [385], forest fire risk indices [386–389], prediction of crustal motion velocities in Earthquake research [390], climate crash [391], Green house effect [392], landslide-susceptibility mapping for shallow landslides in a tropical hilly area [393], Wind Speed and Solar Irradiance Prediction [394], identification of stars called pulsars using wavelet concepts and a fuzzification process using a model based on self organized data aware [395] and the six-layer model proposed by Kisi et al. [140] works with solar temperature prediction are examples of models with different approaches in the literature.

The model of Kumar [168] is a neuro-fuzzy network that deals with hacking identification in social network access and the paper of Zhang et al. [141] deals with estimate Gas Turbine Compressor Temperature. The versatility of these models allows them to work with graphics processing [396], timescales [397] isolation layered optimization [398], radio resource management in multi-radio WSNs [399], multi-attribute Decision Making [400], image classification [401], handwritten character recognition [402], an intelligent Drainage-Humidifying Control System Based on Neo-Fuzzy Neural Networks [403] proposed by Matus et al. helps in analysis of the performance and operational strategies of Heating Ventilation and Air Conditioning [404], software effort estimation [155] and Data-Drive modeling [405]. A model proposed by Todorov et al. [406], whose abilities to handle dynamical data streams and to build rule-based relationships, makes them a flexible solution. Also, the work of Terziyska et al. [296] presents a different approach to problem-solving because it works on methods of evaluating fuzzy neural network errors using a dynamic error based metrics technique. In the paper of Song et al. [407], a dynamic fuzzy neural network is used for the transient probabilistic design of the flexible multibody system.

The model of Asemi et al. [137] evaluates the performance of the ANFIS model in speech system identification. The architecture proposed by Ay et al. [138] works on the identification of oxygen dissolution. So recent models are developed with various applications for routines of industries and people, and an approach with clustering and fuzzy inference systems aid in the resolution of wireless network problems [104]. In the work of Sharifian et al. [408], fuzzy neural networks can able to accurately wind power forecasting under uncertain data and in Souza and Guimaraes [409] a fuzzy neural network based on unineuron is used to detect pulsars. Another model act in real-time traffic flow forecasting [410]. Those models can act to prevent a cyberattack, like Batista et al. that prevents cyberattacks [411] and SQL-Injection attack [152]. A hybrid evolving model that acts in the detection of anomalies in cyberattacks created by de Campos Souza et al. [412] an incremental model used in forecasting efforts on building software proposed by the same author [278], an adaptative neuro-fuzzy approach to intrusion detection systems [413], Chimmanee et al. [110] proposed a neuro-fuzzy model to works on load-balancing prediction for delay-sensitive internet applications, for landslide susceptibility mapping at Penang Hill area in Malaysia [414], computer worms detection [415], research on prediction of internet public opinion [416] and for web attacks [417]. Rocha et al. [418] have used adaptive hybrid models for Black-Box modeling based on an instrumental variable. In Rocha et al. [226], the same problem is attacked using an evolving neuro-fuzzy approach. Already in Rocha et al. [419], the online identification based on an instrumental variable in stochastic dynamic systems was solved by a neuro-fuzzy model. Levchenko et al. [420], used in the management of transport and logistics processes in the Arctic and a neuro-fuzzy approach proposed by Kisi and Yaseen [421] is used for suspended sediment concentration prediction. Conclusively, in Song et al. [422], a fuzzy neural network is used for the design of the multi-failure structure with fluid–structure interaction.

6. Conclusion

Hybrid systems based on artificial neural networks and fuzzy systems provide several models for the development of science. Because they are models able to work with a practical training of the neural networks and the interpretative capacity of the fuzzy systems, they become a source of creation for systems specialists in several areas.

Fuzzy neural networks and neuro-fuzzy models have stood out for more than 40 years and undergo constant changes in the form of training or their architecture. This set of techniques propitiates the use of many types of research for the resolution of problems of different natures.

Because they are a set of models with exceptional ease of adapting the dataset, these systems can develop fuzzy rules to fit different contexts of the literature and allow researchers to perform their research to combine creative techniques to accomplish tasks of machine learning.

In the models that were researched in work, it that allowed the constructions of expert systems based on fuzzy rules were highlighted. This type of approach facilitates problem-solving by those involved in the process without the need for continued systems use. The answers obtained through datasets from experts' knowledge make solving problems closer to the routine of those involved in the process. The main contributions of this review are presented in the vast history of intelligent models and their highlights in different areas of practice in health, economics, industry, and finance. Architectural organizations were presented, their main functionalities, ways of acting, and the construction of intelligent ways to extract knowledge of datasets through fuzzy rules. Another highlight in the paper presents the relevant model organization by its main training methods. Finally, the grouping of hybrid techniques by field of activity helps the reader to identify models that can help in solving their specific problems.

Future work can broaden readers' knowledge by presenting new learning algorithms, conveying their idea, explaining why they work, and showing how they function. Another exciting approach not covered in this review is to explore dynamic hybrid model architectures. This theme is continually evolving, so it is plausible to update revision versions with the new approaches that emerge from the various research on the topic., Another exciting extension to this work, is to explore aspects of the models' interpretability when executing the problem-solving. The fuzzy rules generated by the hybrid models can be the target of another review paper, highlighting the advances in the interpretability of the problems.

Finally, applications other than those addressed in this review may identify the continuity of this research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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