Fuzzy-NNARX based Tool for Monitoring and Predicting Patients Conditions using Selected Vital Signs

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Summary
In this paper, an artificial intelligent tool is proposed using fuzzy logic (FL) and recurrent neural networks (RNN) for definition and forecast of patient's clinical condition. The fuzzy logic-based proposed first phase of the tool permits the analysis of the current state of the patient, which allows the training of the artificial neural network. In the second phase, two Elman networks Multi Input Single Output (MISO), two Elman networks Multi Input Multi Output (MIMO), as well as two Auto-Regressive Neural Networks with eXogenous inputs (NNARX) are evaluated with and without pruning. The fuzzy model agrees 99.76% with the answers given by the experts. After analyzing the six proposed networks, it was verified that the pruned NNARX model can offer the highest overall accuracy (OA) of 99.82%, whereas the others show a decrease of up to 35%. Finally, to implement the smart software of this paper, the best scenario was found to be the Fuzzy-NNARX solution where an OA of 99.25%, a sensivity of 99.62%, and a specificity of 99.83% was obtained by utilizing unseen data from thirty patients. More tests made with higher prediction periods (10, 30 and 60 seconds) demonstrate a slight decrease in the OA reaching up 94.58%. Nevertheless, the OA still remained over 94%. For the data used in this work, NARX networks capture the dynamics of nonlinear dynamic systems much better than Elman networks. Results demonstrate that the Fuzzy-NNARX model proposed has a very good performance in predicting the patient conditions, and it is a useful tool for preventive medicine for chronic patients.

Key words:
Artificial Neural Network, Fuzzy Logic, Recurrent Neural Network, Neural Network Auto-Regressive model with eXogenous inputs, NNARX, Elman.

1. Introduction

Usually patient monitoring is necessary in Intensive Care Units (ICU) in a hospital for patients that need to be connected to pulse oximeters, multi-parameter monitors, and/or electrocardiographic devices in order to analyze the patient's vital signs in real-time. Sometimes, the condition of these patients is not severe enough to remain in an ICU facility. Nonetheless, they need to be monitored periodically. This uncomfortable and expensive situation can be avoided by using WBANs in hospital regular rooms or in the patient's home if the patient's condition can be monitored. Tools based on artificial intelligence can provide support for this type of monitoring. In addition, patients with chronic diseases can be continuously monitored in their home environments, transferring not only the patient's medical information, but also real-time environmental information [1].

In order to analyze and forecast human vital signs, it is important to work with tools that can aid deciphering uncertain and unclear data that is generally dynamic and nonlinear. In dynamic networks, output depends not only on the current input to the network, but also on current or previous inputs, outputs, or states of the network. These kind of network have memory facilitating the learning of time-varying patterns [2]. In order to solve complex problems, often the optimal solution consists of a combination of various techniques, each of which with some particular benefits for the problem. In this work, the definition of the current state of the patient is defined via a fuzzy module where experts provide the rules. On the other hand, the predictive module is performed with a neural network that used the output obtained from the fuzzy module.

Fuzzy logic is a branch of artificial intelligence that helps computers to mimic human reasoning, which can be induced from incomplete, ambiguous and uncertain data, normally by using common sense.

In cases where process information is insufficient, artificial neural networks (ANN) are very useful tools. One of the benefits that they provide for systems identification is that it is not necessary to have process knowledge in order to obtain functional relationships between inputs and outputs of the system. ANNs are regarded as non-linear black boxes since the process used to reach a result is difficult to explain [3]. One important advantage of ANNs is the ability to determine complex relationships between variables in biological data, based on weighing of these variables, while not requiring any background knowledge of diagnostic rules [4].

In this paper, the architectural approaches proposed to deal with dynamic networks are Recurrent Neural Networks (RNNs) and the Nonlinear Autoregressive models with eXogenous input (NARX Networks or NNARXs). The

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main objective of this study is to assess the performance of a fuzzy model and nonlinear techniques like ANNs, RNNs and NNARX to estimate and predict the patient's condition, based on several vital sign inputs. This smart software tool, acting in the field of preventive medicine for chronic diseases, has the potential to provide early warnings and for aiding clinicians to decide upon treatment strategies.

2. Artificial Intelligence Algorithms

2.1 Fuzzy Logic

Fuzzy logic was introduced by Zadeh [5] as a way to represent and manipulate data which is not accurate but rather diffuse. It is a form of multi-valued logic where one variable can have one unique value in two or more classes or sets. That is the main difference between classical logic, which is bivalent, where an object cannot belong to both a set and its complement set or to neither of them [6]. The theory of fuzzy logic provides a mathematical strength to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning. A fuzzy set can be represented as a triangle with a peak (center) m, a left width (m-a) > 0, a right width (b-m) > 0 when its membership function has a form which is shown in Equation 1. The membership function can take other shapes like bell-shape, trapezoid, Gaussian, piecewise linear, depending on how each point in the input space is mapped to a membership value.
Fuzzy logic is used when processes cannot be described by exact algorithms or when they are very difficult to model with conventional mathematical models. It allows to represent, in a mathematical form, sets or imprecise concepts like "cold days", "short person", "high wages", "slightly accelerated heart rate". Because it works with rules and not with equations or tables, it is very often used to acquire expert's knowledge and when dealing with imprecision and uncertainty.

$$\mu_A(x) = \begin{cases} 0 & if\ x < a \\ \dfrac{x-a}{m-a} & if\ a \le x \le m \\ \dfrac{b-x}{b-m} & if\ m < x \le b \\ 0 & if\ x > b \end{cases} \qquad (1)$$

Because fuzzy logic is multivariate, it is very often used in medicine, where the domain is continuous and most medical data is inaccurate [7-9].

2.2 Artificial Neural Networks

ANNs have been applied successfully across various domains including biomedical diagnosis [10-11], to predict disease or its progression [4,12], medical signal processing [3] and medical decision support [3,13]. When the process used to reach a conclusion is not known, and therefore the generation of fuzzy rules is difficult, artificial neural networks are very helpful tools. That is because they are used to model complex relationships between inputs and outputs, to find patterns in data, to predict, classify and approximate values based on their previous states and to identify classes.
A neural network is a parallel and non-linear system, capable of resolving tasks that linear computing might not perform satisfactorily. They need training to operate and, depending on the size of the network, the processing time could be very long. Besides the training, other points that define an ANN are its topology, the activation function and training stopping criteria. Estimating the network size and its parameters is a very challenging task because there are no rules or formulas so that trial and error is generally utilized.

2.3 Recurrent Neural Networks

Depending on the connections between the units and the propagation of data, there are two main categories of neural network structures: 1) Feed-forward Neural Networks (FNNs), which are acyclic networks where the signal is propagated only from the input to the output of the network (also called networks without memory); and 2) Recurrent Neural Networks (RNN), characterized by feedback between the layers, allowing the network to have a memory of immediately preceding events. FNNs are simpler than RNNs in terms of implementation and simulation, but they are only useful for applications where it is not required to retain information about past events to evaluate future events; the output is a result from the inputs through feed-forward connections. On the other hand, in RNNs the output depends not only on the current inputs, but also on the previous inputs and outputs of the network. This memory allows the network to learn sequential or time-varying patterns [15]. They are quite useful for modeling dynamic systems and time series prediction due to their high performance and velocity to converge to a solution. Summarizing, a dynamic RNN is a static feed-forward network plus recurrent connections [13].
The RNNs can be simple or fully connected, depending on the connections between neurons. Examples of partially connected RNN are Jordan and Elman types and of fully connected RNN is the Hopfield RNN.
In biomedical diagnosis there are some studies that use RNN to predict values, signals or parameters [16-18].

2.4 Time Series Prediction

A time series is a sequence of data points, which can be analyzed to extract general characteristics in order to provide a model to predict future values based on previously observed values. These models can be used in domains like physics, business, economy, biology, management, forecasting, signal processing, maintenance and control of industrial processes.

Neural networks have been extensively applied for complex time series processing tasks [19-20] since the 1990s. This is mainly due to their capability of handling nonlinear functional dependencies between past time series values and estimates of the values to be forecast [19]. Some complex problems require the combination of various intelligent techniques in order to achieve the optimal solution. There is also extensive literature about fuzzy neural networks for time series prediction [9,19,21]. These models have the advantages of fuzzy inference systems, such as high-level human-like reasoning and simple creation of rules from the expert's knowledge, and ANNs, such as learning abilities [19].

2.5 Neural Network Auto-Regressive model with eXogenous inputs (NNARX)

NNARX is a dynamic network with feedback connections enclosing several layers of the network. It is based on the discrete linear ARX model, which is commonly used in time-series modeling [2].

The problem of prediction can be formulated as finding a function φ through which it is possible to estimate a ŷ(t + D) of the vector y up to time t + D (with D = 1, 2, …), given the values of y up to time t, plus a set of additional time-independent variables (exogenous features) u:

$$\hat{y}(t + D) = \varphi[y(t),..., y(t- n_o),..., u(t) ..., u(t- n_i)] \qquad (2)$$

where u(t) and y(t) represent the input and output of the model at time t, ni and no are the orders associated with the input and output of the system and φ is a nonlinear function. D can take value 1, meaning one-step ahead, or any value larger than 1, meaning multi-step ahead.

NNARX can be implemented in many ways, but the simplest is to use a feed-forward neural network with a memory. It is highly suitable for modeling nonlinear systems and time series.

NNARX is being widely used in diverse areas like financial markets, agriculture production [2], temporal pattern representation, signal processing, time series prediction [19-22], and the control of industrial processes [23]. Additionally, some published works utilizing NNARX in medical areas were also found, such as to predict the glucose levels in patients with type I diabetes [10,24], as well as the hemoglobin level in patients with dengue infections [25]. Nevertheless, there are not many published applications nowadays for monitoring and forecasting general patient conditions.

During the training, the weights of the model are determined. The vector θ containing the weights represents the best prediction of the real outputs of the system. In this approach, model training is done by using the prediction error method, which attempts to find the minimal value of the following criterion:

$$V_N = \frac{1}{2N}\sum_{t=1}^{N}\left\{\left[Y(t)-\hat{Y}(t\mid\theta)\right]^T\left[Y(t)-\hat{Y}(t\mid\theta)\right]\right\} \qquad (3)$$

where VN is the training error; N is the number of samples used in training; Y(t) = [y1(t), ..., yn(t)] is the vector of real outputs; Ŷ(t) = [ŷ1(t|θ), ..., ŷn(t|θ)] is the vector of predicted outputs; θ = [W2 W1] is the vector of weights to be defined; T is the vector transposition operator; W1 is a vector that contains the weights between inputs and the hidden layer; W2 contains the weights between the hidden layer and outputs.

The order of the NNARX model may be defined as the complexity of the process because it determines the number of inputs and delay time of the model. The selection of model order is done by using Rissanen's Minimum Description Length (MDL) criterion, which is given by

$$V_{MDL} = V\left(1+\frac{d\ \log(N)}{N}\right) \qquad (4)$$

where V is the loss function, d is the number of model parameters, and N is the number of samples used.

The best architecture is not necessarily fully connected, so in order to regulate the complexity of the model it is possible to remove superfluous network weights and units, by keeping the training error as small as possible [26]. This technique is known as pruning.

To validate de NNARX model different metrics can be used. With the coefficient of correlation it is possible to measure the linear dependence between the real and predictive outputs. It can be calculated by (5)

$$r = \frac{\sum_{i=1}^{N}(Xi-\overline{X})(Yi-\overline{Y})}{\sqrt{\sum_{i=1}^{N}(Xi-\overline{X})^2}\sqrt{\sum_{i=1}^{N}(Yi-\overline{Y})^2}} \qquad (5)$$

where X are the inputs, $\overline{X}$ is the arithmetic mean of the inputs, Y are the outputs and $\overline{Y}$ is the arithmetic mean of the outputs.

The correlation index value varies in the range [-1,1], where r = 1 or r = -1 represents perfect correlation, while r = 0 represents that there is no correlation.

Another technique used in this paper to validate the model structure is Akaike's Final Prediction Error (FPE) criterion which is presented on the Equation (6).

$$FPE = \frac{1+\frac{d}{N}}{1-\frac{d}{N}}V \qquad (6)$$

where d is the number of model parameters, N is the number of samples used and V is the loss function.

Finally, the Mean Square Error (MSE) is an estimator to assess the performance of a predictor. The lower the MSE, the higher is the prediction accuracy. MSE is given by (7)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(\hat{Y}i - Yi)^2 \quad (7)$$

where N is the number of samples, $\hat{Y}$ is the vector of predicted outputs and Y is the vector of the real outputs.

In addition to the Coefficient of Correlation, the FPE, and the MSE, other three metrics were used: Sensitivity (Se), Specificity (Sp), and Overall Accuracy (OA) given by Equations (9-10).

$$Sensitivity = \frac{TP}{TP + FN} \quad (8)$$

$$Specificity = \frac{TN}{FP + TN} \quad (9)$$

$$Overal\ Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (10)$$

The problem addressed in this paper requires a ternary classification, i.e., the patient is stable, semi-stable or unstable, then the matrix confusion takes the form showed in the Table 1 and the criteria used to create the confusion matrix were as follows:

- TP (true positive): defines the instants of time where the patient was non-stable (semi-stable and unstable) and which was correctly classified. In the confusion matrix defined in Table 1 these are the values *e* and *i*.
- FP (false positive): denotes the time instants where the patient's condition was classified more severely than it actually was. In the confusion matrix these are the values *d*, *g* and *h*.
- FN (false negative): denotes the time instants where the patient's condition was classified less serious than it actually was. In the confusion matrix these are the values *b*, *c* and *f*.
- TN (true negative): defines the time instants where the patient was stable and was correctly classified. In the confusion matrix this would be the value *a*.

Table 1: Confusion matrix for a three-class classification problem

		Reality			
		Stable	Semi-stable	Unstable	Total
Classifier	Stable	a (TN)	b (FN)	c (FN)	Stable Classifieds= *a+b+c*
	Semi-stable	d (FP)	e (TP)	f (FN)	*Semi-stable Classifieds= d+e+f*
	Unstable	g (FP)	h (FP)	i (TP)	*Unstable Classified = g+h+i*
	Total	Stable Real= *a+d+g*	Semi-stable Real= *b+e+h*	Unstable Real= *c+f+i*	*Total samples*

` TN FN TP FP

Besides the Se, Sp, and OA performance measures, the following three formulas of sensitivity for each patient condition where used for a more detailed analysis: Se_{stable}, $Se_{semi\text{-}stable}$, and $Se_{unstable}$ in the ANNs. These formulas are represented in the Equations 11-13.

$$Se_{stable} = \frac{number\ of\ correctly\ detected\ stable\ states}{number\ of\ actual\ stable\ states} \quad (11)$$

$$Se_{semi-stable} = \frac{number\ of\ correctly\ detected\ semi\text{-}stable\ states}{number\ of\ actual\ semi-stable\ states}$$

(12)

$$Se_{unstable} = \frac{number\ of\ correctly\ detected\ unstable\ states}{number\ of\ actual\ unstable\ states} \quad (13)$$

3. Proposed Fuzzy-ANN model

The proposed Fuzzy-ANN system, integrated into a wireless medical sensor networks, will allow to monitor patients with chronic diseases or elderly people at home. The physiological parameters that it uses are: heart rate (HR), non-invasive systolic blood pressure (SP), non-invasive diastolic blood pressure (DP), non-invasive mean blood pressure (MP) and oxygen saturation (SpO2). With the continuous monitoring of these physiological parameters it is possible to detect tachycardias, bradicardias, and hypoxemia. The Fuzzy-ANN model is composed by two parts. In the first block, a fuzzy logic model mimics human reasoning and create rules for the inference system in order to emulate the specialists' knowledge. Its objective is to classify the patient condition, in real time, for indicating whether a normal (i.e., vital signs with normal values), a semi-stable (i.e., vital signs with values close to normal), or an unstable situation (i.e., vital sign values fairly abnormal). The outputs generated by the fuzzy model, which was fed with the data of real patients, will be the targets to train the neural network. Afterwards, six neural network topologies will be tested and compared with the purpose of selecting the most suitable to forecast the patient's condition in time (t + D).

3.1 Data Acquisition

In order to work with real patient data, all vital signs were obtained from the MIMIC (Multi-parameter Intelligent Monitoring for Intensive Care) database available in PhysioNet [27], which is a freely accessible collection of recorded physiologic signals from healthy and unhealthy patients. Three databases were consulted: MIMIC II Waveform DB version 2, MIMIC II Waveform DB version 3 and MIMIC Database Numerics. Matlab (Mathworks, Natick, MA, U.S.A.) was used to read, load and pre-process data for the patients.

For the training, 2,000 samples from ten different patients were used, i.e., the network was trained with 20,000 samples. For the validation, 1,000 samples from new ten different patients were used.

The pre-processing of the data consisted in selecting those patients with non-zero values in all selected parameters. However, when some small sections of the data had zero-values, mostly caused by loosening of the sensors, they were restored using the previous measured value.

3.2 Fuzzy Model

Fuzzy sets for each variable were determined based on the responses of four experts to questions about the ranges of values for every parameter they considered very low, low, normal, high and very high in healthy adult patients aged between 50 and 65. The values from experts shown in Table 2 are used to calculate the degree of membership of the respective fuzzy sets.

Table 2: Range of values of non-invasive vital signs for a healthy adult

	Very low	Low	Normal	High	Very high
HR (bpm)	< 40	40 – 60	60 – 100	100 – 130	> 130
SP (mmHg)	< 90	90 - 100	100 – 130	130 – 140	> 140
DP (mmHg)	< 60	60 - 70	70 – 85	85 – 90	> 90
MP (mmHg)	< 60	60 - 70	70 – 110	110 – 130	> 130
SpO2 (%)	< 90	90 – 94	94 – 100	---	---

HR: Hearth Rate; SP: Non-invasive Systolic Blood Pressure; DP: Non-invasive Diastolic Blood Pressure; MP: Non-invasive Mean Blood Pressure; SpO2: Oxygen Saturation

In the inference stage, each rule is a particular combination of the fuzzy sets and represents one "condition" of the patient. Some examples of the fifty-one generated rules are shown below:

```
Rule #1: If (HR=N and SP=N and DP=N and MP=N and
SPO2=N) Then (Status=S)
Rule #2: If (HR=L and SP=N and DP=N and MP=N and
SPO2=N) Then (Status=SS)
Rule #3: If (HR=L and SPO2=L) Then (Status=U)
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where VL = very low, L = low, N = normal, H = high, VH = very high, S = stable, SS = semi-stable, U = unstable.

The output of the Fuzzy-ANN system indicates the patient condition, which can be stable, semi-stable or unstable, depending on the values of the physiological parameters and the rules of the fuzzy model.

3.3 Proposed Artificial Neural Networks

To verify the suitability of ANNs, six different architectures were used. Four of them are different approaches to Elman RNNs and the others are two different topologies of NNARX.

The training of all tested networks was interrupted every 200 cycles (epochs) in order to perform an estimation of the generalization error of the network on the validation dataset. When the generalization error was higher than the previous obtained, the training was stopped and was considered the set of weights obtained in the previous epoch. This technique is known as "early stopping" [28].

In order to obtain the arithmetic mean of the MSE value, for each combination of "training algorithm & number of hidden neurons" the system was trained ten times.

3.3.1 Elman MISO (E-MISO)

The Elman – MISO Network, which is shown in Figure 1, was built with five inputs and one output. To decide the optimal number of neurons in the hidden layer, and which training functions to use, several tests were performed. In order to obtain the targets, which allow the training of the network, the input vectors were pre-processed using the fuzzy model proposed in the previous section.

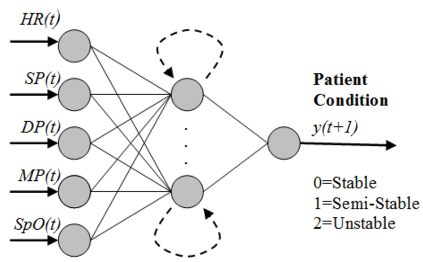

Fig. 1 - Elman MISO network

The criterion to evaluate the best architecture was to obtain the lowest MSE, with the lowest number of neurons in the hidden layer with a short training time. The six training algorithms tested were: Resilient Backpropagation (RB), Levenberg-Marquardt Backpropagation (LM), BFGS quasi-Newton Backpropagation (BFG), Gradient Descendt with Momentum and Adaptative Learning Backpropagation (GDX), Gradient Descendt Backpropagation (GD) e Scaled Conjugate Gradient Backpropagation (SCGB).

After the tests, the best structure was built with five neurons in an unique hidden layer and the algorithm used to train the network was *Scaled Conjugate Gradient* Backpropagation. In the first layer and in the hidden layer a sigmoid and a linear transfer function were utilized, respectively.

3.3.2 Pruned Elman MISO (PE-MISO)

The fully connected E-MISO network has thirty-six active weights and five hidden neurons. In order to improve the network performance, a pruning was performed by using the Optimal Brain Surgeon (OBS) network pruning strategy [26]. The achieved results consisted of five hidden neurons and twenty-one active weights.

3.3.3 Elman MIMO (E-MIMO)

In this case, the Elman – MIMO network was built with five inputs at time (t) and five outputs corresponding to the future values of the inputs at the time (t + D), where D = 1. Since the Elman neural network has five outputs, but only requires one output (stable, semi-stable or unstable patient's condition), it was necessary to add the fuzzy module at the end of the Elman network. Therefore, the third architecture proposed is composed of the modules "E-MIMO" and "Fuzzy module". This network, whose schematic diagram is shown in Figure 2, uses a sigmoid hyperbolic tangent transfer function (known as tansig) and a linear transfer function (known as purelin) for the first layer and the hidden layer, respectively.

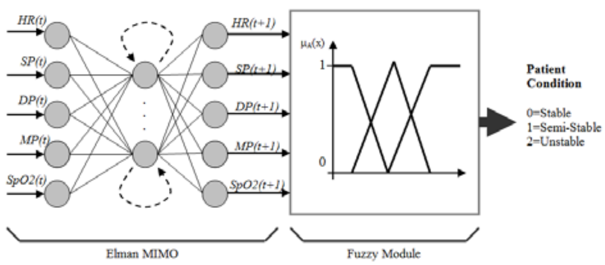

Fig. 2 - Elman MIMO network with the Fuzzy Model to predict the final output

In this architecture, as in E-MISO, the criteria for evaluating the best combination of neurons in the hidden layer were: reduce MSE, keep the number of neurons at the hidden layer as low as possible, and reduce training time. Likewise, the same six training algorithms used for E-MISO were used for the E-MIMO, i.e., RB, LM, BFG, GDX, GD and SCGB.
After the tests, the best structure was built with nine neurons in an unique hidden layer, the algorithm used to best train the network was Levenberg-Marquardt Backpropagation. In the first layer, the hyperbolic tangent transfer function was used and in the hidden layer, the linear transfer function.

3.3.4 Pruned Elman MIMO (PE-MIMO)

The fully connected E-MIMO obtained in the previous section has hundred and four active weights and nine hidden neurons. In order to improve the network performance, a pruning was performed by using the OBS network pruning strategy. The achieved results consisted of nine hidden neurons and fifty-three active weights in the PE-MIMO network.

3.3.7 NARX Network (NNARX)

To select the appropriated model order, two criteria were tested: Rissanen's Minimum Description Length (MDL), and Akaike Information Criterion (AIC). In all cases tested, MDL was the one which offered a lower order, which is [1,1,1] for the HR, SP, DP, MP and SpO2 vectors. These values correspond to [na,nb,nk], where na is the number of previous outputs used to determine the prediction; nb is the number of previous inputs used to determine the prediction; and nk is the delay time.
Several tests were made in order to find the optimal number of neurons in the hidden layer. With three neurons in an unique hidden layer the network provides lower MSE and higher accuracy, with acceptable sensitivity, specificity and accuracy values.
The activation functions for non-linear hidden neurons are the hyperbolic tangent $f(x) = \tanh(x)$ and for the output neuron the linear activation function $f(x) = x$ was selected.
Once all the training parameters were optimized, the NNARX model was trained and validated. The network was trained using the Levenberg-Marquardt algorithm applying the tool developed by Nørgaard [29].

3.3.8 Pruned NNARX (P-NNARX)

The fully connected NNARX obtained in the previous section has twenty-five weights and three hidden neurons. By using the OBS network pruning strategy to remove superfluous weights, the best suited model was found. It has twenty-three weights and three hidden neurons.

3.3.9 Fuzzy-NNARX (FNNARX) system

The FNNARX model for monitoring patients consists on the fuzzy module to monitor patients in the current time (t) and on the NNARX module to forecast the patient condition on time (t + D), with D = 1, 10, 30 and 60. This software was tested with data of thirty new patients obtained from the website PhysioNet [27].

4. Experiments and Results

In order to test the fuzzy model, a reduction in the amount of the samples was performed. Of the 30,000 samples (20,000 used as training and 10,000 as validation data), only those completely different samples were selected, achieving 4,513 totally different measurements. The accuracy of the fuzzy model results compared to the information given was 99.76%. The 0.24% (11 measurements) of errors occurred in the cases where the fuzzy model generated semi-stable state when experts classified the patients as unstable.

All the differences found between the results provided by the experts and the answers given by the model occur on the thresholds of the different functions of membership. For example, a value of 101 bpm of heart rate corresponds to a high level, according to the Table 2 provided by experts, but for the fuzzy model it represents a value nearly normal (quite normal but a little high). This difference in results does not mean that the system was poorly modeled. It is precisely an expected outcome of a multivalued logic.

After successive tests of the six network topologies, by testing training algorithms and varying the number of neurons in the hidden layer, the best combination of every network topology was found and is shown in the Table 3.

Table 3: Architectures with the lowest MSE for every network model

Network	Inputs	Hidden Neurons	Outputs	Training algorithm
E-MISO	5	5	1	SCGB
PE- MISO	5	5	1	SCGB
E-MIMO	5	9	5	LM
PE- MIMO	5	9	5	LM
NNARX	6	3	1	LM
P-NNARX	6	3	1	LM

LM: Levenberg-Marquardt; SCGB: Scaled Conjugate Gradient Backpropagation

By using Equations 7 to 13, every approach was tested obtaining the results shown in Table 4.

The answer of the E-MISO model is represented in the Figure 3. The x-axis shows the number of samples used in the validation of the model and the y-axis represents the different conditions in which a patient may be: Stable, Semi-stable, and Unstable. The curve generated with the data validation reveals some deviations and problems in the classification of the stable and semi-stable states.

With the pruning of the E-MISO a new topology was obtained. The answer of the PE-MISO model, which is represented in Figure 4, shows a somewhat different curve from that generated by E-MISO network, but also with evident problems in the classification of the stable and semi-sable states.

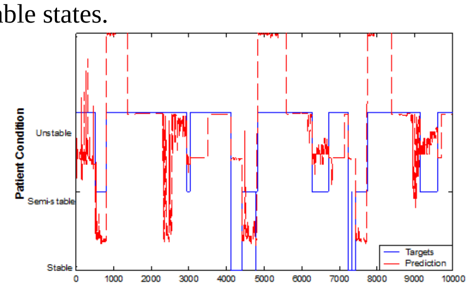

Fig. 3 – E-MISO for the validation dataset

The results of the Elman MISO networks, which can be observed in the Table 4, show that the fully connected E-MISO and its pruned version PE-MISO have a moderate relationship between the forecasted outputs and the targets. Both networks have similar values in MSE, Sp and OA, having some significant difference only in the Se. The Sp and Sestable close to 0% indicate that both networks have problems to classify the stable condition of the patient.

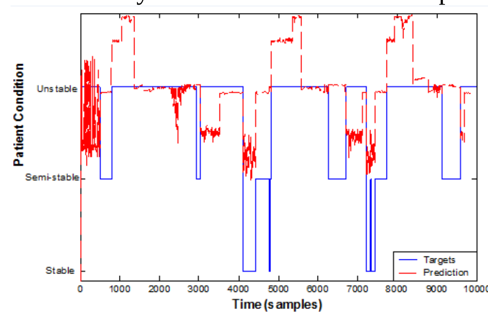

Fig. 4 – PE- MISO for the validation dataset

The answer of the E-MIMO is represented in Figure 5. As one can see in the resulting curve, the model trained with the LMB algorithm, for any combination of input data, can only emit the unstable state as output.

Pruning the E-MIMO a new topology was obtained. The answer of the PE-MIMO model shows the same curve that was generated by E-MIMO network, i.e., the models E-MIMO and PE-MIMO cannot represent accurately the desired output.

The results of the Elman MIMO networks, which can be observed in the Table 4, show that both topologies exhibit the same results. The Sp, Sestable and Sesemi-stable in 0% indicates that none of these topologies can correctly classify the stable and semi-stable conditions of the patient. The correlation coefficient close to zero indicates that there is no linear relationship between the targets and the forecasted outputs.

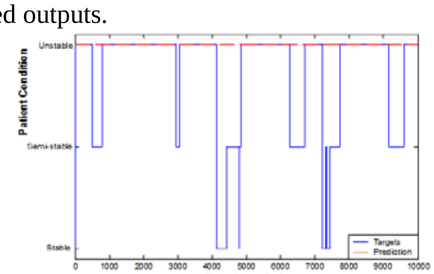

Fig. 5 – E-MIMO and PE-MIMO for the validation dataset

Figure 06 shows the patients' condition - y(t) or targets - and the estimated patients' condition - ŷ(t) or prediction - for the NNARX model described in Equation (2). The curve obtained shows that this network can very well classify all the three possible conditions.

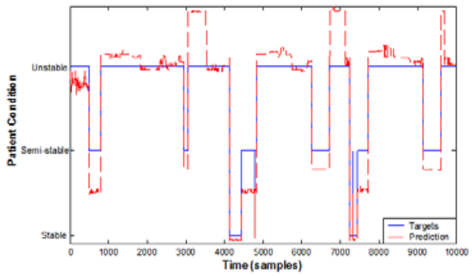

Fig. 6 - NNARX model for the validation set

The answer of the P-NNARX, represented in Figure 7, shows better performance than NNARX. In both networks, the correlation coefficient close to one indicates that there is a strong linear relationship between the targets and the forecasted outputs. The values of Se, Sp, and OA above 98% indicate that the NNARX model is able to classify all the three possible conditions.

According to Table 4, the network model that has the best indicators is the P-NNARX with a better correlation coeficient than NNARX and the values of Se, Sp, OA, Sestable, Sesemi-stable, and Seunstable above 98%, indicating that this network has the potential for forecasting the clinical patient condition.

While the previous results show the performance of the Fuzzy or the ANN structures, a test set of thirty new patients' data was used to test the FNNARX complete solution. For a prediction period D = 1 an OA of 99.25%, a Se of 99.62% and a Sp of 99.83% was obtained. These results demonstrate an appropriate performance to predict the three possible states for the proposed intelligent system.

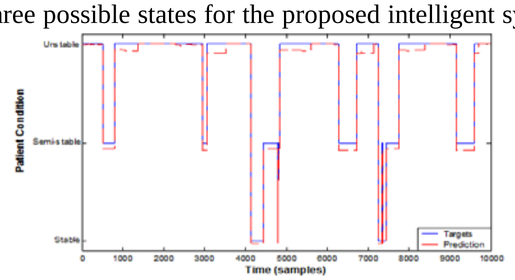

Fig. 7 – P-NNARX model for the validation set

Table 4: Performance indicators of different network architectures analyzed

Indicator	E-MISO	PE-MISO	E-MIMO	PE-MIMO	NNARX	P-NNARX
MSE	0.583	0.519	0.400	0.400	0.004	0.002
Corr. Coef.	0.503	0.360	0.000	0.035	0.945	0.994
Se (%)	71.34	87.83	100.00	100.00	98.57	99.89
Sp(%)	0.79	0.00	0.00	0.00	98.61	98.41
OA (%)	64.16	65.91	74.99	74.99	98.57	99.82
Se_{stable} (%)	1.61	0.00	0.00	0.00	99.40	99.20
$Se_{semi\text{-}stable}$ (%)	32.68	0.15	0.00	0.00	93.30	99.60
$Se_{unstable}$ (%)	76.71	87.83	100.00	100.00	99.92	99.92

Corr. Coef.: Correlation Coefficients

This FNNARX solution was also tested for prediction period D of 10s, 30s and 60s, in addition to the D = 1 previously presented. These results are presented in Table 5. It is shown that networks with higher prediction periods produce a gradual increase of the MSE and a slight decrease in the accuracy, demonstrating that the higher the period to be predicted, the lower the accuracy is. Nevertheless, the values still remain over 94%.

The OA of the FNNARX system, with a value of 99.25% is very close to the accuracy obtained on the validation set for the P-NNARX, which was 99.82%. This slight difference was expected since the FNNARX system was tested with data from 30 patients that were never used in the training section. This high value of OA of the proposed smart system demonstrates the high generalization level of the system.

Table 5: Indicators tendency with different prediction times

Indicator	Prediction (t+1)	Prediction (t+10)	Prediction (t+30)	Prediction (t+60)
MSE	0.008	0.035	0.049	0.054
Se (%)	99.62	97.94	97.05	96.48
Sp (%)	99.83	99.31	99.00	98.33
OA (%)	99.25	96.49	95.10	94.58
Se_{stable} (%)	99.93	99.73	99.58	99.17
$Se_{semi\text{-}stable}$ (%)	98.06	92.23	88.79	92.33
$Se_{unstable}$ (%)	99.10	95.22	92.92	93.32

5. Conclusions

To our knowledge this is the first study on creating a Fuzzy-NNARX model to monitor and forecast chronic patients conditions by using five vital signs (HR, SP, DP, MP and SpO2). In this paper, a fuzzy model, four recurrent neural networks and two NARX networks have been analyzed in order to model the nonlinear behavior of the vital signs of patients.

The fuzzy model responses were excellent, agreeing in 99.76% of the cases with the answers given by the experts, shown in Table 1.

Two Elman MISO networks, two Elman MIMO networks, as well as two NARX networks were analyzed. The results showed a higher performance of the NNARX models compared to the Elman MISO and Elman MIMO networks. Only the NARX networks were able to hold an accuracy above 99% on the validation dataset, whereas the Elman networks shows a decrease in performance of up to 35%.

In both NNARX architectures, the MDL criterion was used to select the number of input variables to the functional approximator (model order). This method allows to identify the autoregressive orders of the model, allowing the removal of irrelevant inputs simplifying its structure and improving its performance.

Furthermore, the Elman networks and the NNARX model were pruned in order to obtain the optimal number of hidden neurons, regressors and connections. However, the results demonstrate that the pruning of the networks offered no a much higher performance. The application of the early stopping technique during the training with the repeated training in order to obtain the mean MSE, FPE and correlation coefficients, have shown its effectiveness in finding the best network topology, making unnecessary in these cases the pruning of the networks.

According to the results observed in Table 4, P-NNARX is the optimal model for the system under test conditions capturing the dynamics of nonlinear dynamic system much better than Elman networks. For this reason, it was chosen to develop the FNNARX system.

Accuracy obtained with the FNNARX in the time prediction D = 1s was of 99.25%. This result exhibits the actual behavior of the system since it was tested with the data of thirty new patients (unseen data) and illustrates the high generalization level of the system. Further tests with time prediction D of 10s, 30s and 60s denoted a slight decrease in the accuracy reaching up 94.58% with D = 60s. That indicates that the higher the period to be predicted, the lower the accuracy is.

The integration of this Fuzzy-NNARX-based proposed solution into wireless medical sensor networks will become a useful tool for preventive medicine. Staff in hospitals, elderly care homes or even private clinics could use it in order to carry out telemonitoring, thus transforming itself into a complementary tool for clinicians, allowing a better quality of life for patients, reducing hospitalization costs, and decreasing the risk of hospital-acquired infections.

In future work, in order to improve the intelligent system here proposed, others variable patient characteristics, like gender, age, height, weight, medication, mobility, time of day should be considered.

Reliability and security of patient data is another very important issue that cannot be neglected. Issues like delays, datasets with zeros, and values of vital signs out of range would have to be treated. In addition, since better results are shown when previous data from a patient is used in the training stage, customization of the system to the needs of every patient could be achieved by integrating a customization module, in which the expert can configure the normal and abnormal values of each vital signal for that given patient during a training period.

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