A GENERIC CLOSED-LOOP MODEL FOR THE CARDIOVASCULAR SYSTEM THERMOREGULATION AND BRAIN ACTIVITY UNDER PHYSICAL STRESS CONDITIONS

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
Tel: +44 (0) 114 222 5607
Email: m.mahfouf@sheffield.ac.uk

Abstract: In this study, a closed-loop model, which includes the cardiovascular, the respiratory and the thermoregulatory systems under physical stress conditions, is presented. The proposed model is based on a 'classical' approach first proposed in the 1970's. Moreover, a simplified model to describe the brain activity, via EEG signals, is also included. The proposed model is based on a grey-box modelling approach, utilising several neural-fuzzy structures, which were used because of the sufficient level of details that they provide. A higher level, represented by a neural network, was hierarchically superimposed on the overall model to produce a 'generic' cardiovascular model which is able to predict a wide range of dynamics associated with previously 'unseen' (new) subjects. Model predictions proved very good when compared with the actual signals obtained under real-time conditions.

Keywords: Stress, Neuro-Fuzzy, Modelling, Generic, cardiovascular, EEG, Thermoregulation.

1. INTRODUCTION

The adequate functioning of the cardiovascular system is very important for our homeostasis. This latter is responsible for the control of blood pressure (BP) and heart rate (HR) through the corresponding brain centres to supply the body cells with their needs for oxygen and nutrients under various conditions. Hence, it is expected that under external perturbations, for example, such as stress or exercise, its function and various interactions with other systems will differ based on new cellular metabolic requirements. In the absence of these 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 of such disturbances. The blood pressure changes in response to the contraction and relaxation of the heart muscle as well as the instantaneous heart rate (beats/min). This is referred to as the "quick control loop" of the blood pressure (Luczak *et al*, 1980). In addition, the vasodilation and vasoconstriction of vessels alter the BP, which is controlled by the vasomotor centre in the brain, and this is referred to as the "slow control loop" of the blood pressure (Luczak *et al*, 1980). On the other hand, HR is controlled by the autonomic nervous system through two branches of effectors: sympathetic and parasympathetic (vagus) fibres. These two fibres are monitored and controlled via the cardiac centre in the brain. Stimulation of the sympathetic branch increases the HR as well as the strength of the cardiac muscle, which will result in an increase of BP, while the stimulation of the parasympathetic branch decreases the HR as well as the strength of the cardiac muscle, which in turn results in a decrease of BP. It has been found that the respiration (RESP) signal, which is controlled by the respiratory centre, acts as a disturbance to BP (Luczak and Raschke, 1975; Luczak *et al*, 1980). Furthermore, the body temperature (TEMP) affects BP either through vasodilation to release the excess of heat, or by vasoconstriction to reserve heat, since preserving a constant body internal temperature is essential for certain metabolic reactions (Huizenga *et al*, 2001).

Luczak and Raschke (1975) proposed a closed-loop model to represent the cardiovascular system and to explore the interactions between the cardiovascular and respiration systems. Certain modifications to this model followed in 1980 (Luczak *et al*, 1980), aimed at matching certain physiological dynamics which exist in the actual HR and BP signals.

In order to establish a detailed model that can faithfully represent the cardiovascular with most of its interactions with other control systems, a closed-loop representation for the cardiovascular system based on Luczak's model and the thermoregulatory system based on Stolwijk's model (Konz *et al*, 1977) as well as the brain is elicited in this research. The model represents a combination of white, black, and grey box representations. The grey-box models were in the form of neuro-fuzzy systems for generating the HR, BP and TEMP signals, while a fuzzy-ARX model was used for generating RESP. The proposed model for the EEG signal generation was elicited using the Phase-Locking technique (Palus, 1997). This is the theme of this research paper which is organised as follows: Section 2 reviews the experimental set-up as well a brief introduction to the modelling tools used in the study, including the neural fuzzy based modelling architectures. Section 3 introduces the new modifications which are introduced to the classical model as originally proposed by Luczak and Raschke, while Section 4 describes the extensions to the model in the form of the EEG and an intelligent supervisory layers. Finally, Section 5 draws some conclusions in relation to the overall study.

2. SYSTEM CONFIGURATION AND FUZZY LOGIC BASED MODELLING

2.1 Materials and Methods

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 for acquisition of respiration and temperature signals.

Two IBM compatible personal computers (PC's); 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 Fig. 1.

In this study, the applied physical workload was chosen to be a sinusoidal wave having the following form.

$$Workload = 0.75 * \sin(2\pi 0.091t) + 1.25 \tag{1}$$

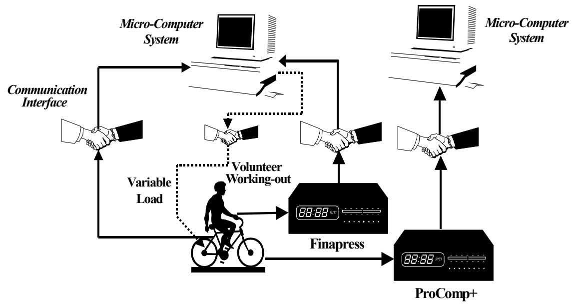

Fig. 1 The experimental set-up

Where " *t"* is the sampling time and "*workload"* is the applied exercise profile.

These values were chosen to reflect a minimum of 0.5 Nm, and a maximum of 2 Nm workloads. These limits were found to be sufficient to excite the cardiovascular and thermoregulatory systems without exhausting the subject during the period of the experiment. This period was chosen to be 5 minutes, which is the reasonable period for which it is reckoned that the human body can maintain its full efficiency under physical stress. The workload frequency was chosen to be slightly different from the spontaneous oscillation frequency of the blood pressure control system, which is approximately 0.1 Hz. The existence of such frequency (0.091 Hz) in the blood pressure spectrum was used to check for the blood pressure entrainment to ensure the full transmission of the workload effect to the cardiovascular system. The volunteer was asked to pedal with a constant speed of 60-70 rpm, which ensures that the effect of the workload was indeed being induced. The sampling frequency was chosen to be 2 Hz, to account for the increase in the respiration frequency under physical stress. Our data set included 12 subjects with an average age of 34 years.

2.2 Fuzzy Modelling

Two types of fuzzy-based models were used in the proposed closed-loop model, which are the neuro-fuzzy and fuzzy-ARX. The neuro-fuzzy model has been widely used during the last decade in many applications such as system identification and control, and it has shown good results. The neuro-fuzzy model is used as a non-linear method for mapping a certain number of inputs to a certain number of outputs. The two most popular fuzzy rules processing are the Mamdani-type (Mamdani, 1974) and the Sugeno-type (Takagi and Sugeno, 1985).

In the Mamdani-type of fuzzy rules processing, both the antecedent (IF) and the consequent (THEN) parts are fuzzy, while in Sugeno-type the consequent part is not fuzzy but a static function, which can either be linear or non-linear. The architecture used in this work is that belonging to ANFIS (Adaptive Networks-based Fuzzy Inference Systems) (Jang, 1992; Chen and Linknes, 1998). It is used for tuning the rules of the fuzzy-based model automatically.
The fuzzy-ARX model, as its name implies, combines both the fuzzy interpretation of the inputs through a number of membership functions and the ARX model. This model, with a second order ARX structure, has the following representation of rules:

$$
\begin{aligned}
&R^{(i)}: IF\ u\ is\ A_i\ \ THEN\\
&y(t+1) = -a_1^{(i)} y(t) - a_2^{(i)} y(t-1) + b_1^{(i)} u(t) \\
&\qquad + b_2^{(i)} u(t-1)
\end{aligned} \tag{2}
$$

where:
u is the input to the system.
y is the output of the system.
A_i is a linguistic label such as: zero (ZE), negative small (NS), positive big (PB), etc.

$R^{(i)}$ denotes the i^{th} rule in the rule-base, $i = 1, 2, \ldots, M$ and M is the number of rules.

3. MODEL DEVELOPMENT

3.1 Modification of the Original Luczak Model

The development of the model is based on the use of both the ANFIS and fuzzy-ARX models to account for the subject differences. Therefore, the main modifications, which were introduced in Luczak's original model, may be summarised as follows:
1. The calculation of the HR signal was carried-out by the multiplication of the sympathetic and vagal branches which are responsible for increasing and decreasing the HR respectively. The modification is related to the use of an ANFIS model to calculate HR using the output from the receptors in muscles block which represents the effect of workload on varying the HR signal; and the output from the presso-receptors which detect any variations in the blood pressure (see Fig. 2).

2. The calculation of the BP signal was carried-out by multiplying the total peripheral resistance and the blood volume per minute which is the blood flow. In this case, the modification lies in the use of an ANFIS model to calculate the BP from the two previously mentioned inputs.

3. The respiration signal was originally represented in Luczak's first model as a sinusoidal signal with a frequency of 0.25 Hz (16 breaths/minute) which increases under the effect of physical stress.

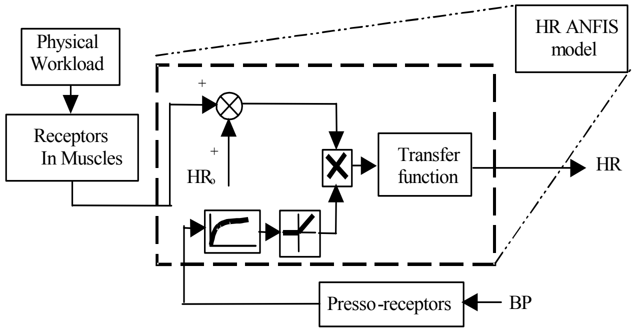

Fig. 2 First modification carried-out on the original Luczak model

4. The inclusion of the thermoregulatory system in the closed-loop model to show its interactions with the cardiovascular system with the addition of an ANFIS model for the generation of the temperature signal (see Fig. 3).

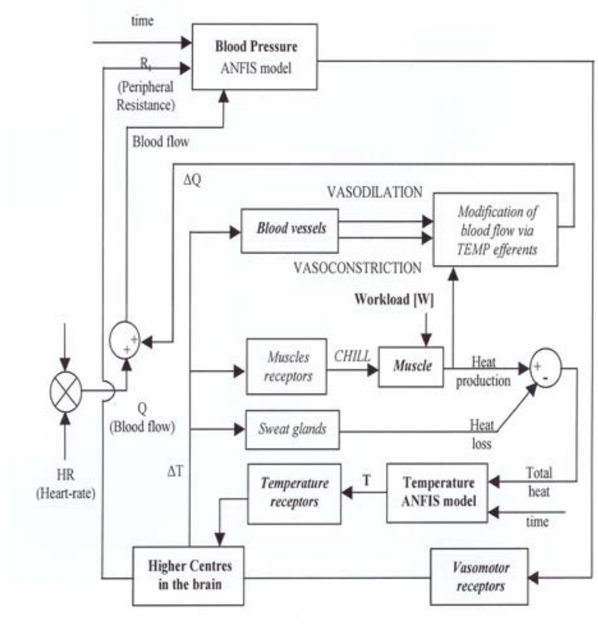

Fig. 3 The proposed thermoregulation model

5. The process of building the ANFIS models was carried out as follows: The data records were divided 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 until the end of the data record which consists of 600 samples.

However, since this process includes a down-sampling for the original data set, this procedure could not be applied to the testing set otherwise some dynamics will disappear from the testing set. Therefore, the testing data set was constructed as the training data set and the left samples during the construction of the training set. Neural networks based clustering was selected as a pre-processing operation to estimate an optimal number of clusters that can efficiently represent the mapping between the input and output. The ANFIS model includes time as an extra input to characterise the dynamic nature of the models and to improve the predictions.

3.2 Results

The closed-loop simulation using the proposed model with the physical stress as the only input for the system for all the subjects, led the frequency spectra of Fig. 4. This figure shows how the estimated signals captured the most important dynamics which existed in the actual (measured) ones. These dynamics are: the workload frequency (0.091 Hz), which is an indication for the blood pressure entrainment at that frequency, and the respiration frequency spread. In turn, Fig. 5 displays the 3D-surface relating to the thermoregulation model which highlights the non-linear nature of the associated interactions.

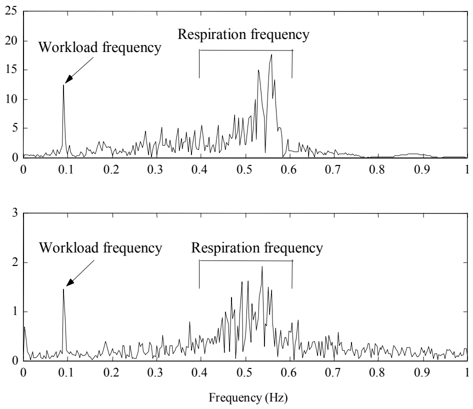

Fig. 4 The actual RESP (top) versus the estimated RESP (bottom) frequency spectra

4. MODEL EXTENSIONS

4.1 A simplified EEG Model

It is well known that the EEG signal, which can be measured on the surface of the scalp, includes the various components relating to all parts of the brain. In order to simplify the identification process, a model that estimates the EEG signal from other signals generated within the cardiovascular closed-loop model will be identified. This model is based on a phenomenon called "phase locking" which was found to exist between the EEG signal and other signals within the human body. If two interacting oscillators coexisted then they are *N: M* phase locked, if marked events of one oscillator occur at fixed phases of the other oscillator (Palus, 1997).

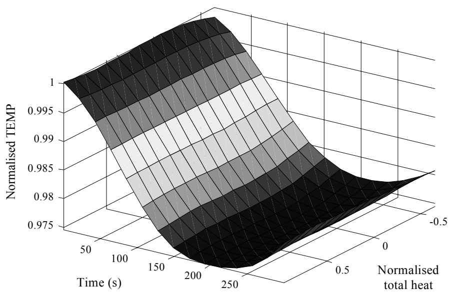

Fig. 5 A 3D-surface relating to the TEMP neural-fuzzy model inputs/output mapping

As a consequence, *N* period of the first rhythm will have the same duration of *M* periods of the second.
This phase synchronisation condition implies also frequency synchronisation between the two rhythms. Therefore, the spectrum of the EEG signal was compared to the spectra of all the signals generated from the closed-loop model, which are: HR, HP, RESP, and TEMP. A pre-processing phase was firstly applied to the EEG signal in order to remove the existing noise, which was carried-out in the following steps:

- A fifth order low-pass Butterworth filter with a cut-off frequency of 32 Hz, was applied to the EEG signal to remove the 50 Hz noise corresponding to the electrical mains.
- The resultant EEG signal was down-sampled from 256 Hz (the original sampling frequency) to 64 Hz.

The results of the spectra comparison (see Fig. 6) revealed that there exist phase locking between the EEG spectrum and the RESP, BP, and TEMP spectra. On the other hand, there was no phase locking between the EEG and the HR spectra. It is worth noting that the differences in magnitude between the estimated and measured RESP signals were due to the fact that the RESP sub-model was identified as a one-step ahead predictor but was used as a full predictor in the closed-loop model.

4.2 A Generic Cardiovascular Model

In order to allow the model to represent the behaviour of a wide range of subjects' dynamics under physical stress **without the need for parameters re-tuning**, the previously elicited model was extended by including an intelligent layer whose main function is to map some features, which are primarily extracted from the actual measurements, to the parameters which were extracted from all the constructed models over all subjects. These include the rise-time, peak-to-peak magnitude, and mean values for HR, BP, and TEMP. The Euclidian Distance is then used as a index measure to decide to which cluster of model parameters the ‘unseen’ (new) subject pertained to. Feature mapping was realised via neural network architectures. Although three types of neural network based intelligent layers were investigated, the Generalised regression neural network (GRNN) was retained as the best candidate. Each network included 1 input layer, two hidden layers having radial basis activation functions for the first one and a linear activation function for the second one, with only biases connected to the first hidden layer, and one output layer.

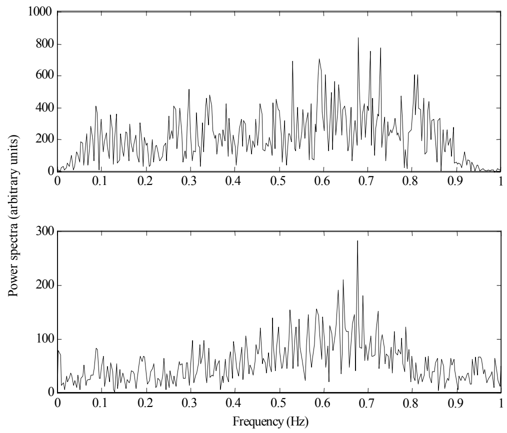

Fig.6 The actual EEG (top) versus the estimated EEG frequency spectra (bottom)

Fig. 7 shows the structure of the intelligent layer which is used for estimating the five models’ parameters for ‘unseen’ (new) subjects.

In order to assess the model prediction performance a validation test was carried out over the 4 subjects of the second group of measurements. The validation results showed good performances from the qualitative point of view. In other words, the selected models represent qualitatively and to a high extent many of the dynamics associated with the new (unseen) subjects. Fig. 8 shows the estimated signal for one subject from the validation group. From this figure, it can be seen that the selected models succeeded in estimating a qualitative representation for the behaviour of the unseen subject for the HR, BP, RESP, and TEMP signals.

It is worth noting that in spite of the difference in amplitude between the actual and estimated RESP signals, the estimated signals were still able to capture the respiration frequency with a good accuracy. In addition, the estimated EEG signal could capture most of the dominant peaks which existed in the actual EEG signal with a good accuracy despite the simplicity of the EEG model structure.

5. CONCLUSIONS

The proposed closed-loop model succeeded in describing the interactions between the cardiovascular system and the other control systems such as respiratory and thermoregulatory. The proposed simplified model for EEG signal provides an acceptable approximation for that signal based on the existing phase locking phenomenon between the EEG and HP, RESP, and TEMP signals. The model has been validated against actual experimental data both in the time and frequency domains and it shows an acceptable accuracy in estimating these signals in both domains.

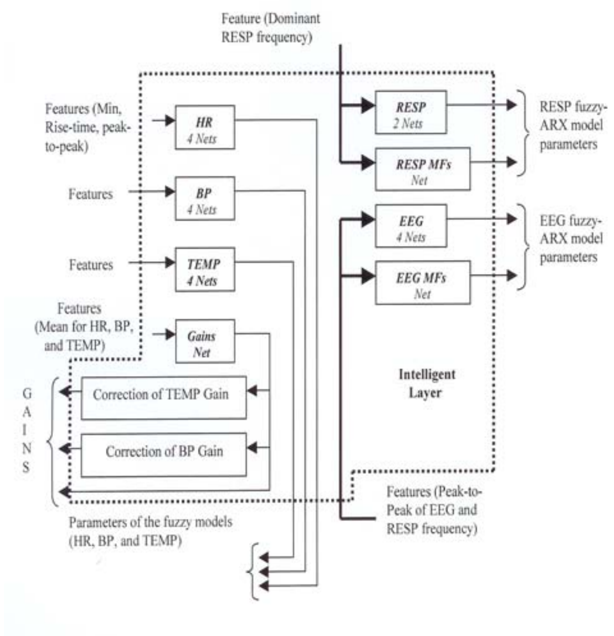

Fig. 7 A schematic diagram of the intelligent layer which predicts the model parameters; ‘MF’ refers to Membership Function

Results show that the cardiovascular model is able to successfully represent the pathways which connect the various control systems and that makes it a good base for extension to include other control systems such as skin conductance This study can be extended to investigate the effect of other types of stresses such as the mental stress on the performance of subjects under test. Additionally, the new added intelligent layer extend the abilities of the model to be able to predict many of the dynamics associated with the cardiovascular system of new (unseen) subjects in a qualitative manner. It is hoped to model the effect of psychological stress in the near future.

REFERENCES

Chen M-Y and Linkens D. A. (1998), A fast fuzzy modelling approach using clustering neural networks, *IEEE World Congress on Computational Intelligence,* New York (USA).

Huizenga C., Zhang H., and Arens E. (2001), A Model of human physiology and comfort for assessing complex thermal environment, *Building and Environment*, **36**, p. 691-699.

Jang J-S R. (1992), Neuro-fuzzy Modeling: Architecture, Analyses and Applications, Electrical Engineering and Computer Science. Berkeley: University of California, 155 pages.

Konz S., Hwang C., Dhiman B., Duncan J., and Masud A. (1977), An Experimental Validation of Mathematical Simulation of Human Thermoregulation, *Computers in Biology and Medicine*, **7**, p. 71-82.

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

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

Mamdani E.H. (1974), Application of fuzzy algorithms for control of simple dynamic plant, *Proceedings IEEE,* **121**, p. 1585-8.

Palus M. (1997), Detecting Phase Synchronization in Noisy Systems, *Physics Letters **A**.* **235**, p. 341-351.

Takagi T. and Sugeno M. (1985), Fuzzy Identification of Systems and its Applications to Modeling and Control, *IEEE Transactions on Systems, Man, and Cybernetics.* **SMC15**, p. 116-132.

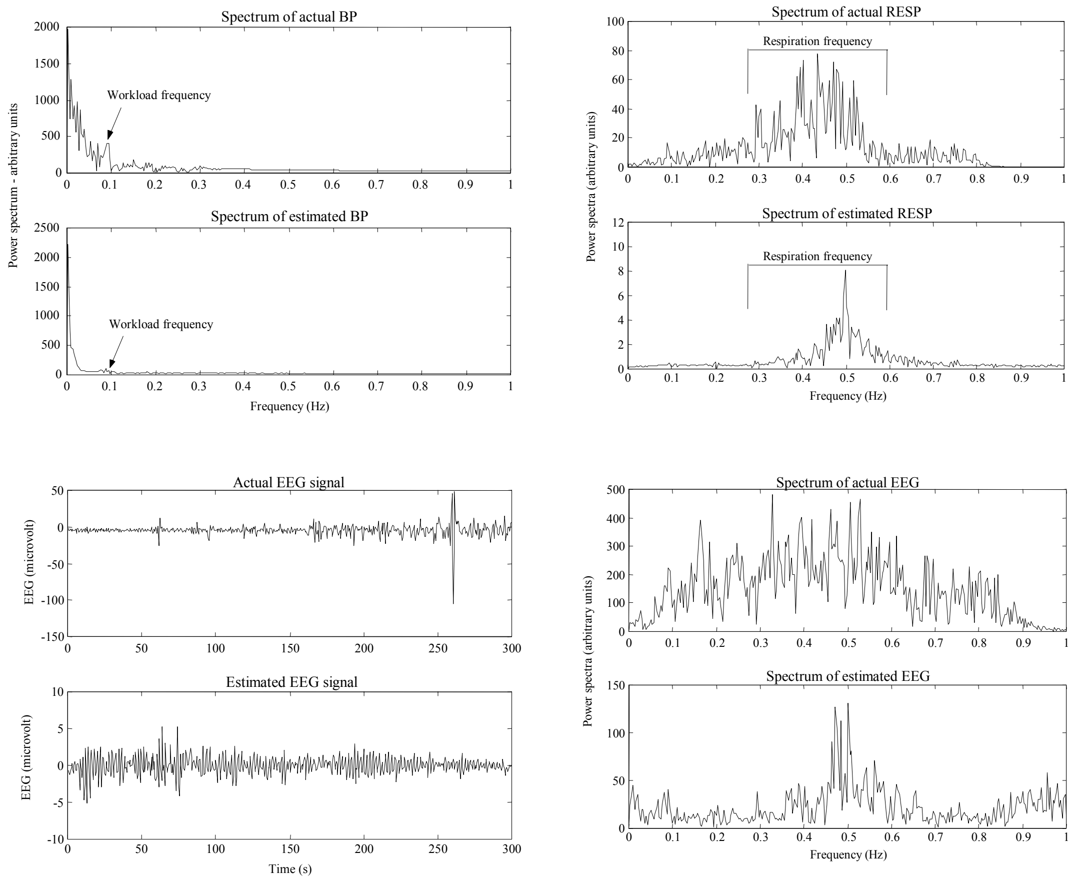

Fig. 8 The actual *versus* the estimated (black) frequency spectra signals for a previously ‘unseen’ subject with the final intelligent layer included in the model