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A NARX neural network model for enhancing cardiovascular rehabilitation therapies

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ABSTRACT

Current medical tendencies in the rehabilitation field are trying to physically rehabilitate patients. Thus, people with cardiovascular illnesses need to exercise their injured systems in order to improve themselves. In training, each person has a different heart rate response according to the demand of physical effort. Hence, it is necessary to know the relationship between the effort (training device power/resistance) and the patient's heartbeat for an optimal training configuration. This relationship has non-linear and complex dynamics, being a complicated identification problem solved by classical techniques. Soft Computing techniques based on artificial neural networks may be a way to implement more efficient control strategies in order to obtain a suitable power demand each and every time. It is necessary to be aware of the pace, length and intensity of the exercises in order to be effective and safe. In this paper, we present the results of the identification of the relationship in time, between the required exercise (machine resistance) and the heart rate of the patient in medical effort tests, using a NARX neural network model. In the experimental stage, test data have been obtained by exercising with a cyclo-ergometer in two different tests: Power Step Response (PSR) and Conconi.

1. Introduction

This work is part of a research project where Artificial Neural Networks (ANNs) are used to enhance rehabilitation processes and cardiovascular training in patients with cardiovascular problems. The main objective of this project is to improve the control of the rehabilitation process, as well as detection of human risk during training. This paper analyzes the capability of ANNs in the process of the identification of human cardiovascular system response where patients perform a controlled rehabilitation training exercise. Specifically, the kind of ANNs selected will reproduce a non-linear autoregressive model by adding recurrent inputs to its topology.

Soft Computing techniques are widely used to solve complex problems in industrial and commercial applications. Bonissone et al. have dealt with these methods and tools in several works which present a detailed view of fields where they are applied [1]. Recent works offer new perspectives in solving complex problems from a general point of view [2], processing complex information [3–5], obtaining hybridised models [6], or more specifically, modelling complex dynamics using ANN [7]. All these works contain more references certifying the satisfactory behaviour of non-linear autoregressive exogenous (NARX) neural networks in modelling and control problems.

Nowadays there are lots of studies using Soft Computing techniques in the medical field for improving patients' lives. Vila et al. present new methodologies to select the best predictive neural network architecture on a food application [8], Thanh and Ahn control a muscle manipulator using ANNs [9], and Harischandra maps EMG signals with ANN and SVM [10]. By enhancing the cardiovascular system in a person, other goals can be reached, such as the improvement of the circulatory system, the respiratory system and the muscular system. These types of exercises are good for the general well-being of any person, and can optimise the therapies of people with cardiovascular problems. Therefore, this kind of medical care is fundamental, not only in patients with these types of illnesses, but also in athletes, whether elite or not, because physical activity is always necessary for people throughout their lives. The responsible and organised improvement of the cardiovascular system is not only desirable for all individuals but also of vital importance to people with cardiac, circulatory or respiratory problems. For this reason, the training carried out needs to be precise, planned and controlled so as not to put the patient involved in danger [11,13,14].

People with cardiovascular illness are traditionally told to rest and to be inactive, because uncontrolled movements can induce heart attacks or worsen the patient's state [15,16]. However, inactivity for long periods of time can provoke irreversible problems

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in the patient's damaged systems, shortening their life and/or causing the quality of life to deteriorate. Currently the medical tendency is to try to physically rehabilitate these systems by exercising the injured systems [17]. In an extremely high percentage of cases the patients have shown significant improvement and, in turn, a better quality of life for the patient [18]. In order to carry out these training sessions it is necessary to plan comprehensive physical tests so as to determine the scale of the injuries and their evolution [19]. The tests must be done beforehand by specialists (medical staff or personal trainers) in order to perform specific and monitored training sessions where the vital signs of the patient are under supervision. These types of therapies are usually highly complex and costly. Therefore, patients have to use these systems under constant medical supervision in medical centres.

A training tool based on a bicycle, capable of precisely measuring physical effort and monitoring the heart's state, has been used in this study. This type of machine requires a series of training sessions to be planned with the doctor or the personal trainer, even when the person does not require specific training or the athlete does not suffer any physical problems [20,12,21]. Currently, it is necessary that a specialist is aware of the cadence, the duration and the intensity of the exercises, in order for them to be effective. To calculate the parameters of training it is necessary for the specialist to know the physical ability of the individual, their weight, age, physical condition, etc [22]. According to these parameters which are to be previously measured using standard tests, a series of general tables are drawn up. These tables enable us to obtain relatively precise values of the intensity, periodicity and length of the exercises. These types of training sessions usually provide good results, despite the fact that they are not always the same for similar persons or even for the same person at different times of their life. There are numerous physical factors that are difficult to evaluate when planning the training session. Furthermore, they depend largely on the experience of the trainer or doctor and their ability to understand the behaviour of the person who is doing the exercise [17,22]. The understanding of these types of parameters sometimes marks the difference between a medal and a disappointing fourth place, and more importantly, the possibility of suffering a heart attack or not.

In order to provide the best performance in rehabilitation exercises, Soft Computing techniques can be used to improve the control of those exercises [10]. Our line of work improves the control of cardiovascular training and test systems, as well as the development of cardiovascular risk alarms in them. It is therefore necessary to identify the system as a starting point for developing healthy and safe solutions. The first objective of this work is to identify the physiological relationship between the power demanded in a training exercise and the heart rate of the patient [12]. This complex and non-linear relationship cannot be studied using classical techniques in real time without expert intervention nor without accepting some tolerances. We propose designing a NARX multilayer Perceptron to reproduce the behaviour of the previously mentioned relationship. Once our NARX neural network is appropriately tuned, it will be included in an adaptive control scheme to automatically supervise the training exercise of a patient, avoiding continuous observation by the specialist and improving the performance during the rehabilitation exercise. NARX solutions are useful for the identification of non-linear systems, especially when using real-world data sets and long-term series prediction [23,36].

This paper presents the results of preliminary studies for the identification of the physiological relationship between the power demanded in a rehabilitation training cyclo-ergometer and the heart rate of a patient. In the next section, we analyse the system composed by the cyclo-ergometer and the patient. Power Step Response and Conconi tests are introduced. The necessity of measured data preprocessing is explained. In the section of tests and results we show preliminary exercises for rehabilitation system analysing. Afterwards, first results with NARX neural network are presented and discussed. The selection of an appropriate NARX-NN configuration is shown through several tests. Finally, some conclusions and future areas for study are presented.

2. Analysis of the rehabilitation system

In this work, we have used a cyclo-ergometer to measure data in standard rehabilitation exercises. Data are basically the configured power/resistance (POW) of the machine and the patient heart rate (HR). Cyclo-ergometers allow the design of different profiles of training exercises and standard tests, in a controlled way, and with high precision. A cyclo-ergometer is a training machine based on a stationary bike structure, with a microprocessor and sensors for measuring several of the physiological and machine parameters. This system has a high level of precision when controlling the pedalling resistance, as well as measuring the patient heart rate, blood oxygen level, volume of air consumed, and other signals. The cyclo-ergometer used in our tests was purchased by the Cardgirus enterprise [24]. This device is connected to a PC where specific software is installed in order to configure, control and measure different rehabilitation training tests. Fig. 1 shows a generic rehabilitation system view with the Cardgirus cyclo-ergometer.

For performing training and tests with cyclo-ergometer systems in rehabilitation processes, it is necessary to configure and schedule a power profile over a period of time. In these processes the patient usually has to keep pedalling continuously, while his/her HR is measured for later analysis. A large variety of tests exist to use in conjunction with cyclo-ergometers [24–28,16]. Among them the most important are: Wingate test, Conconi test, Astrand Maximal cycle test, Fox Maximal cycle test, Astrand-Rhyming Submaximal

Fig. 1. Cyclo-ergometer and data processing PC.

cycle test, YMCA submaximal cycle test, Fox Single-stage submaximal cycle test, and ACSM submaximal cycle test.

The information obtained from this type of test is essential to determine the physical state of a person. Moreover, preliminary tests offer an objective basis for appropriately configuring new rehabilitation training. Information from variables measured in tests directs us towards enhancing the patient cardiovascular fitness. Furthermore, this information allows the scheduling of fixed rehabilitation training and successful control during exercising [29].

In this work, two different tests have been used to obtain the model of the relationship between the training device and the patient (power-heart rate, POW/HR). Both are tests commonly used in medical and sport fields. First one comes from the Astrand type where a power step is demanded in a short period of time, usually called the Power Step Response (PSR) test. The second is the Conconi test where a succession of incremental power steps is scheduled over a longer period of time. The information acquired in those tests from the cyclo-ergometer has been processed to obtain a POW/HR model with a NARX-ANN. The ANN output layer has a neuron that estimates the patient HR for future time samples. The neurons of the ANN input layer receive POW and HR values that are measured from previous time samples. This way, after an appropriate training process the NARX-ANN can learn the dynamics system.

The basis for selecting a solution based on Soft Computing techniques lies initially with the complex dynamics of the POW/HR system and its modelling [10]. To achieve the first objective of this project; the automated control of cardiovascular rehabilitation training by a cyclo-ergometer system, it is necessary to design an adaptive control system which has to calculate the appropriate power/resistance for the patient. This calculation is solved by using one model of the system. Thereby, the estimated patient HR can be linked to a safe reference. In this way, specialists have to work with preliminary standard tests for measuring different signals, to process such signals in a NARX-ANN learning stage, and subsequently to leave the control cyclo-ergometer system during specific rehabilitation training sessions.

One of the main problems when designing a control strategy for sport training or physical tests is to establish a functional model. Mathematical relationships or physiological models are not available for performing a precise analytical development [30]. Moreover, each patient has a different cardiovascular behaviour in relation to their physical effort. Furthermore, this behaviour can vary from exercise to exercise, and over time.

Several works points out that the problem of modelling the relationship between HR and POW in humans is not trivial, as a study of dopamine effect presented by Karabacak and Sengor [37] or the premises in physiological system modelling presented by Ferrairó [38]. There exist some proposals giving a linear solution to this problem, but these approximations can be only used in not complex problems. Certainly, the HR evolution during an effort depend on variables as previous efforts, the demanded POW, and other environmental factors, as the work presented by Polar Electro Oy in [39] where a complex equation (Eq. 1) is used to calculate the energy consumption (EE) of a patient during exercising:

$$\mathrm{EE} = F(HR, Act, Tem, Tair, Time, BP, Nfat, Nch) \tag{1}$$

where F refers to a non-linear and complex function that depends on the variables of the expression in parentheses, HR describes one or more heart rate parameters, Act refers to the activity of the person, Tem is the body temperature of the person, $Tair$ is the air temperature surrounding the body, $Time$ refers to the duration of one period of a measurement, BP is the blood pressure, $Nfat$ refers to the amount of fat obtained from food, and Nch the amount of carbohydrate.

In our studies we have used and fixed the same environmental factors, as food, the exercising time, the temperature, and some aspects as no previously physical efforts before analysing. Despite fixing some variables, the human body does not constantly respond in a similar way to exercise at different hours of the day, neither in different days, nor weekly or monthly. This means to be necessary the training of a new model after no long periods, taking into account the influence of the above mentioned factors. Even under the same exercise profile, the relationship between the cyclo-ergometer system and the patient can differ depending on environmental or psychological factors [31]. All these facts mean that a specialist has to be controlling the patient's cardiovascular exercise, despite a good training design based on classical methods and reference tables. Because of these reasons, the use of advanced computational techniques for cardiovascular system modelling is particularly interesting.

In this work, the selected and utilised NARX-ANN presents in its output y, for each sample time k, an estimation of the HR value $(\hat{y}_k)$ which is calculated by Eqs. (2) and (3). Considering an exogenous input vector $\boldsymbol{x_k}=\{u_k, u_{k-1}, \ldots, y_{k-1}, y_{k-2}, \ldots\}$, with POW as input vector $\mathbf{u_k}$ and HR as output vector $\boldsymbol{y_k}$, and the generated hidden layer neuron outputs $\boldsymbol{o_j}$, being $j=\{1-N\}$ such non-linear hidden neurons, the HR estimated value can be expressed as:

$$\hat{y}_k = \sum_{j=1}^{N} W_{\mathbf{1}j}\, o_j + b \quad \forall k \tag{2}$$

$$o_j = S\left(\sum_{k=1}^{\dim(x_k)} W_{kj}\, x_{\mathbf{k}} + b_j\right) \quad \forall j \tag{3}$$

where $\boldsymbol{W}$ is the matrice with the neural network weights connecting different layers, $\mathbf{b}$ is the bias in each layer, and S is a non-linear logistic sigmoid function.

Basically, this work shows the system composed of the patient and a cyclo-ergometer, analysing the interaction between them. The input of this system is the configured machine resistance profile. The patient's heart rate is the analysed and controlled system output. The final objective of our research line is to design an auxiliary control system for enhancing and optimising patient's cardiovascular exercises. A successful control system has to minimise the risk that is associated with this kind of training, and provide a high degree of adaptability of the cyclo-ergometer resistance during exercises. To design an active control system it is necessary to appropriately identify the whole system in order to calculate the precise reference at any time. Results of the NARX-ANN modelling will be used to implement a control solution into the cyclo-ergometer [32].

On that basis, the first stage to deal with our work is the study of the relationship: cyclo-ergometer/patient. In Soft Computing we have found some paradigms, e.g. artificial neural networks, which can learn complex and non-linear dynamics, as those in our problem [7,5,23]. In order to obtain a system model based on ANN which reproduces the cyclo-ergometer/patient system, a batch of experiments was defined. The measured signals POW and HR have been used to train the NARX multilayer perceptron. Considering that these signals present different levels of magnitude and range, a signal processing stage was defined to adapt each one for use in Neural Network computing. It is commonly used in normalising processes.

Due to the noise that appears in every signal measured with the sensors of the Cardgirus cyclo-ergometer (about 3%), some processing algorithms were employed to filter and normalise all signals, both POW as a HR.

The development with ANN consisted of two phases, one for the neural network learning process, and another for validation of the trained NARX-ANN. In the experiments, the topology of ANNs was changed, selecting different number of neurons in the hidden layer, varying the activation function in neurons, and choosing several sample sets from the signals measured in the cyclo-ergometer experiments. The solutions obtained have been studied statistically through their mean and variance values.

3. Description of the cardiovascular rehabilitation trainings

The rehabilitation training chosen for this work has been selected taking into account its high usefulness in patient cardiovascular problem diagnosis. Moreover, these training profiles provide very representative results which can be used in training designed with several profiles. Both rehabilitation training types, the Conconi test and the Power Step Response test, are presented below.

The first of these is the Conconi test which is a stress test based on short incremental steps. This test calculates the maximum cardiovascular capacity of a person. It consists in gradually increasing the physical effort of a person during the exercise. Little steps of resistance are added to the cyclo-ergometer brake until the person cannot overcome the efforts. At that moment, the individual has reached his/her upper bound capacity effort, changing from an aerobic exercise to an anaerobic exercise, as shown in Fig. 2a. This test sets the maximum cardiovascular state of an individual. Thereby, the relation between the effort and the upper cardiac response of a person is determined by the whole cardiac rhythm interval. A very important feature of this test is that by using short incremental steps, performance loss due to fatigue is avoided. This type of test is always performed under medical supervision, owing to possible risk situations when the cardiovascular limit of a person is reached.

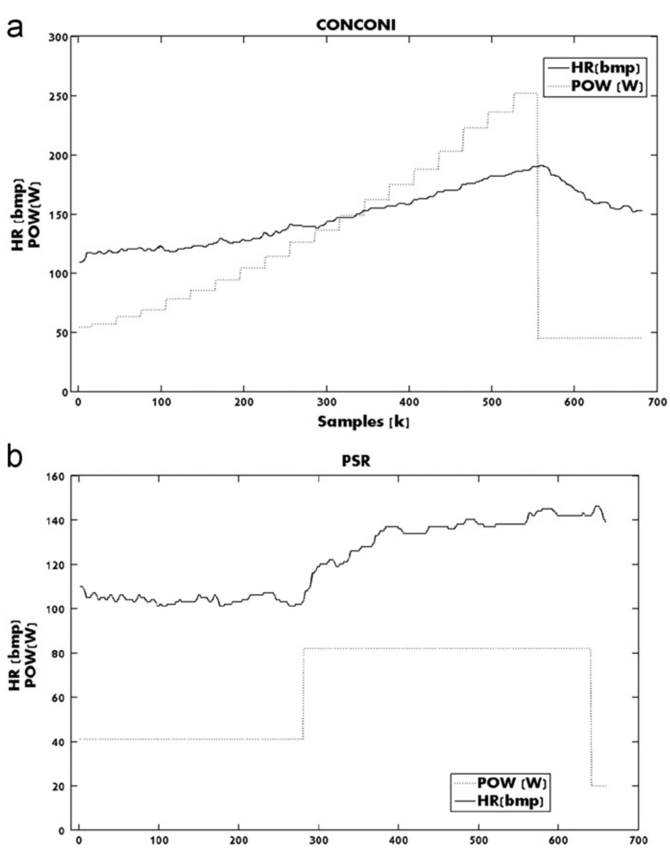


Fig. 2. **(a)** Conconi test, and **(b)** Power step response test.

The other type of stress test to study is the PSR test. This test is divided in two parts in time where the efforts configured are different. The initial part has a low resistance. The second one increases in resistance, usually being double the resistance of the first one, as shown in Fig. 2b. This test presents a longer exercise than the Conconi test. The cardiac rhythm in steady state is studied through a previous low-level effort and later with a moderate effort. In this case, the cardiac rhythm is not forced to its maximum value. The main objective is to obtain information about the cardiovascular system, avoiding the person leave the aerobic exercising interval.

The cyclo-ergometer data from both tests are the HR and POW signals coming out from the device in digitalised format and sampled with a period of one second. Below, are the different units and intervals, for each signal measured:

- Power (POW): 0–3000 W (W).
- Heart rate (HR):30–220 beats per minute (bpm).

In the next section, we present a set of experiments that demonstrate the viability of using NARX-ANN models for cardiovascular rehabilitation system identification. Some figures and tables will show several results for analysing the performance of the NARX models.

4. Tests and results

As mentioned above, the high non-linearity and variability of the system lead to the use of ANN as a solution to the identification problem. In this work, Multilayer Perceptron (MLP) neural networks with external output feedback (NARX) have been selected, which have demonstrated a good performance in similar works as presented by Wahab et al. in [33].

Such an ANN has the capability of identifying highly non-linear systems with significant variability of performance over time, as studied by Menezes et al. in [23]. The structure of a NARX-ANN is similar to the feedforward ones, but with the difference of the previous outputs that are fed back to the input layer. The values in the output layer neuron are the estimated output system values. Then, after the identification process they have to be as close as possible to the real values of the cardiovascular rehabilitation system. The input layer has in its neurons, in addition to output layer values, system input real values measured in previous sample times. The system model order is the maximum number of time delays that are presented as previously estimated system outputs in the feedback [34].

MATLAB programming software has been used in the system identification. A batch of experiments have been developed taking into account different topologies to determine which can be more useful. To this end a neural network with three layers (input, hidden, and output) has been designed, as shown in Fig. 3. In the hidden layer a logistic sigmoid function has been chosen as the neurons' activation function. A linear function has been selected for the neuron of the output layer. During the ANN training the Levenberg–Marquardt algorithm, shown in Eq. 4, has developed good performances in decreasing of the system output estimation error. The LM algorithm calculates the update term for the weights and biases ($\Delta \boldsymbol{W}$) on the basis of the equation (Eq. 4):

$$\Delta W = [J^T(W)\,J(W) + \mu\, I]^{-1} J(W)\, e(W) \tag{4}$$

where $\boldsymbol{W}$ is the weight matrix, $\boldsymbol{I}$ is the identity matrix, μ is a variable parameter and $e(\boldsymbol{W})$ is the error vector on weights ($\boldsymbol{W}$).

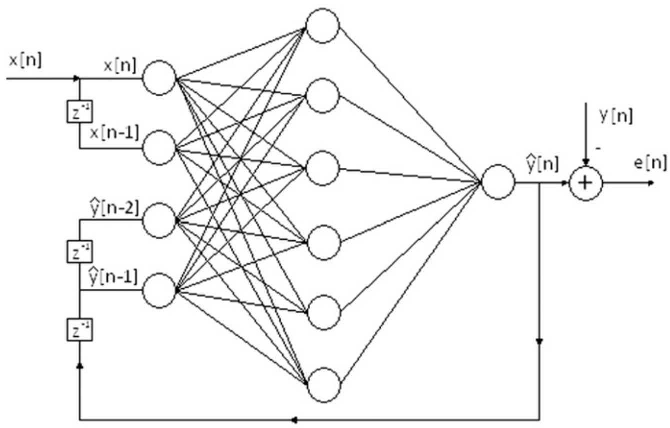
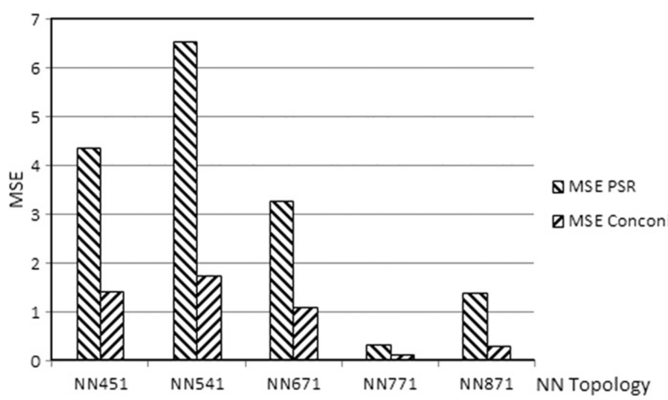


Fig. 3. NARX multilayer perceptron neural network.

Table 1
MSE and covariance values of NARX-ANN topologies trained with data from Conconi and PSR tests.

NN topology	PSR MSE	PSR variance	Conconi MSE	Conconi variance
4–5–1	4,3512	6,5838	1,4304	2,1649
5–4–1	6,5506	9,6915	1,7553	2,4523
6–7–1	3,2634	6,2832	1,0974	3,9769
7–7–1	0,3254	5,1202	0,1171	3,0216
8–7–1	1,3991	6,3993	0,3041	2,2707



Graphic 1. MSE values of NARX-ANN topologies trained with data from Conconi and PSR tests.

To improve the convergence of training in the first epochs, the weight initialisation has been calculated with the proposed work of Irigoyen and Pinzolas [35]. Through this initialisation, a relevant reduction in time has been reached in the batch experiments. This means to assure initial stability of the NARX-ANN training if the initial weight values are accomplished by the equation (Eq. 5):

$$|w_{kl}^{m}| \leq \left[\frac{1}{D}\left(\frac{1}{\prod_{l=1}^{L}(n_l\,\beta_l)}\right)\right]^{1/L} \tag{5}$$

where D is the maximum between the number of delayed inputs and delayed outputs fed into the NARX-ANN, w_{kl}^{m} is every element of each $\boldsymbol{W}$, n_l is the number of neurons on layer l, L is the total number of layers and β_l is 0.25 if layer l is composed of logistic sigmoids, while $\beta_l = 1$ if hyperbolic either tangents or linear neurons are used for that layer.

The first step of the experimental stage is focused on the evaluation of the capability of each NARX-ANN structure for the system identification. Hence, the first data employed in the training of NARX-ANN are taken from the variables measured in the PSR test. This type of aerobic cardiovascular exercise provides essential information for determining the basic cardiovascular performance. For a whole training and validation analysis, two PSR tests of the same length of time are configured, and subsequently performed by the same person. In the second PSR test, bigger resistance steps have been scheduled in order to demand a higher effort. This therefore means a more extensive cardiovascular performance. On the other hand the information obtained from a Conconi test has been used for the training of the neural network. Afterwards, for validation analysis the PSR data obtained in the previous experiment have been used in order to compare results between both.

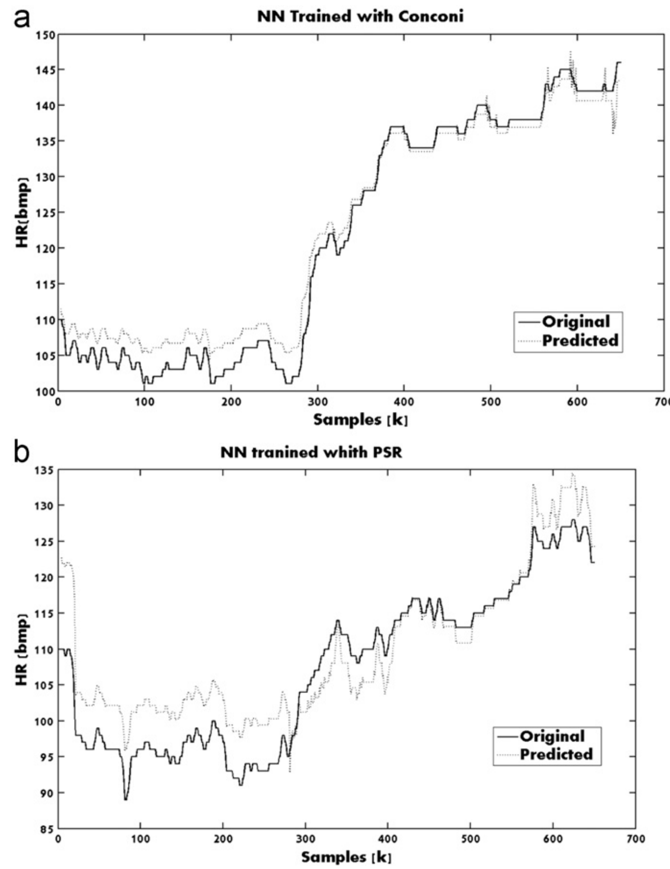


Fig. 4. (**a**) NARX-ANN trained with Conconi Test, and (**b**) NARX-ANN trained with PSR.

We have used the MSE value and the variance value to compare the obtained results, as used in similar studies such as Menezes et al. in "Long-Term Time Series Prediction with the NARX Network: An Empirical Evaluation" [23]. Table 1 and Graphic 1 shows the results after training different neural networks with data from Conconi tests and PSR tests. The main conclusion is that the best results come from the data gathered from the Conconi tests. Fig. 4-a and -b show the simulation results for a NARX-ANN with topology 5–4–1.

5. Conclusions and future works

After carrying out the tests and studying the results of all ANNs used, it can be confirmed that a NARX multilayer perceptron neural network is able to efficiently reproduce the evolution of the heart rate in controlled cardiovascular aerobic training.

The wide range of tests has given good results in configurations where few samples have been used at a time, as well as in the cases where a higher number of samples have been considered. These good results have been reached with both cardiovascular tests, the Power Step Response and Conconi.

Signal filters have provided better values to proceed with the training processes. Also, the neural network weights initialisation has been a good strategy to minimise the ANN training periods, improving the error convergence in those processes.

It has also been observed that the trained ANNs have been able to reproduce the behaviour of a cardiovascular system, showing important changes in the heartbeat when required by the power profile configuration of the machine. This could help to build a more efficient model to control the power of the cardiovascular rehabilitation training, in comparison with the one currently used in the machine for this rehabilitation processes. One of the best structures obtained has been the NARX-ANN with $\{2+3\}-\{7\}-\{1\}$ neurons by layer.

In future work, these results can be employed to analyse and diagnose the development of a cardiovascular system in a patient with health problems. The specialist could estimate the impact that a patient would suffer in case of increasing the difficulty of the rehabilitation training.

Other kind of future exercises can study a series of longer tests (1 h/day a month). These will allow more information to be obtained, such as how the physical condition of a person changes over a period of time. The aim of these exercises will be to control the heartbeat of a person, enabling the machine to adapt itself by varying the resistance level (power) in order to maintain the desired pulse rate. These types of exercises can be recommended for everyone because the machine will be able to automatically control the heart rate of the patient.

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