DEVELOPMENT OF A GREY-BOX CLOSED-LOOP MODEL RELATING TO VOLUNTEERS SUBJECTED TO PHYSICAL STRESS

M.Mahfouf [*], E.Elsamahy and D.A.Linkens

Department of Automatic Control and Systems Engineering
The University of Sheffield, Mappin Street,
Sheffield S1 3JD
The United Kingdom
** Corresponding Author*
Tel: +44 (0) 114 222 5607
Email: m.mahfouf@sheffield.ac.uk

Abstract: Blood is a vital source for delivering oxygen and nutrients to trillions of cells in the body; this makes the function of the cardiovascular system essential to our existence. In the last few years, research interests were directed to exploring its behaviour under different types of stresses, i.e. mental and physical. In this study, we propose a closed-loop model built around the cardiovascular system, and analyse it under physical-stress conditions. In this study, the three signals of interest are: blood pressure, heart rate, and respiration; our proposed model is based on the original Luczak model introduced back in 1975. Three neuro-fuzzy models were elicited and included in the overall control system for generating the blood pressure, heart rate and respiration signals. The estimated signals, generated during simulation, showed good fits when compared with the actual measurements. *Copyright © 2002 IFAC*

Keywords: Fuzzy hybrid modelling, closed-loop systems, biomedical systems.

1. INTRODUCTION

The cardiovascular system is one of the most important systems in the human body. It is responsible for control of blood pressure (BP) and heart rate (HR) through constant regulations to supply the body cells with their needs of oxygen and nutrients. Hence, it is expected that under external perturbations, such as stress or exercise, the function of the cardiovascular system will differ based on new cellular metabolic requirements. In the absence of external perturbations, it might be expected that BP and HR will remain constant, but conversely, there are continuous regulations for BP and HR to meet even the smallest internal perturbations. The most two important signals, which are controlled by the cardiovascular system, are: the BP and HR. The blood pressure changes in response to the contraction and relaxation of the heart muscle. On the other hand, heart rate is controlled by the autonomic nervous system through two branches of effectors: sympathetic and parasympathetic (vagus). Stimulation of the sympathetic branch increases HR and strength of cardiac muscle, which results in increase of BP, while stimulation of the parasympathetic branch decreases HR and strength of cardiac muscle, which results in decrease of BP. The dependency of BP on HR is not the only interaction in the cardiovascular system. It was found that the respiration introduces some disturbances to the blood pressure (Luczak and Raschke, 1975; Luczak *et al.*, 1980). Luczak and Raschke (1975) proposed a closed-loop model to represent the cardiovascular system, and carried out a number of simulations which demonstrated good fits between the estimated HR and BP and the actual ones. Modifications in the model followed in 1980 (Luczak *et al.*, 1980) aimed at matching certain physiological dynamics which exist in the actual HR and BP signals. Figure 1 shows a block diagram of the model which explains the physiological interactions in the cardiovascular system.

Moreover, deBoer *et al.* (1987) introduced a closed-loop model that describes the interaction between the HR and BP control systems on a beat-to-beat basis. In this model, the intervals between heartbeats along both the systolic and diastolic pressures signals were estimated. Whittam *et al.* (2000) introduced a modification to this model in order to improve its performance by extending its ability to match the actual HR and BP signals.

Furthermore, Ohsuga *et al.* (1994) introduced a closed-loop model based on Luczak's model, which was introduced in 1975. The modifications introduced to the original model include the mental load and the optimisation of the constants within it. The modified model improved the estimated signals (HR and BP) under mental load.

In this study, we selected Luczak's first model (Luczak and Raschke, 1975) to be the basis upon which our model, that relates HR, BP, and Respiration, will be built. This model was chosen because of its detailed structure and its ability to include physical and mental stresses. The proposed model focuses on replacing the blocks responsible for generating the HR, BP and Respiration signals with neuro-fuzzy models, to match different subjects' actual measurements and to improve the overall model's interpretability and its ability of generalisation; we labelled the model grey-box because it includes a mixture of white-box models and black-box models.

This paper is organised as follows: Section 2 will discuss the basics of neuro-fuzzy modelling. Section 3 will describe the experimental set-up and the various methods of experiments adopted. Section 4 will introduce the modification applied to the Luczak model and how the neuro-fuzzy models were hence included. Section 5 will present and discuss the simulation results. Finally, in Section 6 conclusions relating to this overall study will be drawn.

2. FUZZY MODELLING

Fuzzy modelling is used as a non-linear method for mapping a certain number of inputs to a certain number of outputs. The two most popular types of fuzzy rules processing are the Mamdani-type and the Sugeno-type. The general form for the two types of rules is given below:

Mamdani: R^i: IF x_1 is A_{i1} and x_2 is A_{i2} and … and x_m is A_{im} THEN y_i is B_i (1)

Sugeno: R^i: IF x_1 is A_{i1} and x_2 is A_{i2} and … and x_m is A_{im} THEN $y_i = f(x_1, x_2, .., x_m)$ (2)

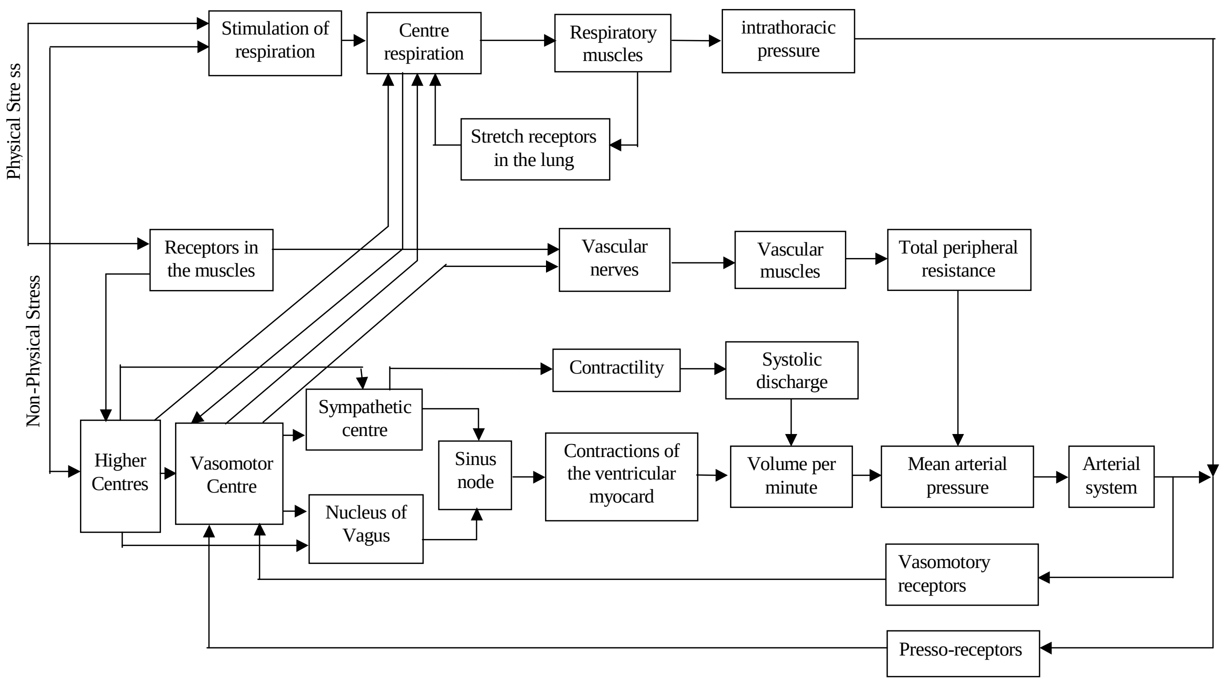

Fig.1. Block Diagram of Luczak's enhanced model (Luczak *et al.*, 1980).

where:

- $(x_1, x_2, \ldots, x_m)$ are the inputs to the system.
- y is the output.
- A_{i1}, A_{i2}, A_{im}, B_i are linguistic labels such as: zero (ZE), negative small (NS), positive big (PB) etc.
- $f(x_1, x_2, \ldots, x_m) = c_0 + c_1x_1 + c_2x_2 + \ldots + c_nx_n$, i.e. a linear function.
- R^i denotes that the above is the i[th] rule in the rule-base.
- $i = 1, 2, \ldots, M$, where M is the number of rules.

It can be seen that, in the Mamdani-type of fuzzy rules processing, both the antecedent (IF) and the consequent (THEN) parts are fuzzy, while in the Sugeno-type of fuzzy rules processing, the consequent part is not fuzzy but a static function, which can either be linear or non-linear.

In our work, we chose the Sugeno-type, because it is able to combine transparency of the rules and the accuracy of the predictions concomitantly. The architecture used here is that belonging to Adaptive Networks-based Fuzzy Inference Systems (ANFIS) (Jang, 1992). It is used for tuning the rules of the fuzzy models automatically. Figure 2 shows the ANFIS structure, which corresponds to a Sugeno-type fuzzy model with two inputs and one output.

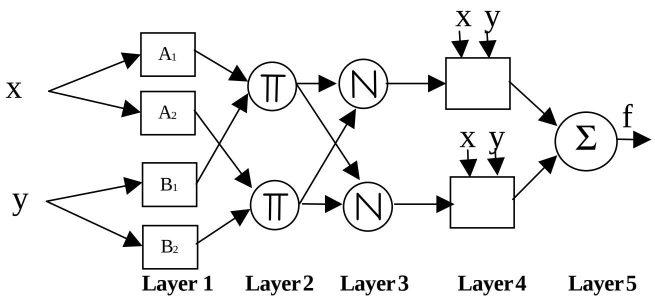

Fig.2. ANFIS Architecture.

As seen in the Figure, this structure consists of five layers that corresponds to the following functions in Sugeno-type fuzzy model:

- Layer 1: It is called the membership functions layer. The output of any node in this layer gives the membership degree of an input (crisp value), A_1, A_2, B_1, and B_2 are the fuzzy membership functions.
- Layer 2: It is called the multiplication layer. Every node here multiplies the inputs of membership degrees and produces the firing strength of the rule.
- Layer 3: It is a normalization layer. It calculates the ratio of the particular rule-firing degree to the sum of all rule degrees.
- Layer 4: This layer applies Sugeno's processing rule and is therefore an output calculating one.
- Layer 5: This layer consists of only one node which calculates the overall output as the sum of all incoming signals.

3. SYSTEM CONFIGURATION

3.1. Experimental Set-Up

The experimental rig used in this study includes:

- A Cateye Ergociser Exercise bicycle.
- An Ohmeda Finapress heart rate and blood pressure monitor.
- A ProComp+ advanced technology system for measurement and data acquisition.
- Two IBM compatible personal computers; one is used to control the workload on the bicycle and acquire signals from both the Finapress and the bicycle, while the other is used for acquiring signals from the ProComp+ system. A schematic diagram of the experimental set-up is shown in Figure 3.

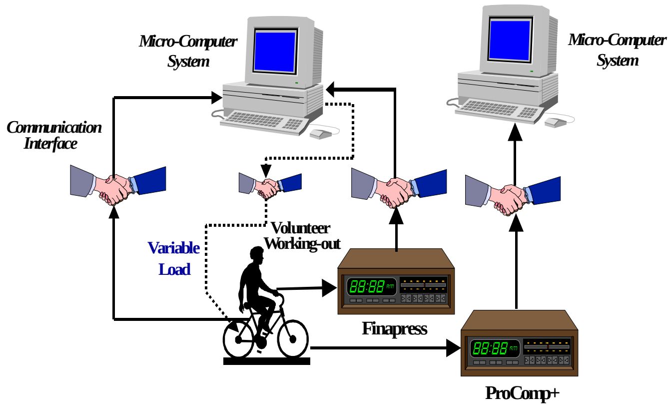

Fig.3. A schematic diagram of the experimental set-up.

3.2. Method

In this study, we chose to represent the physical workload by a sinusoidal wave having the following form.

$$Workload = 1.75 * \sin(2\pi.0.11.t) + 2.25 \qquad (3)$$

These values were chosen to reflect a minimum of 0.5 N.m, and a maximum of 4 N.m workloads as part of the physical constraints of the bicycle. The frequency of 0.11 Hz was chosen to be slightly different from the spontaneous oscillation frequency of the blood pressure control system, which is approximately 0.1 Hz.

The experiment was divided in two parts: First, the volunteer is asked to rest for 5 minutes while we acquire his HR, BP, and respiration values. The volunteer was then asked to start pedalling with a constant speed of 60-70 rpm, which ensures that the effect of the workload was indeed being induced. The experiment lasted for 5 minutes, which is the longest period for which it is reckoned that the human body can maintain its full efficiency under physical stress. The sampling frequency was chosen to be 1 Hz and our data set included 8 volunteers with a mean age of 34 years.

4. MODEL DEVELOPMENT

The main modifications, which were introduced in Luczak's original model, may be summarised as follows:

1. The calculation of the HR signal was previously carried out by the multiplication of the output from the "Stimulation of Respiration" block, which represents the effect of workload on the HR signal, and the output from the presso-receptors, which detect any variations in the blood pressure. The modification is related to the use of the ANFIS model to calculate the same HR using the previously mentioned inputs, as shown in Figure 4.

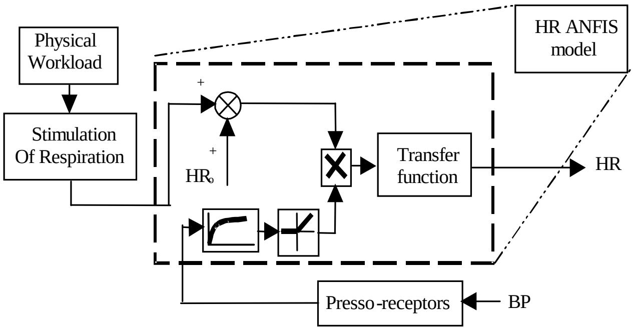

Fig.4. First modification in Luczak's model.

2. The calculation of BP was carried out by multiplying the total peripheral resistance (R_t) and the blood volume per minute, which is the blood flow (Q). In this case, the modification lies in the use of the ANFIS model to calculate the BP from the two previously mentioned inputs as shown in Figure 5.

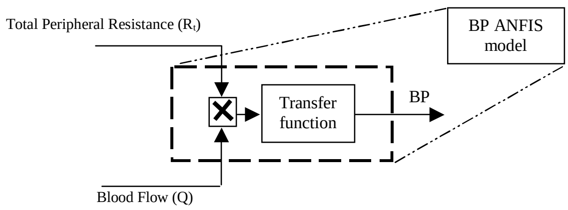

Fig.5. Second modification in Luczak's model.

3. The calculation of the Respiration was carried out by generating a signal with a frequency of 0.3 Hz, and by adding the effect of physical stress through the "Stimulation of Respiration" block. The modification lies in the use of the ANFIS model to calculate the Respiration through physical stress, as shown in Figure 6.

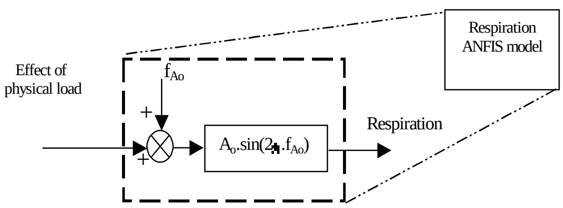

Fig.6. Third modification in Luczak's model.

The process of building the ANFIS models was carried out as follows: The data records, during rest and under workload conditions were divied into two groups, training and testing, with a ratio of 2:1. The training set was constructed such that 2 samples are taken and one is discarded, which will be used for the testing set, until the end of the data record, which consists of 300 samples. Subtractive clustering, (Chiu, 1994), was selecting as a pre-processing operation. The ANFIS model includes time as an extra input to characterise the dynamic nature of the models and to improve the predictions. Table 1 shows the inputs used in each of the three ANFIS models.

Table 1 Inputs used in the three ANFIS models

Input No.	HR ANFIS model	BP ANFIS model	Respiration ANFIS model
1	Workload effect	Resistence (R_t)	Workload effect
2	Presso-receptors reflexes	Flow (Q)	Delayed Load effect (1 sec.)
3	Time	Time	Time

5. SIMULATION RESULTS

First, Figure 7 shows the simulation results under stress. Table 2 shows the mean square errors (MSE's) between the actual and estimated signals.

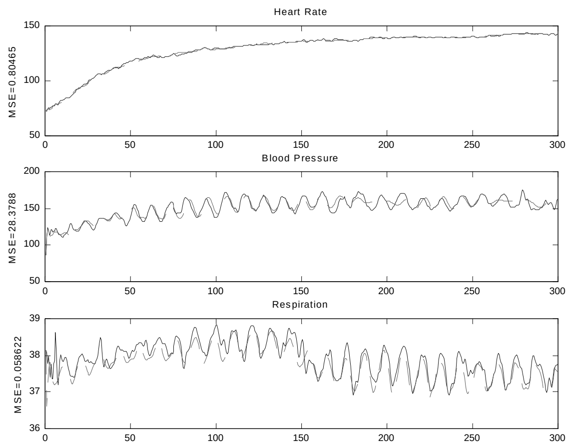

Fig.7. Simulation results for one volunteer under stress before tuning.

Table 2 MSE between actual and estimated signals for one volunteer

Volunteer condition	HR	BP	Respiration
Under stress	0.8047	28.379	0.058622

From Table 2, it can be seen that the three ANFIS models could estimate the three signals reasonably well with small MSE's, except for BP (see middle graph). The MSE relating to the estimated BP signal is relatively large because of its high fluctuations, which makes it difficult for the ANFIS model to capture all the dynamics in the signal.

The stability as well as the accuracy of the ANFIS models are very important issues that can affect the simulation results. By inspecting the 3D surface of one ANFIS model (Respiration model), as shown in Figure 8, some regions revealed the existence of values of the output which were outside the actual range.

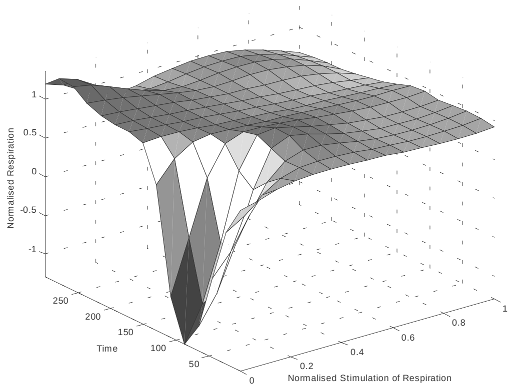

Fig.8. 3D-surface of Respiration ANFIS model between Flow (Q) and Time before tuning.

Hence, a fine-tuning process was performed in which the disrupting rules were removed, (Castellano and Fanelli, 1997). A rule removal includes the removal of corresponding MFs from the input space. Table 3 shows the result of the fine-tuning operation the ANFIS models in terms of the MSE's and the number of rules.

Table 3 MSE and number of rules for the ANFIS model before and after fine-tuning

ANFIS model		HR	BP	Respiration
Before fine-tuning	MSE	1.0216	17.37	0.0302
	No. of rules	9	13	18
After fine-tuning	MSE	1.0216	17.09	0.0320
	No. of rules	9	9	7

From the previous Table, it can be seen that a large reduction in the number of rules for the ANFIS-based Respiration model, from 21 to 7, with a slight decrease in the MSE against the training set have been achieved. Also, another reduction in the number of rules for the ANFIS-based BP model, with a slight improvement in the MSE have also been achieved. However, the ANFIS-based HR model showed no further improvement. A tuned 3D surface for the ANFIS-based Respiration model is shown in Figure 9.

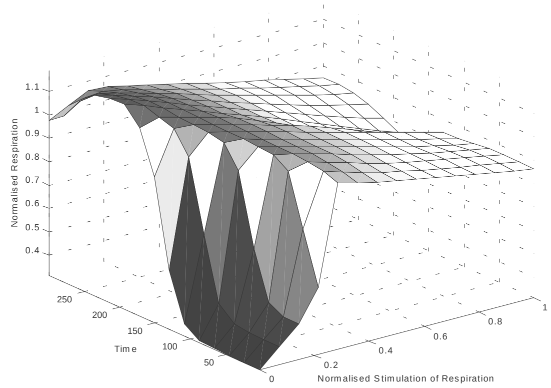

Fig.9. 3D-surface of Respiration ANFIS model between Flow (Q) and Time after tuning.

Figure 9 shows the disappearance of the negative values in the BP with a slight change in the surface of the ANFIS model. Any further fine-tuning will result in a significant deterioration in the performance of the ANFIS model with an increase in the MSE between the actual and estimated signals.

Another simulation with the three tuned ANFIS models is shown in Figure 10. Table 4 summarizes the MSE values between actual and estimated signals.

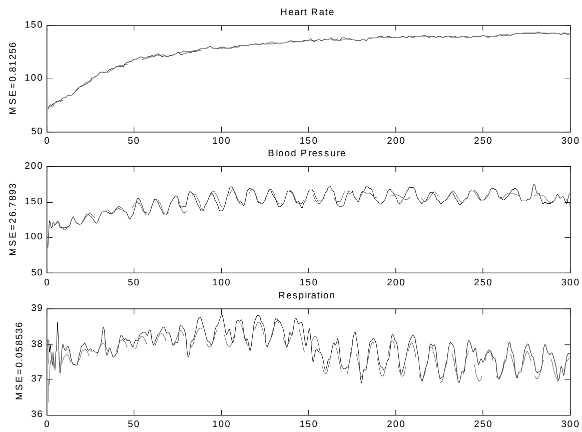

Fig.10. Simulation results for one volunteer under stress after tuning.

Table 4 MSE between actual and estimated signals for one volunteer after fine-tuning

Volunteer condition	HR	BP	Respiration
Under stress	0.8126	26.789	0.05854

From the results of Table 4 and comparing them with those of Table 2, it can be seen that there is a reduction in the MSE value for the BP signal, (see Table 3) and a reduction in the MSE of the training set.
Also, There is a slight reduction in the MSE for the Respiration, in spite of the increase in the MSE of the

training set. Although fine-tuning did not introduce much reduction in the MSE values of the estimated signals, these values are within acceptable ranges. Also, fine-tuning improved the stability of the three ANFIS-based models which is essential for our proposed closed-loop model. Figure 11 displays the overall grey-box closed-loop model with respect to physical workload.

6. CONCLUSION

In this study we proposed a closed-loop model relating to the cardiovascular system of humans who were subjected to physical stress. The model was of a grey-box nature as it included white-box and black-box models, such a hybrid representation, we think, is justified as interpretability and accuracy need to be targeted at specific components within such a complex structure which is the human body. Consequently, we succeeded in establishing an experimental set-up capable of generating the necessary data for mining and eliciting the models to provide good estimates. More research is underway to complete the whole modelling structure by including mental stress and finally comparing the whole hybrid structure to the original Luczak model (1980).

REFERENCES

Castellano, G. and A. M. Fanelli (1997). An Approach to Structure Identification of Fuzzy Models. *Sixth IEEE International Conference on Fuzzy Systems*, Barcelnoa, Spain, **1**, 531-536.

Chiu, S. L. (1994). Fuzzy Model Identification based on Cluster Estimation. *Journal of Intelligent and Fuzzy Systems*, **2**(3), 267-278.

deBoer, R. W., J. M. Karemaker and J. Strackee (1987). Hemodynamics Fluctuations and Baroreflex Sensitivity in humans: a Beat-to-Beat Model. *American Journal of Physiology*, **253**, H680-9.

Jang, J.-S. R. (1992). Neuro-fuzzy Modeling: Architecture, Analyses and Applications, PhD, University of California.

Luczak, H. and F. Raschke (1975). A Model of the Structure and the Behavior of Human Heart Rate Control. *Biological Cybernetics*, **18**: 1-13.

Luczak, H., U. Philipp and W. Rohmert (1980). Decomposition of Heart -Rate Variability under the Ergonomic aspects of Stressos Analysis. In: *The Study of Heart Rate Variability*. (R. I. Kitney, Ed.), 123-153. Oxford Science Publications: Clarendon Press.

Ohsuga, M., H. Terashita, F. Shimono and M. Toda (1994). Assessment of mental workload based on the model of autonomic regulations on cardiovascular system. *The 16th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, New York, USA, **2**, 1156-7.

Whittam, A. M., R. H. Clayton, S. W. Lord, J. M. McComb and A. Murray (2000). Heart Rate and Blood Pressure Variability in Normal subjects Compared with data from Beat-to-Beat Models developed from deBoer's Model of the Cardiovascular System. *Physiological Measurements*, **21**, 305-318.

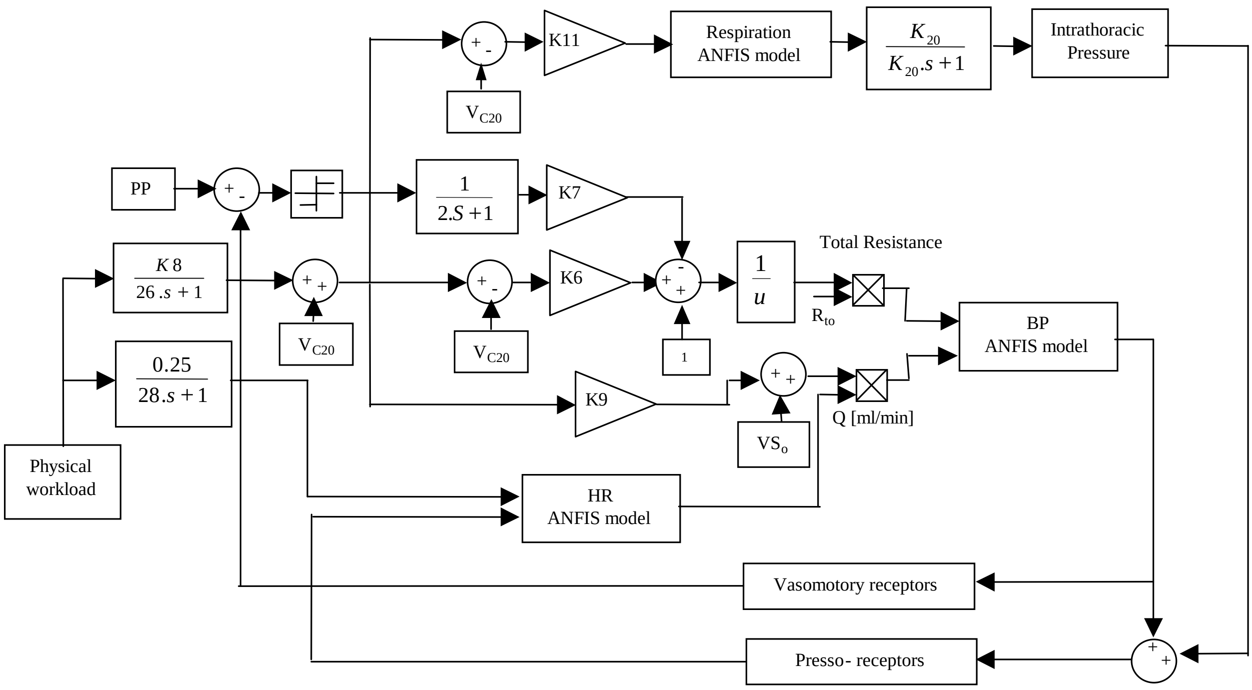

Fig.11. The Neuro-fuzzy based closed-loop model.